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The effect of influencers on brand image and TikTok users' intention to purchase fashion and beauty products, and comparison with YouTube and Instagram.

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Academic year 2022-2023
Master [120] in Management with professional focus
Daytime schedule

Abstract:

Social media influencers have the ability to provide companies with access to new audiences by using their personal brand to promote products. This thesis investigates influencer's attributes and perceived characterizations made by followers. It tests whether those have a positive impact on brand image and intention to purchase fashion and beauty products on TikTok, Instagram and YouTube. Additionally, a comparative analysis is conducted to evaluate the differences between these social networks. The attributes of influencers considered in this study encompass attitude homophily, physical and social attractiveness, while the perceived characterizations made by followers include the credibility of influencers and the para-social relationship they develop with their followers. To answer our research question, an online quantitative study was conducted in the French-speaking part of Belgium. As could be expected based on the existing literature, the results show that brand image, credibility and para-social relationship have a positive effect on intention to purchase fashion and beauty products on those platforms, and brand image mediates the relationship between credibility and purchase intention. However, contrary to previous studies, the findings indicate that credibility has a greater positive impact on purchase intention compared to PSR, suggesting that the arguments presented by influencers carry more weight than the relationships developed between them and their followers. Results also confirm what has been found before as both attitude homophily and physical attractiveness positively impact credibility. Additionally, the impact of attitude homophily and physical attractiveness on brand image and purchase intention is mediated by credibility. Para-social relationship is also positively impacted by attitude homophily, physical and social attractiveness. Moreover, the effect of attitude homophily, physical attractiveness and social attractiveness on purchase intention is mediated by para-social relationship. This thesis found that attitude homophily has a bigger impact on PSR than social and physical attractiveness, which differs from prior research where social attractiveness was found to play a more prominent role in predicting PSR. Interestingly, physical attractiveness, both as predictor for credibility and para-social relationship, is not as influential as other influencer's attributes.

First of all, I would like to thank my supervisor Dr. Isabelle Schuiling for her time, help and valuable advice throughout the writing of my thesis. Thanks to her, I was able to write in a more rigorous and detailed way.

Then, I would like to thank Mrs. Louise Dumont for her support in the quantitative part of my thesis.

A special thanks is given to all respondents of my survey without whom this thesis would not have been possible.

I would also like to thank my girlfriend for her continuous support and proofreading of the following thesis.

Last but not least, I would like to thank my parents and my brother for believing in my abilities to succeed and supporting me during all those years at university.

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1. Introduction

Nowadays, while performances of traditional channels seem to decrease (Weinswig, 2016), social media represent an important channel for brands to reach consumers instantly (Lee & Watkins, 2016). Research shows in fact that 54% of consumers recognize using social media to search for products and services (Chidiac & Bowden, 2022). Influencers, who actively engage on social media, therefore represent a growing industry. The size of the global market of influencer marketing reached US$148 million in 2019 and is expected to surpass US$373 million by 2027 (Ozuem & Willis, 2022). In 2021, 71% of marketers planned to increase their spending in influencer marketing (Linqia, 2021).

A few years ago, influencer marketing was predominantly associated with the Instagram platform. According to 89% of marketers, Instagram was indeed the most important platform for influencer marketing in 2019 (Linqia, 2021). This trend is well-reflected in the existing literature, as the impact of influencers' attributes (i.e., attributes that influencers have and show) and the impact of characterizations made by followers (i.e., how followers perceive influencers) on followers' purchase intention have mostly been studied on Instagram, and occasionally on YouTube (Masuda et al., 2022). However, a newcomer appeared in 2018 and rapidly experienced a huge growth since its introduction. TikTok has indeed become one of the most prominent social networks, counting more than one billions of active users per month (Geyser, 2022).

As a result, a gap exists in the literature, necessitating further investigation into this short video oriented-platform as well as a comparative analysis of the impacts of perceived characterizations and influencers' attributes on purchase intention on TikTok with Instagram and YouTube. This thesis therefore aims to study this, while also focusing on the fields of fashion and beauty. This choice is motivated by the fact that, with more than 257 billion and 176 billion views respectively, fashion and beauty videos are very popular on TikTok[1]. This is also true on Instagram where 1 billion of posts include the fashion hashtag and 519 million the beauty hashtag[2]. The research question of this thesis is therefore as follows:

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[1] TikTok. (n.d.). Online https://www.tiktok.com , consulted on 18 April 2023.
[2] Instagram. (n.d.). Online https://www.instagram.com , consulted on 18 April 2023.

> How do influencers attributes and perceived characterizations affect brand image and TikTok users' intention to purchase fashion and beauty products, and how does it differ from YouTube and Instagram?

Section 2 of this thesis presents the review of literature which is divided into six subsections that discuss previous studies on the topic and introduce relevant theoretical concepts. Based on the literature discussed, research hypotheses are developed as well. Section 3 then moves on to present the methodology and the results of the quantitative study. This section is particularly useful to test the hypotheses developed in the previous section. Finally, Section 4 attempts to make connections between the results of this thesis and the existing literature, and to explore managerial implications and limits.

2. Literature review

This literature review aims to provide the necessary theoretical background for the analysis. The first subchapter (Section 2.1) presents the concepts that will be discussed in this thesis. Those include the concepts of social media, social media marketing, social media influencers and social media influencer marketing. Then, the second subchapter (Section 2.2) gives an overview of the three socials networks that will be analysed, namely TikTok, YouTube, and Instagram. It also covers the age groups most present on those platforms: Gen Z and Gen Y. The third subchapter (Section 2.3) addresses different influencers attributes and perceived characterizations which are known to have an impact on purchase intention and brand image. The fourth subchapter (Section 2.4) deals with the engagement on social media. The fifth subchapter (Section 2.5) addresses the elements that brands should take into account when choosing an influencer. Finally, the last subchapter (Section 2.6) explores the KPIs of influencer marketing.

2.1. Presentation of concepts

Social media

Social media can be defined as platforms which allow their users to communicate information or emotions and to create networks (Li et al., 2021).

Social networks are amongst the most popular kind of social media. In fact, the most popular social media in 2019 included platforms such as Instagram, YouTube and Facebook (Voorveld, 2019). According to Boyd and Ellison (2007), social networks are web-based services enabling people to create a profile that can be public or semi-public within a constrained system, to develop connections with other users and to explore their list of connections and those created by others on the platform. Kane et al. (2014) updated the latter definition and suggested that social networks are characterized by:

> four essential features […], such that users (1) have a unique user profile that is constructed by the user, by members of their network, and by the platform; (2) access digital content through, and protect it from, various search mechanisms provided by the platform; (3) can articulate a list of other users with whom they share a relational

> connection; and (4) view and traverse their connections and those made by others on the platform (Kane et al., 2014).

In addition to social networks, social media also include social streaming platforms allowing for instance to share pictures, social search websites like Google, social knowledge websites such as Wikipedia, social blogging, social forums, social publishing and news and social bookmarking (Lambert & Schuiling, 2021-2022).

Social media marketing

Research shows that consumer environment has become more complex due to the apparition of digital technologies (Masuda et al., 2022). Many people are now searching for information on social media, and 54% agree to say that they use them to search for services and products (Chidiac & Bowden, 2022). Social media thus represent a way for companies to reach consumers instantly. In fact, social media marketing allows companies to achieve their goals at low costs. As traditional channels performances have declined, researchers argue that firms need to consider social media marketing to maintain and improve their market shares (Lee & Watkins, 2016).

Social media marketing is defined by Felix et al. (2017) as:

> an interdisciplinary and cross-functional process that uses social media (often in combination with other communication channels) to achieve organizational goals by creating value for stakeholders (Felix et al., 2017, as cited in Masuda et al., 2022, 2).

One could argue that this definition is more comprehensive than others because it includes the notion of social capital, which refers to the non-monetary value of consumers coming from their interactions in the community. This implies behaviour like advocacy or honesty (Masuda et al., 2022).

Social media influencers

"Social media influencers", also called "SMIs", can be defined as users who have many followers and who produce and share their stories and reviews about some products or brands on social media. They have a tendency to develop content on one or more subjects and are seen as trusted experts on those subjects (De Veirman et al., 2017). They can be found in all sectors such as fashion, food, books, beauty and so on, depending on their field of expertise (Sokolova & Kefi, 2020; Mabkhot et al., 2022). They can also be defined as users who can create engagement, stimulate conversation and/or facilitate the sale of goods/services to the targeted audience (Kim & Kim, 2021).

They influence their community on one or more social networks. SMIs include online celebrities, who have become well known by developing and sharing content on social networks, as well as traditional celebrities, who get many followers thanks the fame they created through institutional channels like sports or entertainment (Rundin & Colliander, 2021).

Other authors such as Nugroho et al. (2022) consider that influencers are not exactly a recent phenomenon, as they already existed before the emergence of social media. Stars were already considered as influencers, for instance, because of their ability to influence the behaviour of consumers who may want to look and act like them. According to them, the only difference between influencers and celebrities is that the latter usually create their influence on traditional media such as TV, while the former create it through social media (Nugroho et al., 2022).

In exchange of posting for brands on social media, influencers can either receive money or receive free products, services, experiences or trips (Campbell & Farrell, 2020). A few years ago, the number of influencers who received free samples was bigger than those who were paid. However, the trend is reversed in 2023 and it seems that 41.6% of influencers are now paid while 29.5% receive free products (Geyser, 2023). Campbell and Farrell (2020) did not mention two other ways that brands can use to pay their influencers, namely discounts and giveaways. In fact, influencers may receive discounts on company's products or services they promote. It seems that it concerns 17.7% of them. Finally, some brands choose to offer to their influencers the chance to enter in a giveaway in exchange of their partnerships. This type of compensation concerns 11.2% of influencers (Geyser, 2023).

Research shows that social media influencers are able to positively affect brands' perceptions and purchase intentions of their followers (Masuda et al., 2022). Aggad et al. (2021) corroborate these findings and argue that the content and characteristics of influencers have a huge effect on purchase intention (as cited in Mabkhot et al., 2022). Gomes et al. (2022) also found that influencers' content quality has a positive impact on purchase intention of fashion products (Gomes et al., 2022).

Types of social media influencers

Influencers can be categorized based on the amount of followers they have (Campbell & Farrell, 2020):

Celebrity influencers are influencers who have more than 1 million of followers. They are known beyond the world of social media and partner with famous brands in exchange of high pay because of their large amount of followers. In other words, those influencers were already famous before or separately from the development of social media. Although celebrity influencers can be seen as huge experts, those tend to create low engagement rates among their followers (Campbell & Farrell, 2020). The fourth subchapter (Section 2.4) will discuss the concepts of social media engagement and engagement rates in more details. Examples of celebrity influencers are Selena Gomez and Nabilla Vergara. Selena Gomez counts 415 millions of followers on Instagram, 58.3 million on TikTok and 33.3 million on YouTube. She gained her popularity outside of social networks as a singer and actress. Moreover, she recently launched her own beauty brand called rare beauty. Nabilla Vergara has 8.4 millions of followers on Instagram. She became famous thanks to reality TV and has also recently launched her own beauty brand called Nabilla Beauty.

Megainfluencers are also influencers having more than one million of followers and thus a celebrity status. However, unlike celebrity influencers, they are often not known outside of their followers and have created their fame on social media based on a recognized expertise (Campbell & Farrell, 2020). Examples of megainfluencers include Lena Situations and Justriadh. Lena Situations counts 4 millions of followers on Instagram, 3 million on TikTok and 2.48 million on YouTube. She gained her popularity on social media and she had partnerships with fashion brands such as Balmain and Longchamp and beauty brands such as MAC. Justriadh counts 4.5 millions of followers on Instagram, 6.6 million on TikTok and 1.43 million on YouTube. He became popular on social networks and had partnerships with fashion brands such as Fendi or Puma.

Macroinfluencers are those having between 100,000 and 1 million followers. They are not yet considered as celebrities but can still create huge engagement rates among their followers. They are leading their fields of expertise such as food, fashion or travel. Their price per post is often lower than celebrity influencers and megainfluencers (Campbell & Farrell, 2020). Examples of macroinfluencers include Milkywaysblueeyes and Kate Hutchins. Milkywaysblueeyes counts 229,000 followers on Instagram. She did partnerships with fashion brands such as Calzedonia or Intimissimi. Kate Hutchins has 858,000 followers on Instagram, 303,000 on TikTok and 204,000 on YouTube. She had partnerships with fashion brands such as Nadine Merabi and New Look and beauty brands such as Costa Brazil.

Microinfluencers are influencers having between 10,000 and 100,000 followers and the latter tend to come from the same geographical area as them. They often make partnerships with many brands from different sectors. Microinfluencers often use videos to interact with their followers and to increase the perception of their accessibility and authenticity. Therefore, they are more and more asked to partner with brands because their videos can have a huge impact on sales as their recommendations are seen as more authentic than larger celebrities (Campbell & Farrell, 2020). Examples of microinfluencers include Make Me Wonder by Jodie and Juliette Kitsch. Make Me Wonder by Jodie counts 19,500 followers on Instagram. She had partnerships with fashion brands such as Kiabi and JBC. Juliette Kitsch has 93,700 followers on Instagram. She had partnerships with fashion brands such as Salut Beauté and Balzac Paris.

Nanoinfluencers are those who have fewer than 10,000 followers and the latter are mostly their friends, acquaintances and nearby neighbours. They are typically the ones having the highest engagement rates among all influencers types due to the advantages of intimate accessibility and high perceived authenticity that they provide their followers with. Unpaid partnerships are more frequent with nanoinfluencers and they often receive free products or services in exchange for opportunities for networking and more exposure on social media (Campbell & Farrell, 2020). An example of nanoinfluencers is Princessemiaxoxo. Princessemiaxoxo counts 7,600 followers on Instagram, 1,417 on TikTok and 3,730 on YouTube. She did partnerships with beauty brands such as Be Creative Make Up and fashion brands such as Kiabi.

Next to the amount of followers, influencers can also be categorized based on the type of content they develop (Santora, 2022; Zalani, 2022). This thesis will focus on influencers from the fashion and beauty sectors. According to Sokolova and Kefi (2020), influencers are indeed widely used by fashion and beauty brands on YouTube and Instagram.

Fashion influencers refer to influencers sharing content about aspects such as clothing, shoes, jewelry or watches (Santora, 2022). They are typically those who show their outfits to their followers, sometimes in the form of an unboxing or a haul. These kind of videos also include fashion tips and reviews of fashion products (Santora, 2022; Zalani, 2022). Fashion videos are very popular on TikTok as they accounted for more than 122 billion views (Izea, 2022). In April 2023, the fashion hashtag accounted for more than 257 billion views on TikTok and 1 billion posts on Instagram.

Beauty influencers can be referred to as influencers who share content about aspects like beauty, make-up, skincare and haircare (Zalani, 2022). They are used to sharing their beauty tips, make-up looks, skin care routine, tutorials and reviews about cosmetic products (Santora, 2022). Beauty videos are very popular on TikTok as they accounted for more than 79 billion views (Izea, 2022). In April 2023, the beauty hashtag accounted for more than 176 billion views on TikTok while it accounted for more than 519 million posts on Instagram.

Social media influencer marketing

Researchers like Sokolova and Kefi (2020) and Mabkhot et al. (2022) argue that firms need to differentiate themselves from the increasingly higher number of competitors and demonstrate their value to customers. As traditional communication channels have declined, brands need to look for digital and social media marketing strategies to maintain and grow their market shares (Masuda et al., 2022). Influencers are the ones who have the ability to give companies access to new audiences by using their personal brand to advertise products. That is why companies consider them important for marketing channels and social relationship assets (Mabkhot et al., 2022).

According to Sokolova and Kefi (2020), the phrase “influencer marketing” is used to refer to a situation in which brands make a partnership with influencers to advertise their products. Liang et al. (2022) also define it as hiring influencers to gain access to a target group.

In 2019, the global influencer marketing market was estimated to 148 millions of dollars. By 2027, it is expected to double, which shows that it is an increasing market (Ozuem & Willis, 2022).

In comparison to traditional ads on TV or radio, influencers seem to have a higher credibility. Influencers have thus a huge impact on their followers due to their higher level of credibility (Mabkhot et al., 2022). This can be explained by the fact that ads made by peers on social media tend to be seen as more credible than traditional ones (Sokolova & Kefi, 2020).

Although the blogger's content is marked as sponsored or appears as less professional, it has been shown that bloggers with many followers as well as their content tend to be more appreciated by potential consumers than traditional ads (Sokolova & Kefi, 2020).

Influencers are also able to influence faster their audience than TV or radio do (Mabkhot et al., 2022). As a result, it seems that influencer marketing could be considered as cheaper than traditional ads.

Nonetheless, SMIs marketing may also represent some problems, such as a lack of honesty from influencers when advertising products. Chidiac and Bowden (2022) reported that solely 51% of followers think that influencers produce content with the willingness to be credible. Consequently, firms have to be vigilant and seek out users who are honest and who can offer trustworthy information about the products they advertise (Mabkhot et al., 2022).

Types of social media influencer marketing

Influencer marketing campaigns can take many different forms. Those include product placement, unboxing, pre-release, sponsored content, brand ambassador, hashtag, contest, giveaway and sweepstake (Ozuem & Willis, 2022).

Product placement

A product placement means that a product, service or brand is introduced in a creative, enjoyable or engaging way in the influencer's content. Product placements were first used on TV but are now also used on social media. Brands can use it to build their awareness and awareness of their products or services. This type of influencer marketing can be interesting for companies as followers have more chances to buy a product which is promoted by their preferred influencer (Ozuem & Willis, 2022).

Unboxing

Another way to use influencer marketing is via unboxing. In this case, influencers share with their followers the unboxing of products or services. They not only open the box but also give recommendations and advice which may have an effect on the audience’s decisions to buy a product or service. It can be beneficial for brands because, like their followers, influencers are products and services users, which allows followers to identify with and to consider influencers as a source of knowledge (Ozuem & Willis, 2022).

Pre-release

Unboxing and pre-release are quite close. The only difference between the two is that in pre-release, influencers benefit from a privileged access to products or services that are not yet on sale. Brands can use pre-release to generate interests from both influencers and their followers (Ozuem & Willis, 2022).

Sponsored content

In this type of influencer marketing, influencers reveal their sponsors via their content several times. Concretely, they receive discounts or money from a brand to cite or discuss about its product or service. We may think that it is quite similar to product placement but there is huge difference between the two. While product placement focuses on the promotion of a product in the media, sponsored content highlights the media (Ozuem & Willis, 2022).

Brand ambassador

When influencers act as brand ambassadors, they share content for one specific brand throughout a long period of time. They become the “face” of this brand, in the same way than celebrities act in traditional advertising. This type of influencer marketing may be used in combination with others. In fact, brand ambassadors may for example use unboxing or contests as part of their partnerships. Brands can be interested in this kind of influencer marketing as followers can become their customers when there is a fit between the brand and the influencer (Ozuem & Willis, 2022).

Hashtag

Influencers can launch a campaign about a specific topic such as a brand, product, service or social issue using hashtags. Hashtags are often used in posts on social media and allow to identify similar content. Brands can be interested to use hashtags as it can motivate consumers to participate in the campaign by using them and it can create virality (Ozuem & Willis, 2022).

Contest, giveaway and sweepstake

Influencers can organize contests, giveaways and sweepstakes as part of an influencer marketing campaign and offer their followers an opportunity to win a prize. This includes for example a like to win, comment to win, like and comment to win or refer-a-friend promotions. Brands can be interested in those type of influencer marketing as it can increase their sales thanks to participants who did not win the contest as well as increasing brand awareness (Ozuem & Willis, 2022).

2.2. Overview of social networks used

In 2019, according to 89% of marketers, the most important social network for influencer marketing was Instagram. YouTube ranked second just behind Instagram with 70% of marketers considering it as most important social network for influencer marketing (Bailis, n.a.).

In 2022, TikTok became the most used social media for influencer marketing and ranked just before Instagram. TikTok has indeed experienced a huge growth since 2018 and has become one of the biggest social networks counting more than one billion users today. Nevertheless, Instagram stayed popular as 50.8% of marketers still used it for influencer marketing. YouTube felt behind Facebook but was still one of the most used platform for influencer marketing (Geyser, 2023). Based on this data, this study will focus on Instagram, TikTok and YouTube as they seem to be the most important social networks for influencer marketing.

This section will present those three social platforms and their characteristics. In fact, each social media platform has its own features which offer marketers the opportunity to adapt the content to the audience’s needs. Some social media are also considered as richer than others. For example, media allowing to produce and share videos are richer. They tend to be less ambiguous, putting users more at ease to understand the message (Chidiac & Bowden, 2022).

Most of the previous studies did not take into account the differences between social networks and studied the impact of influencers on followers by looking at all platforms at the same time (Lee & Watkins, 2016). However, this thesis will consider each social medium individually as suggested by Sokolova & Kefi (2020).

TikTok

Introduction

TikTok is a platform which allows its users to watch, upload and download short videos (Liang et al., 2022). This platform has experienced a huge growth since its introduction in 2018, and is currently one of the biggest social medium with more than one billion users active per month (Geyser, 2022). Users don’t need to have an account to watch videos on TikTok but creators need to create a private or public one in order to share their videos. If viewers want for example to follow other users, like or comment videos, they would still need to create an account. The app counts two major sections called the “for you” section and “following” section. Based on videos users interacted with, similar videos would appear on their “for you” section while the “following” section will allow them to only see videos from people they follow. Finally, it is also possible for users to send private messages on the app (Picaro, 2023).

Features

The app has many characteristics which make it easy to create videos. First, users can either record a video on the app or download an existing one. Then, they have the possibility to edit videos by changing, for example, the playback speed. It also offers users plenty of filters, stickers and songs to add to their contents. Users can also partner together in videos through “Duet video”, while “Stitch video” allows users to react to others’ contents (Geyser, 2022). When the app was launched, users were only able to share 15 seconds videos but they can now share videos up to 10 minutes (Geyser, 2022).

Users

Most users are female and part of Gen Z, as almost one in two users is between 18 and 24 years old in Belgium (Degraux, 2022). There are indeed a little bit more female users than male users (53.8% VS 46.2%) (Degraux, 2023). However, the app is increasingly popular among other demographics: almost 28,1% of users are above 35 years old in Belgium (Degraux, 2022).

YouTube

Introduction

YouTube is a website that allows its users to produce and share videos with viewers (Lee & Watkins, 2016). The platform succeeded in staying one of the most important social networks since its launch in 2005, and is currently the most searched website just after Google (Mileva, 2022). While viewers do not need to have an account to watch videos on YouTube, creators have to create a channel in order to share public or private videos. However, viewers need to create an account in order to subscribe to channels, like, dislike or comment videos. Having a YouTube account also allows viewers to receive personal video recommendations based on videos they interacted with (Moreau, 2020).

Features

The maximum duration for a video is 15 minutes for common users while verified accounts can upload videos up to 12 hours. Traditionally, videos on YouTube tend to be well set up and edited (Mileva, 2022). However, the platform recently launched “YouTube Shorts” in order to compete with TikTok. “Shorts” are videos of 60 seconds or less that creators can upload on the app. Users have the possibility to edit those videos, add texts or music via the app like we can do on TikTok (Beveridge, 2022).

Users

Today, more than two billions of users are active on YouTube. It seems that it is the favourite platform of adults in the US, as 81% of them are using it (Mileva, 2022). Majority of users are Millennials, and there are a little bit more female users than male users in Belgium (50.5% VS 49.5%) (Degraux, 2023).

Instagram

Introduction

Launched in 2010, Instagram is a social network which allows its users to upload and share pictures and videos. To do so, users have to create a personal profile which can be private or public. When users choose to keep it private, it means that only their followers would be able to see their shared content. If users choose to make it public, it means that anybody is able to see their shared content. Users can choose the content they see on their feed by following other users. They are also able to interact with this content by liking or commenting posts (Blystone, 2022). Finally, users can send private messages on the platform (Moreau, 2022).

Features

Instagram offers creators the possibility to edit their pictures by adding for instance a location or a caption with hashtags and a large range of filters (Blystone, 2022). Videos up to 60 minutes can also be uploaded on the app (Moreau, 2022). Instagram has indeed recently launched "Instagram Reels" which allows users to share videos up to 90 seconds, while "IGTV" allows users to share videos up to 60 minutes (Demeku, 2023). Users can also create stories through the app and share thus with their followers pictures or videos available for the next 24 hours. Unlike YouTube for instance, creators only need a smartphone to produce their contents (Stegner, 2021).

Users

The platform counts more than 1 billion active users per month. The most common age category on Instagram is 25 and 34 years old just before the 18 and 24 years old (Wise, 2022). As far as the gender of the users is concerned, the trend is quite similar with TikTok and there are slightly more female users than male users in Belgium (53.9% VS 46.1%) (Degraux, 2022).

Having presented TikTok, YouTube and Instagram and the age category of their users, it could be interesting to define the most important age categories of these platforms, namely Gen Z and Gen Y.

2.3. Definitions of Gen Z and Gen Y

Gen Z

Not all sources agree about when this generation starts and ends. It has been argued that it starts somewhere between 1995 and 1997 and that it ends somewhere between 2010 and 2012 (McKinsey, 2023; Meola, 2023).

Gen Z are also referred to as digital natives because they grew up with digital technologies including internet and social media as part of their daily life (Nugroho et al., 2022). They are used to doing almost everything online such as shopping, working or even making friends. They frequently use internet when searching for information such as purchase reviews or news and they use social media and text to communicate (McKinsey, 2023). While older generations spend their time on television, Gen Z spends as much time on their phone (Meola, 2023).

In the United States, 40% of them recognize that they are influenced online, frequently by the brands that appear in the video they watch (McKinsey, 2023). Therefore, influencer marketing might be one of the most effective way to reach them (Lou & Kim, 2019).

Gen Y

People who are part of Gen Y are also called Millennials (Meola, 2023). Not all sources agree on when this generation starts and ends, but it starts somewhere between 1980 and 1981 and ends somewhere between 1995 and 1996 (Barr, 2022; Meola, 2023). Such as Gen Z, millennials are particularly skilled users of social media and technology (Barr, 2022). While older generations will need the help of others, millennials do not need it any more as they have internet for that (BBC, n.a.).

