A Work Project, presented as part of the requirements for the Award of a Master Degree in Management from the NOVA – School of Business and Economics.

TRADITIONAL AND INFLUENCERS' INSTAGRAM ADVERTISING:

AN APPLICATION OF THE THEORY OF PLANNED BEHAVIOUR

MARGARIDA DE OLIVEIRA SARAIVA DE MELO, 3753

A Project carried out on the Master in Management Program, under the supervision of:

Professor Luís F. Martinez

January 4th, 2019

Table of Contents

Abstract

Instagram has taken a substantial role in social media advertising, as it has gained popularity amongst advertisers and influencers, and both parties are looking for higher engagement rates. However, little is known about what drives these rates. This study aims to apply the Theory of Planned Behaviour on engagement with two types of Instagram advertising (traditional and influencer). A survey with 180 participants was conducted, analysing attitude, subjective norm and perceived behaviour control. Regression analyses partially support the theory and show that it is a better fit with influencers' advertisement. As attitude was found to have a greater influence on traditional advertisement, several strategies to improve it are proposed.

Keywords: Theory of Planned Behaviour, Instagram, Influencers, Engagement, Advertising.

Acknowledgements:

I would like to thank my thesis supervisor, Professor Luís F. Martinez, who pushed me to find the perfect thesis topic – one that was innovative but also aligned with my interests. Without his feedback and unwavering mentoring, it would have been an impossible task. I am extremely grateful for all the knowledge the Professor shared with me.

There were more people who were pivotal in my completion of this thesis. First, my parents, who raised me and gave me all the tools and values I needed to complete this important challenge. My brother and sister, who never doubted me, and who always challenge me and push me to be the best version of myself – they also gave me my nephews, who were the perfect source of fun and laugh-filled breaks. I also want to thank my friends, who were constant and enthusiastic supporters, helping me with feedback.

Lastly, I want to thank Luísa Sobral and Tom Odell for keeping me company night and day, and Uber Eats for keeping me well-fed during busy times.

1. Introduction

Social media has transformed how people communicate with each other. Moreover, it has changed marketing and advertising. In recent years, there has been a shift from traditional marketing – television, radio, and print press – to social media marketing (Lee & Hong, 2016). In the U.S., $15,36 billion were spent on this form of marketing last year, a number that is expected to reach $17.34 billion in 2019 (Statista, 2018a). Marketers find these platforms attractive as they create an online community where consumers, businesses and organisations talk to one another and share their opinions and recommendations (Dwivedi, Kapoor, & Chen, 2015), creating the so-called electronic word-of-mouth (eWOM) – "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet" (Hennig-Thurau et al., 2004).

The number of social network websites' (such as Facebook, Instagram, and Twitter) users has been growing steadily over the years – from 97 million in 2010 to 2.62 billion[1] in 2018 (Statista, 2018b). Last year, Instagram was the fastest growing (+ 33%) and the 3rd social media website with most active users per month (1 billion) (Hartmans & Price, 2018; Kemp, 2018), surpassed only by YouTube and Facebook. Furthermore, 80% of Instagram users follow at least one brand (Instagram, 2018). Although these statistics show its potentially pivotal role in social media marketing, there is a lack of literature about Instagram advertising.

Brands can advertise on Instagram through the "traditional", and influencers' channels. By using the first, brands are simply managing their own pages. Consequently, posts will be featured in users' feeds, either because they follow the brand or as a sponsored post (paid advertisement). With the second option, brands are engaging with the so-called "Influencer Marketing" – the use of opinion leaders, influencers, to promote products and services to a

[1] Forecasted.

targeted audience, providing information users seek (Lin, Bruning, & Swarna, 2018).

Consumers nowadays have the choice to fast forward through commercials on TV (if watching a recording), skip them on YouTube, or even install ad-blocking software on their browsers, making it harder for brands to reach them. However, they also choose to follow influencers on their social media, which helps brands overcome this very same problem (De Veirman, Cauberghe, & Hudders, 2017). Hence, influencer marketing has been on the rise – in 2015, there were 3.6 million influencer posts, a number that increased to 24.2 million[2] in 2018 (Conick, 2018). Besides this extraordinary growth, this approach is currently used by 75% of brands, according to Association of National Advertisers (ANA) (2018). The same report not only reveals that 43% of the surveyed brands plan to invest more in it but also identifies Instagram as the most important channel for influencer marketing.

ANA (2018) and Statista (2018a) point out engagement rate (percentage of people who engage – liking, commenting, sharing – with the post) as the main measure of traditional and influencer marketing effectiveness. A highly regarded model often used to predict engagement is Ajzen's (1991) Theory of Planned Behaviour (TPB). Nevertheless, no academic papers applying TPB on Instagram were found. According to the model, behaviour is determined by behavioural intention to perform it, which in turn is influenced by attitude, subjective norm, and perceived behavioural control (PBC) – the latter also impacts behaviour directly.

Therefore, the aim of this research is to study the application of TPB on predicting engagement with Instagram advertising – both traditional (TIA) and influencer (IIA) – and analyse its differences. It will contribute to theory and practice, as it applies TPB to a new context, which will allow for original insights for marketers and advertisers. In other words, the conclusions and implications of this research will be useful for creating more efficient and effective Instagram campaigns, which will hopefully lead to higher engagement rates.

[2] Forecasted.

2. Literature Review

2.1 Social Media Marketing, Influencers, and eWOM

Advertisement in social media has changed over the years. From early on, marketers understood social media websites were an outstanding vehicle for spreading ideas, products, and services (eWOM). Another great advantage is its ability to target a wider audience than traditional marketing can (Weinberg, 2009) and, consequently, reaching a viral spread of eWOM. Cambria et al. (2012) also refer to this mechanism as "buzz", describing it as the spreading of a message by user-to-user contact, instead of using traditional means of advertising. Therefore, not only does it spread faster, but it is also more cost efficient than other paid advertisement techniques. These users are often consumers who have used the brand and that voluntary share their opinions and advocate for it (Scott, 2015), which is often perceived as more trustworthy than marketer-generated messages by fellow consumers (Chatterjee, 2001).

Social media presence gives brands the opportunity to constantly receive consumer feedback and learn from it. This will improve sales, overall short-term brand performance, and long-term productivity (Lee, Lee, & Oh, 2015; Luo, Zhang, & Wenjing, 2013). Similarly, Rishika et al. (2013) show how it boosts engagement and consumer advocacy, which translates as a higher share of wallet, consumer loyalty, cross-selling, brand equity, and ROI (Schultz & Peltier, 2013; Vivek et al., 2012). Nonetheless, these results are dependent on suitable and sufficient consumer interaction and feedback, community building, and content posted (Dwivedi et al., 2015; Kaun, 2010).

Lin, Bruning, and Swarna (2018) warn brands that being on social media is becoming the norm, and thus, it is crucial to use it more effectively. The authors argue that these platforms were of great importance for the success of e-commerce and online opinion leadership, as they offered the place for influencers (opinion leaders) – any informed individual with power to influence others within his social media circle, affecting their decision making, attitudes, and behaviours (Godey et al., 2016; Rogers & Cartano, 1962) – to act as brand ambassadors. This strategy, influencer marketing, creates a mutually beneficial relationship – brands benefit from low-cost advertising, and influencers are paid and have access to new products and services for free. As the Internet and its related technologies advances, their role has become increasingly important (Turcotte, York, Irving, Scholl, & Pingree, 2015).

