

UNIVERSITY OF MACEDONIA
DEPARTMENT OF APPLIED INFORMATICS

Philosophiae Doctor Dissertation

**SOCIAL MEDIA BEHAVIOR ANALYSIS: EXPLORING THE PARADIGM
IN eHEALTH**

Nikolaos K. Misirlis

Supervision: Maro Vlachopoulou, Professor
George Lekakos, Associate Professor
Konstantinos Fouskas, Assistant Professor

Thessaloniki, January 2019

Copyright © Misirlis K. Nikolaos, 2019

All rights reserved

The approval of the PhD dissertation by the department of the Applied Information of the University of Macedonia does not necessarily imply the acceptance of the opinions of the authors on behalf of the Department.

Acknowledgements

«Μόνο σιωπή ασάλευτη, πες μου τι δεν ταιριάζει, τα παιδικά μου όνειρα κι ο χρόνος που κοχλάζει»

- Θανάσης Παπακωνσταντίνου

Completing the long and almost impossible journey of a doctorate requires hard work, dedication, sacrifices both personal and professional and of course unlimited love for Science. I wouldn't have been able to complete anything without the support of many people involved, over the last three and a half years.

First, I would like to express my gratitude to my main supervisor, Professor Maro Vlachopoulou who believed in me and immersed me in this great world. She taught me how to be a good researcher, academic and teacher and for that I will be eternally grateful. She will always be my mentor.

I would like also to express my gratitude to my other two supervisors, Professors Lekakos George and Fouskas Konstantinos. Always present for me to assist, help and advice.

Last, but not least, I would like to thank my family, Konstantinos, Chrysavgi, Dimitris, Sophia and Konstantinos Jr. for their encouragement in all these long and difficult years and my life partner Dimitra for her support and for being a constant breakwater of negative mood and stress, all the way to the end. I deeply thank you all.

*«Καθώς μένω στο δωμάτιο μου,
μου ἔρχονται άξαφνα φαιινές ιδέες
Φοράω το σακάκι του πατέρα
κι έτσι είμαστε δυο»*
- Τάσος Λειβαδίτης

Στον πατέρα μου
Νικόλαος Κ. Μισιρλής

Abstract

Web 2.0 and social media create a brand new field with great perspectives and interest, almost for every scientist and aspect of knowledge. Based on social media behavior analysis, a huge amount of useful data concerning consumers' behavior is produced leading to insights and predictions of great interest and usefulness.

One of the areas of interest, eHealth, represents an important social media behavior analysis field that is neglected by research and is not fully analyzed due to the difficulties regarding the sensitivity of data and their gathering process.

The objective of this dissertation is to analyze the consumers' behavior towards their intention to use advices from Facebook pages and groups related to well-being, in specific related to healthy diet and leisure activities, in correlation to their personality.

The present study uses one of the most important methods to analyze the users' personality traits (Pe), the Big Five Inventory and together with the Theory of Planned Behavior (Be), paves the ground for the field of social media analytics and the consumer behavior in the eHealth (e-He) research field. Big Five categorizes users of social media in percentages on: Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism. Theory of Planned Behavior uses Attitude, Subjective Norm, Perceived Behavioral Control and Intention to Use variables in order to predict the users' actual behavior on whether they tend to use a technological tool or not.

During our research, two new frameworks for digital marketing analysis are being proposed, the S3M and the Unified framework for data analysis on social media (SMA). These two continuously growing frameworks form a solid base for further research among practitioners and academics. Following these two frameworks, the present dissertation reviews the literature of the field presenting tables of content and statistics related to the major research outcomes. Based on the above literature review, a conceptual framework, entitled "e-HePeBe-SMA" has been suggested with relevant hypotheses formulation, in order to analyze the social media behavior taking into consideration the personality traits of eHealth social media users.

A primary research has been conducted in order to examine the effects on individuals' behavior towards healthy diet and sport activities in combination to Facebook pages and groups. The

theoretical framework 'e-HePeBe-SMA' was tested and evaluated using a questionnaire of 47 items distributed online via Facebook messages and emails obtaining 578 valid answers. We used structural equation modeling in order to confirm our 12 hypotheses. Results show that elevate levels of Agreeableness can lead to positive Attitude regarding the use of groups and pages on Facebook related to well being advices as well as Extraversion can lead to consider the Subjective norms around social media and well being and Perceived Behavioral Control and Conscientiousness to Perceived Behavioral Control.

The conclusions of the present study can contribute to academics and practitioners by helping them assess their marketing research/ decisions based on the knowledge of which combination of personalities and planned behavior influence more the use of social media pages and groups related to healthy diet and sport activities.

The location-based limitation of the research could be surpassed by conducting the same study on different geographical regions taking also into consideration the various cultural differences and conducting a cross-cultural study for multiethnic environments, Furthermore, considering a wider sample from the same region could add to the research with a more depictive view of the social media services penetration. Further research analysis can be applied in other eHealth sectors as well as in other industries. Thus, different fields may lead to different results, considering that eHealth is a quite sensitive field of study, even in terms of 'light' matters such as the well-being.

Contents

Acknowledgements

Chapter 1. Introduction.....16

1.1. Research motivation	16
1.2. Research contribution	19
1.3. Thesis structure.....	19
References.....	24

Chapter 2. Digital and Social Media Marketing.....26

2.1. Social Media Analytics and consumer behavior	30
2.2. Facebook data, actions and measurable activities	54
References.....	56

Chapter 3. Personality traits models on social media....67

3.1. Approach for each theory and model comparison.....	67
3.2. Rationale behind the selected models in the present research and analysis.....	74
References.....	82

Chapter 4. Social Media usage on the eHealth field.....89

4.1. Boolean research of the literature	89
4.2. Models used and hypotheses formulation	90
References.....	102

Chapter 5.	Research methodology.....	109
5.1.	Operationalization of variables.....	109
5.2.	Data collection and sample characteristics.....	112
5.3.	Measurement model	114
	References.....	117
Chapter 6.	Findings and Results' Presentation.....	118
6.1.	Structural model.....	121
	References.....	124
Chapter 7.	Conclusion.....	125
7.1.	Research overview and findings.....	125
7.2.	Interpretation of results.....	128
7.3.	Implications and contributions	130
7.4.	Limitations – Future research.....	131
	References.....	132
References	134
Appendix	151
Publication list	155

List of Figures

Chapter 2

Figure 2.1: A unified framework for Social Media Analytics procedure..... 36

Figure 2.2: Year of distribution / number of articles 40

Chapter 3

Figure 3.1: The Theory of Planned Behavior 79

Figure 3.2: The ‘e-HePeBe-SMA proposed framework..... 81

Chapter 4

Figure 4.1: Initial conceptual model 101

Chapter 6

Figure 6.1: SEM results for the proposed model 122

List of Tables

Chapter 1

Table 1.1: Dissertation layout.....	22
-------------------------------------	----