2.4. Behavioral intentions, brand image, perceived characterizations and influencers attributes

Importance of influencer features

In the social media marketing framework, we consider that the perceived influencer features have an impact on the follower's behaviour. For instance, the follower will tend to purchase more when he/she sees the influencer as trustworthy. This perception is based on influencers attributes that followers see. In this case, the peripheral way from the “elaboration likelihood model of persuasion” is used and followers characterize influencers based on their personal attributes. Arguments are then less important than personal attributes and characterizations of influencers (Masuda et al., 2022).

The “elaboration likelihood model of persuasion” is the most popular model among researchers when dealing with persuasion (Sokolova & Kefi, 2020). It considers that there are two ways of persuasion. The first one is the central way and it has high elaboration likelihood while the second one is the peripheral way and it has low elaboration likelihood. If someone is more in the central way, it means that he/she gives more importance to the information evaluation according to his/her values. If he/she is more in the peripheral way, he/she gives more importance to the attractiveness evaluation of the message source or environment (Masuda et al., 2022).

Authors like Masuda et al. (2022) claim that previous studies made no distinctions between characterizations made by followers and influencers’ attributes. Personal attributes can be defined as attributes that influencers possess and show. Characterizations represent the way followers perceive them. The most important attributes that users use to characterize influencers are physical attractiveness, attitude homophily and social attractiveness (Lee & Watkins, 2016; Lou & Kim, 2019; Sokolova & Kefi, 2020).

Purchase intention

Spears and Singh (2004) define purchase intention as “an individual’s conscious plan to make an effort to purchase a brand” (as cited in Mabkhot et al., 2022). Kotler (2005, as cited in Nugroho et al., 2022) goes further by defining it as a response to a product stimulus, which leads to curiosity in trying it out and, eventually, a desire to purchase it.

Mabkhot et al. (2022) confirms previous researches by stating that influencers have a positive effect on purchase intention of consumers. Purchase intention is going to be analysed in this study as it is a popular measure of marketing strategies effectiveness and it is a strong predictor of sales and market shares.

Brand image

Brand image can be defined as consumer belief and impression like associations that take place in a person's memory. It is known as being able to strongly impact the buying behavior of consumers. In fact, brand image has a positive effect on purchase intention of Gen Z consumers. Gen Z has the tendency to purchase from a brand that is congruent with its self-image in order to gain acceptance in the community (Nugroho et al., 2022).

Therefore, we can formulate this first hypothesis:

H1. The image of the brand which is promoted by the influencer positively impacts follower's purchase intention on TikTok, YouTube and Instagram.

Para-social relationship

Masuda et al. (2022) define PSR (para-social relationship) as:

> an enduring relationship formed through social attractiveness, such as friendship [which] develops even though no physical social interactions occur.

It is said to represent a long term relationship between a spectator and a performer and the spectator feels like he/she is in an intimate relation with him/her as it would be the case in a real relationship. This feeling of friendship will be developed after several exposures to the media personality as uncertainty will be reduced and perceived similarities will be developed (Lee & Watkins, 2016).

Labreque (2014) defines it as:

> an illusionary experience, such that consumers interact with personas (i.e., mediated representations of presenters, celebrities, or characters) as if they are present and engaged in a reciprocal relationship (as cited in Lee & Watkins, 2016).

Para-social relationship cannot be confused with para-social interaction which can be defined as followers' view of ephemeral relationship including only one media exposure (Lou & Kim, 2019).

Compared to traditional ads which are limited to one-way communication, para-social relationship on social media are characterized by two-way communication. Users can interact with influencers by commenting for instance posts which is not possible with traditional ads. However, the communication is said to be limited because influencers cannot take into account all comments posted by followers (Masuda et al., 2022).

Gomes et al. (2022) argue that influencers have to develop this relationship with their followers in order to be effective. When there is a para social relationship between them, users think that they have to interact with influencers. In this case, there is more chance that they copy their advice (Chidiac & Bowden, 2022).

Several authors agree that PSR is positively related to purchase intention of viewers (Lou & Kim, 2019; Masuda et al., 2022). PSR seems to have a bigger impact on purchase intention than trustworthiness and expertise on YouTube according to Masuda et al (2022). Sokolova and Kefi (2020) also found that PSR has a positive impact on purchase intentions in the fields of beauty and fashion on YouTube and Instagram. They also found that PSR has a bigger impact on purchase intentions for Z generation compared to older generations. They argue that PSR between influencers and Z generation cannot be seen as friendly relationships like for older generations, but instead as an addiction. Therefore, it seems that more addictive influencers and contents are more appropriate for them (Sokolova & Kefi, 2020).

As a result, the following hypothesis can be raised:

H2. Para-social relationship between influencers and followers positively impacts followers' purchase intention on TikTok, YouTube and Instagram.

However, the creation of para-social relationship between influencers and Gen Z users may have bad consequences for these users as it can foster their materialism and purchase intention of advertised products. In fact, followers tend to compare socially with influencers and that is why materialism is reinforced (Lou & Kim, 2019).

Influencers should also produce entertaining content if they would like to develop para-social relationship with their followers. Entertainment value has in fact a positive effect on PSR and followers consider this value as more essential than the informative value (Lou & Kim, 2019).

Media richness may affect the degree to which influencers can create para social interaction with their followers, as videos lead to sustained engagement and increased interaction. On YouTube for instance, para social interaction has the tendency to be stronger as influencer directly interacts with followers by looking at the camera. Richer media also lead users to use it more (Chidiac & Bowden, 2022).

Credibility

The notions of *trustworthiness* and *expertise* are used to determine the credibility of a source. Nugroho et al. (2022) also add attractiveness to those factors while Mabkhot et al. (2022) add instead authenticity and define credibility as "the level of reliability and trustworthiness of a source". According to the Source Credibility Theory, expertise, trustworthiness, attractiveness and similarity are factors of source credibility.

Trustworthiness can be defined as the extent to which speaker's claims are seen by spectators as true. Trustworthiness of influencers is argued to have a positive impact on para-social relationship between them and their followers (Lou & Kim, 2019). Nugroho et al. (2022) found that it has a positive impact on brand image. In many studies (Sokolova & Kefi, 2020; Magano et al., 2022), it is also considered as an important factor to explain purchase intentions (Masuda et al., 2022). Nevertheless, Gomes et al. (2022) state that trustworthiness cannot directly explain intention to purchase fashion products.

Expertise can be defined as the extent to which followers see influencers' skills and knowledge to make assessments about a certain topic (Lou & Kim, 2019; Masuda et al., 2022). Research shows that the expertise of influencers has a positive impact on para-social relationship between them and their followers (Lou & Kim, 2019). There is a positive relationship between expertise and brand image. The more followers see the influencer as an expert, the stronger the brand image will be. Expertise has a bigger impact on brand image than attractiveness and trust (Nugroho et al., 2022). It is also an essential factor to explain purchase intentions (Masuda et al., 2022) and this even according to Gen Z consumers. In fact, Gen Z consumers consider expertise as the most important factor of credibility explaining purchase intention compared to trust and attractiveness (Nugroho et al., 2022). Again here, Gomes et al. (2022) found that expertise cannot explain the intention to purchase fashion products. Therefore, seeing influencers as experts is not enough to impact purchase intention positively (Gomes et al., 2022).

Expertise also has an effect on trustworthiness because followers have the tendency to trust an influencer the more they see him/her as an expert (Nugroho et al., 2022). This suggests companies to choose influencers who have expertise in a specific field aligned with the advertised product.

Additionally, ads made by peers are argued to have more credibility than traditional ones (Sokolova & Kefi, 2020). A study conducted on YouTube and Instagram concluded that influencers were seen as having more expertise and leading more to a purchasing behaviour than traditional celebrities (Masuda et al., 2022).

Furthermore, influencers with high credibility have more chances to make followers' behaviour conform their recommendations than low credibility influencers (Liang et al., 2022). Credibility has a positive impact on intention to purchase beauty and fashion products on YouTube and Instagram. This impact tends to be slightly bigger for older generations (Sokolova & Kefi, 2020; Magano et al., 2022). Mabkhot et al. (2022) corroborate these results by showing that influencers' credibility has a significant positive impact on intention to purchase on many social networks and that the impact of influencers on purchase intention is mediated by credibility.

As a result, we can make the following hypotheses:

> *H3a. Credibility of influencers positively impacts followers' purchase intention on TikTok, YouTube and Instagram.*
>
> *H3b. Credibility of influencers positively impacts the image of the promoted brand on TikTok, YouTube and Instagram.*

Attitude homophily

Attitude homophily is defined by Sokolova and Kefi (2020,3) as "the similarity between interacting individuals in terms of beliefs, education and social status". Other authors, such as Magano et al. (2022), also define it as "similarity".

People who look alike tend to interact more than those who are different. In fact, followers tend to spend more time watching videos of influencers they identify with (Masuda et al., 2022). Influencers who are seen by followers as being similar to them deliver better marketing results. Followers are indeed more likely to copy the attitudes, beliefs and behaviors of influencers seen as similar to them (Nugroho et al., 2022). Millennials are also more likely to buy products advertised by influencers who are similar to them.

Attitude homophily has a positive impact on PSR on YouTube (Masuda et al., 2022) and for luxury brands (Lee & Watkins, 2016). In the fields of fashion and beauty, attitude homophily has also a positive impact on PSR and credibility on YouTube and Instagram (Sokolova & Kefi, 2020). However, purchase intention of fashion products is not affected by similarity (Gomes et al., 2022).

Consequently, following hypotheses can be formulated:

> *H4a. Attitude homophily of influencers positively impacts their credibility on TikTok, YouTube and Instagram.*
>
> *H4b. Attitude homophily of influencers positively impacts para-social relationship with their followers on TikTok, YouTube and Instagram.*

Attractiveness

Physical attractiveness

Physical attractiveness is an important attribute because followers can always see influencers. Influencer's physical attractiveness has a positive impact on credibility and PSR on YouTube (Masuda et al., 2022). The results are the same for luxury brands on YouTube as physical attractiveness has a positive impact on PSR (Lee & Watkins, 2016). However, Sokolova and

Kefi (2020) concluded that it has a positive impact on credibility but a negative impact on PSR in the fields of fashion and beauty on YouTube and Instagram.

As a result, we can formulate the following hypotheses:

H5a. Physical attractiveness of influencers positively impacts their credibility on TikTok, YouTube and Instagram.

H5b. Physical attractiveness of influencers positively impacts para-social relationship with their followers on TikTok, YouTube and Instagram.

Social attractiveness

Social attractiveness refers to the kindness of the influencer. It affects users through the identification process, because these tend to try to look like influencers and to create a positive relationship with them (Sokolova & Kefi, 2020).

The social attractiveness of influencers has a positive impact on PSR on YouTube (Masuda et al., 2022; Sokolova & Kefi, 2020; Lee & Watkins, 2016). Masuda et al. (2022) have found that social attractiveness has a bigger impact on PSR compared to physical attractiveness and attitude homophily. Lee and Watkins (2016) have found that social attractiveness and attitude homophily also have a bigger impact on PSR compared to physical attractiveness. However, researchers like Sokolova and Kefi (2020) claim that social attractiveness has not a positive impact on PSR for Z generation.

Consequently, the following hypothesis is proposed:

H6. Social attractiveness of influencers positively impacts para-social relationship with their followers on TikTok, YouTube and Instagram.

Influencers' attractiveness has a positive relationship with brand image. The image of the advertised brand is going to be stronger when his/her attractiveness is higher. Attractiveness also seems to have a positive effect on purchase intention of Gen Z consumers. Their purchase intention tends to be higher when influencer's attractiveness is higher. They show more interest in classy influencers having skills and a strong personality than in influencers who are solely sexy (Nugroho et al., 2022).

These results suggest that physical attractiveness cannot explain on its own the intention to purchase of Gen Z consumers, and need to be combined with social attractiveness.

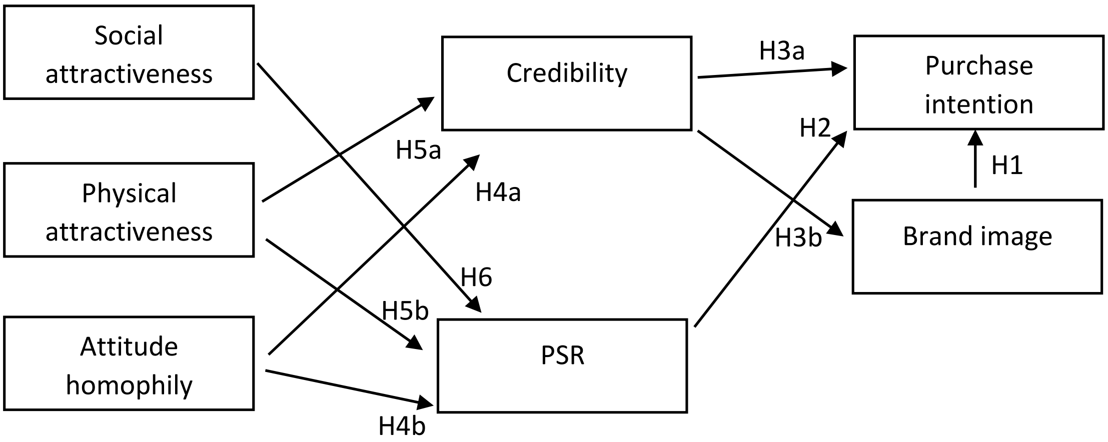

Figure 1: Representation of hypotheses and relations between variables

2.4 Social media engagement

According to some authors (Dolan et al., 2019; Liu et al., 2019; Cao et al., 2021), consumer engagement is composed of three dimensions called cognitive, affective (or emotional) and behavioural. Consumer engagement is referred to as a psychological process that makes consumers loyal to a company (Dolan et al., 2019). Cognitive dimension represents the mental processes needed to pay attention and to absorb information. Affective dimension is about emotional reactions like enjoyment and enthusiasm. Finally, behavioural dimension represents the active involvements including learning, sharing and endorsing behaviors (Cao et al., 2021).

Other authors such as Van Doorn et al. (2010, as cited in Liu et al., 2019) consider that engagement is a unidimensional concept and focus on the behavioural aspect of it. This could be explained by the fact that the cognitive and affective dimensions of consumer engagement are difficult to measure on social media (Liu et al., 2019). Van Doorn et al. (2010, as cited in Liu et al., 2019) define consumer engagement as “the customers' behavioral manifestation toward a brand or firm, beyond purchase”. Social media engagement behaviour can be defined as the engagement behaviour of consumers with content developed by brands and peers on social media (Cao et al., 2021).

Based on the degree of consumer activity, there exist three types of social media consumer engagement namely consumption, contribution and creation. Firstly, consumption can be defined as the lowest level of activity and includes for instance the passive reading of posts or following of a brand account. Secondly, contribution is a middle level of activity and includes for example the liking or commenting of brand posts on social media. Thirdly, creation represents the most active level of consumer engagement and includes the creation of content like posts or reviews related to the brand (Liu et al., 2019).

The social media engagement can be measured thanks to the engagement rate which is the sum of all likes, comments and shares divided by the number of followers. In their study, Chidiac and Bowden (2022) show that the engagement on social media is higher than on traditional ads. However, this engagement still tends to be low. For instance, the average engagement rate on Facebook in 2020 was equal to 0.09%, while the average engagement rate on Instagram in 2020 was bigger and was equal to 1.6%. In 2020, YouTube stayed one of the most effective social media for engagement with brands and influencers (Chidiac & Bowden, 2022). However, TikTok seemed to have in 2022 the higher engagement rate compared to the three social networks previously mentioned with an average engagement rate of 4.25% (Sproutsocial, 2023).

The degree of consumer engagement tends thus to be different on each social media partly due to the richness of it. Instagram has, for example, a higher engagement than Facebook thanks to its unique features associated with high-quality content (Cao et al., 2021).

2.5 How to choose the right influencer?

3 Rs of influence

Brands can consider the three Rs of influence in order to choose the right influencer for their influencer marketing campaigns. Three Rs of influence are made of relevance, reach and resonance (Lambert & Schuiling, 2021-2022).

First, when we think about relevance, it is about the content and audience relevance. Brands should consider influencers having content and audience that are relevant with them and their industries (Lambert & Schuiling, 2021-2022). The next part will discuss this subject in more details.

Then, the reach represents the number of users this influencer may reach (Lambert & Schuiling, 2021-2022). Brands should consider the reach and set it based on their goals. If their objective is to increase brand awareness, a bigger reach would be better. However, if they aim to increase brand credibility, a higher resonance would be more interesting (Solis, 2015). In fact, as we discussed in the previous section, it seems that influencers who have more followers tend to generate lower level of engagement compared to influencers having less followers. Therefore, brands should take into account this aspect when choosing influencers.

Finally, the resonance is about the degree of engagement this influencer may create with a relevant audience (Lambert & Schuiling, 2021-2022).

The 3Rs model does not take into account the influencers' attributes such as their physical attractiveness and the characterizations made by followers like the influencers' credibility. However, as discussed in Section 2.3, those elements are known as having an impact on follower's purchase intention and brand image. Brands should thus also consider them in order to choose the right influencer.

Influencer product/ consumer congruence

The way someone perceives himself/herself is defined as "self-perception". There is a relationship between self-perception and purchase intention. People purchase products to build their self-image. The perceived image of influencers is also an important element for the effect of influencers on followers' behaviour. Higher match between influencers' image and ideal self-image of followers leads to a more effective endorsement as they are more likely to copy their behaviour (Liang et al., 2022).

In marketing, congruence refers to the fit between influencers' characteristics and products' characteristics and between influencers' characteristics and followers' characteristics. A higher congruence results in more effective influencer endorsement (Liang et al., 2022). There is indeed more chance that followers show positive brand attitude and that their purchase intention is positively impacted when there is a higher congruence (Shan et al., 2020).

Many studies agree to say that credibility of influencers is positively affected by the perceived congruence between influencers and products and between influencers and followers. (Magano et al., 2022; Liang et al., 2022). It seems, according to Shan et al. (2020), that more para-social relationship is developed when there is more congruence between the influencer and the follower.

Therefore, companies need to select influencers who fit with the advertised product and who have high credibility (Liang et al., 2022).

Shan et al. (2020) found that the fit between influencers and followers is more important than the number of followers for influencers to be effective. However, on Instagram, the number of followers seems to have an impact on the credibility of influencers (Sokolova & Kefi, 2020).

2.6 Influencer marketing KPIs

One of the main challenge of influencer marketing is to measure the results. This can be done using key performance indicators. There exist two types of KPIs that can be used for influencer marketing: quantitative and qualitative KPIs (Gräve, 2019).

In the quantitative section, there are for instance the number of interactions (sum of likes and comments), the interaction rate (number of followers divided by all likes and comments), the reach (number of unique users exposed to the post), the number of views, the number of clicks, the number of followers, the sales and the click-through rate (number of clicks divided by the number of views). In the qualitative section, there are for instance the sentiment of comments, the influencer quality and the brand image (Gräve, 2019).

Gräve (2019) found that brand marketers use more quantitative and posts KPIs such as the interaction rate and total reach to measure the effectiveness of influencer marketing campaigns. They tend thus to use KPIs that are easily accessible and quantifiable.

Linqia (2021) corroborates those results as engagement seems to be the most used KPI for influencer marketing with 77% of marketers using it. Engagement can be defined as the sum of all likes, comments and shares (Magnus et al., 2021-2022).

Other important KPIs used by at least 60% of marketers are impressions, clicks and conversions (Linqia, 2021). Impressions represent the number of views and can be computed by multiplying the reach by the frequency. As a reminder, the reach can be defined as the number of unique users who are exposed to the post while the frequency represents the number of times these unique users have been exposed to it (Magnus et al., 2021-2022).

When brand marketers had to choose the three best KPIs, Gräve (2019) found that the most used KPI are the net sentiment (positive comments – negative comments) instead of a count-based KPI followed by the number of interactions and the interaction rate. Brand marketers are thus aware of the poor informative value of the metrics they use. This can be explained by the fact that the ultimate goal of an influencer marketing campaign is to generate more positive comments than negative ones.

However, Linqia (2021) highlights the fact that marketers prefer using conversion, sales and engagement KPIs when they are asked to choose the best KPIs to measure the effectiveness of an influencer marketing campaign.

As a conclusion, Gräve (2019) suggests that brand marketers continue to use quantitative KPIs to evaluate influencer marketing effectiveness, while emphasizing the importance of using those in combination with qualitative KPIs such as the net sentiment.

Conclusion of the literature review

This literature review defined first (Section 2.1) the concepts of social media, social media marketing, social media influencers and social media influencer marketing. Masuda et al. (2022) discussed the importance for companies to look for digital and social media marketing strategies because traditional communication channels have declined. As part of those strategies, there are influencers who are able to use their personal brand to promote products and thus give access to new potential consumers (Mabkhot et al., 2022). Social media influencers, i.e., users having many followers and sharing stories and reviews about products or brands on social media, can be found in many sectors such as fashion, beauty, books or food (De Veirman et al., 2017). This thesis will focus on fashion and beauty influencers as those seem to be intensively used by fashion and beauty brands on YouTube and Instagram (Sokolova & Kefi, 2020). Influencers have also been defined by Kim and Kim (2021) as users who are able to facilitate the sale of goods or services to a targeted audience. They are indeed able to positively impact the purchase intention of their followers and brands' perceptions (Masuda et al., 2022). This section finally defined the concept of influencer marketing which is a situation in which companies make a partnership with influencers to promote their products (Sokolova & Kefi, 2020).

Then, the second section (Section 2.2) presented the three social networks on which this thesis will focus: TikTok, YouTube and Instagram as well as the concepts of Gen Z and Gen Y. TikTok, YouTube and Instagram have been chosen because they seemed to be the most important social networks for influencer marketing (Bailis, n.a.; Geyser, 2023). While previous studies analysed influencers' attributes and characterizations made by followers on social networks in general (Lee & Watkins, 2016), this thesis will take into account the differences between those three platforms and analyse attributes and characterizations of influencers on each social network individually.

Then, the third section (Section 2.3) discussed what this thesis will mainly focus on, namely the attributes and perceived characterizations of influencers which are known to have an impact on the purchase intention of followers. This latter being itself positively influenced by brand image (Nugroho et al., 2022). Masuda et al. (2022) defined personal attributes of influencers as attributes that they have and show while perceived characterizations of influencers are the way followers see them. Perceived characterizations of influencers include the para-social relationships they develop with their followers and their credibility. Para-social relationships and credibility have a positive impact on followers' purchase intention in the fashion and beauty sectors on Youtube and Instagram (Sokolova & Kefi, 2020). Sokolova and Kefi (2020) found that para-social relationships have a bigger impact on purchase intention of Gen Z users compared to older generations while credibility had a bigger impact on purchase intention of older generations. Personal attributes of influencers include attitude homophily, physical and social attractiveness. Attitude homophily has a positive effect on PSR and credibility on Youtube and Instagram in the fashion and beauty sectors (Sokolova & Kefi, 2020). The physical attractiveness of influencers has a positive impact on PSR and credibility on YouTube and on credibility on YouTube and Instagram in the fashion and beauty sectors (Masuda et al., 2022; Sokolova & Kefi, 2020). Finally, the social attractiveness of influencers has a positive effect on PSR on YouTube (Masuda et al., 2022).

The fourth section (Section 2.4) addressed the engagement on social media. Cao et al. (2021) defined it as the engagement behaviour that consumers have with the content created by brands and peers on social media. Amongst all social networks, it seemed that TikTok had the higher engagement rate followed respectively by YouTube and Instagram (Chidiac & Bowden, 2022; Sproutsocial, 2023).

Then, the fifth section (Section 2.5) dealt with the aspects that brands should take into account when choosing influencers. Three Rs of influence were discussed: Relevance, Reach and Resonance as well as the importance of taking into account the influencer's attributes and perceived characterizations made by followers (Solis, 2015; Lambert & Schuiling, 2021-2022).

Finally, the sixth section (Section 2.6) explored the KPIs of influencer marketing. Those KPIs can be either quantitative such as the interaction rate or qualitative such as the net sentiment. According to Gräve (2019), companies should stop using only quantitative KPIs and instead use both types of KPIs to measure the effectiveness of their influencer marketing campaigns.

3. Quantitative study

In order to test the hypotheses developed in the previous section, a quantitative study has been conducted. Unlike a qualitative study, it allows to survey a more representative sample and to make conclusions at the scale of the targeted population (Pleyers, 2021-2022).

3.1. Survey

Hypotheses, constructs and items

Hypothesis	Construct	Item	Sources
	Purchase intention	I would purchase the fashion/ beauty products promoted by this influencer in the future.	Gomes et al., (2022)
		I would purchase a brand based on the advice I am given by this influencer.	
		I would follow brand recommendations from this influencer.	
		I would encourage people close to me to buy the fashion/ beauty products promoted by this influencer.	
H1. The image of the brand which is promoted by the influencer positively impacts follower's purchase intention on TikTok, YouTube and Instagram.	Brand image promoted by the influencer	The promoted fashion/beauty product has a high quality.	Lin et al., (2020)
		The promoted fashion/beauty product has better characteristics than competitors.	
		The promoted brand is nice.	
		The promoted brand has a personality that distinguishes it from competitors.	
		The promoted brand does not disappoint its customers.	
		The promoted brand is one of the best brands in the sector.	
H2. Para-social relationship between influencers and followers positively		I look forward to watching this influencer on their account or on my feed.	Lee & Watkins , (2016)

impacts followers' purchase intention on TikTok, YouTube and Instagram.	Para-social relationship	If this influencer appeared on another person account, I would watch that video.	
		When I'm watching this influencer, I feel as if I am part of their group.	
		I think this influencer is like an old friend.	
		I would like to meet this influencer in person.	
		If there were a story about this influencer in a newspaper or magazine, I would read it.	
		This influencer makes me feel comfortable, as if I am with friends.	
		When this influencer shows me how they feel about a brand, it helps me make up my own mind about the brand.	
H3a. Credibility of influencers positively impacts followers' purchase intention on TikTok, YouTube and Instagram. *H3b. Credibility of influencers positively impacts the image of the promoted brand on TikTok, YouTube and Instagram.*	Credibility	I do believe that this influencer is convincing.	Magano et al., (2022)
		I do believe that this influencer is credible.	
		I do believe that this influencer advertising is a good reference for purchasing products.	
		I find purchasing product/service advertised by this influencer to be worthwhile.	
H4a. Attitude homophily of influencers positively impacts their credibility on TikTok, YouTube and Instagram. *H4b. Attitude homophily of influencers positively impacts para-social relationship with their followers on TikTok, YouTube and Instagram.*	Attitude homophily	This influencer and I have a lot in common.	Masuda et al., (2022)
		This influencer and I are a lot alike.	
		This influencer thinks like me.	
		This influencer shares my values.	
H5a. Physical attractiveness of influencers positively impacts their credibility on TikTok, YouTube and Instagram.	Physical attractiveness	I find her/him very attractive physically.	Lee & Watkins , (2016)
		I think she/he is quite pretty.	
		She/he is very sexy looking.	