Influencers are a great marketing weapon and have contributed to the success of many marketing campaigns, as they are constantly giving away information consumers are looking for, by communicating with them (Lin, Bruning, & Swarna, 2018; Casaló, Flavián, & Ibáñez-sánchez, 2018). Usually, they start the aforementioned "buzz" with a paid post that is then shared and commented on, spreading the message even further than the influencer's community.

Several studies (Casaló, Flavián, & Ibáñez-Sánchez, 2018; Johnstone & Lindh, 2018) have concluded that influencers and eWOM do influence consumer behavioural intention, sometimes even more so than traditional advertising. Unexpectedly, consumers find smaller influencers, meaning fewer followers, more influential and trustworthy than bigger ones, and place greater value in their opinions (Djafarova & Rushworth, 2017). De Veirman, Cauberghe, and Hudders (2017) argue that consumers often perceive influencers' posts and opinions as highly credible eWOM rather than paid advertisement. Furthermore, the authors state that influencers are set apart from celebrities because they are seen as believable, accessible, intimate, and easy to relate to.

In the past, influencers were incorporating these advertisements as opinions in everyday-life posts (Abidin, 2016), and consumers were not perceiving them as such. To ensure a fair and honest environment, guidelines have been created to regulate their promotional activity on social media. Many national authorities have made it mandatory for influencers to disclose their relationship with brands when posting paid content. With these guidelines in place, consumers are told that what they are seeing is, in fact, an advertisement and not an opinion. There are several articles studying the effect of disclosure (Evans, Phua, Lim, & Jun, 2017; Tessitore & Geuens, 2013), which found it negatively affects purchase intention.

Finally, authors such as Casaló, Flavián, and Ibáñez-sánchez (2018), and De Veirman, Cauberghe, and Hudders (2017) identify Instagram as a suited channel for eWOM and influencer marketing because it allows for aesthetically-pleasing and creative content – leading to higher engagement rates –, and for its intrinsic immediacy, proximity, and sense of community. On the other hand, Djafarova and Rushworth (2017) argue that the success and persuasiveness of Instagram eWOM are due to social media popularity and wide accessibility.

2.2 Theory of Planned Behaviour

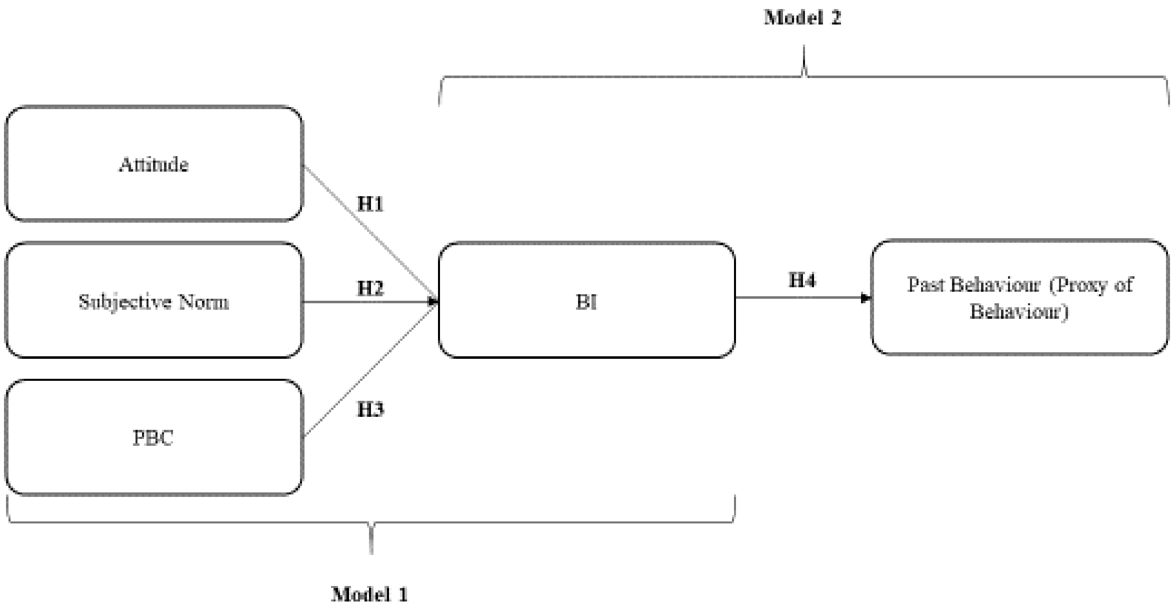
TPB was built upon the Theory of Reasoned Action (Ajzen & Fishbein, 1980), adding a new variable – perceived behavioural control –, which increased its explanatory capacity. It proposes that behaviours are predicted by behavioural intention, which is influenced by three variables: attitude, subjective norm, and PBC – the last is said to have a direct effect on behaviour. The theory defends that these three variables have a positive effect on behavioural intention (Ajzen, 1991) – the stronger they are, the more likely it is to perform said behaviour.

In the past, this framework has been used to study several social media related questions, such as the impact of opinion leadership (Raghupathi & Fogel, 2015), the decision of following brands on Twitter (Chu, Chen, & Sung, 2016), and engagement with Facebook advertising (Sanne & Wiese, 2018).

For the purposes of this study, past behaviour is used as a proxy for actual behaviour. Below (Figure 1), the whole framework is presented, including the two models that will be tested for both kinds of advertising (TIA and IIA). Thus, we propose the following hypothesis which will be tested for each of the two types of Instagram advertising, individually:

H1: *Attitude, subjective norm, and perceived behavioural control towards Instagram* *advertising influence behaviour intention to engage with it.*

Figure 1: TPB Framework – Model 1 and 2 (Adapted from Ajzen, 1991; Sanne & Wiese, 2018).



2.2.1 Attitude

Attitude is the evaluation of performing a certain behaviour (Pelling & White, 2009) – is it good, bad, positive, or negative? If an individual believes that doing something is good, positive and valuable, there is a greater incentive for doing so. On the contrary, if they believe that an action is bad and useless, they have less incentive to perform it. In summary, attitude positively correlates with behavioural intention. For this study, attitude is the users' evaluation of engaging with each of the two types of Instagram advertising. Hence, it is expected that a positive attitude towards Instagram advertising will lead to a higher intention to engage with it. Specifically, we propose the following hypothesis which will be tested for each of the two types of Instagram advertising, individually:

H2: *Attitude towards engaging with Instagram advertising predicts behavioural intention to engage with it.*

2.2.2 Subjective Norm

The literature describes subjective norm as a "social influence construct" (J. Lee & Hong, 2016) regarding one's awareness of others' expectations to perform the behaviour in question (Pelling & White, 2009). However, others' behaviour might also lead one to adopt it. When an individual is considering something, they contemplate what those of importance expect them to do, and what they would think about it (Ajzen & Fishbein, 1980). Upon such expectations, they may choose to comply (or not) with other's opinions. Ho et al. (2015) argue that an individual considers people of personal importance – the ones that they know personally –, and those of social importance – the ones present on mass media channels.

If an individual perceives that others expect them to engage in said behaviour, they have a greater disposition to do so – subjective norm is positively correlated with behavioural intention. When it comes to Instagram advertising, it is the individual's perceived expectations of others about engaging with TIA and IIA. Thus, the following hypothesis is postulated, which will be tested for each of the two types of Instagram advertising, individually:

H3: *Subjective norms of engaging with Instagram advertising predicts behavioural intention to engage with it.*

Taking into account the fact that Instagram is a social media website, where an individual interacts with their friends and others of importance, it is expected that subjective norm has a particularly meaningful impact on behavioural intention (Sanne & Wiese, 2018).