Chapter 2

Table 2.1: Main classifications of social media.....	29
--	----

Table 2.2: SMA definitions.....	30
---------------------------------	----

Table 2.3: Literature review for SMA related articles.....	37
--	----

Table 2.4: Software for different types and techniques of analysis.....	38
---	----

Table 2.5: S3M typology framework for social media metrics and analytics on marketing.....	42
--	----

Table 2.6: Articles' classification concerning the methodology of research...	43
---	----

Table 2.7: Articles' classification concerning the type of analysis.....	46
--	----

Table 2.8: Articles' classification concerning the field of study.....	48
--	----

Table 2.9: Articles' classification concerning the marketing objectives	50
---	----

Table 2.10: Articles' classification concerning the social media types/ platforms	52
---	----

Chapter 3

Table 3.1: Primary factors, low and high range descriptors of 16PF	68
--	----

Table 3.2: Factor analysis and measurements of the alternative five model of personality (ALT-FFM) 71

Table 3.3: HEXACO’s factors, facets and its adjectives 73

Chapter 4

Table 4.1: The conceptual definitions of the research variables 95

Table 4.2: References for research hypotheses 98

Table 4.3: The definitions of the research hypotheses 99

Chapter 5

Table 5.1: Operational definitions of the study instruments 110

Table 5.2: Demographic characteristics of the respondents 112

Table 5.3: Social media platforms' with active accounts 113

Table 5.4: The model's fit indices 115

Chapter 6

Table 6.1: Factor loadings for survey's items.....	119
Table 6.2: Construct Reliability (CR) and Average Variance Extracted (AVE).....	120
Table 6.3: Discriminant Validity	120
Table 6.4: Hypotheses' paths, coefficients and t-values	121

Chapter 7

Table 7.1: Accomplishments of the research steps.....	125
---	-----

List of acronyms

16PF	Sixteen Personality Factor Questionnaire
A	Agreeableness
AGFI	adjusted goodness of fit index
ALT-FFM	The alternative five model of personality
ATT	Attitude
AVE	Average Variance Extracted
B	Behavior
C	Conscientiousness
CD	Consumer Data
CDT	Cognitive Dissonance Theory
CFA	Confirmatory Factor Analysis
CFI	comparative fit index
CR	Construct Reliability
CRM	Consumer Relationship Management
DOI	Diffusion of Innovation
DTPB	Decomposed Theory of Planned Behavior
E	Extraversion
EDT	Expectation-Disconfirmation Theory
FFM	Five Factor Model
GFI	goodness of fit index

List of acronyms

I	Intention
KPI	Key Performance Indicator
N	Neuroticism
NLP	Natural Language Process
NNFI	non-norm fit index
O	Openness
PBC	Perceived Behavioral Control
PD	Platform Data
RMR	Root mean square residual
RMSEA	Root mean square error of approximation
ROI	Return of Investment
S3M	Social Media Marketing Metrics Analysis model
SCT	Social Cognitive Theory
SD	Suppliers' and Business Data
SEM	Structural Equation Modeling
SMA	Social Media Analytics
SMM	Social Media Marketing
SN	Subjective Norms
TAM	Technology of Acceptance Model
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Actions

List of acronyms

TTF	Task Technology Fit Model
UTAUT	Unified Theory of Acceptance and Use of Technology

Chapter 1.

Introduction

Web 2.0 and social media create a brand new field with great perspectives and interest, almost for every scientist and aspect of knowledge. Social media are simple on their notions, yet complex to fully understand if not classified and understood from the very beginning. That is why social media are highly used and researched among analysts and practitioners. Together with social media, a huge amount of useful data is produced every second. Focus on these data can lead to outcomes and predictions of great interest and usefulness. Part of this analysis is the consumer-related data, to wit, data that are generated from social media users and refer to behaviors, usage, acceptance and other measurable activities. The research on social media and consumer behavior can be, and has already been, applied to several fields of study such as smart cities data decision making processes, education or e-Government or Tourism and Hospitality, finance, psychology and electronic health (eHealth) field. The present chapter represents the introductory part of the dissertation, presenting the research motivation and the research objectives as well as the overall contribution of the research in science and its originality. The chapter concludes with the thesis structure, chapter by chapter.

1.1. Research motivation

The advent of Web 2.0 and social media created a new field of study interesting to marketers and data analysts. Though complex, social media can be classified in specific categories and frameworks, giving the opportunity to researchers to better define their goals as well as the fields of study, the objectives of marketing and the measurable activities needed so as to produce useful insights. Social media are highly rewarding among researchers, analysts and users due to the importance of the produced data and their elevate reflection to the community. One of the most important and interesting fields of study is the eHealth, due to its importance of outcomes on the users' health and its complexity and sensitivity of data.

Simultaneously with social media, the research of the consumers' generated data related to their behavior is of a great interest because of their reciprocity with social media planning.

Researchers can produce useful outcomes for social media planning, beginning from data related to consumers' behavior and vice versa. Among all social media, researchers understood that Facebook can also be focused on users' behavior and personalities with several models to be used in order to explain or predict users' online behavior with respect to their personality.

The research on social media and consumer behavior can be, and has already been, applied to several fields of study. In literature there are several studies for diverse fields related, but not limited to, smart cities data decision making processes, education or e-Government or Tourism and Hospitality, finance and psychology.

One of the fields of interest, eHealth, represents an important sector that has been neglected by research, not only due to the sensitivity of data but also to the difficulty of gathering data for analysis. Eyzenbach (2001) formed so far the most complete definition of eHealth as “*an emerging field in the intersection of medical informatics, public health and business, referring to health services and information delivered or enhanced through the Internet and related technologies. In a broader sense, the term characterizes not only a technical development, but also a state-of-mind, a way of thinking, an attitude, and a commitment for networked, global thinking, to improve health care locally, regionally, and worldwide by using information and communication technology*”.

This field presents a great importance and interest since its outcomes have straight connection to the users' health. Social media, representing one of the most influencing technologies today, have a direct connection to society concerns. One of these, the actual use of technologies related to eHealth; produce a vast amount of useful data to practitioners and researchers. Though important, social media in eHealth are not fully analyzed and researched. Especially for the social media's most powerful representative, Facebook, literature provides with a huge amount of scientific articles, but only few of them focus on the niche market of users' interaction and the users' behavior on Facebook related to specific groups and purposes, such as the healthy diet acceptance advisory and the well-being. This research gap is what the present dissertation will analyze and cover. Specifically, regarding literature and research, there is a vast amount of articles related to users' behavior in social media. Furthermore, there is some literature on eHealth, but not related to personality traits and planned behaviors. This research presents great originality since it is, to the best of our knowledge, the first that combines personality theories (in specific the most used model – the Big Five) and planned behavior methodologies (in specific

the Theory of Planned Behavior). The report of relevant literature for the aforementioned fields contributes to the existing literature, creating a more complete database of knowledge. The sessions that are examined in this analysis are: a. the social media typology, b. the social media analytics landscape, c. the social media metrics, d. the psychological trait models in social media and e. several research methodologies regarding the behavioral analysis. These sessions are combined in the eHealth field.