H5b. Physical attractiveness of influencers positively impacts para-social relationship with their followers on TikTok, YouTube and Instagram.			
H6. Social attractiveness of influencers positively impacts para-social relationship with their followers on TikTok, YouTube and Instagram.	Social attractiveness	I think this influencer could be my friend.	Masuda et al., (2022)
		I want to have a friendly chat with this influencer.	
		We could be able to establish a personal friendship with each other.	
		This influencer would be pleasant to be with.	

Table 1: Overview of hypotheses, constructs and items

To measure purchase intention, four items were used and slightly modified to also take into account beauty products (Gomes et al., 2022). Six items were used to measure brand image and were also modified to take into account the influencer context as well as fashion and beauty products. One item of brand image was removed to ensure a good understanding from respondents (Lin et al., 2020). Eight items were used to measure para-social relationship and modified to not only take into account YouTubers but instead influencers in general (Lee & Watkins, 2016). To measure credibility, four items from Magano et al. (2022) were used and adapted for influencers in general and not only fashion influencers. The four items of attitude homophily (Masuda et al., 2022) were used and adapted to be able to use them for each platform. Three items measured physical attractiveness of influencers (Lee & Watkins, 2016) while four items from Masuda et al. (2022) measuring social attractiveness were modified to be able to use them for each social network. As the study was conducted in the French speaking part of Belgium, items were translated in French (see appendix 1.).

Questionnaire

The objective of this thesis was to define which influencers' characteristics have the biggest effect on followers' purchase intention and brand image and to test whether those results are different among TikTok, YouTube and Instagram. As a reminder, the research question of this thesis was the following one:

> How do influencers attributes and perceived characterizations affect brand image and TikTok users' intention to purchase fashion and beauty products, and how does it differ from YouTube and Instagram?

To address this question, an online survey was conducted to gather information among TikTok, YouTube and Instagram users in the French speaking part of Belgium. The survey was thus self-administered (Steils, 2020-2021). This data collection method ensures that the interviewer does not create any biases when the respondent answers questions, to offer relatively high anonymity, time to answer and to have more control regarding for instance filters or time that respondents take to answer (Pleyers, 2021-2022). The survey was shared on various social networks as done by other researchers (Mabkhot et al., 2022; Magano et al., 2022; Gomes et al., 2022) and those included Instagram, Facebook, LinkedIn and Snapchat.

In order to be able to compare the same variables among the different platforms, data regarding the three social networks were collected. In fact, respondents only had the possibility to answer the survey for their preferred social network and they were informed that they were going to answer the rest of the questionnaire only based on their preferred platform (see Appendix 1.).

The survey was designed on Qualtrics and included structured and close questions, mostly due to the time constraint of this thesis and the fact that structured questions are less costly than open ones (Steils, 2020-2021). Filtering questions were also included to make sure to collect data from the targeted population. Respondents had to be active on at least one social network amongst the three selected platforms, to follow at least one fashion or beauty influencer on TikTok, YouTube or Instagram and to have already purchased a product or service promoted by this influencer. The type of questions used in the survey included dichotomous, multiple choice and scales questions. Regarding scales questions, a seven point Likert scale from 1 (strongly disagree) to 7 (strongly agree) was used, as it is most used to measure attitudes (Pleyers, 2021-2022). An odd scale was created on purpose to let respondent chooses it when he/she has no opinion, does not want to share it or does not know (Steils, 2020-2021) (see Appendix 1.).

Pre-test

A pre-test was conducted to make sure that everything was working and to solve any potential problems. Five people who correspond to the target population's criteria were interviewed in face-to-face interviews. Based on the interviewees' suggestions, we added inclusive writing and changed the wording of some questions in order to make them clearer. The pre-test also allowed us to estimate the time it took to answer the questionnaire which was on average between 4 and 6 minutes.

Sample

The target population is represented by people in the French speaking part of Belgium who are active on at least one social network amongst the three selected apps, follow at least one fashion or beauty influencer on TikTok, YouTube or Instagram and have already purchased a product or service promoted by this influencer. Ideally, the sampling frame represents all people in the French speaking part of Belgium who are active on at least one social network amongst the three selected apps, follow at least one fashion or beauty influencer on TikTok, YouTube or Instagram and have already purchased a product or service promoted by this influencer. However, it is impossible to survey this sampling frame and the sample is thus composed of people on Instagram, Facebook, LinkedIn and Snapchat (i.e., the social networks through which the questionnaire was spread) who meet those criteria.

Due to the difficulty of implementing probability sampling methods in reality, non-probability sampling techniques were used. The questionnaire was shared on various social networks and each person from the target group had thus not the same probability to be selected in the sample. Snowball sampling was used because potential respondents needed to have very specific characteristics. In fact, this type of method is particularly useful when the target population has characteristics that are relatively rare (Pleyers, 2021-2022). Moreover, this type of method was also used in other studies (Gomes et al., 2022; Mabkhot et al., 2022) dealing with the impact of influencers' characteristics on purchase intention. Concretely, respondents were asked to share the survey with their friends and acquaintances at the end of the questionnaire and on the posts published on social networks (see Appendix 1.).

A quota sampling method using age and gender as criteria would not have been as relevant. In fact, Sokolova and Kefi (2020) found that most respondents interested in fashion and beauty influencers were woman and part of Gen Z.

Sample size

A total of 355 answers were collected between the 15th of April and the 24th of May 2023. Among the 355 answers collected, 16 were not taken into account because those were not 100% complete and respondents stopped the questionnaire before the end. Then, as a reminder, 3 filtering questions were included in the questionnaire. That is why 18 answers were deleted as respondents were not active on TikTok, YouTube or Instagram. 111 responses were also deleted because respondents did not follow at least one fashion or beauty influencer on TikTok, YouTube or Instagram. Finally, 106 respondents were not taken into account because they had never bought a product or service promoted by an influencer on those platforms. Therefore, 120 valid answers were collected.

3.2. Analysis of data

Sample description

Among the 120 valid answers, 114 respondents are female while 6 respondents are male, which means that our sample is made of 95% of female and 5% of male respondents. As could be expected from Sokolova and Kefi (2020), the number of female respondents was significantly higher compared to male respondents. In fact, this can be explained by the fact that women tend to show more interest in fashion and beauty than men (Sokolova & Kefi, 2020).

GENDER

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Homme	6	5,0	5,0	5,0
	Femme	114	95,0	95,0	100,0
	Total	120	100,0	100,0	

Table 2: Frequency of "gender" variable

Regarding the different age categories, 75% of respondents (90 individuals) fall under the Gen Z category, with one respondent being under 18 years old and the remaining 89 respondents falling between the ages of 18 and 24. Here again, this is not surprising as Sokolova & Kefi (2020) also collected data mostly from Gen Z respondents. 20% of respondents (24 individuals) are part of Gen Y as 22 of them are between 25 and 34 years old and 2 are between 35 and

44 years old. The remaining 5% (6 individuals) are between 45 and 54 years old and there are no respondents over 55 years old.

AGE

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Moins de 18 ans	1	,8	,8	,8
	18-24 ans	89	74,2	74,2	75,0
	25-34 ans	22	18,3	18,3	93,3
	35-44 ans	2	1,7	1,7	95,0
	45-54 ans	6	5,0	5,0	100,0
	Total	120	100,0	100,0	

Table 3: Frequency of “age” variable

Then, regarding their preferred social network, Instagram is dominating the sample as 60.83% of respondents (73 individuals) reported preferring Instagram. It is followed by TikTok with 23.33% of respondents reporting preferring TikTok (28 individuals). YouTube is the least preferred social network as 15.83% of respondents (19 individuals) reported preferring YouTube.

PREFERRED_SM

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	TikTok	28	23,3	23,3	23,3
	Instagram	73	60,8	60,8	84,2
	YouTube	19	15,8	15,8	100,0
	Total	120	100,0	100,0	

Table 4: Frequency of “preferred social network” variable

Regarding the usage of their preferred social network, 99.17% of respondents (119 individuals) use at least once a day their preferred social network, while the remaining 0.83% (1 individual) use it at least once a week.

FREQUENCE

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Au moins une fois par jour	119	99,2	99,2	99,2
	Au moins une fois par semaine	1	,8	,8	100,0
	Total	120	100,0	100,0	

Table 5: Frequency of “preferred social network usage” variable

Lena Situations and Gaelle Garcia Diaz were the most cited influencers by respondents, as 14.17% mentioned Lena Situations and 13.33% Gaelle Garcia Diaz. They were followed by influencers such as Enjoy Phoenix, Milkywaysblueyes, Nabila, Silent Jill, Jessica Thivenin and Mayadorable. Those influencers have either more than 1 million followers or between 100,000 and 1 million followers. As a result, our sample is mainly represented by mega influencers and macro influencers.

Verification of scales

Before testing our hypotheses, we have to verify the scales used for each variable via a factor analysis. A factor analysis allows to condense a set of items into a few key axes. It allows thus to check which items are correlated with each other and which can be put together. In this thesis, we will use one specific type of factor analysis called principal component analysis (PCA) as it is most often used. Based on the total variance of items, this method sets the minimum number of principal components. Therefore, it would help us know if it is a good idea to put items together (Pleyers, 2021-2022).

Then, a reliability analysis will also be needed in order to check the reliability of those scales. The reliability analysis allows to make sure that a scale measures what it is supposed to measure. In this case, the Cronbach's alpha will be calculated (Steils, 2020-2021).

1. **Purchase intention (see appendix 2.1).**

First, we can look at the items of purchase intention. KMO is greater than 0.5 which means that it is quite a good idea to put those items together. Then, the p-value of the Bartlett coefficient is less than 0.05 and we can reject the null hypothesis that items are uncorrelated.

Thanks to the communalities table, we are able to check if some items need to be deleted. The communality is indeed the variance that one item share with other items. It must be greater than 0.5. Here, we can see that all items have a communality greater than 0.5, which means that no items need to be deleted.

Then, we know that we will keep 77% of the total variance by putting items together in one component and this latter has an eigenvalue greater than 1. Therefore, the four items of purchase intention can be put together in one variable. The break on the scree plot between 1 and 2 also allows us to know that the four items can be put together in one variable.

Finally, in order to check the reliability of items, we need to look at the Cronbach's alpha and it must be greater than 0.7. Here, the Cronbach's alpha is greater than 0.7 and the scale is reliable.

2. Image of the promoted brand (see appendix 2.2).

Second, we can look at the items of brand image. KMO is greater than 0.5 and it is thus quite a good idea to put items together. The p-value of the Bartlett coefficient is less than 0.05 and we can reject the null hypothesis that items are uncorrelated.

Then, no items need to be deleted as all items have a communality that is greater than 0.5.

We know that we will keep 71% of the total variance by putting items together in one component and this latter has an eigenvalue greater than 1. As a result, the six items of brand image can be put together in one variable.

Finally, the Cronbach's alpha is greater than 0.7 and the scale is reliable.

3. Para-social relationship (see appendix 2.3).

Thirdly, we can look at items of para-social relationship. KMO is greater than 0.5 and it is thus quite a good idea to put items together. The p-value of the Bartlett coefficient is less than 0.05 which means that we can reject the null hypothesis that items are uncorrelated.

Then, the first, second, sixth and last items of para-social relationship have communalities that are less than 0.5. Therefore, we can first delete the sixth item, namely "If there were a story about this influencer in a newspaper or magazine, I would read it", as it has the lowest communality. We can then restart the PCA analysis.

After deleting the sixth item, the KMO value is still greater than 0.5 and it is still advisable to put items together. The p-value of the Bartlett coefficient is also less than 0.05, which means that the correlations between items are not null. However, the first, second and last items have still communalities that are less than 0.5. As a result, we can remove the last item "When this influencer shows me how they feel about a brand, it helps me make up my own mind about the brand”. Then, we can start again the PCA analysis.

After deleting the last item, KMO is still greater than 0.5, and it is still a good idea to put items together. The p-value of the Bartlett coefficient is also less than 0.05 which means that the correlations between items are not null. Nevertheless, the first and second items have still communalities that are less than 0.5. Therefore, we can delete the first item “I look forward to watching this influencer on their account or on my feed” and we can restart the PCA analysis.

Even after deleting the first item, the KMO value remains above than 0.5, indicating that it is still advisable to group the items together. The p-value of the Bartlett coefficient is also less than 0.05, which means that the correlations between items are not null. However, the second item has still communality that is less than 0.5. We can thus delete the second item “If this influencer appeared on another person account, I would watch that video” and we can restart the PCA analysis.

After deleting the second item, KMO is still greater than 0.5, and it is still advisable to put items together. The p-value of the Bartlett coefficient is also less than 0.05 which means that the correlations between items are not null.

No items need to be deleted anymore as they all have a communality that is greater than 0.5. As a result, the following four items were removed:

- I look forward to watching this influencer on their account or on my feed.
- If this influencer appeared on another person account, I would watch that video.
- If there were a story about this influencer in a newspaper or magazine, I would read it.
- When this influencer shows me how they feel about a brand, it helps me make up my own mind about the brand.

And the four following items were kept:

- When I’m watching this influencer, I feel as if I am part of their group.
- I think this influencer is like an old friend.
- I would like to meet this influencer in person.

- This influencer makes me feel comfortable, as if I am with friends.

We can see that items which have been kept are well aligned with the definitions of PSR given in the review of literature. As a reminder, PSR was defined as a long term relationship between a spectator and a performer and the spectator has the feeling that he/she is in an intimate relation with the performer as it would be the case in a real friendship (Lee & Watkins, 2016). Therefore, our para-social relationship scale puts emphasis on the friendship side of para-social relationship.

Then, we know that we will keep 68% of the total variance by putting items together in one component and this latter has an eigenvalue greater than 1. As a result, the four items of para-social relationship can be put together in one variable.

Finally, the Cronbach's alpha is greater than 0.7 and the scale is reliable.

4. **Credibility (see appendix 2.4).**

Fourthly, we can look at the items of credibility. KMO exceeds 0.5 and it is thus advisable to put the items together. The p-value of the Bartlett coefficient is below 0.05, enabling us to reject the null hypothesis that items are uncorrelated.

Then, no items need to be deleted as they all have a communality that is greater than 0.5.

We know that we will keep 64% of the total variance by putting items together in one component and this latter has an eigenvalue greater than 1. As a result, the four items of credibility can be put together in one variable.

Finally, the Cronbach's alpha is greater than 0.7 which means that the scale is reliable.

5. **Attitude homophily (see appendix 2.5).**

Moving on to the fifth aspect, we can look at the items related to attitude homophily. With a KMO value surpassing 0.5, it is recommended to put items together. The p-value of the Bartlett coefficient is below than 0.05 which means that we can reject the null hypothesis that items are uncorrelated.

No items need to be deleted as all items have a communality that is greater than 0.5.

Then, we know that we will keep 68% of the total variance by putting items together in one component and this latter has an eigenvalue greater than 1. Therefore, the four items of attitude homophily can be put together in one variable.

Finally, the Cronbach's alpha is greater than 0.7 which means that the scale is reliable.

6. Physical attractiveness (see appendix 2.6).

Sixth, we can look at the items of physical attractiveness. KMO is greater than 0.5 meaning that it is quite a good idea to put items together. Furthermore, the p-value of the Bartlett coefficient is below 0.05 which means that we can reject the null hypothesis that items are uncorrelated.

Then, no items need to be deleted as they all have a communality that is greater than 0.5.

We know that we will keep 71% of the total variance by putting items together in one component and this latter has an eigenvalue greater than 1. As a result, the three items of physical attractiveness can be put together in one variable.

Finally, the Cronbach's alpha is greater than 0.7 which means that the scale is reliable.

7. Social attractiveness (see appendix 2.7).

Finally, we can look at items of social attractiveness. It is advisable to put those items together as the KMO value is higher than 0.5. The p-value of the Bartlett coefficient is less than 0.05 which means that we can reject the null hypothesis that items are uncorrelated.

No items need to be deleted as all items have a communality that is greater than 0.5.

Then, we know that we will keep 71% of the total variance by putting items together in one component and this latter has an eigenvalue greater than 1. As a result, the four items of social attractiveness can be put together in one variable.

Finally, the Cronbach's alpha is greater than 0.7 and the scale is reliable.

3.3 Hypotheses testing

H1. The image of the brand which is promoted by the influencer positively impacts follower's purchase intention on TikTok, YouTube and Instagram (see appendix 3.1).

In order to test the first hypothesis, a simple linear regression is needed. Four conditions must be met when we are conducting a simple linear regression.

First, the residuals have to be independent. This can be verified thanks to Durbin-Watson statistic which needs to be close to 2. Here, Durbin-Watson statistic is equal to 1.970 which is close to 2. Consequently, we cannot reject the null hypothesis of no autocorrelations of errors and we can conclude that residuals are independent.

Second, residuals must follow a normal distribution. Here, data points are close to the line and residuals follow thus a normal distribution.

Third, the residuals must respect the condition of homoscedasticity. This condition is respected when all the points are randomly distributed on the scatterplot and no models appear. Here, the residuals respect well this condition as all the points are randomly distributed on the graph.

Fourth, no collinearity between the variables can be found, which means that variables cannot move in the same direction. Here, the VIF statistic is less than 3 as it is equal to 1 and there is thus no collinearity between the variables.

As a result, the four conditions are met. We can now look to the adjusted R-square which represents the percentage of the variations of purchase intention that is explained by brand image. Here, it is very high as it is possible to know 48.7% of variations of purchase intention only thanks to brand image.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,701[a]	,491	,487	,94225	1,970

a. Predictors: (Constant), BI

b. Dependent Variable: PI

Table 6: Regression of H1.

Then, as the p-value is equal to less than 0.05, we can reject the null hypothesis and say that the model is significant. We can explain a part of purchase intention thanks to this model.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	101,184	1	101,184	113,967	<,001[b]
	Residual	104,764	118	,888		
	Total	205,948	119			

a. Dependent Variable: PI

b. Predictors: (Constant), BI

Table 7: Regression of H1.

Here again, we can reject the null hypothesis that image of the promoted brand does not influence purchase intention as the p-value is less than 0.05. The coefficient of brand image is positive and is equal to 0.847, which means that for each additional unit of brand image, purchase intention increases by 0.847. Therefore, H1. is validated and image of the promoted brand positively impacts purchase intention on TikTok, YouTube and Instagram.

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	,327	,410		,797	,427		
	BI	,847	,079	,701	10,676	<,001	1,000	1,000

a. Dependent Variable: PI

Table 8: Regression of H1.

As mentioned earlier, this thesis aims to fill a gap in the literature as it aims to analyse the impacts of some variables on others for each social network. As a result, a simple linear regression will be conducted for each platform separately. Moreover, a comparison between Gen Z and Gen Y consumers will also be made.

TikTok

All four conditions are met on TikTok, and the adjusted R-square demonstrates a favourable outcome, as it is possible to know 21.2% of variations of purchase intention only thanks to brand image.

Then, we can reject the null hypothesis and conclude that the model is significant as the p-value is less than 0.05. A part of purchase intention can be explained thanks to this model.

We can also reject the null hypothesis that brand image does not influence purchase intention because the p-value is below 0.05. The coefficient of brand image is positive and equals 0.593, indicating that for each additional unit of brand image, purchase intention increases by 0.593. Therefore, it can be concluded that the image of the promoted brand positively impacts purchase intention on TikTok.

Instagram

On Instagram, the four conditions are met too. It is possible to know 57.8% of variations of purchase intention only thanks to brand image and the adjusted R-square is thus very high.

The model is significant as the p-value is less than 0.05. We can explain a part of purchase intention thanks to this model.

Finally, the null hypothesis that brand image does not influence purchase intention can be rejected as the p-value is below 0.05. The coefficient of brand image has a positive value of 0.908, which indicates that for each additional unit of brand image, purchase intention increases by 0.908. Image of the promoted brand positively impacts purchase intention on Instagram.

YouTube

The four conditions are also met on YouTube. The adjusted R-square is very high as it is possible to know 53.3% of variations of purchase intention only thanks to brand image.

Then, we can reject the null hypothesis and say that the model is significant. We can explain a part of purchase intention thanks to this model.

As the p-value is below 0.05., we can reject the null hypothesis that brand image does not influence purchase intention. The coefficient of brand image is positive and equals 0.901, which means that for each additional unit of brand image, purchase intention increases by 0.901. Therefore, we can conclude that the image of the promoted brand positively impacts purchase intention on YouTube.

Gen Z & Gen Y

In order to test if the age of respondents modifies the impact that brand image has on purchase intention, a moderation study can be conducted. To do this, we can use MACRO Process in SPSS.

Here, the p-value of the interaction between the 2 variables is bigger than 0.05. As a result, the age does not influence the effect that brand image has on purchase intention.

H2. Para-social relationship between influencers and followers positively impacts followers' purchase intention on TikTok, YouTube and Instagram *(see appendix 3.2).*

The second hypothesis which is about the impact of PSR on purchase intention was tested thanks to a simple linear regression. As mentioned earlier, four conditions must be met when we are conducting a simple linear regression. Here, residuals are independent, follow a normal distribution, respect the condition of homoscedasticity and there is no collinearity. Therefore, we can continue the analysis.

The adjusted R-square is high because it is possible to know 27.1% of variations of purchase intention only thanks to para-social relationship.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,527[a]	,277	,271	1,12312	2,115

a. Predictors: (Constant), PR
b. Dependent Variable: PI

Table 9: Regression of H2.

A part of purchase intention can be explained thanks to this model. In fact, the model is significant as the p-value is below 0.05.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	57,103	1	57,103	45,269	<,001[b]
	Residual	148,845	118	1,261		
	Total	205,948	119			

a. Dependent Variable: PI
b. Predictors: (Constant), PR

Table 10: Regression of H2.

Here again, we can reject the null hypothesis that para-social relationship does not influence purchase intention because the p-value is less than 0.05. The coefficient of para-social relationship has a positive value of 0.494, indicating that for each additional unit of para-social relationship, purchase intention increases by 0.494. As a result, H2 is validated and para-social relationship positively impacts purchase intention on TikTok, YouTube and Instagram.

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	2,517	,327		7,703	<,001		
	PR	,494	,073	,527	6,728	<,001	1,000	1,000

a. Dependent Variable: PI

Table 11: Regression of H2.

TikTok

All conditions are met and the adjusted R-square is high, indicating that it is possible to account for 27.7% of the variations of purchase intention solely through para-social relationship.

Then, we can explain a part of purchase intention thanks to this model as the model is significant.

The null hypothesis that para-social relationship does not influence purchase intention can be rejected because the p-value is below 0.05. The coefficient of para-social relationship is positive and equals 0.537 which means that for each additional unit of para-social relationship, purchase intention increases by 0.537. As a result, para-social relationship positively impacts purchase intention on TikTok.

Instagram

The four conditions are met and 30.4% of variations of purchase intention is known only thanks to para-social relationship. The adjusted R-square is thus high.

As the p-value is equal to less than 0.05, we can say that the model is significant. A part of purchase intention can be explained thanks to this model.

We can reject the null hypothesis that para-social relationship does not influence purchase intention as the p-value is less than 0.05. The coefficient of para-social relationship has a positive value of 0.491, meaning that with each additional unit of para-social relationship, there is a corresponding increase of 0.491 in purchase intention. Therefore, para-social relationship positively impacts purchase intention on Instagram.

YouTube

All conditions are met and the adjusted R-square is good. In fact, 17.9% of variations of purchase intention is known only thanks to para-social relationship.

Then, since the p-value is less than 0.05, the model is considered significant. This implies that we can explain a part of purchase intention thanks to this model.

We can reject the null hypothesis that para-social relationship does not influence purchase intention as the p-value is less than 0.05. The coefficient of para-social relationship is positive and equals 0.481 which means that for each additional unit of para-social relationship, purchase intention increases by 0.481. Para-social relationship positively impacts purchase intention on YouTube.

Gen Z & Gen Y

Here, the p-value is also higher than 0.05. Therefore, the age does not influence the impact that para-social relationship has on purchase intention.

H3a. Credibility of influencers positively impacts followers' purchase intention on TikTok, YouTube and Instagram *(see appendix 3.3).*

Here again, a simple linear regression is used to test the hypothesis 3a. and all conditions are respected.

The adjusted R-square is high as it is possible to know 32.3% of variations of purchase intention only thanks to credibility.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,573[a]	,329	,323	1,08242	1,978

a. Predictors: (Constant), CRED

b. Dependent Variable: PI

Table 12: Regression of H3a.

Then, as the p-value is below 0.05, we can say that the model is significant. We can explain a part of purchase intention thanks to this model.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	67,696	1	67,696	57,780	<,001[b]
	Residual	138,252	118	1,172		
	Total	205,948	119			

a. Dependent Variable: PI

b. Predictors: (Constant), CRED

Table 13: Regression of H3a.

The null hypothesis that credibility does not influence purchase intention can be rejected as the p-value is less than 0.05. The coefficient of credibility is positive and equals 0.854, meaning that for each additional unit of credibility, purchase intention increases by 0.854. As a result, the hypothesis 3a. is validated and credibility positively impacts purchase intention on TikTok, YouTube and Instagram.