2.2.3 Perceived Behavioural Control

Pelling and White (2009) have described PBC as the perceived ease an individual feels about performing a behaviour. It not only affects behavioural intention but also behaviour, as a person might have the intention to perform it but not the ability to do so (Ajzen, 1991; Sanne & Wiese, 2018).

If someone believes they have all the tools, knowledge, and ability – perceived ease –

needed for some action, they are more likely to do it. Again, PBC is believed to have a positive correlation with behavioural intention. For this study, PBC is the individual's perception of their own ability to engage with each of the two types of Instagram advertising. Therefore, we posit the following hypothesis, which will be tested for each of the two types of Instagram advertising, individually:

H4: *Perceived behavioural control of engaging with Instagram advertising predicts behavioural intention to engage with it.*

2.2.4 Behavioural Intention

As mentioned before, behavioural intention is the best predictor of behaviour (Ajzen, 1991). The author describes it as "indication of how hard people are willing to try, of how much of an effort they are planning to exert, in order to perform the behaviour", hence it is positively correlated with behaviour. In the context of this study, behavioural intention is the intention to engage with each of the two types of Instagram advertising (the behaviour). Thus, we propose the following hypothesis, which will be tested for each of the two types of Instagram advertising, individually:

H5: *Behavioural intention to engage with the Instagram advertising predicts actual engagement with it.*

3. Methodology

To collect data, a survey was developed through Qualtrics, based on Ajzen's (2013) guidelines, and using items from published articles (Ho, Lwin, Yee, & Lee, 2017; Sanne & Wiese, 2018), reworded to adapt them to the context of Instagram advertising – which proves them as reliable and valid. All variables (attitude, subjective norm, PBC, behavioural intention, and past behaviour – used as a proxy of behaviour) were evaluated by presenting a set of affirmations to which the respondent had to answer using a 7-point Likert scale (1=Strongly Agree; 7=Strongly Disagree).

First, there was a screening question to guarantee the respondent had used Instagram in the last month. In case of a negative answer, the survey would end. If positive, the respondent would continue answering the survey. It was composed of two main segments, one regarding TIA, and the other on IIA. Within each segment, there were five sets of multiple-items, one for each variable. For each segment, there were 21 items: 4 on attitude, 5 on subjective norms, 5 on PBC, 2 on behavioural intention, and 5 on past behaviour. To end, there were three demographics-related questions (Gender, Age, and Nationality). The survey may be consulted in Appendix 1.

The survey was then distributed on Facebook and Instagram – as the population in studying is Instagram users, these channels seemed appropriate. Respondents were selected using convenience and snowball techniques, which are nonprobability sampling techniques. In total, 180 responses were collected between October 19th and November 20th. Of all responses, 20 did not pass the screening question, and other 39 were incomplete (dropout rate = 21.67%). The final sample is thus composed of 121 valid responses. The data was uploaded and analysed on SPSS.

The sample is composed of 71.9% women, M_{age} = 24.91; *SD* = 7.16. Moreover, the age difference between women and men was not significant (25.30 and 23.91, respectively). 89.25% were aged between 18 and 35, 9.92% were over 35 years old, and only one person (0.83%) was under 18. Finally, the majority was Portuguese (83.47%). The remaining (16.53%) were German, Italian, American, Finnish, Belgian, British, and Spanish.

Table 1 shows the absolute (and relative) frequency of answers according to the level of accordance for each of variable (bundle of items):

Table 1: Number of answers (and percentage) for each variable

	Somewhat Disagree, Disagree, Strongly Disagree	Neither Agree nor Disagree	Somewhat Agree, Agree, Strongly Agree
TIA Attitude	221 (45.66%)	153 (31.61%)	110 (22.73%)
TIA Subjective Norms	304 (50.25%)	162 (26.78%)	139 (22.98%)
TIA PBC	161 (26.61%)	407 (67.27%)	37 (6.12%)
TIA Behavioural Intention	143 (59.09%)	66 (27.27%)	33 (13.64%)
TIA Past Behaviour	352 (58.18%)	225 (37.19%)	28 (4.63%)
IIA Attitude	170 (35.12%)	216 (44.63%)	98 (20.25%)
IIA Subjective Norm	224 (37.02%)	255 (42.15%)	126 (20.83%)
IIA PBC	91 (15.04%)	475 (78.51%)	39 (6.45%)
IIA Behavioural Intention	91 (37.60%)	109 (45.04%)	42 (17.63%)
IIA Past Behaviour	254 (41.98%)	317 (52.40%)	34 (5.62%)

4. Results

4.1 Reliability and Correlation Analyses

To verify if multiple items could be grouped into one single scale, Cronbach's Alphas were calculated. All results are above the 0.7 acceptance value, which may be verified in the table below (Table 2), and thus, there was no need of eliminating any item. Five new variables were computed – one for each type of advertising –, by taking the average of the related items.

Table 2: Cronbach's Alphas

	TIA Cronbach's Alpha	IIA Cronbach's Alpha	Number of Items
Attitude	0.914	0.933	4
Subjective Norm	0.861	0.902	5
PBC	0.874	0.880	5
Behavioural Intention	0.959	0.955	2
Past Behaviour	0.835	0.887	5

Pearson correlation values were computed (Table 3) to analyse how these variables are related. The results show that all variables are positively correlated. For example, regarding IIA, the relationship between subjective norm and behavioural intention seems to be stronger than the one between PBC and behavioural intention, as the coefficient is greater for the first one (Pallant, 2007).

Table 3: Correlations (Lower half: TIA; Upper half: IIA)

	Attitude	Subjective Norm	PBC	Behavioural Intention	Past Behaviour
Attitude	1	0.675	0.220	0.583	0.611
Subjective Norm	0.575	1	0.233	0.704	0.664
PBC	0.161	0.130	1	0.223	0.228
Behavioural Intention	0.590	0.621	0.124	1	0.852
Past Behaviour	0.606	0.574	0.206	0.769	1

4.2 Multiple Linear Regression Analyses

The multiple linear regression will allow testing Model 1 (Figure 1) for both TIA and IIA. It will not only verify if the independent variables – attitude, subjective norm, and PBC – have a significant influence on the dependent variable – behavioural intention – but also quantify that influence. However, it is necessary to ensure that some requisites regarding sample size, multicollinearity, outliers, and homoscedasticity, linearity and normality of residuals are met. Concerning the first, Tabachnick and Fidell (2007) defend that it should be greater than 50 plus eight times the number of independent variables. Since there are 121 respondents, this condition is met.

For multicollinearity, Pallant (2007) suggest two methods: checking high correlations (>0.9), and Tolerance and Variance Influence Factor (VIF) values. Firstly, all correlations are below 0.9 (Table 3). Moreover, Tolerance and VIF are above 0.1 and below 10, respectively, meaning there is no multicollinearity presented (Appendix 2). Regarding outliers, none were found, as seen on the boxplots present in Appendix 3.

To evaluate the normality, linearity, and homoscedasticity of residuals, several tests were conducted. In Appendix 4 are two histograms with the residuals distributions – both are close to the normal distribution. In Appendix 5, there are the PP plots which show how close the data points fall to the diagonal, thus proving linearity. Finally, the Breusch-Pagan was run, and the homoscedasticity assumption was met ($p > 0.05$) (Appendix 6).