In specific, the objective of this dissertation is to record the users' behavior towards the intention to use advices from Facebook pages and groups related to well-being, in specific related to healthy diet and leisure activities, in correlation to their personality. Subsequently we will study if; who and which way users make use of Facebook pages/ groups in the aforementioned field of eHealth. In order to ensure that all the aforementioned gaps will be covered, a series of steps need to be followed. The next list presents these steps that will lead to the dissertation's objectives.

- a. Explain the research motivation, paradigm, method and techniques that fit the current research objectives and lead to valid research results
- b. Analyze the fields, the objectives, the types of analysis and the social media platform environment
- c. Provide a new typology and framework for the aforementioned research objectives and focus on eHealth field, behavioral analysis (personality traits and theories of planned behavior) and Social Networking Sites (Facebook)
- d. Develop the theoretical framework for the behavioral theories of Facebook users regarding the individuals' planned behavior over Facebook pages and groups related to eHealth activities
- e. Develop the theoretical framework for the personality traits analysis of Facebook users regarding the individuals' planned behavior over Facebook pages and groups related to eHealth activities
- f. Identify the research gap on the field
- g. Explain the research methodology that fits the testing of the theoretical model and leads to the final artifact of this research

- h. Provide with the statistical analysis of the proposed model in order to test the theoretical frameworks
- i. Evaluate the research conclusions in terms of their significance to theory and practice and identify future research directions that are important to continue refining this important area of research.

1.2. Research contribution

The accomplishments of these research steps would reflect high value contributions to both theory and practice. To be more specific, the contributions made to theory could be summarized to the following points:

- Cover the emerged research gap on social media analytics and consumer behavior in eHealth field
- Pave the ground for conducting future research with our proposed methodology, applied in different research field
- Extend existing behavioral models
- Create base frameworks, continuously growing and expanding

On the other hand, practitioners can also take advantage of the present research by applying this dissertation's tools and methodologies for decision making and predictive analytics.

The applied techniques of this study and the final results would be valuable data at the hands of those in the digital marketing community interested in emerging sectors.

1.3. Thesis structure

The dissertation is structured around eight chapters achieving the diverse objectives and constructing the entire research.

Chapter 1 is introductory, describing the research motivation as well as the research contribution.

Chapter 2 presents a complete base for understanding and describing digital marketing, social media, social media metrics and social media analytics related to digital marketing strategy, policy and research, by reviewing the relevant literature. The objective of this chapter is an extensive review of articles related to social media metrics and analytics in marketing, creating a mapping review/ systematic map of the relevant material. The primary goal in this chapter is to create, among others, a conceptual classification scheme (named S3M) for the extant literature by using five distinct dimensions/ criteria of classification, such as: Methodology of research, Type of analysis, Field of study, Marketing objectives, and Social media types/ platforms. As a result, the most used subsectors from each category are identified, featuring the new upcoming trends in social media marketing. Furthermore, a second framework related to social media analytics is proposed, again derived from the considered literature. Analytically, the proposed framework categorizes the literature in two main fields (structural analysis and content-based analysis), divided each in community detection and influencer detection, and natural language process (NLP), sentiment, text and geospatial analysis, respectively. The findings of this chapter are expected to benefit researchers and marketers by helping them to better understand what has been hitherto achieved. It is our primary hope that the proposed framework will serve as a valuable classification system for researchers, academics and practitioners who conduct similar research. The two main proposed frameworks of this chapter can be used as a base for further research in specific fields, methodologies and tools of study. Each focused research can constitute a brand new research article or a new thesis. Our research (explained further on chapters to come) is focused on Facebook, Consumer behavior and Platform Data.

Chapter 3 aims to present and analyze the diverse personality traits together with their extensions, focusing on the Big Five model. A comparison analysis of the most used models in order to facilitate future research focused on different fields is provided. More analytically, we present, confront and analyze: the 16 Personality Factor questionnaires, the Alternative Five model of personality, the HEXACO personality model and the Big Five model. Furthermore we provide with the rationale behind the selection of the model in the present research.

Chapter 4 explains the research gap using the Boolean analysis of the online search. The chapter is focused on the eHealth field, analyzing the specific sector in-depth. The hypotheses formulation is analyzed on this chapter too, after a short introduction to the two basic models

used on the dissertation, the Big Five and the Theory of Planned Behavior. Conceptual definition of the research variables are given as well as the literature this study based for the research hypotheses. Finally the analytical definitions of the research hypotheses are provided.

Chapter 5 presents the methodology used on the research. The first part describes the hypotheses formulated from the previous research. We provide with the analysis of the methodology used, the operational definitions of the study instruments and the sample characteristics and demographics. For each factor of the model, we analyze which item was used on the survey. The aim of this chapter is to provide with the base knowledge, first for the present research and second for any future research that will use the same methodology, models and theories.

Chapter 6 summarizes the results of the study in four tables including the factor loadings for each item of the questionnaire, the construct reliability (CR) of the results, the average variance extracted (AVE) and finally, the structural model with the paths the coefficients and the t-values, for each hypothesis. The aim of this chapter is to present and explain each result and table before proceeding with the explanation of each result in the next chapter. Definitions and explanations are provided for each table as well as an overall summary, before the in-depth analysis on the next chapter.

Chapter 7 aims to conclude the entire previous research by analyzing the results regarding the hypotheses, interpret the statistical analysis of the previous chapters, and provide with the managerial implications of the study, the limitations and guides for future research on the field. The results of the analysis have important meaning, considering also the cultural characteristics of the research and great managerial implications for practitioners and academics.

Table 1.1: Dissertation layout

Chapter	Steps to accomplish
Chapter 1. Introduction	Explain the research motivation, paradigm, method and techniques that fit the current research objectives and lead to valid research results
Chapter 2. Digital and social media marketing	Analyze the fields, the objectives, the types of analysis and the social media platform environment. Provide a new typology and framework for the aforementioned research objectives and focus on eHealth field, behavioral analysis (personality traits and theories of planned behavior) and Social Networking Sites (Facebook)
Chapter 3. Personality traits models on social media	Develop the theoretical framework for the personality traits analysis of Facebook users regarding the individuals' planned behavior over Facebook pages and groups related to eHealth activities
Chapter 4. Social media usage on the eHealth field	Identify the research gap on the field
Chapter 5. Research methodology	Explain the research methodology that fits the testing of the theoretical model and leads to the final artifact of this research
Chapter 6. Findings and results' presentation	Provide with the statistical analysis of the proposed model in order to test the theoretical frameworks
Chapter 7. Conclusion	Evaluate the research conclusions in terms of their significance to theory and practice and identify future research directions that are important to continue refining this important area of research.

In order to understand the basic notions of the present research, some basic definitions and frameworks need to be fully analyzed. Next chapter defines the notion of digital social media marketing and proceeds to more detailed subjects of the science field, such as the analysis of the data as well as the necessary procedures to follow in order to conduct what is called social media analysis.