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	-,258	,647		-,399	,691		
	CRED	,854	,112	,573	7,601	<,001	1,000	1,000

a. Dependent Variable: PI

Table 14: Regression of H3a.

TikTok

All conditions are met and the adjusted R-square is good. It is indeed possible to know 20.2% of variations of purchase intention only thanks to credibility.

Then, we can reject the null hypothesis and say that the model is significant. A part of purchase intention can be explained thanks to this model.

As the p-value is less than 0.05, we can reject the null hypothesis that credibility does not influence purchase intention. The coefficient of credibility equals 0.832 which means that for each additional unit of credibility, purchase intention increases by 0.832. Therefore, credibility positively impacts purchase intention on TikTok.

Instagram

On Instagram, the four conditions are met and 28.7% of variations of purchase intention is known only thanks to credibility. The adjusted R-square is thus high.

Then, we can explain a part of purchase intention thanks to this model as this latter is significant.

We can also reject the null hypothesis that credibility does not influence purchase intention because the p-value is less than 0.05. The coefficient of credibility is positive and equals 0.768 which means that for each additional unit of credibility, purchase intention increases by 0.768. On Instagram, credibility positively impacts purchase intention.

YouTube

The four conditions are met and the adjusted R-square is very high as it is possible to know 49.4% of variations of purchase intention only thanks to credibility.

As the p-value is below 0.05, we can reject the null hypothesis and say that the model is significant. We can explain a part of purchase intention thanks to this model.

We can reject the null hypothesis that credibility does not influence purchase intention as the p-value is below 0.05. The coefficient of credibility is positive and is equal to 1.133 which means that for each additional unit of credibility, purchase intention increases by 1.133. Therefore, credibility positively impacts purchase intention on YouTube.

Gen Z & Gen Y

As the p-value is less than 0.05, we can conclude that the age influences the effect that credibility has on purchase intention. In fact, we can see that the effect is positive and significant when the age is equal to 1 and 2 which means that the effect is significant for Gen Z and Gen Y respectively. Moreover, this effect tends to be higher for Gen Z.

H3b. Credibility of influencers positively impacts the image of the promoted brand on TikTok, YouTube and Instagram *(see appendix 3.4).*

A simple linear regression was also conducted to test the hypothesis 3b. and all conditions were respected.

The adjusted R-square is high as it is possible to know 39.9% of variations of brand image only thanks to credibility.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,636[a]	,404	,399	,84377	1,879

a. Predictors: (Constant), CRED
b. Dependent Variable: BI

Table 15: Regression of H3b.

The model is significant and we can explain a part of credibility thanks to this model.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	57,024	1	57,024	80,096	<,001[b]
	Residual	84,009	118	,712		
	Total	141,033	119			

a. Dependent Variable: BI
b. Predictors: (Constant), CRED

Table 16: Regression of H3b.

Here again, we can reject the null hypothesis that credibility does not influence image of the promoted brand as the p-value is less than 0.05. The coefficient of credibility has a positive value of 0.783, meaning that for each additional unit of credibility, brand image increases by 0.783. As a result, the hypothesis 3b. is validated and credibility positively impacts image of the promoted brand on TikTok, YouTube and Instagram.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	,587	,505		1,164	,247		
	CRED	,783	,088	,636	8,950	<,001	1,000	1,000

a. Dependent Variable: BI

Table 17: Regression of H3b.

TikTok

On TikTok, the four conditions are respected. 31.2% of variations of brand image is known only thanks to credibility and the adjusted R-square is high.

Then, the model is significant and we can explain a part of brand image thanks to this model.

We can also reject the null hypothesis that credibility does not influence image of the promoted brand because the p-value is below 0.05. The coefficient of credibility is positive and is equal to 0.799 which means that for each additional unit of credibility, brand image increases by 0.799. On TikTok, credibility positively impacts image of the promoted brand.

Instagram

The four conditions are met on Instagram. The adjusted R-square is high because it is possible to know 36.2% of variations of brand image only thanks to credibility.

As the p-value is equal to less than 0.05, we can reject the null hypothesis and say that the model is significant. We can explain a part of brand image thanks to this model.

The null hypothesis that credibility does not influence image of the promoted brand can be rejected as the p-value is less than 0.05. The coefficient of credibility is positive and equals 0.721 which means that for each additional unit of credibility, brand image increases by 0.721. Therefore, credibility positively impacts image of the promoted brand on Instagram.

YouTube

All conditions are met on YouTube. The adjusted R-square is remarkably high, enabling us to account for 66% of variations of brand image solely through credibility.

The model is significant and we can explain a part of brand image thanks to this model.

We can also reject the null hypothesis that credibility does not influence image of the promoted brand as the p-value is below 0.05. The coefficient of credibility is positive and equals 1.071 which means that for each additional unit of credibility, brand image increases by 1.071. Thus, it can be concluded that on YouTube, credibility has a positive impact on the image of the promoted brand.

Gen Z & Gen Y

The age influences the effect that credibility has on brand image as the p-value equals less than 0.05. In fact, the effect is positive and significant for Gen Z and Gen Y. Additionally, this effect tends again to be higher for Gen Z.

H4a. Attitude homophily of influencers positively impacts their credibility on TikTok, YouTube and Instagram *(see appendix 3.5).*

A simple linear regression was realized in order to test the hypothesis 4a. dealing with the impact of attitude homophily of influencers on their credibility on the three social networks studied. For this regression, the four conditions are met.

8.9% of variations of credibility can be known only thanks to attitude homophily and the adjusted R-square is thus low.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,310[a]	,096	,089	,84348	2,371

a. Predictors: (Constant), AH
b. Dependent Variable: CRED

Table 18: Regression of H4a.

Here, we can reject the null hypothesis and say that the model is significant. We can explain a part of credibility thanks to this model.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8,945	1	8,945	12,573	<,001[b]
	Residual	83,953	118	,711		
	Total	92,898	119			

a. Dependent Variable: CRED
b. Predictors: (Constant), AH

Table 19: Regression of H4a.

Then, the null hypothesis that attitude homophily does not influence credibility can be rejected because the p-value is less than 0.05. The coefficient of attitude homophily is positive and is equal to 0.230 which means that for each additional unit of attitude homophily, credibility increases by 0.230. As a result, the hypothesis 4a. is validated and attitude homophily positively impacts credibility on TikTok, YouTube and Instagram.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	4,687	,295		15,895	<,001		
	AH	,230	,065	,310	3,546	<,001	1,000	1,000

a. Dependent Variable: CRED

Table 20: Regression of H4a.

TikTok

On TikTok, all conditions are met. The adjusted R-square is very low because we can know -3.8% of variations of credibility only thanks to attitude homophily.

Since the p-value is more than 0.05, we cannot reject the null hypothesis and cannot say that the model is significant. Consequently, we cannot explain a part of credibility thanks to this model.

We cannot reject the null hypothesis that attitude homophily does not influence credibility as the p-value is more than 0.05. As a result, attitude homophily does not positively impact credibility on TikTok.

Instagram

The four conditions are met on Instagram and the adjusted R-square is good as it is possible to know 11.6% of variations of credibility only thanks to attitude homophily.

Then, we can say that the model is significant and we can explain a part of credibility thanks to this model.

As the p-value is less than 0.05, we can reject the null hypothesis that attitude homophily does not influence credibility. The coefficient of attitude homophily has a positive value of 0.268 which means that for each additional unit of attitude homophily, credibility increases by 0.268. Therefore, attitude homophily positively impacts credibility on Instagram.

YouTube

Here, Durbin-Watson statistic is equal to 3.068 which is not close to 2. Therefore, the first condition is not met and the regression cannot be conducted.

Gen Z & Gen Y

As the p-value is higher than 0.05, the age does not influence the effect that attitude homophily has on credibility.

H4b. Attitude homophily of influencers positively impacts para-social relationship with their followers on TikTok, YouTube and Instagram *(see appendix 3.6).*

Here again, a simple linear regression was conducted to verify the hypothesis 4b. and all conditions were met.

The adjusted R-square is high as it is possible to know 36.5% of variations of para-social relationship solely thanks to attitude homophily.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,608[a]	,370	,365	1,11717	2,066

a. Predictors: (Constant), AH

b. Dependent Variable: PR

Table 21: Regression of H4a.

Then, the model is significant and we can explain a part of para-social relationship thanks to this model.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	86,452	1	86,452	69,268	<,001[b]
	Residual	147,273	118	1,248		
	Total	233,724	119			

a. Dependent Variable: PR

b. Predictors: (Constant), AH

Table 22: Regression of H4a.

We can reject the null hypothesis that attitude homophily does not influence para-social relationship because the p-value is below 0.05. The coefficient of attitude homophily is positive and equals to 0.715, which means that for each additional unit of attitude homophily, para-social relationship increases by 0.715. Therefore, the hypothesis 4b. is validated and attitude homophily positively impacts para-social relationship on TikTok, YouTube and Instagram.

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	1,085	,391		2,779	,006		
	AH	,715	,086	,608	8,323	<,001	1,000	1,000

a. Dependent Variable: PR

Table 23: Regression of H4a.

TikTok

Regarding the simple linear regression on TikTok, all conditions are met. However, the adjusted R-square value is relatively modest, as it allows us to know only 9.7% of the variations in para-social relationship based only on attitude homophily.

Then, we cannot reject the null hypothesis and cannot say that the model is significant. We cannot explain a part of para-social relationship thanks to this model.

The null hypothesis that attitude homophily does not influence para-social relationship on TikTok cannot be rejected as the p-value is more than 0.05. As a result, attitude homophily does not positively impact para-social relationship on TikTok.

Instagram

On Instagram, the four conditions are met. 41.4% of variations of para-social relationship can be known only thanks to attitude homophily and the adjusted R-square is thus very high.

Then, the model is significant and we can explain a part of para-social relationship thanks to this model.

We can reject the null hypothesis that attitude homophily does not influence para-social relationship on Instagram because the p-value is less than 0.05. The coefficient of attitude homophily is positive and equals 0.781 which means that for each additional unit of attitude homophily, para-social relationship increases by 0.781. Consequently, attitude homophily positively impacts para-social relationship on Instagram.

YouTube

All conditions are met and the adjusted R-square is very high as it is possible to know 47.5% of variations of para-social relationship only thanks to attitude homophily.

Then, we can say that the model is significant and we can explain a part of para-social relationship thanks to this model.

As the p-value is less than 0.05., we can reject the null hypothesis that attitude homophily does not influence para-social relationship on YouTube. The coefficient of attitude homophily is positive and equals 0.723 which means that for each additional unit of attitude homophily, para-social relationship increases by 0.723. Therefore, attitude homophily positively impacts para-social relationship on YouTube.

Gen Z & Gen Y

Here, the p-value is higher than 0.05. Therefore, we can conclude that the age does not influence the impact that attitude homophily has on para-social relationship.

H5a. Physical attractiveness of influencers positively impacts their credibility on TikTok, YouTube and Instagram *(see appendix 3.7).*

In order to test the hypothesis 5a. dealing with the impact of physical attractiveness of influencers on their credibility, a simple linear regression was also conducted and all conditions were met.

The adjusted R-square is low as it is possible to know 5.2% of variations of credibility only thanks to physical attractiveness.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,244[a]	,060	,052	,86044	2,378

a. Predictors: (Constant), PA
b. Dependent Variable: CRED

Table 24: Regression of H5a.

Then, as the p-value is below 0.05, we can reject the null hypothesis and say that the model is significant. We can explain a part of credibility thanks to this model.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5,536	1	5,536	7,478	,007[b]
	Residual	87,362	118	,740		
	Total	92,898	119			

a. Dependent Variable: CRED
b. Predictors: (Constant), PA

Table 25: Regression of H5a.

The null hypothesis that physical attractiveness does not influence credibility can be rejected because the p-value is below 0.05. The coefficient of physical attractiveness is positive and is equal to 0.190 which means that for each additional unit of physical attractiveness, credibility increases by 0.190. As a result, the hypothesis 5a. is validated and physical attractiveness positively impacts credibility on TikTok, YouTube and Instagram.

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	4,671	,383		12,197	<,001		
	PA	,190	,070	,244	2,735	,007	1,000	1,000

a. Dependent Variable: CRED

Table 26: Regression of H5a.

TikTok

On TikTok, all conditions are met. The adjusted R-square is relatively low because we can know 1.1% of variations of credibility only thanks to physical attractiveness.

Then, the model is not significant and we cannot explain a part of credibility thanks to this model as the p-value is more than 0.05.

We cannot reject the null hypothesis that physical attractiveness does not influence credibility on TikTok. Therefore, physical attractiveness does not positively impact credibility on TikTok.

Instagram

The four conditions are met on Instagram and the adjusted R-square is good as it is possible to know 13.5% of variations of credibility only thanks to physical attractiveness.

Then, we can explain a part of credibility thanks to this model as this latter is significant.

We can reject the null hypothesis that physical attractiveness does not influence credibility on Instagram as the p-value is less than 0.05. The coefficient of physical attractiveness is positive and equals 0.354 which means that for each additional unit of physical attractiveness, credibility increases by 0.354. As a result, physical attractiveness has a positive impact on credibility on Instagram.

YouTube

On YouTube, the four conditions are met. 4.7% of variations of credibility can be known only thanks to physical attractiveness, which means that the adjusted R-square is very low.

Then, as the p-value equals more than 0.05, we cannot reject the null hypothesis and cannot say that the model is significant. We cannot explain a part of credibility thanks to this model.

The null hypothesis that physical attractiveness does not influence credibility on YouTube cannot be rejected. Therefore, physical attractiveness does not positively impact credibility on YouTube.

Gen Z & Gen Y

The age does not influence the impact that physical attractiveness has on credibility because the p-value exceeds 0.05.

H5b. Physical attractiveness of influencers positively impacts para-social relationship with their followers on TikTok, YouTube and Instagram *(see appendix 3.8).*

A simple linear regression was done in order to test the hypothesis 5b. and all conditions were respected.

The adjusted R-square is very low as it is possible to know 3.3% of variations of para-social relationship only thanks to physical attractiveness.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,203[a]	,041	,033	1,37800	2,104

a. Predictors: (Constant), PA
b. Dependent Variable: PR

Table 27: Regression of H5b.

As the p-value is below 0.05, we can conclude that the model is significant. We can explain a part of para-social relationship thanks to this model.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9,656	1	9,656	5,085	,026[b]
	Residual	224,069	118	1,899		
	Total	233,724	119			

a. Dependent Variable: PR
b. Predictors: (Constant), PA

Table 28: Regression of H5b.

Here again, we can reject the null hypothesis that physical attractiveness does not influence para-social relationship because the p-value is less than 0.05. The coefficient of physical attractiveness is equal to 0.251, which means that for each additional unit of physical attractiveness, para-social relationship increases by 0.251. As a result, the hypothesis 5b. is validated and physical attractiveness positively impacts para-social relationship on TikTok, YouTube and Instagram.

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	2,869	,613		4,679	<,001		
	PA	,251	,111	,203	2,255	,026	1,000	1,000

a. Dependent Variable: PR

Table 29: Regression of H5b.

TikTok

On TikTok, the four conditions are satisfied, and the adjusted R-square is low because 8% of variations of para-social relationship can be known only thanks to physical attractiveness.

Given that the p-value exceeds 0.05, we cannot consider the model significant. Consequently, we cannot explain a part of para-social relationship through this model.

We cannot reject the null hypothesis that physical attractiveness does not influence para-social relationship on TikTok. Therefore, physical attractiveness does not positively impact para-social relationship on TikTok.

Instagram

On Instagram, all conditions are met. It is possible to know 6.2% of variations of para-social relationship only thanks to physical attractiveness, and the adjusted R-square is thus low.

Then, we can explain a part of para-social relationship thanks to this model because this latter is significant.

We can also reject the null hypothesis that physical attractiveness does not influence para-social relationship on Instagram as the p-value is less than 0.05. The coefficient of physical attractiveness is equal to 0.405, which means that for each additional unit of physical attractiveness, para-social relationship increases by 0.405. Therefore, physical attractiveness positively impacts para-social relationship on Instagram.

YouTube

First, the residuals have to be independent. Here, Durbin-Watson statistic is equal to 1.336 which is not close to 2. Therefore, the first condition is not met and the regression cannot be performed.

Gen Z & Gen Y

Here again, the p-value is bigger than 0.05. As a result, the age does not influence the effect that physical attractiveness has on para-social relationship.

H6. Social attractiveness of influencers positively impacts para-social relationship with their followers on TikTok, YouTube and Instagram *(see appendix 3.9).*

In order to verify the sixth hypothesis, a simple linear regression was conducted and the four conditions were respected.

The adjusted R-square is high as it is possible to know 41.7% of variations of para-social relationship only thanks to social attractiveness.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,650[a]	,422	,417	1,06990	1,944

a. Predictors: (Constant), SA
b. Dependent Variable: PR

Table 30: Regression of H6.

Then, we can reject the null hypothesis and say that the model is significant. We can explain a part of para-social relationship thanks to this model.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	98,651	1	98,651	86,181	<,001[b]
	Residual	135,074	118	1,145		
	Total	233,724	119			

a. Dependent Variable: PR
b. Predictors: (Constant), SA

Table 31: Regression of H6.

Here again, we can reject the null hypothesis that social attractiveness does not influence para-social relationship as the p-value is less than 0.05. The coefficient of social attractiveness is positive and is equal to 0.670, indicating that for each additional unit of social attractiveness, para-social relationship increases by 0.670. Therefore, the sixth hypothesis is validated and social attractiveness has a positive impact on para-social relationship on TikTok, YouTube and Instagram.

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	,984	,362		2,716	,008		
	SA	,670	,072	,650	9,283	<,001	1,000	1,000

a. Dependent Variable: PR

Table 32: Regression of H6.

TikTok

On TikTok, all conditions are met. The adjusted R-square is high as it is equal to 39.2% which means that it is possible to know 39.2% of variations of para-social relationship only thanks to social attractiveness.

Then, we can explain a part of para-social relationship thanks to this model because this latter is significant.

Since the p-value is below 0.05, we can reject the null hypothesis that social attractiveness does not influence para-social relationship on TikTok. The coefficient of social attractiveness is equal to 0.618, meaning that for each additional unit of social attractiveness, para-social relationship increases by 0.618. As a result, social attractiveness positively impacts para-social relationship on TikTok.

Instagram

The four conditions are met on Instagram. It is possible to know 44.6% of variations of para-social relationship only thanks to social attractiveness and the adjusted R-square is thus considerably high.

Then, since the p-value is equal to less than 0.05, the model is significant and we can explain a part of para-social relationship through to this model.

The null hypothesis that social attractiveness does not influence para-social relationship on Instagram can be rejected because the p-value is below 0.05. The coefficient of social attractiveness is equal to 0.728 which means that for each additional unit of social attractiveness, para-social relationship increases by 0.728. As a result, social attractiveness has a positive effect on para-social relationship on Instagram.

YouTube

Here, Durbin-Watson statistic is equal to 1.295 which is not close to 2. Therefore, the first condition is not met and the regression cannot be conducted.

Gen Z & Gen Y

Once again, the age does not exert any influence on the impact of social attractiveness on para-social relationship, as indicated by the p-value exceeding 0.05.

Hypothesis		β	Conclusion
H1	*The image of the brand which is promoted by the influencer positively impacts follower's purchase intention on TikTok, YouTube and Instagram.*	0.847	Validated
H2	*Para-social relationship between influencers and followers positively impacts followers' purchase intention on TikTok, YouTube and Instagram.*	0.494	Validated
H3a.	*Credibility of influencers positively impacts followers' purchase intention on TikTok, YouTube and Instagram.*	0.854	Validated
H3b.	*Credibility of influencers positively impacts the image of the promoted brand on TikTok, YouTube and Instagram.*	0.783	Validated
H4a.	*Attitude homophily of influencers positively impacts their credibility on TikTok, YouTube and Instagram.*	0.230	Validated
H4b.	*Attitude homophily of influencers positively impacts para-social relationship with their followers on TikTok, YouTube and Instagram.*	0.715	Validated
H5a.	*Physical attractiveness of influencers positively impacts their credibility on TikTok, YouTube and Instagram.*	0.190	Validated

H5b.	*Physical attractiveness of influencers positively impacts para-social relationship with their followers on TikTok, YouTube and Instagram.*	0.251	Validated
H6	*Social attractiveness of influencers positively impacts para-social relationship with their followers on TikTok, YouTube and Instagram.*	0.670	Validated

Table 33: Resume of hypotheses and results

3.4 Mediation analysis

A mediation analysis can also be conducted to try to explain the relationship between an independent variable and a dependent variable (Pleyers, 2021-2022). To this end, we can use MACRO Process in SPSS.

First, we can test whether brand image mediates the impact that credibility has on purchase intention. To do this, we need to verify if credibility influences brand image. Since the p-value is less than 0.05, we can conclude that credibility influences brand image. Then, we need to verify if the impacts of credibility and brand image on purchase intention are significant. Credibility and brand image influence purchase intention because their p-values are below 0.05. Lastly, the indirect effect is significant because 0 is not included in the Bootstrap confidence interval. As a result, brand image plays a mediating role in the relationship between credibility and purchase intention. This indicates that the credibility of influencer increases brand image, which in turn positively impacts purchase intention. Moreover, as the effect of credibility on purchase intention is significant when we add brand image as mediator, we can conclude that there is partial mediation (see appendix 4.1).

Figure 2: Mediation analysis between credibility and purchase intention

Then, we can test whether credibility mediates the impact that attitude homophily has on purchase intention. As the p-value is below 0.05, attitude homophily influences credibility. Then, while credibility influences purchase intention, attitude homophily does not influence purchase intention because its p-value is bigger than 0.05. Nevertheless, as 0 is not included in the confidence interval, we can conclude that the indirect effect is significant. Credibility thus plays a mediating role in the relationship between attitude homophily and purchase intention. This means that influencer's attitude homophily increases their credibility, which in turn positively influences purchase intention. Additionally, as the impact of attitude homophily on purchase intention is not significant when we add credibility as mediator, we can conclude that the mediation is full (see appendix 4.2).

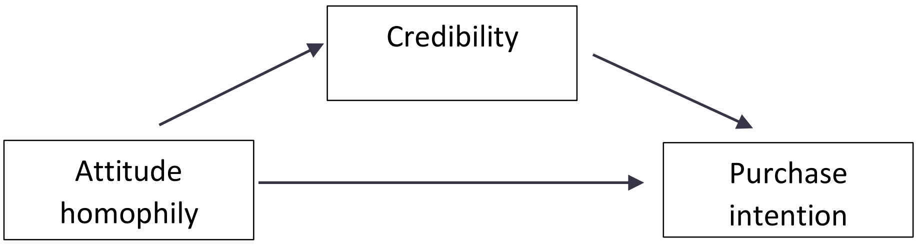

Figure 3: Mediation analysis between attitude homophily and purchase intention

We can also test whether credibility mediates the impact that attitude homophily has on brand image. Attitude homophily influences credibility as the p-value is less than 0.05. Then, attitude homophily and credibility influence purchase intention because their p-values are less than 0.05. Finally, as 0 is not included in the confidence interval, we can conclude that the indirect effect is significant. Credibility consequently plays a mediating role in the relationship between attitude homophily and brand image. In other words, this means that influencer's attitude homophily increases their credibility, which in turn positively influences brand image. Furthermore, as the impact of attitude homophily on brand image is significant when we add credibility as mediator, we can conclude that there is partial mediation (see appendix 4.3).

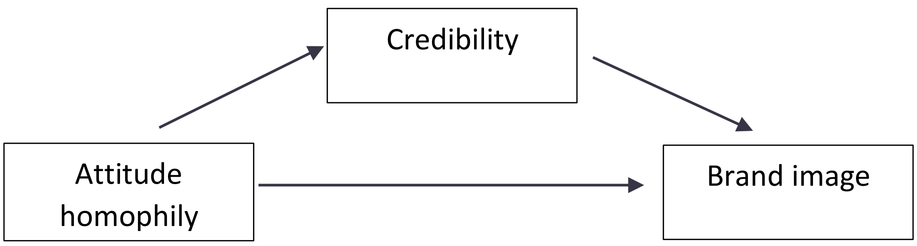

Figure 4: Mediation analysis between attitude homophily and brand image

We can also test if para-social relationship mediates the impact that attitude homophily has on purchase intention. Since the p-value is below 0.05, we can claim that attitude homophily influences para-social relationship and para-social relationship influences purchase intention. Attitude homophily has no impact on purchase intention because the p-value exceeds 0.05. Nevertheless, as 0 is not included in the confidence interval, the indirect effect is significant. Para-social relationship plays thus a mediating role in the relationship between attitude homophily and purchase intention. This indicates that influencer's attitude homophily increases their para-social relationship, which in turn positively impacts purchase intention. Furthermore, as the impact of attitude homophily on purchase intention is not significant when we add para-social relationship as mediator, we can conclude that there is full mediation (see appendix 4.4).

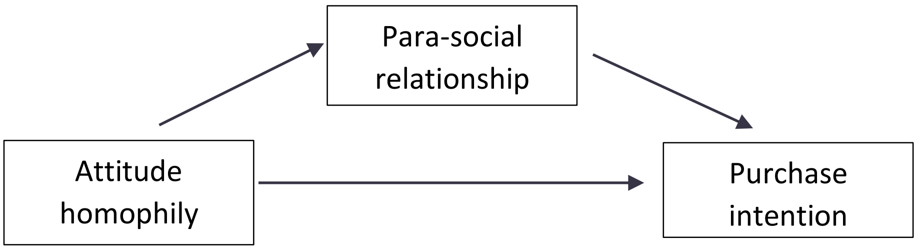

Figure 5: Mediation analysis between attitude homophily and purchase intention

We can also verify if credibility mediates the impact that physical attractiveness has on purchase intention. As the p-value is less than 0.05, we can say that physical attractiveness influences credibility significantly. Then, credibility influences purchase intention but physical attractiveness does not influence purchase intention as its p-value is bigger than 0.05. However, the indirect effect is significant as 0 is not included in the Bootstrap confidence interval. Credibility plays thus a mediating role in the relationship between physical attractiveness and purchase intention. This means that the physical attractiveness of influencers increases their credibility, which in turn positively impacts purchase intention. Moreover, there is full mediation because the effect of physical attractiveness on purchase intention is not significant when we add credibility as mediator (see appendix 4.5).