4.2.1 Traditional Instagram Advertising

The first conclusion is that Model 1 is significant for TIA ($p < 0.05$), as shown in the ANOVA table (Appendix 7). Additionally, the variance in the independent variable explained 46.7% of the behavioural intention variance (R^2) – the adjusted R^2 is 45.3%. However, when analysing the coefficient table (Appendix 7) it is observable that PBC is not statistically significant ($p > 0.05$), unlike attitude and subjective norm ($p < 0.05$). Therefore, ***H1 and H4 are not confirmed***, and a second regression was run without PBC. The R^2 and adjusted R^2 did not change, showing that PBC did not impact the variance explained by the model. The ANOVA table shows the model is statistically significant ($p < 0.05$) (Appendix 8).

Table 4: Coefficients Table for Traditional Instagram Advertising Model 1 (Final Regression)

	β	**t**	**p-value**
Constant	0.271	0.576	0.565
Attitude	0.462	4.237	0.000
Subjective Norm	0.552	5.122	0.000

By analysing the table above (Table 4), it becomes clear that both attitude and subjective norm are statistically significant ($p < 0.05$), ***confirming both H2 and H3***. The β-coefficients slightly increased –for example, if subjective norm increases by 1, behavioural intention will increase by 0.552.

In summary, for TIA ***H2 and H3 are confirmed, but H1 and H4 are not***.

4.2.2 Influencer Instagram Advertising

After running the first regression with all three independent variables, the ANOVA showed that the model was statistically significant ($p < 0.05$), but the coefficient table pointed out that PBC was not ($p > 0.05$) (Appendix 9). Consequently, ***H1 and H4 are not confirmed***. Nevertheless, the R^2 and adjusted R^2 are 0.519 and 0.507, meaning that 51.9% of the independent variables variance explains the dependent variable variance. A second regression without PBC was run. R^2 slightly decreased (0.517) and adjusted R^2 increased (0.509). The ANOVA guaranteed the significance ($p < 0.05$) of this second regression (Appendix 10).

Table 5: Coefficients Table for Influencer Instagram Advertising Model 1 (Final Regression)

	β	**t**	**p-value**
Constant	0.381	1.101	0.273
Attitude	0.225	2.303	0.023
Subjective Norm	0.672	6.563	0.000

Table 5 shows how the two independent variables are statistically significant ($p < 0.05$), which ***confirms H2 and H3***. Again, subjective norm has a greater influence on behavioural intention than attitude.

Finally, according to the second regression, ***H2 and H3 are confirmed, but H1 and H4 are not confirmed.***

4.3 Simple Linear Regression Analyses

Running a single linear regression will allow for testing Model 2 (Figure 1) for TIA and IIA, thus assessing if behavioural intention (independent variable) influences (past) behaviour (dependent variable). Again, it is necessary to ensure some requisites. Regarding sample size, it is sufficiently big. Second, the correlation between behavioural intention and past behaviour is 0.769 (TIA) and 0.852 (IIA) (Table 2). Again, no outliers were found (Appendix 11). The same tests as before were conducted to evaluate the normality, linearity, and homoscedasticity of residuals. All results ensure these and are in Appendixes 12, 13, and 14.

4.3.1 Traditional Instagram Advertising

The R^2 and adjusted R^2 are 0.591 and 0.587, meaning that 59.1% of the variance in behavioural intention explains the variance in past behaviour. The ANOVA table (Appendix 15) shows that the regression is significant ($p < 0.05$). Individually, behavioural intention is significant ($p < 0.05$), and has a β of 0.675 – for each unit it increases, past behaviour increases by 0.675. ***The results confirm H5***.

4.3.2 Influencer Instagram Advertising

The regression of behavioural intention on past behaviour regarding influencer Instagram advertising produced similar conclusions to the previous one. For this regression, the R^2 and adjusted R^2 are both higher – 0.726 and 0.723 –, meaning there is a higher percentage of behavioural intention explaining past behaviour. In addition, the regression is also significant ($p < 0.05$), as shown in the ANOVA table (Appendix 16). Finally, behavioural intention is also significant ($p < 0.05$) and its influence seems to be greater on this case, as β is 0.835. In conclusion, ***these results also confirm H5***.

Table 6 presents a summary of the hypotheses testing for both types of advertising:

Table 6: Summary Table of Hypotheses Testing

	TIA	**IIA**
H1	Not confirmed	
H2	Confirmed	
H3	Confirmed	
H4	Not confirmed	
H5	Confirmed	

5. Discussion

This study evaluates the application of TPB on Instagram advertising, both traditional and from influencers. It contributes to literature as it applies the theory to a new context, which allowed for new findings regarding engagement drivers on a never-studied social media website, Instagram.

Overall, all variables are negatively evaluated (Neither Agree nor Disagree, Somewhat Disagree, Disagree, Strongly Disagree) by respondents. Marketers and advertisers should focus on strategies to improve the main three – attitude, subjective norm, and PBC –, in order to increase behavioural intention and, in consequence, intention itself. Nevertheless, results are marginally better for IIA than TIA, even more so when considering behavioural intention and past behaviour. This means respondents find advertisements posted by influencers better and have more intention to engage with them, rather than the marketer-generated ones.

According to the proposed hypotheses, we expected attitude, subjective norm, and PBC to have a positive correlation with behavioural intention, both collectively and individually. Against our beliefs, PBC was found not to be significant for both types of advertising, which goes against what some authors have defended. Attitude and subjective norm were found to be significant for TIA an IIA, reiterating the literature.

Regarding the relationship between behavioural intention and behaviour itself, we found that it is significant and positive for both types of Instagram advertising. This result is in accordance with several authors. Moreover, and for the two forms of advertising, subjective norm was found to be the strongest predictor of behavioural intention, which reiterates the finding of many authors.

These results give new insights into challenges marketers and advertisers are facing regarding engagement. In other words, this study, besides adding value to literature, also contributes to practice, as it highlights problems and enables more efficient solutions to increase engagement rates on both types of Instagram advertising. More specifically, since subjective norm is the strongest predictor of behavioural intention, that variable should be the main focus of both marketing professionals and influencers.

5.1 Theoretical Implications

The data analysis proved that attitude and subjective norm are predictors of behavioural intention, which in turn predicts behaviour (engagement with TIA and IIA). These results are in accordance with several studies that are related to social media and social media marketing (Chu et al., 2016; Ho et al., 2017; Pelling & White, 2009; Raghupathi & Fogel, 2015; Sanne & Wiese, 2018).

Results showed that PBC is not significant for predicting intention to engage with TIA and IIA. It goes against the findings of Chu, Chen, and Sung (2016) and Ho et al. (2017), but it supported by Sanne and Wiese (2018), Pelling and White (2009), and Raghupathi and Fogel (2015). Sanne and Wiese (2018) studied Facebook advertising – another form of social media advertising –, so this result is particularly interesting. The similarity between these suggests that perhaps behavioural intention to engage with social media advertising is only predicted by attitude and subjective norm.

This may be a consequence of users being extremely capable of using the Internet and Instagram and interacting with ads – which are just another Instagram post –, meaning it does not require any additional effort. Furthermore, this phenomenon might have been accentuated by the sample's average age (24.91), as younger users are more familiarised with social media and technology. Finally, if PBC is not a significant variable, then TPB is not a good model for explaining engagement with Instagram advertising. The results suggest that the aforementioned Theory of Reasoned Action would be a better model, as it only considers attitude and subjective norms as predictors of behavioural intention.