References

- Bhattacharya, A., Kolovson, S., Sung, Y.-C., Eacker, M., Chen, M., Munson, S. A., & Kientz, J. A. (2018). Understanding pivotal experiences in behavior change for the design of technologies for personal wellbeing. *Journal of Biomedical Informatics*, *79*, 129-142. doi: <https://doi.org/10.1016/j.jbi.2018.01.002>
- Dixit, S., Jyoti Badgaiyan, A., & Khare, A. (2017). An integrated model for predicting consumer's intention to write online reviews. *Journal of Retailing and Consumer Services*. doi: <https://doi.org/10.1016/j.jretconser.2017.10.001>
- Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behavior: An introduction to theory and research*.
- Freeman, J. L., Caldwell, P. H. Y., Bennett, P. A., & Scott, K. M. (2018). How Adolescents Search for and Appraise Online Health Information: A Systematic Review. *The Journal of Pediatrics*, *195*, 244-255.e241. doi: <https://doi.org/10.1016/j.jpeds.2017.11.031>
- Godino, J. G., Merchant, G., Norman, G. J., Donohue, M. C., Marshall, S. J., Fowler, J. H., . . . Patrick, K. (2016). Using social and mobile tools for weight loss in overweight and obese young adults (Project SMART): a 2 year, parallel-group, randomised, controlled trial. *The Lancet Diabetes & Endocrinology*, *4*(9), 747-755. doi: [https://doi.org/10.1016/S2213-8587\(16\)30105-X](https://doi.org/10.1016/S2213-8587(16)30105-X)
- Heirman, W., Walrave, M., Vermeulen, A., Ponnet, K., Vandebosch, H., & Hardies, K. (2016). Applying the theory of planned behavior to adolescents' acceptance of online friendship requests sent by strangers. *Telematics and Informatics*, *33*(4), 1119-1129. doi: <https://doi.org/10.1016/j.tele.2016.01.002>
- Kim, E., Lee, J.-A., Sung, Y., & Choi, S. M. (2016). Predicting selfie-posting behavior on social networking sites: An extension of theory of planned behavior. *Computers in Human Behavior*, *62*, 116-123. doi: <https://doi.org/10.1016/j.chb.2016.03.078>
- Koban, K., Stein, J.-P., Eckhardt, V., & Ohler, P. (2018). Quid pro quo in Web 2.0. Connecting personality traits and Facebook usage intensity to uncivil commenting intentions in public online discussions. *Computers in Human Behavior*, *79*, 9-18. doi: <https://doi.org/10.1016/j.chb.2017.10.015>

- Koohikamali, M., Peak, D. A., & Prybutok, V. R. (2017). Beyond self-disclosure: Disclosure of information about others in social network sites. *Computers in Human Behavior*, *69*, 29-42.
- Lee, S.-Y., Hansen, S. S., & Lee, J. K. (2016). What makes us click “like” on Facebook? Examining psychological, technological, and motivational factors on virtual endorsement. *Computer Communications*, *73, Part B*, 332-341. doi: <https://doi.org/10.1016/j.comcom.2015.08.002>
- Mouakket, S. (2017). The role of personality traits in motivating users' continuance intention towards Facebook: Gender differences. *The Journal of High Technology Management Research*. doi: <https://doi.org/10.1016/j.hitech.2016.10.003>
- Rauschnabel, P. A., Rossmann, A., & tom Dieck, M. C. (2017). An adoption framework for mobile augmented reality games: The case of Pokémon Go. *Computers in Human Behavior*, *76*, 276-286. doi: <https://doi.org/10.1016/j.chb.2017.07.030>
- Tang, J.-H., Chen, M.-C., Yang, C.-Y., Chung, T.-Y., & Lee, Y.-A. (2016). Personality traits, interpersonal relationships, online social support, and Facebook addiction. *Telematics and Informatics*, *33*(1), 102-108.
- Terzis, V., Moridis, C. N., & Economides, A. A. (2012). How student's personality traits affect Computer Based Assessment Acceptance: Integrating BFI with CBAAM. *Computers in Human Behavior*, *28*(5), 1985-1996. doi: <https://doi.org/10.1016/j.chb.2012.05.019>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425-478.
- Xu, R., Frey, R. M., Fleisch, E., & Ilic, A. (2016). Understanding the impact of personality traits on mobile app adoption—Insights from a large-scale field study. *Computers in Human Behavior*, *62*, 244-256.

Chapter 2.

Digital and Social Media Marketing

This chapter presents a complete base for understanding and describing social media, social media metrics and social media analytics related to digital marketing strategy, policy and research, by reviewing the relevant literature. The objective of this chapter is an extensive review of articles related to social media metrics and analytics in marketing, creating a mapping review/ systematic map of the relevant material. The primary goal in this article is to create, among others, a conceptual classification scheme (named S3M) for the extant literature by using five distinct dimensions/ criteria of classification, such as: Methodology of research, Type of analysis, Field of study, Marketing objectives, and Social media types/ platforms. As a result, the most used subsectors from each category are identified, featuring the new upcoming trends in social media marketing. Furthermore, a second framework related to social media analytics is proposed, again derived from the considered literature. Analytically, the proposed framework categorizes the literature in two main fields (structural analysis and content-based analysis), divided each in community detection and influencer detection, and natural language process (NLP), sentiment, text and geospatial analysis, respectively. The findings of this chapter are expected to benefit researchers and marketers by helping them to better understand what has been hitherto achieved. It is our primary hope that the proposed framework will serve as a valuable classification system for researchers, academics and practitioners who conduct similar research. The two main proposed frameworks of this chapter can be used as a base for further research in specific fields, methodologies and tools of study. Each focused research can constitute a brand new research article or a new thesis. Our research (explained further on chapters to come) is focused on Facebook, Consumer behavior and Platform Data.

Digital Marketing is defined as the field of marketing science that uses digital technologies from Internet and Web 2.0. Together with Information Technology, has great interest in understanding and analyzing social media and their created data. Social media provide practitioners and researchers with the relevant communication tools with customers and vice versa. Consumers, in