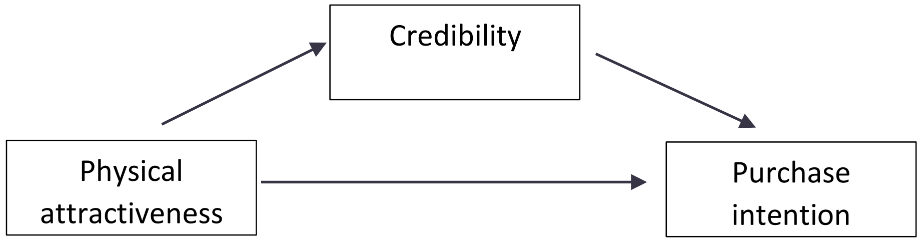

Figure 6: Mediation analysis between physical attractiveness and purchase intention

We can see that physical attractiveness influences credibility because the p-value equals less than 0.05. Then, while credibility influences brand image, physical attractiveness does not influence brand image as its p-value is more than 0.05. Nevertheless, as 0 is not included in the confidence interval, the indirect effect is significant. As a result, credibility plays a mediating role in the relationship between physical attractiveness and brand image. This implies that the physical attractiveness of an influencer increases their credibility, consequently leading to a positive impact on brand image. Additionally, the mediation is full because the effect of physical attractiveness on brand image is not significant when we add credibility as mediator (see appendix 4.6).

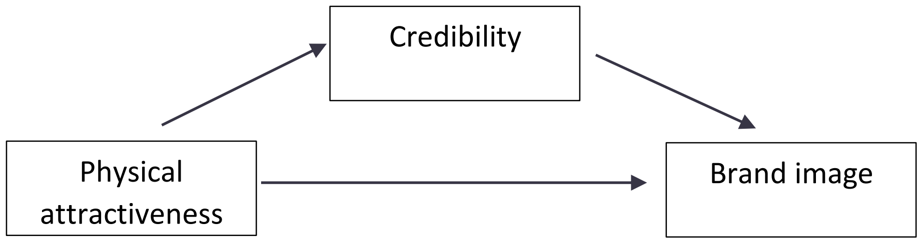

Figure 7: Mediation analysis between physical attractiveness and brand image

We can also test whether para-social relationship mediates the effect that physical attractiveness has on purchase intention. Since the p-value is below 0.05, physical attractiveness influences para-social relationship. Para-social relationship influences purchase intention but physical attractiveness does not influence purchase intention because the p-value is more than 0.05. However, the indirect effect is significant as 0 is not included in the confidence interval. Para-social relationship thus plays a mediating role in the relationship between physical attractiveness and purchase intention. This implies that the physical attractiveness of influencer increases their para-social relationship, which in turn positively influences purchase intention. Additionally, there is full mediation because the impact of attitude homophily on purchase intention is not significant when we add para-social relationship as mediator (see appendix 4.7).

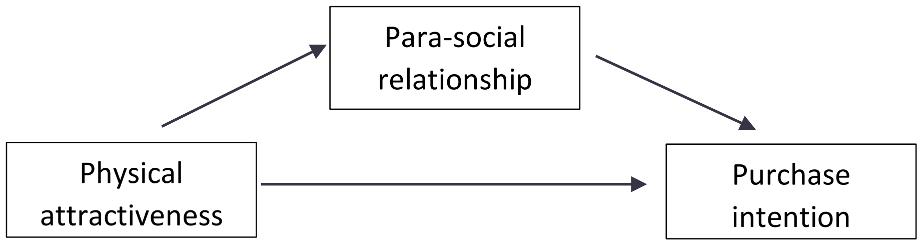

Figure 8: Mediation analysis between physical attractiveness and purchase intention

Finally, we can verify if para-social relationship mediates the impact that social attractiveness has on purchase intention. We can see that social attractiveness influences para-social relationship because the p-value is below 0.05. Para-social relationship influences purchase intention but since the p-value is bigger than 0.05, social attractiveness does not influence purchase intention. Nevertheless, here again, the indirect effect is significant because 0 is not included in the confidence interval. Therefore, para-social relationship plays a mediating role in the relationship between social attractiveness and purchase intention. This indicates that influencer's social attractiveness increases their para-social relationship, which in turn positively influences purchase intention. Moreover, as the effect of social attractiveness on purchase intention is not significant when we add para-social relationship as mediator, there is full mediation (see appendix 4.8).

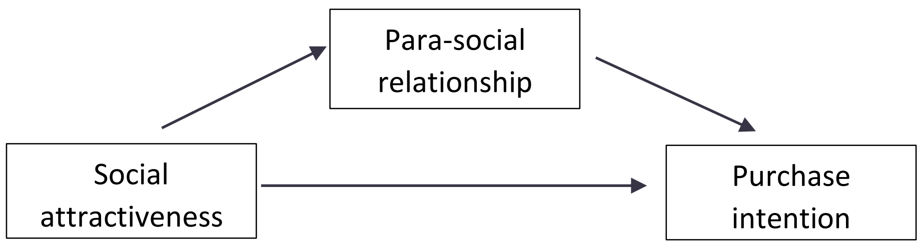

Figure 9: Mediation analysis between social attractiveness and purchase intention

3.5 Multiple linear regressions

In addition to simple linear regressions, it can be also interesting to conduct multiple linear regressions. First, a multiple linear regression which includes purchase intention as dependent variable and brand image, credibility and para-social relationship as independent variables, is conducted. In this case, the four conditions are respected. 53.9% of variations of purchase intention can be known only thanks to brand image, credibility and para-social relationship, which implies that the adjusted R-square value is very high. Then, the model is significant because the p-value is below 0.05. Both brand image and para-social relationship contribute significantly to the prediction of purchase intention. Nevertheless, credibility does not contribute significantly because its p-value is higher than 0.05. As a result, credibility can be removed from the model. Once we restart the analysis, we can see that the coefficient of brand image is much higher than the one of para-social relationship, as the first one is equal to 0.704 and the second one is equal to 0.233. Consequently, both brand image and para-social relationship have a positive impact on purchase intention on the three selected platforms. (see appendix 5.1).

Then, another multiple linear regression including para-social relationship as dependent variable and attitude homophily, physical attractiveness and social attractiveness as independent variables is conducted. Here again, all conditions are respected and it is possible to know 52.4% of variations of para-social relationship only thanks to attitude homophily, physical attractiveness and social attractiveness. Therefore, the adjusted R-square value is very high. As the p-value is equal to less than 0.05, we can conclude that the model is significant. Then, we can see that both attitude homophily and social attractiveness contribute significantly to the prediction of para-social relationship. However, as its p-value is bigger than 0.05, physical attractiveness does not contribute significantly to the prediction of para-social relationship. The physical attractiveness variable can be thus removed from the model. Once we restart the analysis, we can see that the coefficients of attitude homophily and social attractiveness are quite the same as the first one is equal to 0.445 and the second one is equal to 0.476. Therefore, both attitude homophily and social attractiveness positively impact para-social relationship on TikTok, YouTube and Instagram (see appendix 5.2).

Finally, a last multiple linear regression which includes credibility as dependent variable and attitude homophily and physical attractiveness as independent variables can be conducted. In this case, the four conditions are also respected. 13.2% of variations of credibility can be known solely through attitude homophily and physical attractiveness, meaning that the adjusted R-square is relatively modest. We can explain a part of credibility thanks to this model because this latter is significant. Lastly, we can see that both attitude homophily and physical attractiveness contribute significantly to the prediction of credibility as their p-values are below 0.05. The coefficient of attitude homophily is slightly bigger than the one of physical attractiveness as the first one is equal to 0.219 and the second one is equal to 0.175. As a result, both attitude homophily and physical attractiveness positively impact credibility on the three selected social networks (see appendix 5.3).

4. Conclusion

4.1 Discussion

Throughout this thesis, the main objective was to find which influencers' attributes and perceived characterizations made by followers were more important to predict brand image and intention to purchase fashion and beauty products on TikTok, Instagram and YouTube. Furthermore, this study aimed to compare the results across these three platforms. As a reminder, the research question guiding this thesis was as follows:

> How do influencers attributes and perceived characterizations affect brand image and TikTok users' intention to purchase fashion and beauty products, and how does it differ from YouTube and Instagram?

The results obtained thanks to statistical analyses showed that the literature was quite representative of the French-speaking Belgians population, as all hypotheses were empirically validated.

First, the analysis revealed that our initial hypothesis, namely that "the image of the brand which is promoted by the influencer positively impacts follower's purchase intention on TikTok, YouTube and Instagram", was validated. This thesis confirms what has been previously demonstrated in the literature, as Nugroho et al. (2022) found that brand image positively impacts purchase intention of Gen Z consumers. Our study takes a step further because the positive impact of brand image on purchase intention has been observed for Gen Y as well. Additionally, the age was found as having no significant impact on the relationship between brand image and purchase intention. However, this result must be interpreted with caution, given that our sample was mainly composed of Gen Z respondents (75%). Regarding the different social networks, our results indicate that the positive impact of brand image on purchase intention is more pronounced on Instagram and Youtube (0.908, 0.901) in comparison to TikTok (0.593).

The second hypothesis, namely that "para-social relationship between influencers and followers positively impacts followers' purchase intention on TikTok, YouTube and Instagram" was also validated. This result reflects those of several researchers (Lou & Kim, 2019; Masuda et al., 2022) who also demonstrated that PSR has a positive impact on follower's purchase intention. This outcome is not surprising, as Sokolova and Kefi (2020) also concluded that PSR positively impacts intention to purchase fashion and beauty products on Instagram and YouTube. Notably, our study also indicates that the positive impact of PSR on purchase intention is relatively consistent across TikTok, Instagram and YouTube (0.537, 0.491, 0.481). When comparing Gen Z to Gen Y, age seems to have no significant impact on the relationship between PSR and purchase intention. This finding is contrary to that of Sokolova and Kefi (2020) who found that PSR has a stronger effect on purchase intention for Gen Z compared to older generations.

Thirdly, hypothesis 3a. "credibility of influencers positively impacts followers' purchase intention on TikTok, YouTube and Instagram" was also validated. This finding aligns with the conclusions drawn by Sokolova and Kefi (2020), Mabkhot et al. (2022) and Magano et al. (2022). As a reminder, credibility was known as having a positive effect on intention to purchase fashion and beauty products on YouTube and Instagram (Sokolova & Kefi, 2020). Mabkhot et al. (2022) drew the same conclusions and found that credibility positively impacts purchase intention on social networks. It has also been suggested that the positive impact of PSR on purchase intention is bigger than the positive impact of credibility on purchase intention on YouTube (Masuda et al., 2022). However, this thesis presents an opposite finding, as the positive influence of credibility on purchase intention (0.854) surpasses that of PSR on purchase intention (0.494). Moreover, the positive effect of credibility on purchase intention is more pronounced on YouTube (1.133) than on TikTok and Instagram (0.832, 0.768). A possible explanation for this difference may be the fact that videos are traditionally longer on YouTube, which could prompt influencers to use more arguments in order to convince their followers. When analyzing the factors which affect purchase intention, credibility seems to have a bigger impact than brand image and PSR on TikTok, Instagram and YouTube. Then, age emerges as determinant in the relationship between credibility and purchase intention, as the impact of credibility on purchase intention tends to be higher for Gen Z. This finding contradicts previous studies (Sokolova & Kefi, 2020; Magano et al., 2022), which suggested that the impact of credibility on purchase intention is slightly higher among older generations. Lastly, it also appears that credibility positively contributes to purchase intention through brand image, as Nugroho et al. (2022) reported for Gen Z. This implies that credibility of an influencer enhances the image of the promoted brand, which in turn increases intention to purchase fashion and beauty products.

Similarly, hypothesis 3b. "credibility of influencers positively impacts the image of the promoted brand on TikTok, YouTube and Instagram" was also confirmed. This is well in line with what Nugroho et al. (2022) reported. Moreover, it appears that the positive impact of credibility on brand image is higher on YouTube (1.071) compared to TikTok and Instagram (0.799, 0.721). The effect that credibility has on brand image is also higher for Gen Z, and age has an influence in the relationship between credibility and brand image.

Hypothesis 4a., namely that "attitude homophily of influencers positively impacts their credibility on TikTok, YouTube and Instagram*",* was also validated. A positive impact of attitude homophily on credibility in the fashion and beauty fields on YouTube and Instagram was already mentioned in the literature (Sokolova & Kefi, 2020). Upon closer examination of each social network, TikTok reports a different outcome compared to Instagram (0.268), as attitude homophily does not positively impact credibility on TikTok. YouTube was not analysed because residuals were not independent. When comparing Gen Z to Gen Y, it is evident that age does not influence the effect that attitude homophily has on credibility. It has also been observed that attitude homophily of an influencer positively impacts purchase intention via credibility. This implies that the perceived similarity between an influencer and a follower increases their credibility, which in turn leads to a higher intention to purchase fashion and beauty products. Furthermore, the analysis has revealed that attitude homophily positively impacts brand image via credibility. As a result, this means that the similarity between an influencer and a follower increases their credibility, which in turn leads to a higher image of the promoted brand.

Hypothesis 4b., which investigates "attitude homophily of influencers positively impacts para-social relationship with their followers on TikTok, YouTube and Instagram", was also validated. Prior studies have acknowledged the positive impact of attitude homophily on PSR (Lee & Watkins, 2016; Sokolova & Kefi, 2020; Masuda et al., 2022). In fact, Lee and Watkins (2016) found it for luxury brands on YouTube while Sokolova and Kefi (2020) reported this positive impact in the fields of fashion and beauty on YouTube and Instagram, and Masuda et al. (2022) on YouTube. In our study, on Instagram and YouTube, the positive impact of attitude homophily on PSR remains quite similar (0.781, 0.723), but the finding is different on TikTok where attitude homophily does not positively impact para-social relationship. Another interesting result is the fact that attitude homophily is the only significant factor for PSR on YouTube. Regarding Gen Z and Gen Y, there is again no impact of age on the relationship between attitude homophily and para-social relationship. Interestingly, attitude homophily of an influencer has also a positive effect on purchase intention via para-social relationship. Consequently, this outcome implies that the similarity between an influencer and a follower increases the follower's feeling of friendship, which finally increases intention to purchase fashion and beauty products.

Regarding physical attractiveness, hypothesis 5a. "physical attractiveness of influencers positively impacts their credibility on TikTok, YouTube and Instagram" has been validated, aligning with the findings of Sokolova and Kefi (2020) in the fashion and beauty fields on YouTube and Instagram, as well as the observations made by Masuda et al. (2022) on YouTube. The impact of physical attractiveness (0.190) on credibility is slightly lower than the impact of attitude homophily (0.230). When analysing each platform separately, it becomes evident that physical attractiveness positively impacts credibility on Instagram but not on TikTok and YouTube. Interestingly, the impact of physical attractiveness (0.354) on credibility on Instagram is slightly higher than the impact of attitude homophily (0.268). This result might be attributed to the fact that Instagram is mainly a platform for sharing pictures, while TikTok and YouTube are more videos-oriented. As a result, physical attractiveness may have a bigger effect on credibility on Instagram because users are mainly exposed to pictures of influencers. There is no difference in terms of generations, as age does not influence the effect that physical attractiveness has on credibility. Then, it seems that physical attractiveness has a positive effect on purchase intention via credibility. In fact, physical attractiveness of an influencer increases their credibility which in turn increases intention to purchase fashion and beauty products. Finally, it also seems that physical attractiveness has a positive effect on brand image via credibility. In fact, physical attractiveness of an influencer positively impacts their credibility, which in turn positively impacts the image of the promoted brand.

Hypothesis 5b., i.e. "physical attractiveness of influencers positively impacts para-social relationship with their followers on TikTok, YouTube and Instagram", was confirmed as noticed by Lee and Watkins (2016) for luxury brands on YouTube and Masuda et al. (2022) on YouTube. This finding is contrary to that of Sokolova and Kefi (2020) who found that physical attractiveness negatively impacts PSR in the fashion and beauty fields on YouTube and Instagram. If we look at each social network separately, physical attractiveness positively impacts PSR on Instagram (0.405) but not on TikTok and YouTube. The reason behind this outcome might be the same as the previous hypothesis. Here again, age does not influence the relationship between physical attractiveness and PSR. Physical attractiveness also influences purchase intention via para-social relationship. Therefore, this implies that physical attractiveness of an influencer fosters a heightened feeling of friendship between a follower and an influencer, which in turn increases their purchase intention.

Finally, the sixth hypothesis, namely that "social attractiveness of influencers positively impacts para-social relationship with their followers on TikTok, YouTube and Instagram", was validated. Several studies (Lee & Watkins, 2016; Sokolova & Kefi, 2020; Masuda et al., 2022) reported the positive impact of social attractiveness on PSR whether for luxury brands on YouTube, beauty and fashion products on YouTube and Instagram or on YouTube. This result means that followers tend to consider an influencer they regularly follow as a friend. In contrast to earlier finding of Masuda et al. (2022), who found that social attractiveness has a bigger impact on PSR than physical attractiveness and attitude homophily, this thesis found that attitude homophily has a bigger impact on PSR (0.715), closely followed by social attractiveness (0.670) and finally physical attractiveness (0.251). This thesis nevertheless supports what Lee and Watkins (2016) demonstrated as social attractiveness and attitude homophily have a bigger impact on PSR compared to physical attractiveness. When analysing Instagram, TikTok and YouTube distinctly, it seems that social attractiveness has a bigger impact on PSR on Instagram (0.728) compared to TikTok (0.618). YouTube was not included in this analysis as residuals were non-independent. This finding is interesting for TikTok as social attractiveness seems to be the only important characteristic to predict PSR. Regarding the different generations, the finding of the current thesis does not support previous research of Sokolova and Kefi (2020) who reported that social attractiveness does not positively impact PSR for Gen Z but does positively impact PSR for older generations. In this thesis, it seems that age does not influence the relationship between social attractiveness and PSR. It also appears that social attractiveness has a positive effect on purchase intention via para-social relationship which means that social attractiveness of an influencer increases the feeling of friendship that a follower has with an influencer, which in turn increases their purchase intention.

4.2 Managerial implications

Companies active in the fashion and beauty sectors should consider that the image of the promoted brand, the credibility of influencers and the para-social relationship developed between them and their followers are important predictors of purchase intention. As Sokolova & Kefi (2020) already reported, long-term followers of credible influencers are more inclined to buy the promoted product. Furthermore, credibility emerges as an important predictor of purchase intention via brand image. However, future conclusions must be taken with caution as a multiple linear regression showed that only the brand image and para-social relationship appear to have a positive effect on purchase intention.

Then, it appears that attitude homophily, physical attractiveness and social attractiveness are important predictors of para-social relationship, whereas attitude homophily and physical attractiveness are important predictors of credibility. Additionally, it is noteworthy that attitude homophily, physical attractiveness and social attractiveness are important predictors of purchase intention via para-social relationship, while attitude homophily and physical attractiveness are important predictors of purchase intention and brand image via credibility. Here again, future conclusions should be treated with caution given that a multiple linear regression has indicated that only attitude homophily and social attractiveness seemed to have a positive effect on para-social relationship.

As far as the image of the brand promoted by the influencer is concerned, fashion and beauty companies focusing on Instagram and YouTube should pay even more attention to their image than companies focusing on TikTok as brand image has a bigger impact on purchase intention on those two social networks. Then, fashion and beauty brands should also consider credibility of influencers as it has a positive impact on their image and this impact is even more important for companies focusing on YouTube.

Some perceived characterizations are also more important than others. For example, the credibility of influencers seems to exert the biggest impact on followers' purchase intention compared to para-social relationship and brand image. Credible influencers are thus more persuasive than those having para-social relationship with their followers. This suggests that fashion and beauty companies should privilege credibility when hiring influencers, whether they are focusing on TikTok, Instagram or YouTube. Fashion and beauty brands mainly active on YouTube should put even more emphasis on credibility. However, it does not imply that para-social relationship created between influencers and followers are not important when choosing an influencer. It signifies that while valuable, this relationship ranks lower in importance than credibility. Firms in the fashion and beauty fields targeting Gen Z consumers should also put more emphasis on credibility of influencers rather than PSR.

Then, regarding influencer's attributes, attitude homophily of influencers has a slightly higher impact on credibility than physical attractiveness on TikTok, Instagram and YouTube. This may suggest to firms to pay less attention to physical attractiveness of influencers compared to attitude homophily. Firms should thus understand the values shared by influencers, and followers and the promoted product should be aligned with those values as they are important for persuasion. Nevertheless, when analyzing each social network distinctly, physical attractiveness has a higher impact on credibility than attitude homophily on Instagram. Fashion and beauty brands should thus pay more attention to physical attractiveness than attitude homophily when choosing an influencer on Instagram. Those impacts are nonetheless low and future studies may need to study other influencer's attributes. In fact, neither attitude homophily nor physical attractiveness have a positive impact on credibility on TikTok and YouTube.

Lastly, attitude homophily also seems to have the biggest impact on para-social relationship compared to social attractiveness and physical attractiveness. Brands active in fashion and beauty sectors should thus pay more attention to attitude homophily, a little bit less to social attractiveness and even less to physical attractiveness when choosing an influencer. The results are quite similar if companies are focusing on Instagram. On TikTok, only social attractiveness has a positive impact on PSR, which suggests that companies focusing on TikTok should pay particular attention to this influencer's attribute, while fashion and beauty brands focusing on YouTube should put more emphasis on attitude homophily when selecting an influencer, as it is the only significant attribute for PSR.

4.3 Limits

This master thesis has some limitations mainly related to the quantitative study that was conducted.

Firstly, it would have been interesting to have a bigger sample of respondents given that the current one is composed of 120 people. Although 355 responses were collected, the analysed population was so specific that almost two third of respondents had to be removed. However, to achieve statistical robustness, a sample size of 196 respondents and at least 65 respondents per social network would have been needed, as indicated to the following formula used to determine the adequate sample size (Steils, 2020-2021):

$$n = \frac{p\,(1-p)\,z^2}{D^2}$$

Figure 10: Formula to determine the adequate sample size

In fact, estimating the percentage of population having the adequate criteria - namely active engagement on at least one social network amongst the three selected platforms (TikTok, Youtube or Instagram), following at least one fashion or beauty influencer, and having already purchased a product or service promoted by this influencer – is very challenging. In such a scenario, p = 0.5 can be used (Steils, 2020-2021). A level of confidence of 95% can be set, giving "z" equals 1.96 while the tolerated margin of error can be set at 7%. These values gave us a sample of 196 respondents. Consequently, at least 65 respondents were necessary for each social network. Time was thus a constraint, and future studies would need to collect more answers.

Furthermore, the distribution of participants across the various social networks was uneven, with Instagram dominating the sample with 60.83% of respondents, while TikTok and YouTube accounted only for 23.33% and 15.83% respectively. Future studies might try to collect a more representative sample by using, for example, a quota sampling method with social networks as criteria.

Regarding the age distribution and the comparison between Gen Z and Gen Y, it would have been interesting to collect more answers from Gen Y participants in order to have more representative results. As previously noted, the majority of our sample consisted of Gen Z respondents (75%), with Gen Y respondents comprising just 20% of the sample. This difference in distribution could be explained by the fact that influencers in the fashion and beauty fields are mainly followed by Gen Z users (Sokolova & Kefi, 2020).

Snowball sampling was used when conducting the survey. Nevertheless, it is important to acknowledge that this non-probability sampling method might create some problems of representativeness. Respondents were indeed asked to share the survey with people they thought would belong to the target population. Therefore, they might have selected people who shared similarities with them, thereby creating a bias (Steils, 2020-2021).

Another limit to consider pertains to the type of influencers that this thesis mainly focused on. In fact, our sample is mainly composed of mega influencers and macro influencers. Future studies may investigate whether those results are true for influencers having fewer followers as well.

Lastly, some conclusions must be taken with caution. In fact, in addition to simple linear regressions, multiple linear regressions were conducted, revealing slightly different results from simple linear regressions. While credibility was found as most important predictor of intention to purchase fashion and beauty products thanks to simple linear regressions, multiple linear regression showed that credibility was not a significant predictor for purchase intention. Moreover, physical attractiveness was found to be a non-significant factor in predicting para-social relationship when a multiple linear regression was conducted.

By integrating those suggestions in future studies, the present thesis would be enriched all the more and gain a greater degree of depth.

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Appendix

Appendix 1: Questionnaire

Bonjour,

Dans le cadre de mon mémoire en dernière année de master à la Louvain School of Management, je réalise une étude qui a pour objectif d'analyser le comportement des utilisateurs belges vis-à-vis des influenceurs.

Ce questionnaire est complètement anonyme et il vous faudra 5 à 10 minutes pour y répondre. Rappelez-vous qu'il n'y a pas de bonnes ou de mauvaises réponses.

Merci d'avance pour votre aide !
Sabri.

Q1 *

Lequel/lesquels de ces réseaux sociaux utilisez-vous ?

- ☐ TikTok
- ☐ Instagram
- ☐ YouTube
- ☐ Aucun

Q2 *

Parmi ces réseaux sociaux, lequel préférez-vous?

- ○ TikTok
- ○ Instagram
- ○ YouTube

Q3 *

A quelle fréquence utilisez-vous votre réseau social préféré ?

- ○ Au moins une fois par jour
- ○ Au moins une fois par semaine
- ○ Au moins une fois par mois
- ○ Moins d'une fois par mois

Un influenceur est une personne qui a acquis un grand nombre d'abonnés et qui développe du contenu dans un ou plusieurs domaines. En échange d'argent ou de produits gratuits par exemple, ils partagent des histoires et des critiques sur des produits ou des marques.

Un influenceur mode est une personne qui partage par exemple ses tenues et ses conseils modes avec ses abonnés.
Un influenceur beauté est une personne qui partage par exemple ses idées maquillages et ses conseils beauté.