Subjective norm was found to be the strongest significant predictor of behavioural intention for both TIA ($\beta = 0.552$) and IIA ($\beta = 0.672$). While it is supported by the findings of Pelling and White 2009, Ho et al. (2017), and Raghupathi and Fogel (2015), it goes against what some researchers, such as Sanne and Wiese (2018) and Chu, Chen, and Sung (2016), have found in their studies – that attitude was the strongest predictor.

Instagram has been named the worst app for mental health for it creates pressure to live the "perfect Instagram life" that other users seem to be living (Royal Society for Public Health, 2017). As such, others' behaviours and opinions of what one should and should not do (subjective norms) may affect one's behavioural intention. Consequently, these facts might justify why subjective norms play such a significant role in predicting behavioural intention.

Since the TIA and IIA's final Models 1 and 2 have the same variables, it is possible to compare them. The first conclusion is that the explanatory power of both is greater for IIA than

TIA, as both R^2 and adjusted R^2 are higher. This means that attitude and subjective norms – the two independent variables in the final Model 1 – better explain intention to engage with IIA than with TIA. In other words, TPB is a better fit for studying engagement with IIA rather than TIA.

As aforementioned, subjective norm is the strongest predictor of behavioural intention to engage with both types of Instagram advertising. Nevertheless, its effect is stronger for IIA, as the β-coefficient is greater for this type – 0.672, opposite to 0.552 for TIA. This means that the opinions and behaviours of others, as well as the perception of what one should do, have a stronger effect on influencing behavioural intention to engage and, consequently, to engage with IIA.

Over the last years, influencers have gained a more prominent role on social media. Furthermore, there is at least one relevant influencer for each individual, as they cover a wide spectrum of interests. Since people share their interests with friends and family, their opinions and behaviours regarding advertisement generated by influencers (IIA) might affect how one engages with it. Moreover, the sample is composed of young people, and these are more likely to be influenced by other's behaviours, opinions, and expectations, and online trends. The combination of these three factors might explain the greater influence of subjective norms on engagement with IIA.

Interestingly, attitude has a much weaker influence on intention to engage with IIA than TIA – $\beta = 0.225$ and $\beta = 0.462$, respectively. The study seems to suggest that the value people attribute to engaging with Instagram advertising plays a smaller role in influencing their behavioural intentions when it comes from influencers rather than brands.

The overall attitude towards Instagram advertising appears to be negative, as the percentage of negative answers are 45.66% and 35.12% for TIA and IIA, respectively. Notwithstanding, regarding attitude towards IIA, most answers (44.63%) were neutral. Perhaps this might be due to users' confliction between the advantages and disadvantages of influencers.

In recent years, influencers have gained a bad reputation for creating unrealistic expectations of what life should look like, as well as disguising their paid advertisements as day-to-day posts, even with regulation in place. Nevertheless, people are now becoming aware of this phenomenon. Despite this, influencers are still being used and paid to promote products, and people are still following them, learning of new products and services through them and often engaging with those. Since some people have a bad opinion of influencers but still engage with their content, it may justify why attitude has a diminished influence on behavioural intention.

Again, the majority (59.09%) of answers were negative, when evaluating behavioural intention to engage with TIA. This value decreases to 37.60% when it is related to IIA. Moreover, there is a slight increase in positive answers, from 13.64% (TIA) to 17.63% (IIA). In summary, data shows that Instagram users are more predisposed to engage with IIA. Past behaviour confirms this – even though positive answers are scarce (4.63% for TIA and 5.62% IIA), they are more for IIA.

5.2 Managerial Implications

From the managerial point of view, for both brands and influencers, the main objective is to increase user engagement. Therefore, the focus should be on how to improve attitude towards Instagram advertising and change subjective norms.

Since attitude is a better predictor of behavioural intention with TIA (than with IIA), marketers should focus on conveying the benefits of Instagram advertising, and how positive and enjoyable it can be. This may be achieved through interactive campaigns, where consumers are shown how engaging with advertisement is beneficial. Furthermore, TIA should blend into users' feeds, and not feel intrusive (Sanne & Wiese, 2018). Instagram's most recent development regarding TIA is the introduction of sponsored "Ad Stories" in between stories from other users – stories are temporary content, only available for 24 hours, that are available on the top part of the feed. This is a bad example, as users find it annoying and intrusive (Welch, 2018), harming attitude towards TIA.

Attitude has less influence on behavioural intention to engage with influencers' paid posts. Nevertheless, marketers should aim to improve it. As such, the relationship between brands and influencers should always be disclosed. Even though it has been found to have a negative effect on purchase intention (Evans et al., 2017), consumers also value transparency and honesty, and thus marketers should promote these, as it may positively affect consumers' attitude towards IIA.

Changing subjective norms is harder, but there are still some options that marketers can take advantage of. Since they are related to copying others' behaviours, marketers should invest in making Instagram ads as interactive as possible. Many of the current campaigns involve following the brand, liking, tagging other users and sharing. Besides increasing engagement, it might encourage users to copy their friends' behaviour, thus impacting subjective norms.

5.3 Limitations and Future Research

The first main limitation of the present study is its sample. Most studies regarding social media websites have much larger samples, allowing for generalisations. Furthermore, most respondents were Portuguese and females, which is another impediment. Future research should aim to have a bigger and unbiased sample, by using a probability sampling technique. It would allow for investigating differences between countries and culture but also between gender and age groups. Moreover, future researches may evaluate the differences between the application of TPB on different social media websites advertising – for example, assessing if there are any differences between predictors of engagement with Facebook and Instagram advertising.

The relative frequencies for behavioural intention and past behaviour were low for both TIA and IIA. In the future, researchers should ensure that their samples have a more even representation of users that do engage with Instagram advertising. Additionally, the survey was self-reported, meaning respondents evaluated their attitudes and behaviour by themselves. Therefore, it is hard to ensure that all the provided answers were truthful, and thus no objective conclusions can be taken.

Regarding the Model 1 (regression of attitude and subjective norm on behavioural intention), both types scored a relatively low R^2, meaning there are still other variables with explanatory value that weren't included in this research. Future research should build upon it to further investigate what affects behavioural intention to engage with Instagram advertising – including variables such as the type of content (video versus image), privacy concerns, and weekday and time of the posts.

Still regarding the studied variables, previous studies on TPB usually employ long and very complete surveys, with multiple items for each variable. The present study also did so, but not as thoroughly. Future research should include more items per variable, in order to improve, reiterate and validate these results and conclusions.

Finally, the findings of this study and of Sanne and Wiese's (2018) seem to indicate that the Theory of Reasoned Action is a better fit for studying advertisement on social media than TPB. As such, future researchers should address this question.

6. Conclusion

Research into advertising on other social media websites, such as Facebook, is vast, but research into Instagram advertising is extremely limited, and thus this study contributes to it. This study showed partial support for the application of TPB on TIA and IIA, as PBC was not statistically significant – thus, it seems that the Theory of Reasoned Action is probably a better fit for both. Amongst the findings, some stand out, such as subjective norms having a stronger, and attitude a weaker, influence on intention to engage with IIA rather than TIA. These findings are useful for marketers, brands, and influencers – by knowing what predicts engagement (attitude and subjective norms) and what works best for each type of advertising, they have the tools needed to improve and optimise both and, consequently, to increase engagement. Moreover, advertisers may use the proposed models to predict engagement with Instagram advertising, by collecting data on attitude and subjective norms. Finally, the focus of marketers and advertisers should be to improve interactivity, transparency and honesty of TIA but especially IIA.