that way, acquire a voice that marketers use in order to convert social media data into useful marketing insights. On January 2017, Facebook counts more than 1.8 billion active users and Google more than 415 million. We upload 10000 photos on Instagram and we perform over 20000 times of Skype calls every second. Internet produces 31500 GB of data every second (www.internetstats.com). If Facebook was a country it would be bigger than China or India, two times bigger than Europe, ten times bigger than Russia and 1.8 million times bigger than Vatican City (esa.un.org). Kaplan and Haenlein (2010) define social media as a group of Internet-based applications that build on the ideological and technological foundation of Web 2.0 and that allow the creation and exchange of user generated content (UGC). In 2010 social media represented a revolutionary way for companies to do business and could be seen as the most remarkable innovation penetrating the everyday life. Five years later, more than 70% of marketers use Facebook to successfully gain new customers in a total of 93% of marketers who use social media for business matters (shortstack.com). Forrester Research, Inc. predicts that social media will be the second-fastest growing marketing channel in US in 2016 (Gandomi & Haider, 2015). Constantinides and Fountain (2008) claim that Internet of Things and Web 2.0 (social media are part of it) will offer endless possibilities in the business world. As a result of these innovative web models and technologies on the social media landscape, considerable research issues and questions arise, regarding social media analytics: How to render actionable the large datasets from social media? How to classify all the relevant techniques? How to capitalize all the existing information? Which are the Facebook's (as the most used platform) features in interest, which are the actions to take and which are the exact measurable activities and metrics to take into consideration? Web 2.0 tools and the appearance of social media seem to have redefined the marketing strategy, research and practice, broadening marketing's potential. These potentials go beyond customers' information and expand on commitment and engagement levels. Constantinides and Fountain (2008) define Web 2.0 "as a collection of open-source, interactive and user-controlled online applications expanding the experiences, knowledge and marketing power of the users as participants in business and social process [...] supporting the creation of informed users' networks facilitating the flow of ideas and knowledge by allowing the efficient generation, dissemination, sharing and editing/ refining of information content". Social media produce a vast amount of measurable useful data to analysts and marketers whose goal is to monitor and analyze behavioral targeting, brand loyalty and further marketing

performance indicators, rendering these data effective. To do that, specific marketing metrics goals need to be clearly defined. Without a specific plan, regarding also the key performance indicators choices, data analysts together with marketers will fail to direct the social media data into useful insights for the companies. For that purpose, firms must precisely raise questions and search answers from social media listening in order to transform data in social media metrics. Social media analysis, therefore, consists of collecting, measuring, evaluating and finally interpreting data (Kaplan & Haenlein, 2010).

Since the first appearance of social media, marketers have noticed the potential of such technology in business (Mangold & Faulds, 2009). Social media can serve as an effective marketing tool in business, valuable for both consumers and companies, offering a wide range of opportunities (Kaplan & Haenlein, 2010). Therefore, social media show an unprecedented increase of use inside business. Even though, understanding social media is a crucial but not a simple procedure. Several definitions are classified in order to fully explore the dynamics of social media in marketing.

The assemblage of the extrapolated social data is the main subject for further analysis. In order to study Social Media Analytics (SMA), analysts need to understand fully the complete social media landscape. Current literature consists on diverse theories and frameworks regarding social media taxonomy. Constantinides and Fountain (2008) present a five-group classification system composed from: Blogs, social networks, content communities, forums and content aggregators. Respects to the same authors, back in 2008, blogs were the most known and fastest-growing category of Web 2.0 applications. Today the scenery is completely different, with social media, and especially Facebook, to be the dominant platform, followed by Google+, Twitter and Pinterest (www.pewresearch.org). Kaplan and Haenlein (2010) divide social media on collaborative wikis, blogs, social content and virtual communities. Mangold and Faulds (2009) separate social media on social networking sites, creativity work sharing sites, user sponsored websites, company sponsored cause, invitation-only social networks, business networking sites, collaborative web sites, virtual worlds, commerce communities, podcasts, news delivery sites, educational material sharing sites, open-source software communities and social bookmarking sites.

Table 2.1: Main classifications of social media.

Authors	Social media categories
Constantinides and Fountain (2008)	Blogs, social networks, content communities, forums, content aggregators
Kaplan and Haenlein (2010)	Collaborative wikis, blogs, social content, virtual communities
Mangold and Faulds (2009)	Social networking sites, creativity work sharing sites, users sponsored websites, company sponsored cause, invitation-only social networks, business networking sites, collaborative websites, virtual worlds, commerce communities, podcasts, news delivery sites, educational material sharing sites, open-source software communities, social bookmarking sites

The aforementioned classifications are the most cited in literature and therefore we follow these frameworks in order to base our research and classification. Based on this research, we proceed with our study by analyzing further the social media, data originated online and the consumer behavior that is related to these media. Finally we focus on Facebook as it is the most used platform and the one that is used on the present research.

2.1.Social Media Analytics and consumer behavior

Social media constitute a source of data, information and knowledge, which analysis leads to understanding real-time consumer choices, intentions and sentiments. The most prevalent application of social media analytics is to get to know the customer base on a more emotional level to help better target customer service and marketing. As we notice, the social media environment is complex enough with a plethora of definitions and classifications. As a consequence, SMA is also not yet fully clarified. Many researches argue that there is a scientific gap concerning the taxonomy of the field of SMA and the relative techniques/ methodologies. Next we provide with several definition approaches for SMA, four from scientific journals and four from the business world. Thus, understanding the field exactly will help us to choose the appropriate sub-category related to the SMA objectives.

Table 2.2: SMA definitions

Authors	SMA definition approaches
Daniel, Hsinchun, Lusch, and Shu-Hsing (2010)	<i>[...] developing and evaluating informatics tools and frameworks to collect, monitor, analyze, summarize, and visualize social media data, usually driven by specific requirements from a target application.</i>
Yang, Kiang, Ku, Chiu, and Li (2011)	<i>[...] developing and evaluating informatics tools and frameworks to measure the activities within social media networks from around the web. Data on conversations, engagement, sentiment, influence, and other specific attributes can then be collected, monitored, analyzed, summarized, and visualized.</i>
Mayeh, Scheepers, and Valos (2012)	<i>[...] scanning social media to identify and analyze information about a firm's external environment in order to assimilate and utilize the acquired external intelligence for business purposes.</i>

Authors	SMA definition approaches
Grubmüller, Götsch, and Krieger (2013)	<i>[...] social listening and measurements [...] based on use generated public content (such as postings, comments, conversations in online forums, etc.).</i>
Sterne and Scott (2010)	<i>SMA is the study of social media metrics that help drive business strategy.</i>
Nielsen (2012)	<i>SMA is the ability to analyze performance of social media initiatives and social data for business intelligence.</i>
Bensen Connie - Dell Company (conniebensen.com)	<i>[...] consist on web analytics, engagement and revenue generated from social media.</i>
Awareness (2012)	<i>[...] an evolving business discipline that aggregates and analyzes online conversation (industry, competitive, prospect, consumer, and customer) and social activity generated by brands across social channels. SMA enable organizations to act on the derived intelligence for business results, improving brand awareness and reputation, marketing and sales effectiveness and customer satisfaction and advocacy.</i>

Next, we classify SMA in main methodologies and sub-methodologies. More analytically, SMA can be divided in two main methodologies - each one following by further sub-divisions: a. structural analysis and b. content-based analysis.

SMA is the practice of gathering data from social media platforms and applications and analyzing that data to make effective business/ marketing decisions. The most common use of SMA is to mine customers' sentiment, support marketing and customer service activities.