Q4 *

Suivez-vous au moins un influenceur beauté ou un influenceur mode sur votre réseau social préféré ?

- ○ Oui
- ○ Non

Q5 *

Vous souvenez-vous du nom de cet influenceur ?

- ○ Oui
- ○ Non

Q6 *

Pouvez-vous le nommer ?

Q7 *

Avez-vous déjà acheté un produit ou service promu par un influenceur beauté ou un influenceur mode ?

- ○ Oui
- ○ Non

Le reste du questionnaire porte uniquement sur TIKTOK et votre influenceur beauté ou mode préféré sur TIKTOK.

Le reste du questionnaire porte uniquement sur YOUTUBE et votre influenceur beauté ou mode préféré sur YOUTUBE.

Le reste du questionnaire porte uniquement sur INSTAGRAM et votre influenceur beauté ou mode préféré sur INSTAGRAM.

Q8 *

Choisissez parmi les affirmations suivantes « de pas du tout d'accord » à « tout à fait d'accord ».

	Tout à fait en désaccord	En désaccord	Plus ou moins en désaccord	Pas d'opinion	Plus ou moins d'accord	D'accord	Tout à fait d'accord
Je pense que cet(te) influenceur/influenceuse pourrait être mon ami(e)	○	○	○	○	○	○	○
J'aimerais avoir une discussion amicale avec cet(te) influenceur/influenceuse	○	○	○	○	○	○	○
Nous pourrions créer une amitié personnelle entre nous	○	○	○	○	○	○	○
Cet(te) influenceur/influenceuse serait agréable à fréquenter	○	○	○	○	○	○	○

Q9

Choisissez parmi les affirmations suivantes « de pas du tout d'accord » à « tout à fait d'accord ».

	Tout à fait en désaccord	En désaccord	Plus ou moins en désaccord	Pas d'opinion	Plus ou moins d'accord	D'accord	Tout à fait d'accord
Je le/la trouve physiquement très attractif/attractive	○	○	○	○	○	○	○
Je le/la trouve très joli(e)	○	○	○	○	○	○	○
Il/Elle a un look très sexy	○	○	○	○	○	○	○

Q10

Choisissez parmi les affirmations suivantes « de pas du tout d'accord » à « tout à fait d'accord ».

	Tout à fait en désaccord	En désaccord	Plus ou moins en désaccord	Pas d'opinion	Plus ou moins d'accord	D'accord	Tout à fait d'accord
Cet(te) influenceur/influenceuse et moi avons beaucoup en commun	○	○	○	○	○	○	○
Cet(te) influenceur/influenceuse et moi nous ressemblons beaucoup	○	○	○	○	○	○	○
Cet(te) influenceur/influenceuse pense comme moi	○	○	○	○	○	○	○
Cet(te) influenceur/influenceuse partage mes valeurs	○	○	○	○	○	○	○

Q11

Choisissez parmi les affirmations suivantes « de pas du tout d'accord » à « tout à fait d'accord ».

	Tout à fait en désaccord	En désaccord	Plus ou moins en désaccord	Pas d'opinion	Plus ou moins d'accord	D'accord	Tout à fait d'accord
Je pense que cet(te) influenceur/influenceuse est convaincant(e)	○	○	○	○	○	○	○
Je pense que cet(te) influenceur/influenceuse est crédible	○	○	○	○	○	○	○
Je pense que la publicité de cet(te) influenceur/ influenceuse est une bonne référence pour l'achat de produits	○	○	○	○	○	○	○
Je trouve que l'achat de produits ou services promus par cet(te) influenceur/influenceuse est utile	○	○	○	○	○	○	○

Q12

Choisissez parmi les affirmations suivantes « de pas du tout d'accord » à « tout à fait d'accord ».

	Tout à fait en désaccord	En désaccord	Plus ou moins en désaccord	Pas d'opinion	Plus ou moins d'accord	D'accord	Tout à fait d'accord
J'ai hâte de voir cet(te) influenceur/influenceuse sur son compte ou dans mon fil d'actualité	○	○	○	○	○	○	○
Si cet(te) influenceur/influenceuse apparaissait sur le compte d'une autre personne, je regarderais cette vidéo	○	○	○	○	○	○	○
Lorsque je regarde cet(te) influenceur/influenceuse, j'ai l'impression de faire partie de son groupe	○	○	○	○	○	○	○
Je pense que cet(te) influenceur/influenceuse est comme un(e) vieil(le) ami(e)	○	○	○	○	○	○	○
J'aimerais rencontrer cet(te) influenceur/influenceuse en personne	○	○	○	○	○	○	○
S'il y avait un article sur cet(te) influenceur/influenceuse dans un journal ou un magazine, je le lirais	○	○	○	○	○	○	○
Cet(te) influenceur/influenceuse me met à l'aise, comme si j'étais avec des amis	○	○	○	○	○	○	○
Lorsque cet(te) influenceur/influenceuse me montre ce qu'il/elle pense d'une marque, cela m'aide à me faire ma propre opinion sur la marque	○	○	○	○	○	○	○

Q13

Choisissez parmi les affirmations suivantes « de pas du tout d'accord » à « tout à fait d'accord ».

	Tout à fait en désaccord	En désaccord	Plus ou moins en désaccord	Pas d'opinion	Plus ou moins d'accord	D'accord	Tout à fait d'accord
Le produit de mode/beauté promu est de grande qualité	○	○	○	○	○	○	○
Le produit de mode/beauté promu présente de meilleures caractéristiques que ses concurrents	○	○	○	○	○	○	○
La marque promue est sympa	○	○	○	○	○	○	○
La marque promue a une personnalité qui la distingue de ses concurrents	○	○	○	○	○	○	○
La marque promue ne déçoit pas ses clients	○	○	○	○	○	○	○
La marque promue est une des meilleures marques du secteur	○	○	○	○	○	○	○

Q14

Choisissez parmi les affirmations suivantes « de pas du tout d'accord » à « tout à fait d'accord ».

	Tout à fait en désaccord	En désaccord	Plus ou moins en désaccord	Pas d'opinion	Plus ou moins d'accord	D'accord	Tout à fait d'accord
J'achèterais à l'avenir les produits de beautés ou de modes promus par cet(te) influenceur/influenceuse	○	○	○	○	○	○	○
J'achèterais une marque sur la base des conseils donnés par cet(te) influenceur/influenceuse	○	○	○	○	○	○	○
Je suivrais les recommandations de marque de cet(te) influenceur/influenceuse	○	○	○	○	○	○	○
J'encouragerais mes proches à acheter les produits de beautés ou de modes promus par cet(te) influenceur/influenceuse	○	○	○	○	○	○	○

Q15

Quel est votre genre ?

- ○ Homme
- ○ Femme
- ○ Autre

Q16

Quel âge avez-vous ?

- ○ Moins de 18 ans
- ○ 18-24 ans
- ○ 25-34 ans
- ○ 35-44 ans
- ○ 45-54 ans
- ○ Plus de 55 ans

Fin de l'enquête

Merci d'avoir participé à cette enquête.

Si vous pensez connaitre d'autres personnes suivant des influenceurs dans le secteur de la mode ou de la beauté, merci de bien vouloir partager cette enquête avec eux.

Appendix 2: Verification of scales

Appendix 2.1: Purchase intention variable

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,794
Bartlett's Test of Sphericity	Approx. Chi-Square	318,314
	df	6
	Sig.	<,001

Communalities

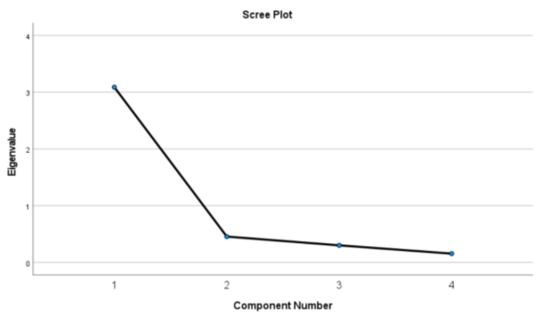
	Initial	Extraction
PI_1	1,000	,709
PI_2	1,000	,842
PI_3	1,000	,786
PI_4	1,000	,751

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,089	77,217	77,217	3,089	77,217	77,217
2	,456	11,388	88,605			
3	,301	7,523	96,127			
4	,155	3,873	100,000			

Extraction Method: Principal Component Analysis.



Reliability Statistics

Cronbach's Alpha	N of Items
,895	4

Appendix 2.2: Image of the promoted brand variable

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,900
Bartlett's Test of Sphericity	Approx. Chi-Square	495,368
	df	15
	Sig.	<,001

Communalities

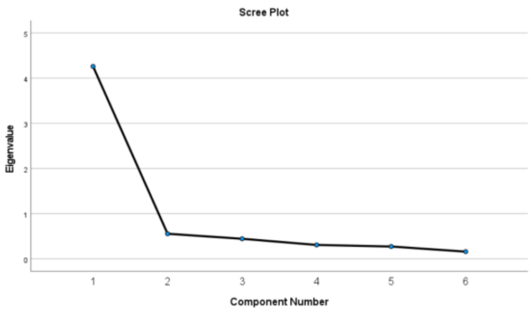
	Initial	Extraction
BI_1	1,000	,683
BI_2	1,000	,767
BI_3	1,000	,673
BI_4	1,000	,555
BI_5	1,000	,865
BI_6	1,000	,718

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues Total	% of Variance	Cumulative %	Extraction Sums of Squared Loadings Total	% of Variance	Cumulative %
1	4,260	71,007	71,007	4,260	71,007	71,007
2	,555	9,257	80,264			
3	,444	7,403	87,667			
4	,308	5,131	92,798			
5	,273	4,548	97,346			
6	,159	2,654	100,000			

Extraction Method: Principal Component Analysis.



Reliability Statistics

Cronbach's Alpha	N of Items
,916	6

Appendix 2.3: Para-social relationship variable

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,854
Bartlett's Test of Sphericity	Approx. Chi-Square	323,294
	df	28
	Sig.	<,001

Communalities

	Initial	Extraction
PR_1	1,000	,415
PR_2	1,000	,483
PR_3	1,000	,622
PR_4	1,000	,597
PR_5	1,000	,656
PR_6	1,000	,176
PR_7	1,000	,541
PR_8	1,000	,315

Extraction Method: Principal Component Analysis.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,850
Bartlett's Test of Sphericity	Approx. Chi-Square	308,725
	df	21
	Sig.	<,001

Communalities

	Initial	Extraction
PR_1	1,000	,420
PR_2	1,000	,474
PR_3	1,000	,630
PR_4	1,000	,603
PR_5	1,000	,666
PR_7	1,000	,559
PR_8	1,000	,318

Extraction Method: Principal Component Analysis.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,836
Bartlett's Test of Sphericity	Approx. Chi-Square	279,740
	df	15
	Sig.	<,001

Communalities

	Initial	Extraction
PR_1	1,000	,410
PR_2	1,000	,489
PR_3	1,000	,662
PR_4	1,000	,628
PR_5	1,000	,671
PR_7	1,000	,555

Extraction Method: Principal Component Analysis.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,808
Bartlett's Test of Sphericity	Approx. Chi-Square	239,886
	df	10
	Sig.	<,001

Communalities

	Initial	Extraction
PR_2	1,000	,458
PR_3	1,000	,686
PR_4	1,000	,678
PR_5	1,000	,687
PR_7	1,000	,579

Extraction Method: Principal Component Analysis.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,792
Bartlett's Test of Sphericity	Approx. Chi-Square	194,245
	df	6
	Sig.	<,001

Communalities

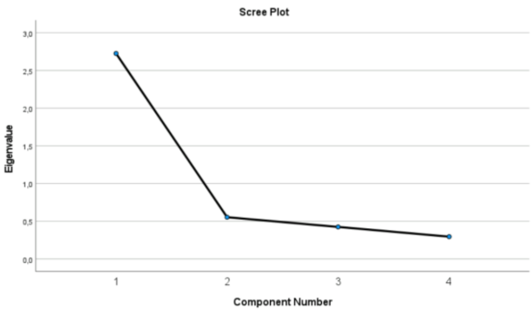
	Initial	Extraction
PR_3	1,000	,704
PR_4	1,000	,750
PR_5	1,000	,680
PR_7	1,000	,592

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,726	68,140	68,140	2,726	68,140	68,140
2	,554	13,845	81,985			
3	,425	10,623	92,607			
4	,296	7,393	100,000			

Extraction Method: Principal Component Analysis.



Reliability Statistics

Cronbach's Alpha	N of Items
,842	4

Appendix 2.4: Credibility variable

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,699
Bartlett's Test of Sphericity	Approx. Chi-Square	182,655
	df	6
	Sig.	<,001

Communalities

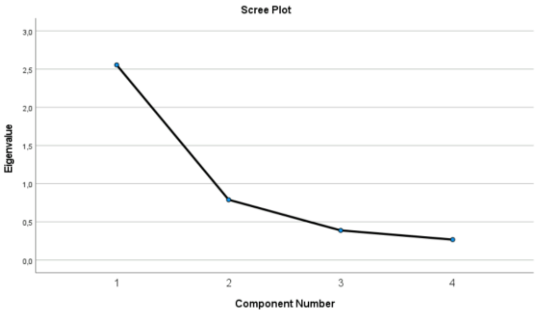
	Initial	Extraction
CRED_1	1,000	,607
CRED_2	1,000	,595
CRED_3	1,000	,724
CRED_4	1,000	,628

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues Total	% of Variance	Cumulative %	Extraction Sums of Squared Loadings Total	% of Variance	Cumulative %
1	2,555	63,872	63,872	2,555	63,872	63,872
2	,790	19,738	83,610			
3	,388	9,701	93,311			
4	,268	6,689	100,000			

Extraction Method: Principal Component Analysis.



Reliability Statistics

Cronbach's Alpha	N of Items
,809	4

Appendix 2.5: Attitude homophily variable

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,723
Bartlett's Test of Sphericity	Approx. Chi-Square	211,787
	df	6
	Sig.	<,001

Communalities

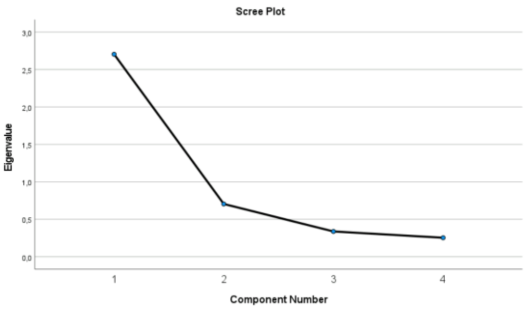
	Initial	Extraction
AH_1	1,000	,646
AH_2	1,000	,751
AH_3	1,000	,722
AH_4	1,000	,586

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues Total	% of Variance	Cumulative %	Extraction Sums of Squared Loadings Total	% of Variance	Cumulative %
1	2,704	67,599	67,599	2,704	67,599	67,599
2	,705	17,618	85,217			
3	,338	8,442	93,659			
4	,254	6,341	100,000			

Extraction Method: Principal Component Analysis.



Reliability Statistics

Cronbach's Alpha	N of Items
,839	4

Appendix 2.6: Physical attractiveness variable

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,648
Bartlett's Test of Sphericity	Approx. Chi-Square	123,275
	df	3
	Sig.	<,001

Communalities

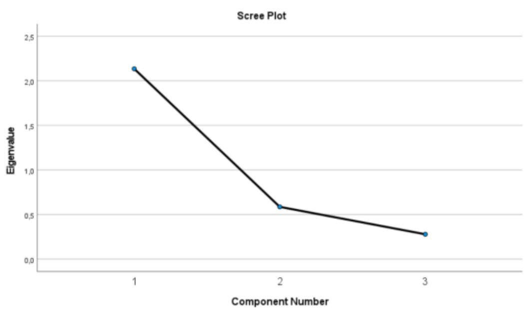
	Initial	Extraction
PA_1	1,000	,817
PA_2	1,000	,725
PA_3	1,000	,592

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,135	71,154	71,154	2,135	71,154	71,154
2	,586	19,548	90,702			
3	,279	9,298	100,000			

Extraction Method: Principal Component Analysis.



Reliability Statistics

Cronbach's Alpha	N of Items
,783	3

Appendix 2.7: Social attractiveness variable

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,779
Bartlett's Test of Sphericity	Approx. Chi-Square	241,273
	df	6
	Sig.	<,001

Communalities

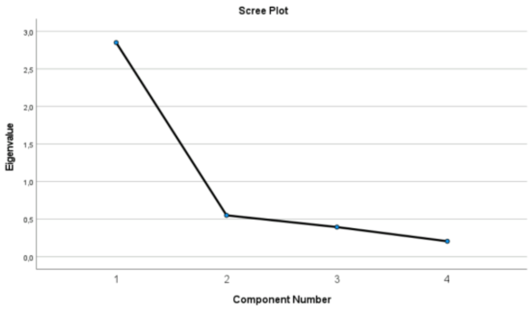
	Initial	Extraction
SA_1	1,000	,780
SA_2	1,000	,689
SA_3	1,000	,806
SA_4	1,000	,575

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,850	71,262	71,262	2,850	71,262	71,262
2	,550	13,757	85,019			
3	,394	9,853	94,872			
4	,205	5,128	100,000			

Extraction Method: Principal Component Analysis.



Reliability Statistics

Cronbach's Alpha	N of Items
,866	4

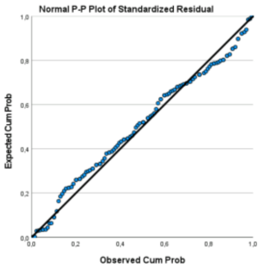
Appendix 3: Hypotheses testing

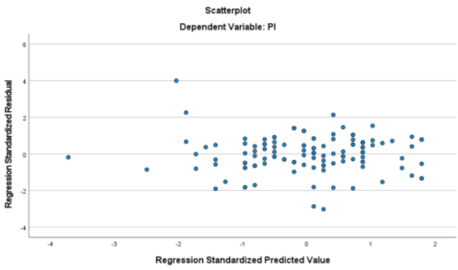
Appendix 3.1: H1.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,701[a]	,491	,487	,94225	1,970

a. Predictors: (Constant), BI
b. Dependent Variable: PI





Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	,327	,410		,797	,427		
	BI	,847	,079	,701	10,676	<,001	1,000	1,000

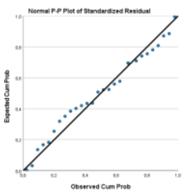
a. Dependent Variable: PI

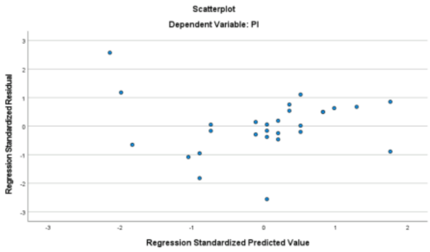
TikTok

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,491[a]	,241	,212	1,14682	1,563

a. Predictors: (Constant), BI
b. Dependent Variable: PI





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10,847	1	10,847	8,248	,008[b]
	Residual	34,195	26	1,315		
	Total	45,042	27			

a. Dependent Variable: PI
b. Predictors: (Constant), BI

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	1,865	1,079		1,728	,096		
	BI	,593	,207	,491	2,872	,008	1,000	1,000

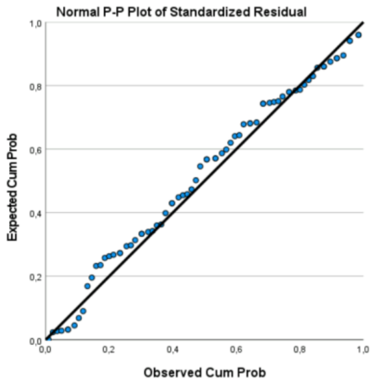
a. Dependent Variable: PI

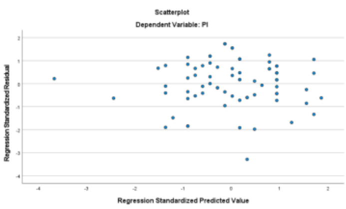
Instagram

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,764[a]	,584	,578	,83762	2,011

a. Predictors: (Constant), BI
b. Dependent Variable: PI





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	69,843	1	69,843	99,547	<,001[b]
	Residual	49,814	71	,702		
	Total	119,658	72			

a. Dependent Variable: PI

b. Predictors: (Constant), BI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	69,843	1	69,843	99,547	<,001[b]
	Residual	49,814	71	,702		
	Total	119,658	72			

a. Dependent Variable: PI

b. Predictors: (Constant), BI

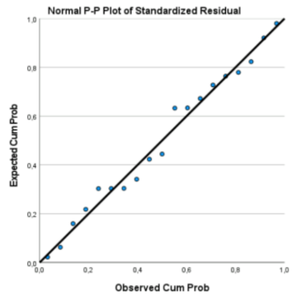
YouTube

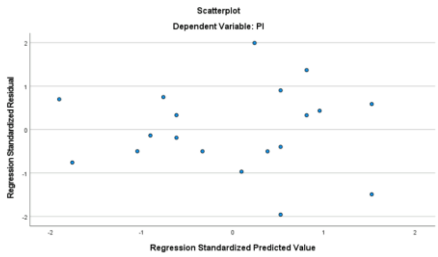
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,748[a]	,559	,533	,96165	2,101

a. Predictors: (Constant), BI

b. Dependent Variable: PI





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	19,911	1	19,911	21,530	<,001[b]
	Residual	15,721	17	,925		
	Total	35,632	18			

a. Dependent Variable: PI

b. Predictors: (Constant), BI

Coefficients[a]

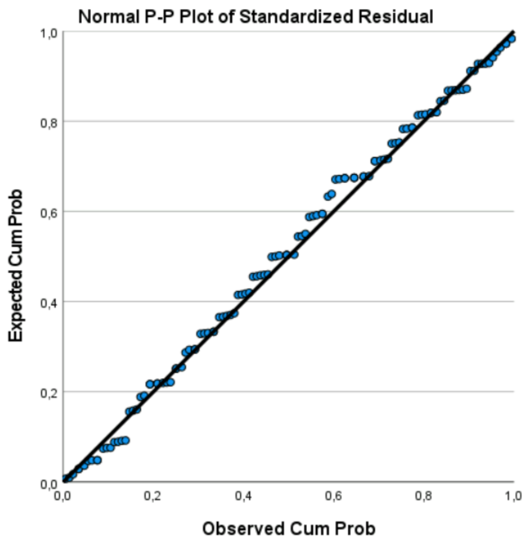
Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	,124	1,038		,120	,906		
	BI	,901	,194	,748	4,640	<,001	1,000	1,000

a. Dependent Variable: PI

Gen Z & Gen Y

```
Model  : 1
    Y  : PI
    X  : BI
    W  : AGE_2

Sample
Size:  114

**************************************************************************
OUTCOME VARIABLE:
 PI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,7164      ,5132      ,8614    38,6566     3,0000   110,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,8826     1,2858      ,6864      ,4939    -1,6656     3,4307
BI            ,7935      ,2532     3,1341      ,0022      ,2917     1,2953
AGE_2        -,4116     1,0057     -,4093      ,6831    -2,4046     1,5814
Int_1         ,0369      ,2015      ,1832      ,8550     -,3625      ,4363

Product terms key:
 Int_1    :        BI       x        AGE_2

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0001      ,0336     1,0000   110,0000      ,8550
```

Appendix 3.2: H2.