7. References

Abidin, C. (2016). Visibility labour: Engaging with influencers' fashion brands and #OOTD advertorial campaigns on Instagram. *Media International Australia*, *161*(1), 86–100. https://doi.org/10.1177/1329878X16665177

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behaviour and Human Decision Processes*, *50*(3), 179–211.

Ajzen, I. (2013). *Theory of planned behaviour questionnaire*. *Measurement Instrument Database for the Social Science.* https://doi.org/http://dx.doi.org/10.13072/midss.649

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. Englewood Cliffs, N.J: Prentince Hall.

Association of National Advertisers. (2018). *Survey report: How ANA members are using influencer marketing*. Retrieved at October, 15th from https://www.ana.net/miccontent/show/id/ii-2018-members-using-influencer

Cambria, E., Grassi, M., Hussain, A., & Havasi, C. (2012). Sentic computing for social media marketing. *Multimedia Tools and Applications*, *52*(2), 557–577. https://doi.org/10.1007/s11042-011-0815-0

Casaló, L. V, Flavián, C., & Ibáñez-Sánchez, S. (2018). Influencers on Instagram: Antecedents and consequences of opinion leadership. *Journal of Business Research*. https://doi.org/10.1016/j.jbusres.2018.07.005

Chatterjee, P. (2001). Online reviews: Do consumers use them? *Advances in Consumer Research*, *28*(1), 129–134.

Chu, S., Chen, H., & Sung, Y. (2016). Following brands on Twitter: An extension of theory of planned behavior. *International Journal of Advertising*, *35*(3), 421–437.

Conick, H. (2018, August). How to win friends and influence millions: The rules of influencer marketing. *Marketing News*, 36–45.

De Veirman, M., Cauberghe, V., & Hudders, L. (2017). Marketing through Instagram influencers: The impact of number of followers and product divergence on brand attitude. *International Journal of Advertising*, *36*(5), 798–828. https://doi.org/10.1080/02650487.2017.1348035

Djafarova, E., & Rushworth, C. (2017). Exploring the credibility of online celebrities' Instagram profiles in influencing the purchase decisions of young female users. *Computers in Human Behavior*, *68*, 1–7. https://doi.org/10.1016/j.chb.2016.11.009

Dwivedi, Y. K., Kapoor, K. K., & Chen, H. (2015). Social media marketing and advertising. *The Marketing Review*, *15*(3), 289–309.

Evans, N. J., Phua, J., Lim, J., & Jun, H. (2017). Disclosing Instagram influencer advertising: The effects of disclosure language on advertising recognition, attitudes, and behavioral intent. *Journal of Interactive Advertising*, *17*(2), 138–149. https://doi.org/10.1080/15252019.2017.1366885

Godey, B., Manthiou, A., Pederzoli, D., Rokka, J., Aiello, G., Donvito, R., & Singh, R. (2016). Social media marketing efforts of luxury brands: Influence on brand equity and consumer behavior. *Journal of Business Research*, *69*(12), 5833–5841. https://doi.org/10.1016/j.jbusres.2016.04.181

Goldsmith, R. E., & Clark, R. A. (2008). An analysis of factors affecting fashion opinion leadership and fashion opinion seeking. *Journal of Fashion Marketing and Management:*

An International Journal, *12*(3), 308–322. https://doi.org/10.1108/13612020810889272

Hartmans, A., & Price, R. (2018). Instagram just reached 1 billion users. Retrieved October 12th from https://www.businessinsider.com/instagram-monthly-active-users-1-billion-2018-6

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the internet? *Journal of Interactive Marketing*, *18*(1), 38–52. https://doi.org/10.1002/dir.10073

Ho, S. S., Liao, Y., Rosenthal, S., Ho, S. S., Liao, Y., & Rosenthal, S. (2015). Applying the theory of planned behavior and media dependency theory: predictors of public pro-environmental behavioral intentions in Singapore. *Environmental Communication*, *9*(1), 77–99. https://doi.org/10.1080/17524032.2014.932819

Ho, S. S., Lwin, M. O., Yee, A. Z. H., & Lee, E. W. J. (2017). Understanding factors associated with singaporean adolescents' intention to adopt privacy protection behavior using an extended theory of planned behavior. *Cyberpsychology, Behavior, and Social Networking*, *20*(9), 572–579. https://doi.org/10.1089/cyber.2017.0061

Instagram. (2018). Retrieved October, 20th from https://business.instagram.com/

Johnstone, L., & Lindh, C. (2018). The sustainability-age dilemma: A theory of (un)planned behaviour via influencers. *Journal of Consumer Behaviour*, *17*, 127–139. https://doi.org/10.1002/cb.1693

Kaun, L. (2010). Business: Look, listen, leap: Plan your strategy to make social media marketing your interactive advantage. *Speciality Fabrics Review*, *95*(3), 51–54.

Kemp, S. (2018). Digital in 2018: World's internet users pass the 4 billion mark. Retrieved November, 20th from https://wearesocial.com/blog/2018/01/global-digital-report-2018

Lee, J., & Hong, I. B. (2016). Predicting positive user responses to social media advertising:

The roles of emotional appeal, informativeness, and creativity. *International Journal of Information Management*, *36*(3), 360–373. https://doi.org/10.1016/j.ijinfomgt.2016.01.001

Lee, K., Lee, B., & Oh, W. (2015). Thumbs up, sales up? The contingent effect of Facebook likes on sales performance in social commerce. *Journal of Management Information Systems*, *32*(4), 109–143. https://doi.org/10.1080/07421222.2015.1138372

Lin, H., Bruning, P. F., & Swarna, H. (2018). Using online opinion leaders to promote the hedonic and utilitarian value of products and services. *Business Horizons*, *61*(3), 431–442. https://doi.org/10.1016/j.bushor.2018.01.010

Luo, X., Zhang, J., & Wenjing, D. (2013). Social media and firm equity value. *Information Systems Research*, *24*(1), 146–163.

Pallant, J. (2007). *SPSS survival manual*: *a step by step guide to data analysis using SPSS*. Maidenhead: Open University Press/McGraw-Hill.

Pelling, E. L., & White, K. M. (2009). The theory of planned behavior applied to young people' s use of social networking web sites. *Cyberpsychology & Behavior*, *12*(6), 755–759.

Raghupathi, V., & Fogel, J. (2015). The impact of opinion leadership on purchases through social networking websites. *Journal of Theoretical and Applied Electronic Commerce Research*, *10*(3), 18–29. https://doi.org/10.4067/S0718-18762015000300003

Rishika, R., Kumar, A., Janakiraman, R., & Bezawada, R. (2013). The effect of customers' social media participation on customer visit frequency and profitability: An empirical investigation. *Information Systems Research*, *24*(1), 108–127.

Rogers, E. M. ., & Cartano, D. G. . (1962). Methods of measuring opinion leadership. *The Public Opinion Quarterly*, *26*(3), 435–441.

Royal Society for Public Health. (2017). *Social media and young people's mental health and* *wellbeing*. Retrieved December, 1st from https://www.rsph.org.uk/our-work/campaigns/status-of-mind.html

Sanne, P. N. C., & Wiese, M. (2018). The theory of planned behaviour and user engagement applied to Facebook Advertising. *South African Journal of Information Management*, *20*(1), a915. https://doi.org/https://doi.org/ 10.4102/sajim.v20i1.915

Schultz, D. E., & Peltier, J. (Jimmy). (2013). Social media's slippery slope: Challenges, opportunities and future research directions. *Journal of Research in Interactive Marketing*, *7*(2), 86–99. https://doi.org/10.1108/JRIM-12-2012-0054

Scott, D. M. (2015). *The new rules of marketing and PR*. Hoboken, NJ: John Wiley & Sons.