In specific, research on social media marketing and analytics is divided into three areas, according to the point of focusing the involved entities and their roles. Therefore, social media analytics can be approached from several perspectives, related to the different involved entities:

the users'/ customers' perspective, the platform and application providers' perspective, and the suppliers'/organizations' one. Therefore, consumer-centric studies generally focused on social media use and their impact on consumer behavior. Researchers need to study several perspectives of usage alternatives. For example, which is the specific platform and application used, how often used, how and when or what do they seek, what is their demographics and which is the specific field of interest (e.g. health, tourism, general info, travel, sports, games, etc.). This research analysis leads to large volumes of data, here and after known as *CustomerData* or **CD** that constitute valuable resource for the marketing strategy related to the decision making of several organizations. On the other side, **platforms** and applications of social media, concentrate also the interest of researchers posing a series of questions, like: which are the appropriate or most preferred platforms and applications, what data they record, which is the relationship between platforms and customers. We call these data, *PlatformData* or **PD**. The third perspective is consisted of the supplier-related social media studies, focusing on the specific use of social media by several organizations/ brands (e.g. TripAdvisor, Skyscanner, Uber, Booking, Trivago, etc.). Companies may have doubt as to whether their investments in social media marketing could turn into business or how much resources they should invest in several social media platforms/ applications. These research questions can be answered based on data collected and analyzed in order to provide clues or directions for their future marketing strategy. The ultimate goal of the organizations for employing several social media is to convert social media visitors to actual customers, using social media platforms for information dissemination – sharing, brand awareness, engagement, advocacy, and direct sales. The companies' social media sites are the intermediates between platforms and customers, combining useful, but different data from alternative sources and media (also known as *Suppliers' BusinessData* or **SD**), rendering these data actionable for business insights and decision-making procedures. The raised challenge for marketers and data analysts is what to do with this amount of user-generated data, and how exactly to analyze these data in order to be more effective (Kobielus, 2010).

According to A. Smith, Pilecki, and McAdams (2014) social media analytics should be used, in order to make the emerging social data actionable based on the following four P's procedure: People (assign responsibilities, clarify tasks and identify skills), Purpose (set goals and metrics in continuous way), Platform (determine the exact platform - source of data - to use) and Process (identify and distribute the insights to the involved entities).

The first step in a social media analytics initiative is to determine which business goals data gathered and analyzed will benefit. Typical objectives include brand awareness & engagement, increasing revenues, reducing customer service costs, getting feedback on products and services and improving public opinion of a particular product or business division. Once the business goals have been identified, specific metrics (e.g. key performance indicators -KPIs) for objectively evaluating the data should be defined. SMA refers to the approach of collecting data from social media platforms and evaluating that data to support business decisions. With the emergence of social data and the advance of analytical technologies and methodologies, organizations can apply SMA in order to create a competitive advantage within their markets. Studying several approaches on SMA, we conclude that there is not a specific choice suitable for every decision, but it is common the combined use of several analyses. In specific, according to the literature, SMA can be divided in structural and content-based. Each of them contains different subcategories of analyses. Through structural analysis we conduct community and/ or influencer detection. With content-based analysis we conduct sentiment, text, geospatial analysis and natural language processing. Next figure summarizes the above mentioned processes and their interactions. More analytically, we present each analysis methodology, based on the existing literature.

Structural analysis

Structural analysis is performed mainly by graphs. It is the base notion for two important techniques; community and influencers' detection (Gandomi & Haider, 2015). Community detection is capable of revealing homophily and shared characteristics among users, as well as personality's correlations with social media (Chu & Chen, 2016). Behavioral patterns of community can also be detected from graphs (Aggarwal, 2011). Influencers' detection is also another useful technique on structural analysis and graphs. By counting, for example, the number of edges of a node, analysts understand which user is more active, who interacts with whom,

who posts more item etc. Community and influencers' detection is strongly correlated with behavioral analytics and social science and represents a field of study for many researchers (Amichai-Hamburger & Vinitzky, 2010; Bishop, 2007; Kaptein, Markopoulos, de Ruyter, & Aarts, 2009; Moore & McElroy, 2012; Ryan & Xenos, 2011).

Content-based analysis

Content-based analysis is the most complete type of analysis on social media. This subcategory contains all the data mining techniques based on statistics, computing, engineering and machine learning. Generally, the content-based analysis focus on user generated content, whether this content is text, video, images and/ or geospatial data. This type of data is mostly unstructured, noisy and dynamic. Today, 2.5 billion GB of unstructured content (sensors, social media posts and photos) is created every day, while only a 1% of the data is finally analyzed. Unstructured data represent the 90% of all data available (IBM, n.d.; Syed, Gillela, & Venugopal, 2013; Valkanas & Gunopulos, 2013).

Four sub- analysis processes are included in content-based analysis:

a. **Natural Language Process (NLP)**. In this type of analysis, data mining is performed on text, trying to produce meaningful outcomes. NLP is related to computer-human interaction, artificial intelligence and linguistics. After studying relevant definitions, we conduct that text analysis is supplementary for NLP. Text analysis conducts lexical analysis by recognizing patterns and word frequencies (Bello-Orgaz, Jung, & Camacho, 2016; Gandomi & Haider, 2015).

b. **Sentiment analysis**. This type of analysis applies the NLP outcomes in order to extract users' sentiments and opinions on a subject. Sentiment analysis adapts tools from machine learning, such as automatic procedures for determining opinions and extracting subjective information from users (Batinca & Treleaven, 2015).

c. **Text analysis**. The text data are commonly related to information associated to context and content. Aggarwal (2011) considers important to extend text mining to incorporate context in order to obtain powerful text analysis. Regarding social media, text analysis refers to the lexicon analysis of posts, comments, even photos.

d. **Geospatial analysis**. This type of analysis includes four types of diverse data such as: a. both location and time sensitive data (e.g. foursquare), b. location sensitive only data (e.g. yelp), c.

time sensitive only data (e.g. Facebook status updates and tweets), and d. neither location nor time sensitive data (YouTube videos and Wikipedia entries).

Next we propose a unified framework that collects both existent and original schemes for SMA. In order to summarize the SMA process we use the Smith's et al. (2014) model of 4 P's together with this article's proposed models of Data Interaction and SMA methodologies. On Figure 2.1 the correlations and the process from one model to another are shown. On previous paragraphs we explained all the mid-processes analytically. Figure 2.1 shows the alternate usage among the different proposed frameworks. More analytically, after clarifying People involved, the Purpose of the research, the social media Platform used and the Process chosen, the study has to be focused on the Data Interaction and Gathering. Consequently the framework indicates the internal interactions among all SMA methodologies. We notice that every item of the proposed framework is correlated with the others, interchanging measurable data or techniques. We can notice this interchangeable nature also on Table 2.3, where diverse methodologies are used in common according to the literature review, since several of the research articles use techniques and methods that are mutual.