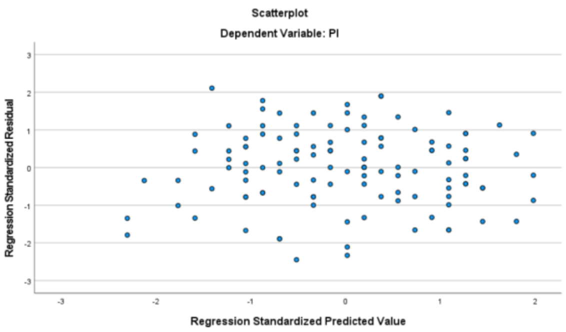


Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,527[a]	,277	,271	1,12312	2,115

a. Predictors: (Constant), PR

b. Dependent Variable: PI



Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	2,517	,327		7,703	<,001		
	PR	,494	,073	,527	6,728	<,001	1,000	1,000

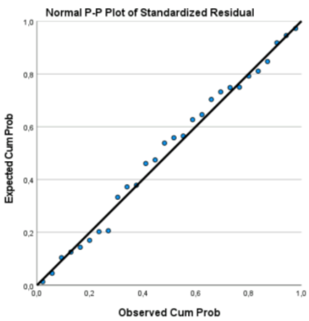
a. Dependent Variable: PI

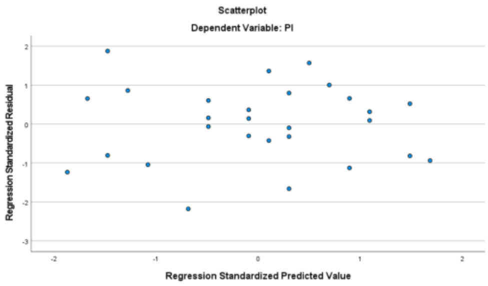
TikTok

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,527[a]	,277	,249	1,11896	1,465

a. Predictors: (Constant), PR
b. Dependent Variable: PI





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12,488	1	12,488	9,974	,004[b]
	Residual	32,554	26	1,252		
	Total	45,042	27			

a. Dependent Variable: PI
b. Predictors: (Constant), PR

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	2,692	,731		3,682	,001		
	PR	,537	,170	,527	3,158	,004	1,000	1,000

a. Dependent Variable: PI

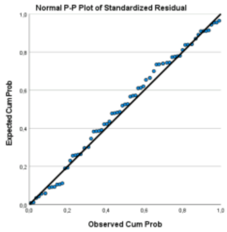
Instagram

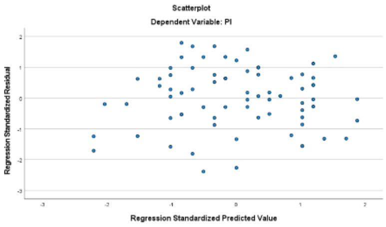
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,560[a]	,313	,304	1,07565	2,299

a. Predictors: (Constant), PR

b. Dependent Variable: PI





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	37,509	1	37,509	32,418	<,001[b]
	Residual	82,149	71	1,157		
	Total	119,658	72			

a. Dependent Variable: PI

b. Predictors: (Constant), PR

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2,348	,387		6,067	<,001		
	PR	,491	,086	,560	5,694	<,001	1,000	1,000

a. Dependent Variable: PI

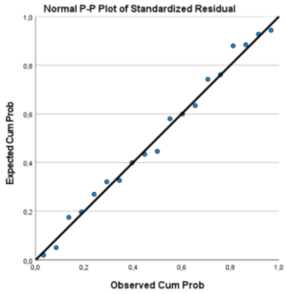
YouTube

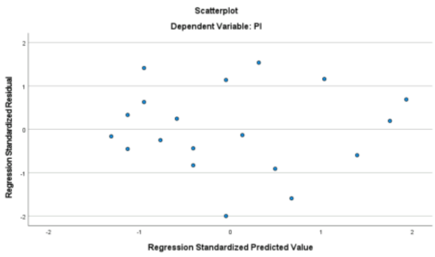
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,474[a]	,225	,179	1,27462	2,588

a. Predictors: (Constant), PR

b. Dependent Variable: PI





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8,012	1	8,012	4,932	,040[b]
	Residual	27,619	17	1,625		
	Total	35,632	18			

a. Dependent Variable: PI
b. Predictors: (Constant), PR

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2,752	,980		2,809	,012		
	PR	,481	,217	,474	2,221	,040	1,000	1,000

a. Dependent Variable: PI

Gen Z & Gen Y

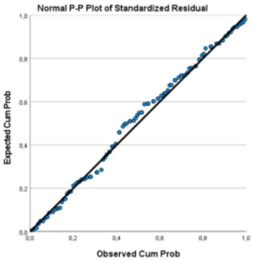
```
Model  : 1
    Y  : PI
    X  : PR
    W  : AGE_2

Sample
Size:  114

**************************************************************************
OUTCOME VARIABLE:
 PI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5392      ,2907     1,2550    15,0304     3,0000   110,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1,5318     1,0670     1,4356      ,1540     -,5828     3,6464
PR            ,8180      ,2505     3,2653      ,0015      ,3215     1,3144
AGE_2         ,9025      ,8414     1,0726      ,2858     -,7650     2,5701
Int_1        -,2909      ,2049    -1,4201      ,1584     -,6969      ,1151

Product terms key:
 Int_1    :        PR       x        AGE_2

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0130     2,0166     1,0000   110,0000      ,1584
```

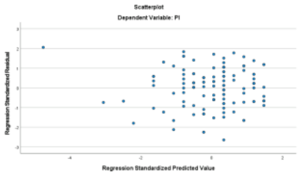
Appendix 3.3: H3a.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,573[a]	,329	,323	1,08242	1,978

a. Predictors: (Constant), CRED
b. Dependent Variable: PI





Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	-,258	,647		-,399	,691		
	CRED	,854	,112	,573	7,601	<,001	1,000	1,000

a. Dependent Variable: PI

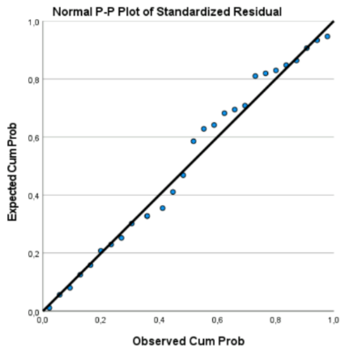
TikTok

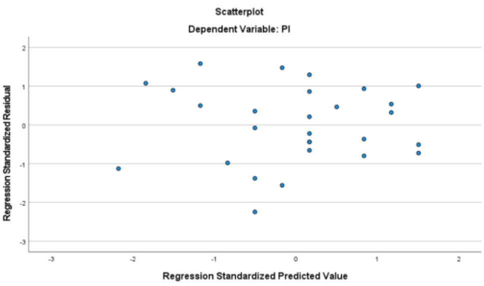
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,481[a]	,231	,202	1,15387	1,524

a. Predictors: (Constant), CRED

b. Dependent Variable: PI





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10,425	1	10,425	7,830	,010[b]
	Residual	34,617	26	1,331		
	Total	45,042	27			

a. Dependent Variable: PI

b. Predictors: (Constant), CRED

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	,014	1,760		,008	,994		
	CRED	,832	,297	,481	2,798	,010	1,000	1,000

a. Dependent Variable: PI

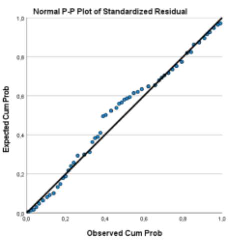
Instagram

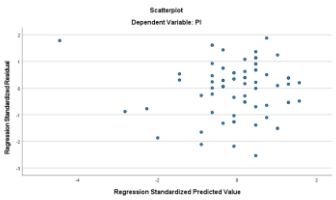
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,545[a]	,297	,287	1,08853	2,241

a. Predictors: (Constant), CRED

b. Dependent Variable: PI





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	35,530	1	35,530	29,986	<,001[b]
	Residual	84,128	71	1,185		
	Total	119,658	72			

a. Dependent Variable: PI

b. Predictors: (Constant), CRED

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	,156	,791		,198	,844		
	CRED	,768	,140	,545	5,476	<,001	1,000	1,000

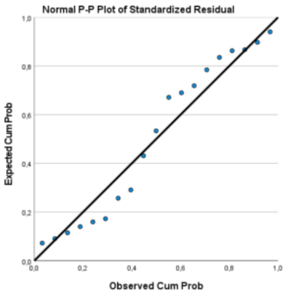
a. Dependent Variable: PI

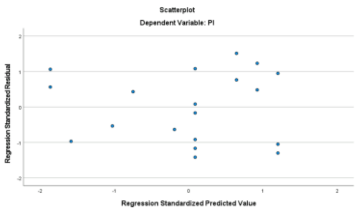
YouTube

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,723[a]	,522	,494	1,00062	2,641

a. Predictors: (Constant), CRED
b. Dependent Variable: PI





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	18,611	1	18,611	18,588	<,001[b]
	Residual	17,021	17	1,001		
	Total	35,632	18			

a. Dependent Variable: PI
b. Predictors: (Constant), CRED

Coefficients[a]

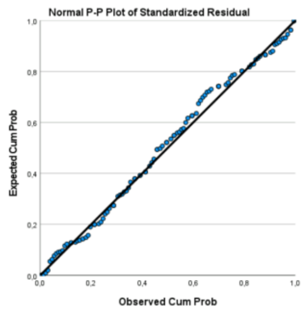
Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	-1,878	1,572		-1,194	,249		
	CRED	1,133	,263	,723	4,311	<,001	1,000	1,000

a. Dependent Variable: PI

Gen Z & Gen Y

```
Model  : 1
    Y  : PI
    X  : CRED
    W  : AGE_2

Sample
Size:  114

**************************************************************************
OUTCOME VARIABLE:
 PI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,6116      ,3740     1,1077    21,9079     3,0000   110,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant    -4,1682     1,9121    -2,1800      ,0314    -7,9575     -,3790
CRED         1,5986      ,3349     4,7729      ,0000      ,9349     2,2624
AGE_2        3,0450     1,3551     2,2470      ,0266      ,3595     5,7305
Int_1        -,5850      ,2417    -2,4202      ,0172    -1,0639     -,1060

Product terms key:
 Int_1    :        CRED     x        AGE_2

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0333     5,8571     1,0000   110,0000      ,0172


----------
    Focal predict: CRED     (X)
          Mod var: AGE_2    (W)

Conditional effects of the focal predictor at values of the moderator(s):

      AGE_2     Effect         se          t          p       LLCI       ULCI
     1,0000     1,0137      ,1339     7,5721      ,0000      ,7484     1,2790
     2,0000      ,4287      ,2012     2,1305      ,0354      ,0299      ,8275
```

Appendix 3.4: H3b.

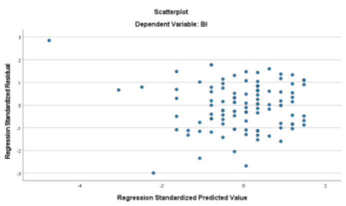


Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,636[a]	,404	,399	,84377	1,879

a. Predictors: (Constant), CRED

b. Dependent Variable: BI



Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	,587	,505		1,164	,247		
	CRED	,783	,088	,636	8,950	<,001	1,000	1,000

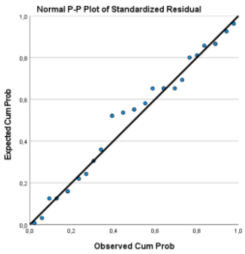
a. Dependent Variable: BI

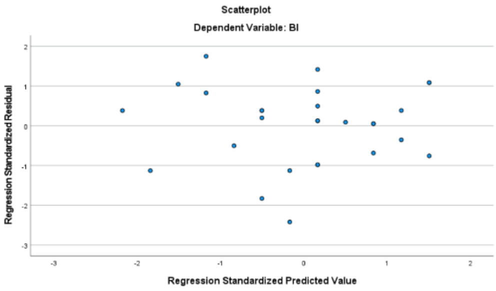
TikTok

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,559[a]	,312	,286	,90296	2,279

a. Predictors: (Constant), CRED
b. Dependent Variable: BI





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9,627	1	9,627	11,807	,002[b]
	Residual	21,199	26	,815		
	Total	30,825	27			

a. Dependent Variable: BI
b. Predictors: (Constant), CRED

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	,422	1,377		,307	,762		
	CRED	,799	,233	,559	3,436	,002	1,000	1,000

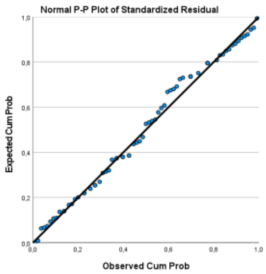
a. Dependent Variable: BI

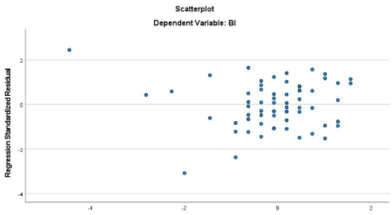
Instagram

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,609[a]	,370	,362	,86648	2,253

a. Predictors: (Constant), CRED
b. Dependent Variable: BI





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	31,358	1	31,358	41,766	<,001[b]
	Residual	53,306	71	,751		
	Total	84,664	72			

a. Dependent Variable: BI
b. Predictors: (Constant), CRED

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	,963	,630		1,530	,131		
	CRED	,721	,112	,609	6,463	<,001	1,000	1,000

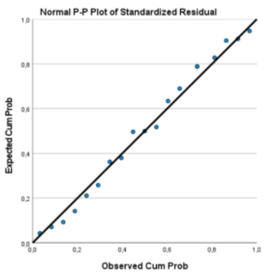
a. Dependent Variable: BI

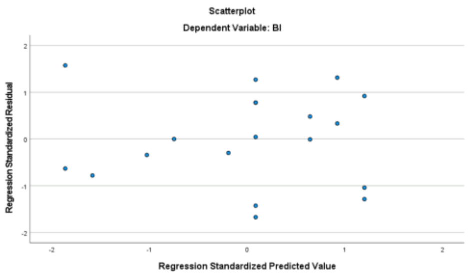
YouTube

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,824[a]	,679	,660	,68004	1,605

a. Predictors: (Constant), CRED
b. Dependent Variable: BI





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	16,641	1	16,641	35,985	<,001[b]
	Residual	7,862	17	,462		
	Total	24,503	18			

a. Dependent Variable: BI

b. Predictors: (Constant), CRED

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	-1,122	1,069		-1,050	,308		
	CRED	1,071	,179	,824	5,999	<,001	1,000	1,000

a. Dependent Variable: BI

Gen Z & Gen Y

```
Model  : 1
    Y  : BI
    X  : CRED
    W  : AGE_2

Sample
Size:  114

**************************************************************************
OUTCOME VARIABLE:
 BI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,6604      ,4361      ,7068    28,3563     3,0000   110,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant    -2,5789     1,5274    -1,6885      ,0942    -5,6058      ,4480
CRED         1,3560      ,2676     5,0682      ,0000      ,8258     1,8862
AGE_2        2,3969     1,0825     2,2143      ,0289      ,2517     4,5421
Int_1        -,4371      ,1931    -2,2640      ,0255     -,8197     -,0545

Product terms key:
 Int_1    :        CRED     x        AGE_2

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0263     5,1259     1,0000   110,0000      ,0255


----------
    Focal predict: CRED     (X)
          Mod var: AGE_2    (W)

Conditional effects of the focal predictor at values of the moderator(s):

      AGE_2     Effect         se          t          p       LLCI       ULCI
     1,0000      ,9189      ,1069     8,5928      ,0000      ,7070     1,1308
     2,0000      ,4818      ,1608     2,9970      ,0034      ,1632      ,8003
```

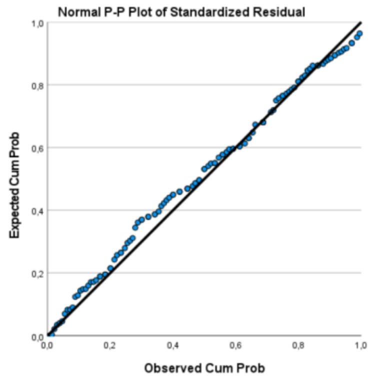
Appendix 3.5: H4a.

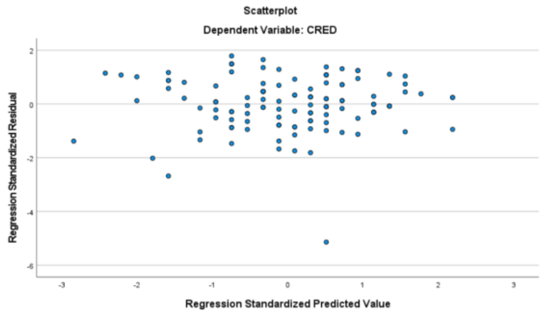
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,310[a]	,096	,089	,84348	2,371

a. Predictors: (Constant), AH

b. Dependent Variable: CRED





Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	4,687	,295		15,895	<,001		
	AH	,230	,065	,310	3,546	<,001	1,000	1,000

a. Dependent Variable: CRED

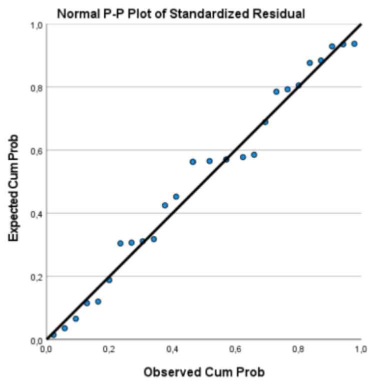
TikTok

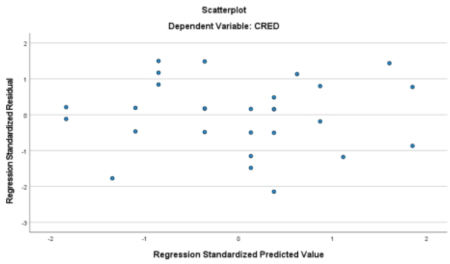
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,026[a]	,001	-,038	,76088	2,206

a. Predictors: (Constant), AH

b. Dependent Variable: CRED





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,010	1	,010	,017	,896[b]
	Residual	15,052	26	,579		
	Total	15,063	27			

a. Dependent Variable: CRED
b. Predictors: (Constant), AH

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	5,792	,645		8,983	<,001		
	AH	,019	,144	,026	,132	,896	1,000	1,000

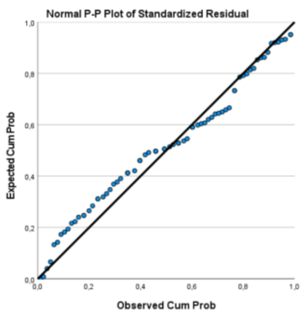
a. Dependent Variable: CRED

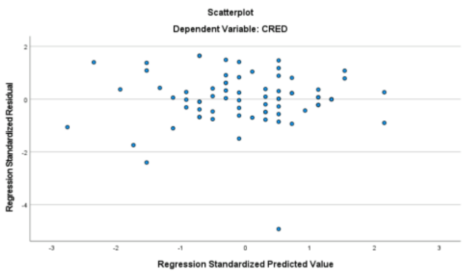
Instagram

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,359[a]	,129	,116	,86009	2,383

a. Predictors: (Constant), AH
b. Dependent Variable: CRED





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7,760	1	7,760	10,490	,002[b]
	Residual	52,523	71	,740		
	Total	60,283	72			

a. Dependent Variable: CRED
b. Predictors: (Constant), AH

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	4,395	,376		11,690	<,001		
	AH	,268	,083	,359	3,239	,002	1,000	1,000

a. Dependent Variable: CRED

YouTube

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,406[a]	,165	,116	,84412	3,068

a. Predictors: (Constant), AH
b. Dependent Variable: CRED

Gen Z & Gen Y

```
Model  : 1
    Y  : CRED
    X  : AH
    W  : AGE_2

Sample
Size:  114

**************************************************************************
OUTCOME VARIABLE:
 CRED

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3981      ,1585      ,7000     6,9060     3,0000   110,0000      ,0003

Model
              coeff         se          t          p       LLCI       ULCI
constant     3,5237      ,9597     3,6717      ,0004     1,6218     5,4257
AH            ,5870      ,2098     2,7983      ,0061      ,1713     1,0028
AGE_2         ,8574      ,7541     1,1369      ,2580     -,6371     2,3519
Int_1        -,2746      ,1646    -1,6688      ,0980     -,6007      ,0515

Product terms key:
 Int_1    :        AH        x        AGE_2

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0213     2,7848     1,0000   110,0000      ,0980
```

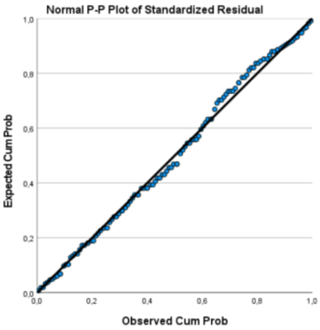
Appendix 3.6: H4b.

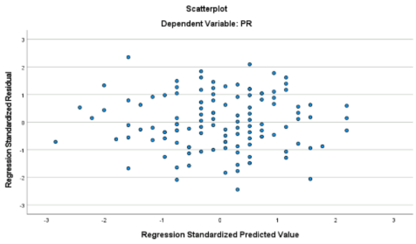
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,608[a]	,370	,365	1,11717	2,066

a. Predictors: (Constant), AH

b. Dependent Variable: PR





Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	1,085	,391		2,779	,006		
	AH	,715	,086	,608	8,323	<,001	1,000	1,000

a. Dependent Variable: PR

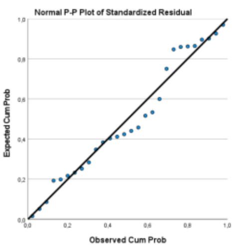
TikTok

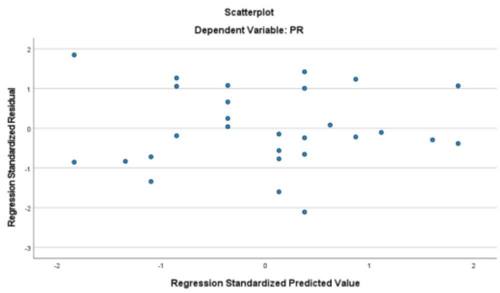
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,361[a]	,130	,097	1,20357	1,707

a. Predictors: (Constant), AH

b. Dependent Variable: PR





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5,647	1	5,647	3,899	,059[b]
	Residual	37,663	26	1,449		
	Total	43,310	27			

a. Dependent Variable: PR
b. Predictors: (Constant), AH

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	2,153	1,020		2,111	,045		
	AH	,450	,228	,361	1,974	,059	1,000	1,000

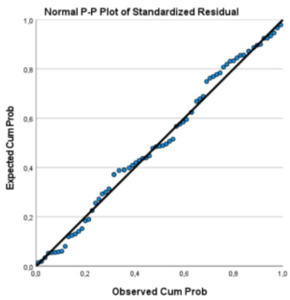
a. Dependent Variable: PR

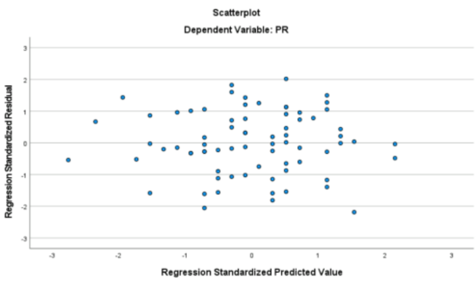
Instagram

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,650[a]	,422	,414	1,12406	2,147

a. Predictors: (Constant), AH
b. Dependent Variable: PR





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	65,595	1	65,595	51,915	<,001[b]
	Residual	89,709	71	1,264		
	Total	155,305	72			

a. Dependent Variable: PR

b. Predictors: (Constant), AH

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	,828	,491		1,686	,096		
	AH	,781	,108	,650	7,205	<,001	1,000	1,000

a. Dependent Variable: PR

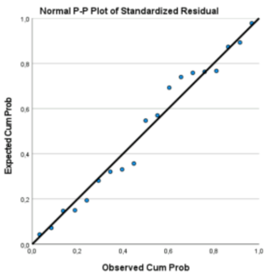
YouTube

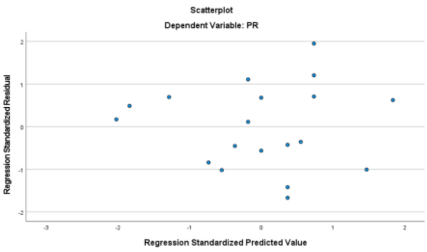
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,710[a]	,504	,475	1,00489	2,032

a. Predictors: (Constant), AH

b. Dependent Variable: PR





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	17,439	1	17,439	17,269	<,001[b]
	Residual	17,167	17	1,010		
	Total	34,605	18			

a. Dependent Variable: PR

b. Predictors: (Constant), AH

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	1,063	,816		1,303	,210		
	AH	,723	,174	,710	4,156	<,001	1,000	1,000

a. Dependent Variable: PR

Gen Z & Gen Y

```
Model  : 1
    Y  : PR
    X  : AH
    W  : AGE_2

Sample
Size:  114

**************************************************************************
OUTCOME VARIABLE:
 PR

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,6185      ,3826     1,2447    22,7220     3,0000   110,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1,4445     1,2797     1,1287      ,2615    -1,0917     3,9806
AH            ,7718      ,2797     2,7591      ,0068      ,2174     1,3262
AGE_2        -,3129     1,0056     -,3112      ,7562    -2,3058     1,6799
Int_1        -,0474      ,2194     -,2159      ,8294     -,4822      ,3875

Product terms key:
 Int_1    :        AH       x        AGE_2

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0003      ,0466     1,0000   110,0000      ,8294
```

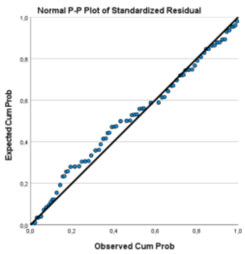
Appendix 3.7: H5a.