Statista. (2018a). *Influencer marketing*. Retrieved October 15th from https://fesrvsd.fe.unl.pt:2058/study/28362/influence-marketing-statista-dossier/

Statista. (2018b). *Social media usage worldwide*. Retrieved October 15th from https://fesrvsd.fe.unl.pt:2058/study/12393/social-networks-statista-dossier/

Tabachnick, B. G., & Fidell, L. S. (2007). *Using multivariate statistics*. Boston, MA.: Pearson Education.

Teng, S. (2015). Persuasive communication: A study of major attitude-behavior theories in a social media context. *Journal of Internet Commerce*, *14*, 42–64. https://doi.org/10.1080/15332861.2015.1006515

Tessitore, T., & Geuens, M. (2013). PP for "product placement " or “puzzled public”? *International Journal of Advertising*, *32*(3), 419–442. https://doi.org/10.2501/IJa-32-3-419-442

Turcotte, J., York, C., Irving, J., Scholl, R. M., & Pingree, R. J. (2015). News recommendations from social media opinion leaders: Effects on media trust and information seeking. *Journal of Computer-Mediated Communication*, *20*(2012), 520–535. https://doi.org/10.1111/jcc4.12127

Vivek, S. D., Beatty, S. E., & Morgan, R. M. (2012). Customer engagement: Exploring customer relationships beyond purchase. *Journal of Marketing Theory & Practice*, *20*(2), 127–145. https://doi.org/10.2753/MTP1069-6679200201

Weinberg, T. (2009). An introduction to social media marketing. In *The New Community Rules: Marketing on the Social Web* (First Edition, p. 3). O'Reilly Media.

Welch, C. (2018). Ads between Instagram stories are about to get more annoying. Retrieved December 1st from https://www.theverge.com/2018/2/1/16956486/instagram-stories-ads-three-parts

8. Appendixes

8.1 List of Abbreviations

eWOM: Electronic Word-of-Mouth

IIA: Influencer Instagram Advertising

PBC: Perceived Behavioural Control

TIA: Traditional Instagram Advertising

TPB: Theory of Planned Behaviour

8.2 Appendix 1: Survey

Screening Question: *Have you used Instagram, even if you have not posted, in the last month?* Yes/No

(If No, survey would end. If Yes, survey would continue)

This study focuses on two types of Instagram advertising: traditional Instagram ads and influencers' paid posts. For this section and until further instructions, please focus on traditional Instagram ads that appear on your feed.

Please select to what extent you agree with the following statements: (7-point Likert scale – 1 = Strongly Agree; 7 = Strongly Disagree – evaluating attitude)

- *I think engaging with Instagram ads is good.*
- *I think engaging with Instagram ads is positive*
- *I think engaging with Instagram ads is valuable.*
- *I think engaging with Instagram ads is enjoyable.*

Please select to what extent you agree with the following statements: (7-point Likert scale – 1 = Strongly Agree; 7 = Strongly Disagree – evaluating subjective norm)

- *People who are important to me think I should engage with Instagram ads.*
- *People who influence my behaviour think I should engage with Instagram ads.*
- *It is expected of me to engage with Instagram ads. (Which of them?)*
- *People who are important to me engage with Instagram ads.*

- *People like me engage with Instagram ads.*

Please select to what extent you agree with the following statements: (7-point Likert scale – 1 = Strongly Agree; 7 = Strongly Disagree – evaluating PBC)

- *Engaging with Instagram ads is entirely in my control.*
- *I can choose the Instagram ads I want to engage with.*
- *I am free to engage with Instagram ads as I want to.*
- *I have the knowledge and ability to engage with Instagram ads.*
- *I have the resources needed to engage with Instagram ads.*

Please select to what extent you agree with the following statements: (7-point Likert scale – 1 = Strongly Agree; 7 = Strongly Disagree – evaluating behavioural intention and past behaviour)

- *I have the intention to engage with Instagram ads in the next month.*
- *I will engage with Instagram ads in the next month.*
- *I have engaged with Instagram ads in the last month.*
- *I have liked Instagram ads in the last month.*
- *I have commented on Instagram ads in the last month.*
- *I have clicked on Instagram ads in the last month.*
- *I have sent to someone I know an Instagram ad in the last month.*

For this section and until further instructions, please focus on influencers' paid posts on Instagram. (Questions for this section were the same ones, switching the expression "Instagram ad" for "Influencers' paid posts")

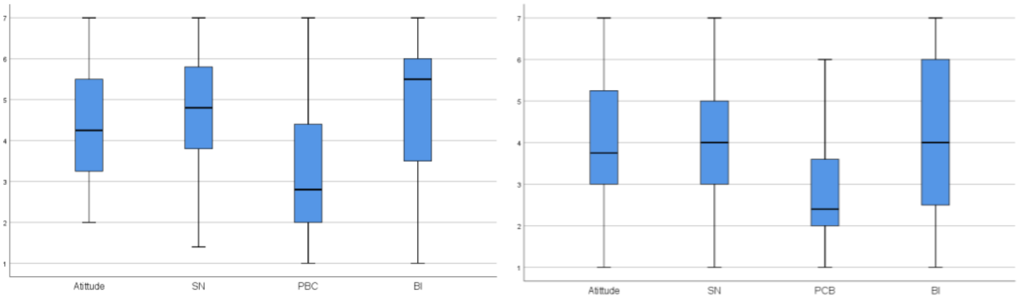
Please indicate your:

  - *Age:*
  - *Gender*
  - *Nationality*

8.3 Appendix 2: Tolerance and VIF Values

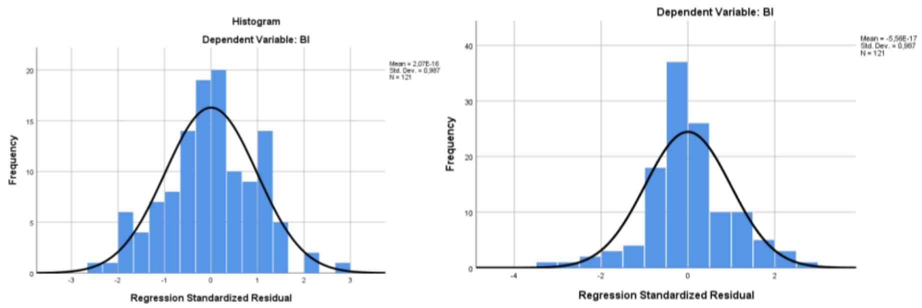
	TIA		IIA	
	Tolerance	**VIF**	**Tolerance**	**VIF**
Attitude	0.662	1.510	0.541	1.849
Subjective Norm	0.668	1.496	0.537	1.861
PBC	0.972	1.029	0.938	1.066