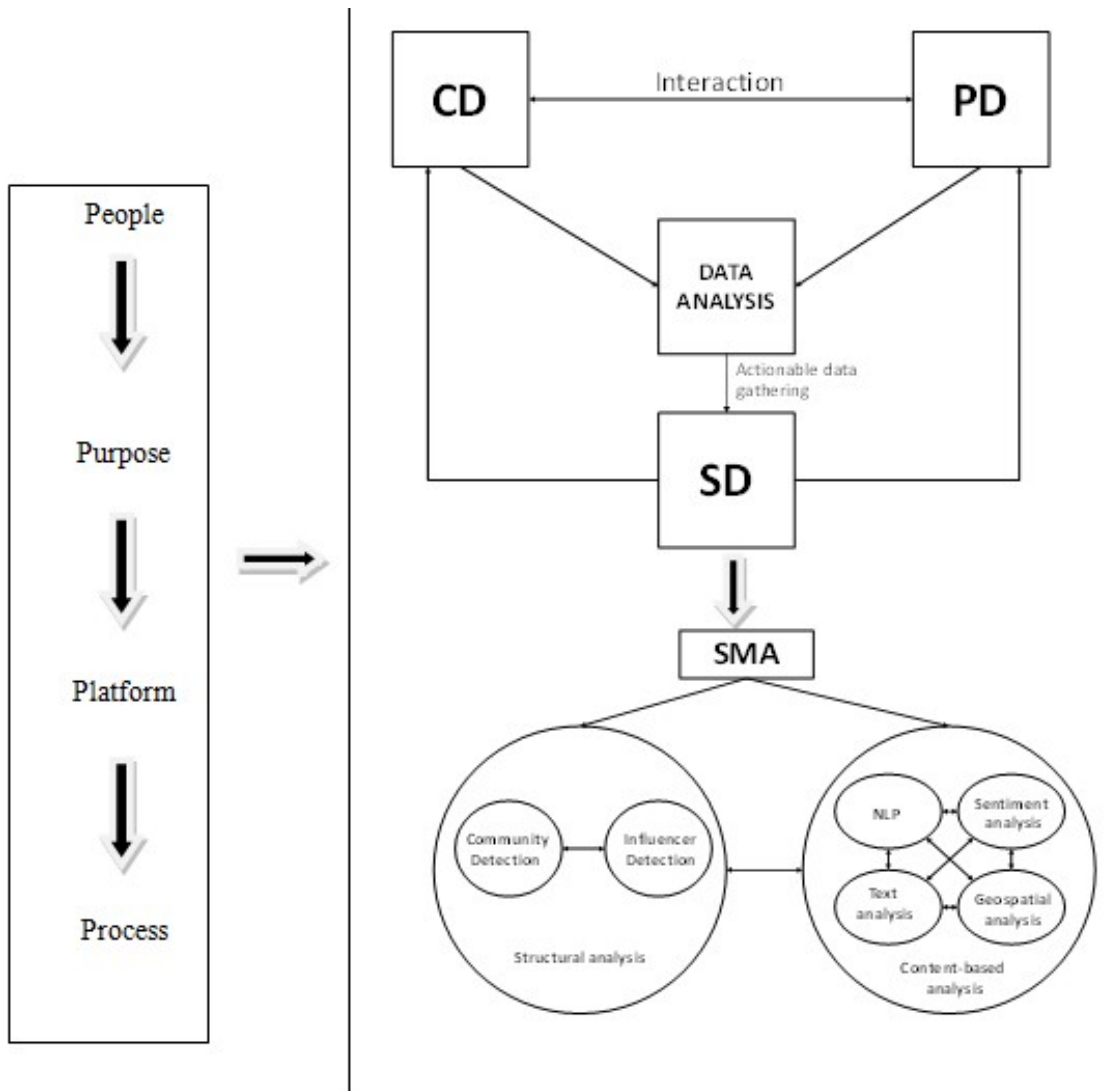


Figure 2.1: A unified framework for Social Media Analytics procedure

Lastly, Table 2.3 summarizes for each sub-methodology proposed, the relevant literature. This table will provide researchers and practitioners the necessary information for further research of the methodologies, depending on their specific choice.

Table 2.3: Literature review for SMA related articles

Main SMA methodology	Sub-methodology	Articles
Structural analysis	Community detection	Amichai-Hamburger and Vinitzky (2010); Bishop (2007); Kaptein et al. (2009); Moore and McElroy (2012); Ryan and Xenos (2011); Aggarwal (2011); Gandomi and Haider (2015)
	Influencer detection	Chang and Chen (2014b); Fan and Gordon (2014); Leong, Ooi, Chong, and Lin (2013); Taneja, Vitrano, and Gengo (2014)
Content-based analysis	NLP	Bello-Orgaz et al. (2016); Gandomi and Haider (2015); Huang (2015); Koohikamali et al. (2017)
	Sentiment analysis	Batrinca & Treleaven, (2015); Amjad and Wood (2009); Hajli et al. (2015); Mandilas, Karasavvoglou, Nikolaidis, and Tsourgiannis (2013); Tang et al. (2016)
	Text analysis	Agner et al. (2014); Armitage (2005); Asur and Huberman (2010); Bollen, Mao, and Zeng (2011); Gayo-Avello et al. (2013); He, Zha, and Li (2013); F. Liu and Lee (2010); O'Connor and Paunonen (2007)
	Geospatial analysis	Al-Debei et al. (2013); Bozionelos and Bennett (1999); Mandilas et al. (2013)

As we notice, articles are almost equally distributed in each category. This can be explained by the fact that it is difficult to use only one methodology without consider the others, nor use them. So if a researcher studies one method, it is common to consider and further methodologies. Even though, in order to classify the articles, the most used method of each article was taken into consideration, although other methods may have been mentioned.

Additionally, we provide an index with related software in order to perform each sub-methodology, together with the relative links, where applicable (Table 2.4). We notice that same tools are used for different methodologies, since many times, these are being used interchangeably. An exception is noticed on community detection methodology. In this case, we provide with the main algorithms that are used for this type of analysis and not only the software used.

Table 2.4: Software for different types and techniques of analysis

Main SMA methodology	Sub-methodology	Related software
Structural analysis	Community detection	Algorithms: <i>Infomap</i> , <i>Label propagation</i> , <i>Multilevel</i> , <i>Walktrap</i> , <i>Spinglass</i> , <i>Edge betweenness</i> Software: <i>Gephi</i> , <i>NodeXL</i> , <i>MIT's senseable</i> (http://senseable.mit.edu/community_detection/)
	Influencer detection	Upfluence (search.upfluence.com), followerwonk (moz.com/followerwonk), Buzzsumo (buzzsumo.com), .Kred(home.kred/), Klout (klout.com/home), Klear (klear.com), Traackr (traackr.com), Linkdex (linkdex.com), brandwatch (brandwatch.com/audiences), Inkybee (inkybee.com)
Content-based analysis	NLP	IBM SPSS Text Analytics for Surveys, Google Translate API, IBM Watson Conversation, Epic,