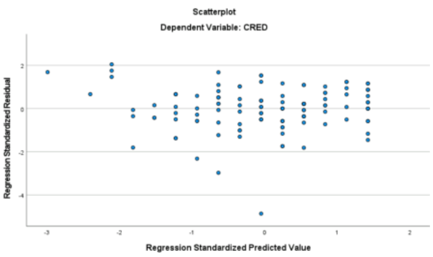
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,244[a]	,060	,052	,86044	2,378

a. Predictors: (Constant), PA

b. Dependent Variable: CRED





Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	4,671	,383		12,197	<,001		
	PA	,190	,070	,244	2,735	,007	1,000	1,000

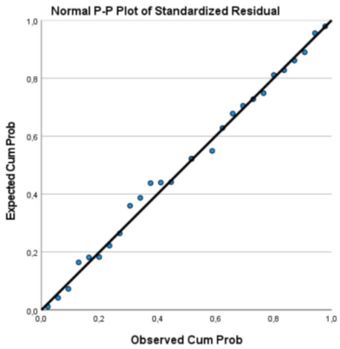
a. Dependent Variable: CRED

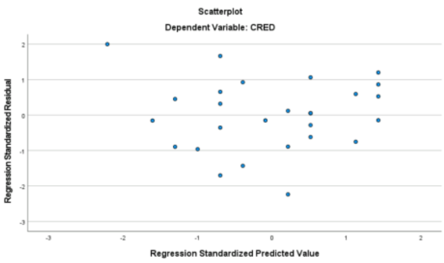
TikTok

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,218[a]	,048	,011	,74283	2,384

a. Predictors: (Constant), PA
b. Dependent Variable: CRED





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,716	1	,716	1,297	,265[b]
	Residual	14,347	26	,552		
	Total	15,063	27			

a. Dependent Variable: CRED
b. Predictors: (Constant), PA

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	5,071	,720		7,046	<,001		
	PA	,148	,130	,218	1,139	,265	1,000	1,000

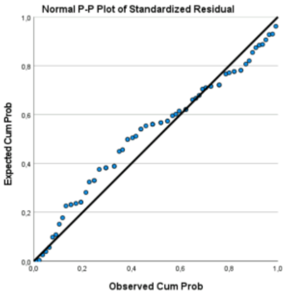
a. Dependent Variable: CRED

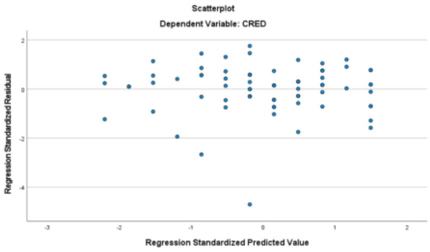
Instagram

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,384[a]	,147	,135	,85090	2,309

a. Predictors: (Constant), PA
b. Dependent Variable: CRED





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8,877	1	8,877	12,260	<,001[b]
	Residual	51,406	71	,724		
	Total	60,283	72			

a. Dependent Variable: CRED
b. Predictors: (Constant), PA

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3,617	,566		6,387	<,001		
	PA	,354	,101	,384	3,501	<,001	1,000	1,000

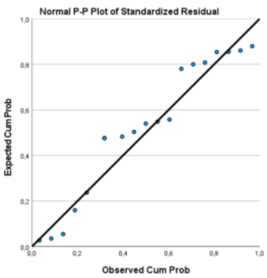
a. Dependent Variable: CRED

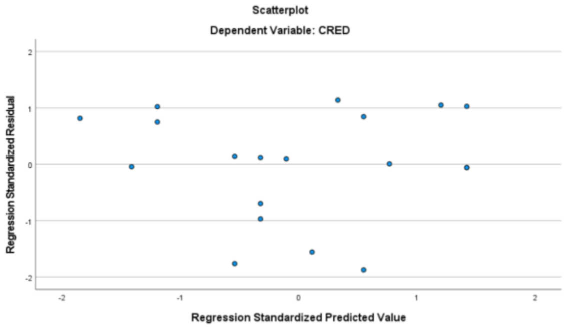
YouTube

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,104[a]	,011	-,047	,91875	2,395

a. Predictors: (Constant), PA
b. Dependent Variable: CRED





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,157	1	,157	,186	,672[b]
	Residual	14,350	17	,844		
	Total	14,507	18			

a. Dependent Variable: CRED
b. Predictors: (Constant), PA

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	5,626	,715		7,868	<,001		
	PA	,061	,142	,104	,431	,672	1,000	1,000

a. Dependent Variable: CRED

Gen Z & Gen Y

```
Model  : 1
    Y  : CRED
    X  : PA
    W  : AGE_2

Sample
Size:  114

**************************************************************************
OUTCOME VARIABLE:
 CRED

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2998      ,0899      ,7571     3,6220     3,0000   110,0000      ,0154

Model
              coeff         se          t          p       LLCI       ULCI
constant     5,5959     1,2686     4,4111      ,0000     3,0818     8,1100
PA            ,1042      ,2292      ,4545      ,6504     -,3500      ,5583
AGE_2        -,8159     1,0148     -,8040      ,4231    -2,8270     1,1952
Int_1         ,0790      ,1819      ,4344      ,6649     -,2815      ,4395

Product terms key:
 Int_1    :        PA       x        AGE_2

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0016      ,1887     1,0000   110,0000      ,6649
```

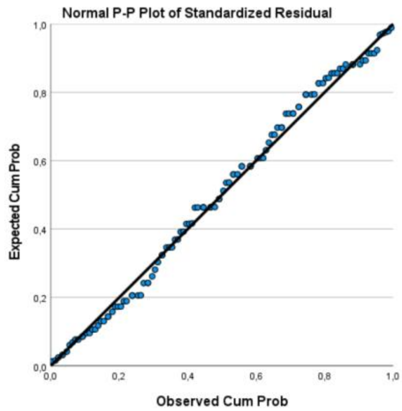
Appendix 3.8: H5b.

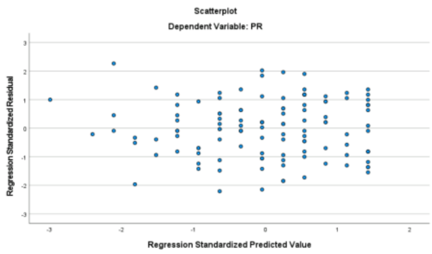
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,203[a]	,041	,033	1,37800	2,104

a. Predictors: (Constant), PA

b. Dependent Variable: PR





Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	2,869	,613		4,679	<,001		
	PA	,251	,111	,203	2,255	,026	1,000	1,000

a. Dependent Variable: PR

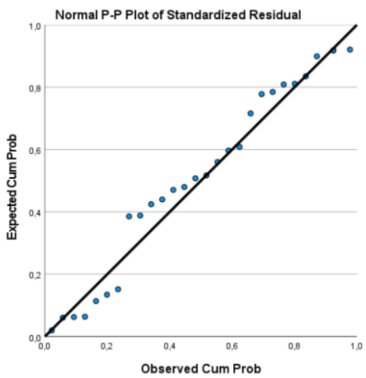
TikTok

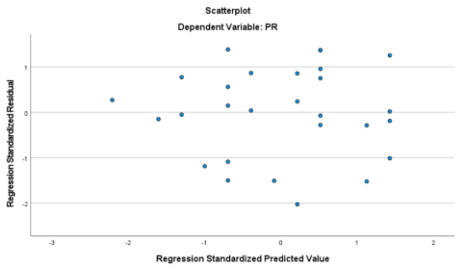
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,338[a]	,114	,080	1,21490	2,032

a. Predictors: (Constant), PA

b. Dependent Variable: PR





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4,935	1	4,935	3,343	,079[b]
	Residual	38,375	26	1,476		
	Total	43,310	27			

a. Dependent Variable: PR
b. Predictors: (Constant), PA

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2,005	1,177		1,703	,100		
	PA	,389	,213	,338	1,829	,079	1,000	1,000

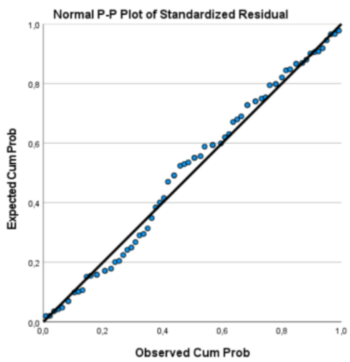
a. Dependent Variable: PR

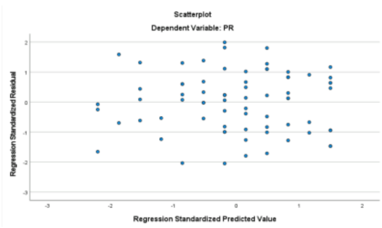
Instagram

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,274[a]	,075	,062	1,42251	2,079

a. Predictors: (Constant), PA
b. Dependent Variable: PR





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	11,634	1	11,634	5,750	,019[b]
	Residual	143,670	71	2,024		
	Total	155,305	72			

a. Dependent Variable: PR
b. Predictors: (Constant), PA

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2,005	,947		2,118	,038		
	PA	,405	,169	,274	2,398	,019	1,000	1,000

a. Dependent Variable: PR

YouTube

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,053[a]	,003	-,056	1,42472	1,336

a. Predictors: (Constant), PA
b. Dependent Variable: PR

Gen Z & Gen Y

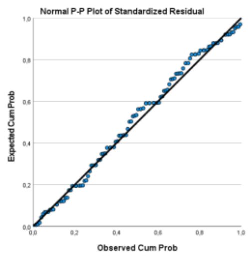
```
Model  : 1
    Y  : PR
    X  : PA
    W  : AGE_2

Sample
Size:  114

**************************************************************************
OUTCOME VARIABLE:
 PR

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2890      ,0835     1,8476     3,3423     3,0000   110,0000      ,0219

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,9672     1,9818      ,4880      ,6265    -2,9603     4,8947
PA            ,7216      ,3580     2,0156      ,0463      ,0121     1,4312
AGE_2        1,5286     1,5853      ,9642      ,3371    -1,6132     4,6704
Int_1        -,3791      ,2842    -1,3341      ,1849     -,9423      ,1841

Product terms key:
 Int_1    :        PA       x        AGE_2

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0148     1,7797     1,0000   110,0000      ,1849
```

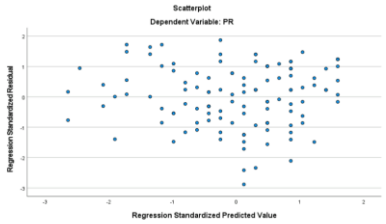
Appendix 3.9: H6.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,650[a]	,422	,417	1,06990	1,944

a. Predictors: (Constant), SA
b. Dependent Variable: PR





Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	,984	,362		2,716	,008		
	SA	,670	,072	,650	9,283	<,001	1,000	1,000

a. Dependent Variable: PR

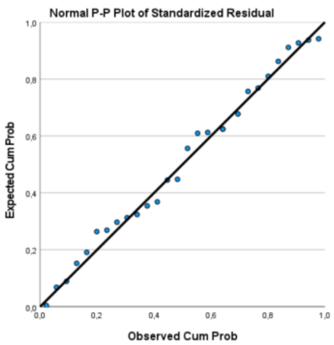
TikTok

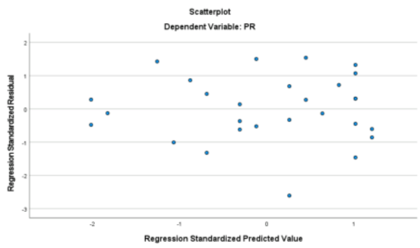
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,643[a]	,414	,392	,98795	1,623

a. Predictors: (Constant), SA

b. Dependent Variable: PR





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	17,933	1	17,933	18,373	<,001[b]
	Residual	25,377	26	,976		
	Total	43,310	27			

a. Dependent Variable: PR

b. Predictors: (Constant), SA

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	1,238	,697		1,776	,087		
	SA	,618	,144	,643	4,286	<,001	1,000	1,000

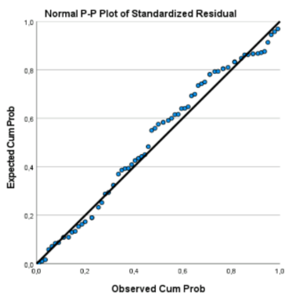
a. Dependent Variable: PR

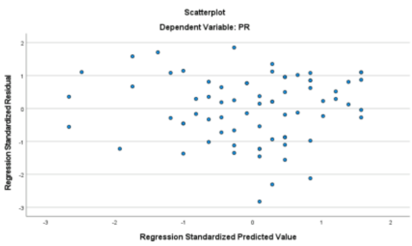
Instagram

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,674[a]	,454	,446	1,09321	1,765

a. Predictors: (Constant), SA
b. Dependent Variable: PR





ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	70,451	1	70,451	58,949	<,001[b]
	Residual	84,853	71	1,195		
	Total	155,305	72			

a. Dependent Variable: PR
b. Predictors: (Constant), SA

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	,697	,479		1,456	,150		
	SA	,728	,095	,674	7,678	<,001	1,000	1,000

a. Dependent Variable: PR

YouTube

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,565[a]	,319	,279	1,17706	1,295

a. Predictors: (Constant), SA

b. Dependent Variable: PR

Gen Z & Gen Y

```
Model  : 1
    Y  : PR
    X  : SA
    W  : AGE_2

Sample
Size:  114

**************************************************************************
OUTCOME VARIABLE:
 PR

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,6782      ,4600     1,0888    31,2288     3,0000   110,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,5854     1,1469      ,5104      ,6108    -1,6874     2,8582
SA            ,8238      ,2353     3,5007      ,0007      ,3574     1,2901
AGE_2         ,3342      ,9154      ,3651      ,7157    -1,4799     2,1483
Int_1        -,1284      ,1923     -,6677      ,5057     -,5095      ,2527

Product terms key:
 Int_1    :        SA       x        AGE_2

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0022      ,4458     1,0000   110,0000      ,5057
```

Appendix 4: Mediation analysis

Appendix 4.1:

```
**************************************************************************
Model  : 4
    Y  : PI
    X  : CRED
    M  : BI

Sample
Size:  120

**************************************************************************
OUTCOME VARIABLE:
 BI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,6359      ,4043      ,7119    80,0963     1,0000   118,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,5874      ,5045     1,1643      ,2466     -,4117     1,5866
CRED          ,7835      ,0875     8,9497      ,0000      ,6101      ,9568
```

```
**************************************************************************
OUTCOME VARIABLE:
 PI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,7202      ,5187      ,8473    63,0338     2,0000   117,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     -,6589      ,5536    -1,1903      ,2363    -1,7552      ,4374
CRED          ,3190      ,1237     2,5781      ,0112      ,0740      ,5641
BI            ,6824      ,1004     6,7949      ,0000      ,4835      ,8813

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,3190      ,1237     2,5781      ,0112      ,0740      ,5641

Indirect effect(s) of X on Y:
       Effect     BootSE   BootLLCI   BootULCI
BI      ,5346      ,1335      ,3144      ,8394
```

Appendix 4.2:

```
Model  : 4
    Y  : PI
    X  : AH
    M  : CRED

Sample
Size:  120

**************************************************************************
OUTCOME VARIABLE:
 CRED

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3103      ,0963      ,7115    12,5732     1,0000   118,0000      ,0006

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,6866      ,2949    15,8947      ,0000     4,1027     5,2705
AH            ,2299      ,0648     3,5459      ,0006      ,1015      ,3583


**************************************************************************
OUTCOME VARIABLE:
 PI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5859      ,3433     1,1560    30,5775     2,0000   117,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     -,5387      ,6661     -,8088      ,4203    -1,8579      ,7805
AH            ,1400      ,0869     1,6108      ,1099     -,0321      ,3122
CRED          ,7950      ,1173     6,7749      ,0000      ,5626     1,0274

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,1400      ,0869     1,6108      ,1099     -,0321      ,3122

Indirect effect(s) of X on Y:
       Effect     BootSE   BootLLCI   BootULCI
CRED    ,1828      ,0678      ,0716      ,3372
```

Appendix 4.3:

```
Model  : 4
    Y  : BI
    X  : AH
    M  : CRED

Sample
Size:  120

**************************************************************************
OUTCOME VARIABLE:
 CRED

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3103      ,0963      ,7115    12,5732     1,0000   118,0000      ,0006

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,6866      ,2949    15,8947      ,0000     4,1027     5,2705
AH            ,2299      ,0648     3,5459      ,0006      ,1015      ,3583

**************************************************************************
OUTCOME VARIABLE:
 BI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,6546      ,4285      ,6889    43,8676     2,0000   117,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,2881      ,5142      ,5602      ,5764     -,7303     1,3064
AH            ,1494      ,0671     2,2259      ,0279      ,0165      ,2823
CRED          ,7209      ,0906     7,9585      ,0000      ,5415      ,9003

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,1494      ,0671     2,2259      ,0279      ,0165      ,2823

Indirect effect(s) of X on Y:
         Effect     BootSE   BootLLCI   BootULCI
CRED      ,1657      ,0616      ,0656      ,2998
```

Appendix 4.4:

```
Model  : 4
    Y  : PI
    X  : AH
    M  : PR

Sample
Size:  120

**************************************************************************
OUTCOME VARIABLE:
 PR

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,6082      ,3699     1,2481    69,2684     1,0000   118,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1,0855      ,3905     2,7795      ,0063      ,3121     1,8588
AH            ,7148      ,0859     8,3228      ,0000      ,5447      ,8848
```

```
**************************************************************************
OUTCOME VARIABLE:
 PI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5277      ,2785     1,2701    22,5785     2,0000   117,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,6234      ,4066     6,4514      ,0000     1,8181     3,4287
AH           -,0483      ,1091     -,4430      ,6586     -,2645      ,1678
PR            ,5193      ,0929     5,5920      ,0000      ,3354      ,7032

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
     -,0483      ,1091     -,4430      ,6586     -,2645      ,1678

Indirect effect(s) of X on Y:
       Effect     BootSE   BootLLCI   BootULCI
PR      ,3712      ,0784      ,2224      ,5282
```

Appendix 4.5:

```
Model  : 4
    Y  : PI
    X  : PA
    M  : CRED

Sample
Size:  120

**************************************************************************
OUTCOME VARIABLE:
 CRED

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2441      ,0596      ,7404     7,4777     1,0000   118,0000      ,0072

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,6709      ,3829    12,1972      ,0000     3,9126     5,4293
PA            ,1903      ,0696     2,7345      ,0072      ,0525      ,3281


**************************************************************************
OUTCOME VARIABLE:
 PI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5734      ,3288     1,1814    28,6610     2,0000   117,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     -,2102      ,7274     -,2889      ,7731    -1,6507     1,2303
PA           -,0133      ,0906     -,1467      ,8836     -,1928      ,1662
CRED          ,8578      ,1163     7,3765      ,0000      ,6275     1,0881

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
     -,0133      ,0906     -,1467      ,8836     -,1928      ,1662

Indirect effect(s) of X on Y:
         Effect     BootSE   BootLLCI   BootULCI
CRED      ,1632      ,0701      ,0430      ,3229
```

Appendix 4.6:

```
Model  : 4
    Y  : BI
    X  : PA
    M  : CRED

Sample
Size:  120

**************************************************************************
OUTCOME VARIABLE:
 CRED

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2441      ,0596      ,7404     7,4777     1,0000   118,0000      ,0072

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,6709      ,3829    12,1972      ,0000     3,9126     5,4293
PA            ,1903      ,0696     2,7345      ,0072      ,0525      ,3281

**************************************************************************
OUTCOME VARIABLE:
 BI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,6364      ,4050      ,7172    39,8182     2,0000   117,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,4956      ,5667      ,8744      ,3837     -,6268     1,6180
PA            ,0255      ,0706      ,3611      ,7186     -,1144      ,1654
CRED          ,7755      ,0906     8,5587      ,0000      ,5960      ,9549

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,0255      ,0706      ,3611      ,7186     -,1144      ,1654

Indirect effect(s) of X on Y:
         Effect     BootSE   BootLLCI   BootULCI
CRED      ,1476      ,0653      ,0410      ,2974
```

Appendix 4.7:

```
Model  : 4
    Y  : PI
    X  : PA
    M  : PR

Sample
Size:  120

**************************************************************************
OUTCOME VARIABLE:
 PR

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2033      ,0413     1,8989     5,0848     1,0000   118,0000      ,0260

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,8694      ,6133     4,6786      ,0000     1,6549     4,0839
PA            ,2513      ,1114     2,2550      ,0260      ,0306      ,4720

**************************************************************************
```

```
**************************************************************************
OUTCOME VARIABLE:
 PI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5270      ,2778     1,2713    22,5002     2,0000   117,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,3910      ,5464     4,3760      ,0000     1,3089     3,4730
PA            ,0268      ,0931      ,2881      ,7738     -,1576      ,2113
PR            ,4899      ,0753     6,5036      ,0000      ,3407      ,6390

***************** DIRECT AND INDIRECT EFFECTS OF X ON Y ****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,0268      ,0931      ,2881      ,7738     -,1576      ,2113

Indirect effect(s) of X on Y:
       Effect     BootSE   BootLLCI   BootULCI
PR      ,1231      ,0608      ,0191      ,2546
```

Appendix 4.8:

```
**************************************************************************
Model  : 4
    Y  : PI
    X  : SA
    M  : PR

Sample
Size:  120

**************************************************************************
OUTCOME VARIABLE:
 PR

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,6497      ,4221     1,1447    86,1811     1,0000   118,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,9839      ,3623     2,7155      ,0076      ,2664     1,7014
SA            ,6701      ,0722     9,2834      ,0000      ,5272      ,8131

**************************************************************************
OUTCOME VARIABLE:
 PI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5271      ,2778     1,2712    22,5069     2,0000   117,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,5831      ,3936     6,5633      ,0000     1,8036     3,3625
SA           -,0305      ,1001     -,3044      ,7614     -,2286      ,1677
PR            ,5135      ,0970     5,2929      ,0000      ,3213      ,7056

***************** DIRECT AND INDIRECT EFFECTS OF X ON Y ****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
     -,0305      ,1001     -,3044      ,7614     -,2286      ,1677

Indirect effect(s) of X on Y:
       Effect     BootSE   BootLLCI   BootULCI
PR      ,3441      ,0670      ,2194      ,4800
```

Appendix 5: Multiple linear regressions

Appendix 5.1:

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,742[a]	,551	,539	,89308	1,836

a. Predictors: (Constant), PR, BI, CRED
b. Dependent Variable: PI

ANOVA[a]

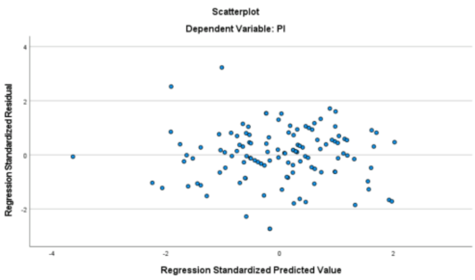
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	113,428	3	37,809	47,404	<,001[b]
	Residual	92,520	116	,798		
	Total	205,948	119			

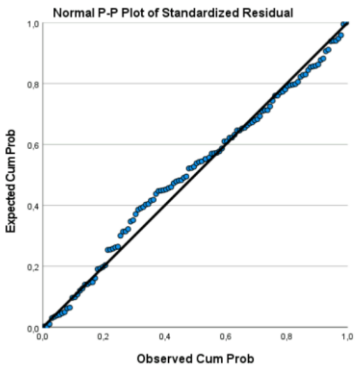
a. Dependent Variable: PI
b. Predictors: (Constant), PR, BI, CRED

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-,574	,538		-1,067	,288		
	BI	,611	,101	,506	6,076	<,001	,559	1,788
	CRED	,220	,125	,148	1,759	,081	,550	1,817
	PR	,199	,069	,212	2,879	,005	,712	1,404

a. Dependent Variable: PI





Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,734[a]	,539	,531	,90103	1,785

a. Predictors: (Constant), PR, BI
b. Dependent Variable: PI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	110,960	2	55,480	68,337	<,001[b]
	Residual	94,988	117	,812		
	Total	205,948	119			

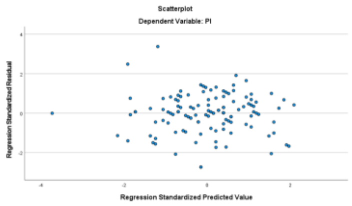
a. Dependent Variable: PI

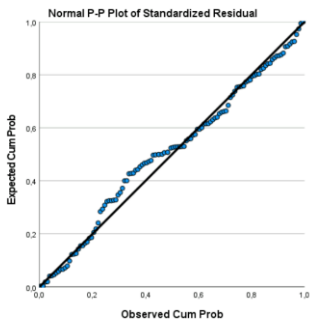
b. Predictors: (Constant), PR, BI

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	,067	,399		,169	,866		
	BI	,704	,086	,582	8,145	<,001	,771	1,297
	PR	,233	,067	,248	3,470	<,001	,771	1,297

a. Dependent Variable: PI





Appendix 5.2:

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,732[a]	,536	,524	,96720	2,037

a. Predictors: (Constant), SA, PA, AH

b. Dependent Variable: PR

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	125,209	3	41,736	44,615	<,001[b]
	Residual	108,516	116	,935		
	Total	233,724	119			

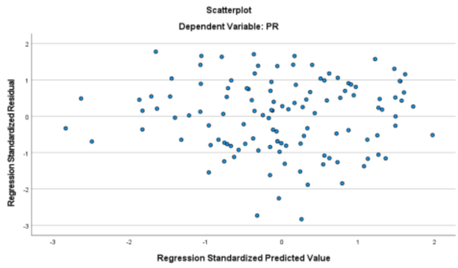
a. Dependent Variable: PR

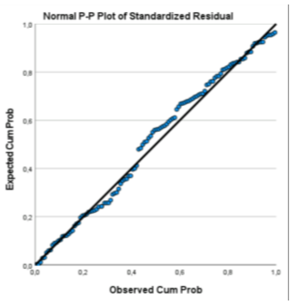
b. Predictors: (Constant), SA, PA, AH

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	-,480	,532		-,903	,368		
	AH	,451	,086	,384	5,248	<,001	,749	1,334
	PA	,098	,080	,079	1,217	,226	,946	1,057
	SA	,455	,077	,441	5,889	<,001	,714	1,400

a. Dependent Variable: PR





Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,728[a]	,530	,522	,96919	2,039

a. Predictors: (Constant), SA, AH

b. Dependent Variable: PR

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	123,822	2	61,911	65,909	<,001[b]
	Residual	109,902	117	,939		
	Total	233,724	119			

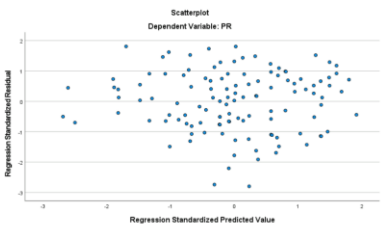
a. Dependent Variable: PR

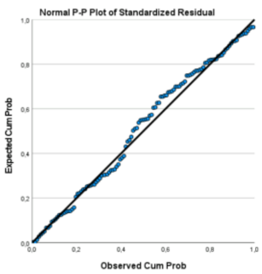
b. Predictors: (Constant), SA, AH

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-,029	,382		-,075	,940		
	AH	,445	,086	,378	5,177	<,001	,752	1,330
	SA	,476	,075	,461	6,307	<,001	,752	1,330

a. Dependent Variable: PR





Appendix 5.3:

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,383[a]	,147	,132	,82310	2,153

a. Predictors: (Constant), PA, AH

b. Dependent Variable: CRED

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13,631	2	6,816	10,060	<,001[b]
	Residual	79,267	117	,677		
	Total	92,898	119			

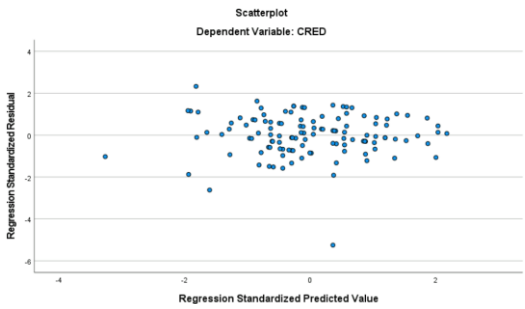
a. Dependent Variable: CRED

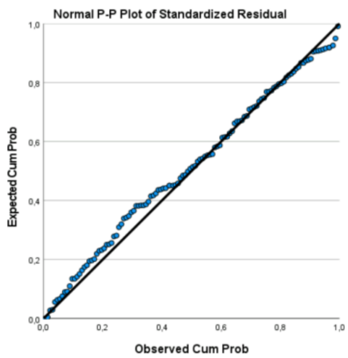
b. Predictors: (Constant), PA, AH

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3,789	,446		8,487	<,001		
	AH	,219	,063	,296	3,457	<,001	,996	1,004
	PA	,175	,067	,225	2,630	,010	,996	1,004

a. Dependent Variable: CRED





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