8.4 Appendix 3: Boxplots for Model 1



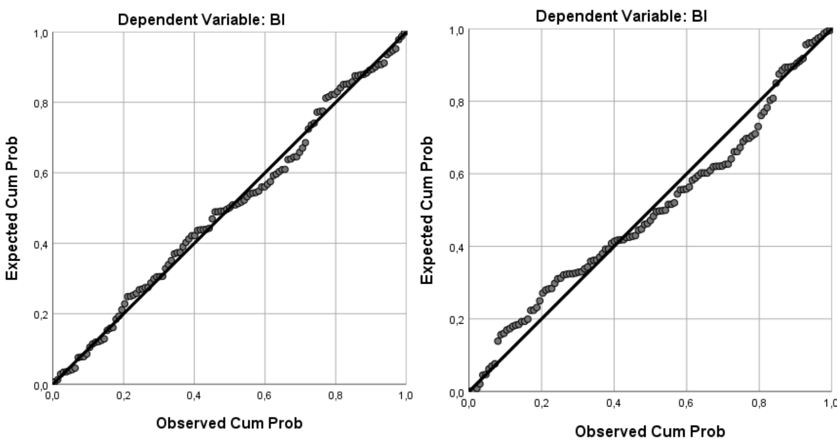
Note: Traditional Instagram (Left) and Influencer Instagram (Right) Advertising

8.5 Appendix 4: Distribution of Residuals for Model 1



Note: Traditional Instagram (Left) and Influencer Instagram (Right) Advertising

8.6 Appendix 5: PP Plots for Model 1



Note: Traditional Instagram (Left) and Influencer Instagram (Right)

8.7 Appendix 6: Breusch-Pagan Test Results for Model 1

```
------- Breusch-Pagan and Koenker test statistics and sig-values --------
                  LM          Sig
BP             5,552        ,136
Koenker        5,629        ,131
```

```
------- Breusch-Pagan and Koenker test statistics and sig-values --------
                  LM          Sig
BP             6,812        ,078
Koenker        4,499        ,212
```

Note: Traditional Instagram (Up) and Influencer Instagram (Down)

8.8 Appendix 7: TIA ANOVA, and Coefficients Table (Model 1)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	172,759	3	57,586	34,141	,000[b]
	Residual	197,344	117	1,687		
	Total	370,103	120			

a. Dependent Variable: BI

b. Predictors: (Constant), PBC, SN, Atittude

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	,236	,503		,469	,640
	Atittude	,459	,110	,346	4,174	,000
	SN	,551	,108	,420	5,086	,000
	PBC	,016	,081	,014	,199	,842

8.9 Appendix 8: TIA ANOVA (Final Model 1)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	172,692	2	86,346	51,612	,000[b]
	Residual	197,411	118	1,673		
	Total	370,103	120			

a. Dependent Variable: BI

b. Predictors: (Constant), SN, Atittude

8.10 Appendix 9: IIA ANOVA, and Coefficients Table (Model 1)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	186,066	3	62,022	42,101	,000[b]
	Residual	172,359	117	1,473		
	Total	358,426	120			

a. Dependent Variable: BI

b. Predictors: (Constant), PCB, Atittude, SN

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	,254	,386		,658	,512
	Atittude	,218	,098	,194	2,225	,028
	SN	,663	,103	,561	6,416	,000
	PCB	,072	,096	,050	,753	,453

8.11 Appendix 10: IIA ANOVA (Final Model 1)

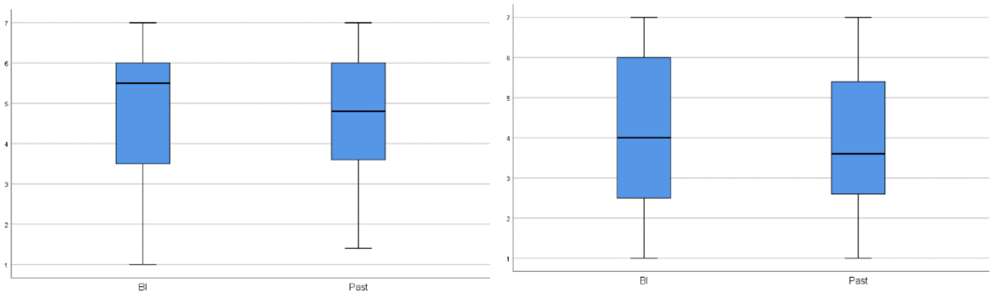
ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	185,231	2	92,615	63,100	,000[b]
	Residual	173,195	118	1,468		
	Total	358,426	120			

a. Dependent Variable: BI

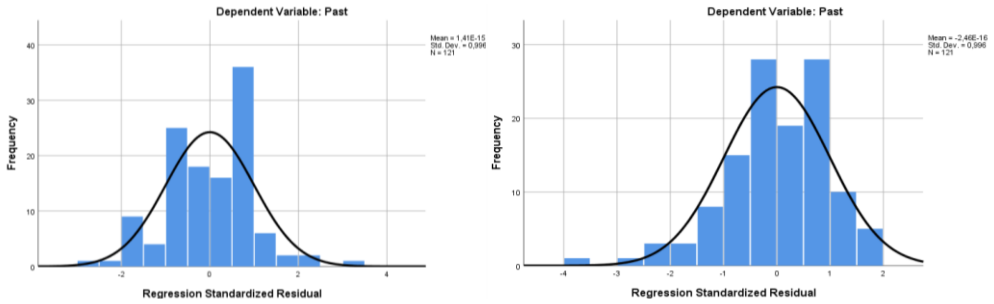
b. Predictors: (Constant), SN, Atittude

8.12 Appendix 11: Boxplots for Model 2



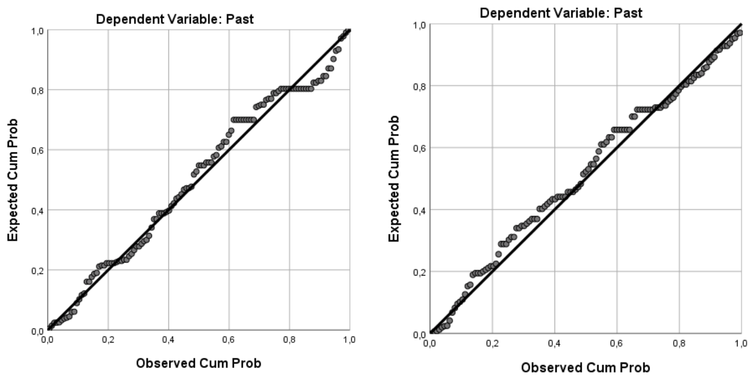
Note: Traditional Instagram (Left) and Influencer Instagram (Right) Advertising

8.13 Appendix 12: Distribution of Residuals for Model 2



Note: Traditional Instagram (Left) and Influencer Instagram (Right) Advertising

8.14 Appendix 13: PP Plots for Model 2



Note: Traditional Instagram (Left) and Influencer Instagram (Right) Advertising

8.15 Appendix 14: Breusch-Pagan Test Results for Model 2

```
------- Breusch-Pagan and Koenker test statistics and sig-values --------
                LM          Sig
BP            2,156       ,142
Koenker       1,716       ,190
```

```
------- Breusch-Pagan and Koenker test statistics and sig-values ---
                LM          Sig
BP            2,862       ,091
Koenker       1,751       ,186
```

Note: Traditional Instagram (Up) and Influencer Instagram (Down)

8.16 Appendix 15: TIA ANOVA (Model 2)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	168,521	1	168,521	171,828	,000[b]
	Residual	116,710	119	,981		
	Total	285,231	120			

a. Dependent Variable: Past

b. Predictors: (Constant), BI

8.17 Appendix 16: IIA ANOVA (Model 2)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	250,153	1	250,153	314,970	,000[b]
	Residual	94,511	119	,794		
	Total	344,664	120			

a. Dependent Variable: Past

b. Predictors: (Constant), BI