Main SMA methodology	Sub-methodology	Related software
		BLLIP Parser, Apache cTAKES, OdinText, NVivo, ClearTK, CogComp NLP, Colibri Core, Cortical.io, CRF++, Deeplearning4J, FACTORIE, FoLiA, Google Cloud Natural Language API, CoreNLP (stanfordnlp.github.io/CoreNLP), Apache Open NLP (opennlp.apache.org)
	Sentiment analysis	PeopleBrowsr (peoplebrowsr.com), Google analytics (www.google.com/analytics), hootsuite (hootsuite.com), TweetStats (tweetstats.com), Facebook Insights, Unified (unified.com), Socialmention (socialmention.com), DatumBox (datumbox.com/machine-learning-framework)
	Text analysis	RapidMiner, KH Coder, Coding analysis toolkit (CAT), TAMS (tamsys.sourceforge.net), Apache Mahout, Natural Language Toolkit (nltk.org), DatumBox, TwinWord (twinword.com), Apache UIMA, LingPipe (alias-i.com/lingpipe), Gensim (radimrehurek.com/gensim), GATE (gate.ac.uk), IBM Watson Analytics
	Geospatial analysis	Hootsuite, ElasticSearch.co, IBM Watson Analytics

We observe that multinational big companies like IBM, Hootsuite, Apache and Google, produce software that is capable of analysis in multiple fields and sub-methodologies. On the other hand, smaller companies are limited in one or two methodologies but they are available for free usage or even for open source edit.

Social media marketing and SMA as science fields are difficult to restrict only in few specific disciplines. This difficulty arises due to the multidisciplinary nature of the sciences and industry-

fields involved. Based on our research, articles associated to the field of Social Media Marketing, Metrics and Analytics (what we call in our model S3M) can be found in five types of journals: Marketing and e-Marketing, E-Business and Management, Behavioral sciences, ICT/Information systems and Social media. We provide with a literature review of these articles, by taking into consideration some limitations and restrictions. All the articles to be included on the literature review were initially searched on Internet and academic databases such as Science Direct, Scopus and Emerald. Articles from books and book chapters are excluded from the research. The search returned 101 articles, covering the time span 2011-2016. Of them, 35 were rejected due to lack of compatibility of the content with our research scope. From the 66 remaining relative articles, we excluded 6, for being white papers. From the remaining 60 articles, 52 are scientific articles from peer-review journals and 8 from conferences and proceedings. Each article was reviewed and classified initially into the five above mentioned categories and furthermore in relation with the year of publication. The year distribution can reveal useful outcomes for the research tendencies.

As it is shown in Figure 2.2, the research has increased significantly since 2012. This year together with 2014 contribute 8 articles. The pick on publications is noticed during 2013 with 12 articles. 2014 and 2015 present a significant decrease in publications with 2016 showing a small promising increase.

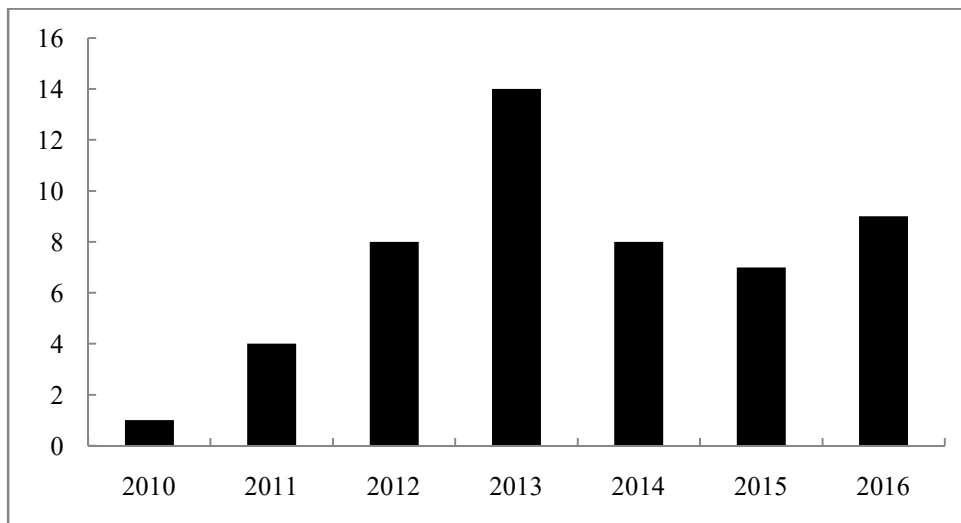


Figure 2.2: Year of distribution / number of articles

The amount of the techniques related to social media and their applications in order to spread brand awareness or promote particular products is called Social Media Marketing (SMM). SMM uses mainly the features of social media, such as online communities, social data etc. (Neti, 2011). In the literature, social media marketing is combined with metrics and/ or analytics tools, methodologies and techniques. Social media metrics represent the tangible outcome of monitoring, measuring, reporting, calculating content from social media

Furthermore, we classify each article based on five different criteria. More analytically, we subdivide the articles based on methodology, the specific type of analysis, the field of study, the marketing objectives and the social media types/ platforms used. As a result, the most common subsectors of each category can be identified, featuring the new upcoming trends on social media marketing. The findings are expected to benefit researchers and marketers by helping them better understand what has been hitherto achieved.

Creating a classification constitutes a complex concept to manipulate and conceive, especially in new scientific fields, where literature is still in its early stages. As Bailey (1994) defines, classification is one of the most central and generic of all our conceptual exercises, being the foundation and a necessary process in social science. Typology and taxonomy are two terms that define classification. Typologies are characterized by labels and names. We use the term typology, instead of taxonomy, because our classification system was derived in a deductive manner, without using any cluster analysis or other statistical method, as it occurs with taxonomies. Initially, we did not know which would be our labels, in order to classify the articles. Our selection of articles contained a plethora of labels, which made our mapping process quite complex but challenging. By studying carefully all the articles, we first identified several methodologies, types of analysis, fields of study and marketing objectives. Based on this study, we formed the subsequent Table 2.5 with the basic labels. This first collection of labels is editable, so future researchers can add, unify or divide the different topics.

Table 2.5: S3M typology framework for social media metrics and analytics on marketing

Main research categories	Subcategories and fields	
1. Methodology of research	Literature review and/ or Theoretical approach	
	Surveys	Questionnaire-based research
		Non questionnaire-based research
2. Type of analysis	Predictive analysis	
	Natural language process (NLP) – Text analysis	
	Effectuation analysis	
	Statistical analysis	
	Sentiment analysis	
	Behavioral analysis	
	Social media activity analysis	
	Content analysis	
3. Field of study	Banking	
	Education	
	Child welfare and advocacy	
	Tourism industry	
	Stock market	
	Entertainment	
	E-government	
	Food industry	
	Alternative marketing	
	Clothing	
4. Marketing objectives	Awareness & Branding	
	Engagement	
	eWOM advertising & promotion	
	Predictive marketing research	
	Consumer behavior research	

Main research categories	Subcategories and fields	
	Social capital - Value (business, firm equity) - ROI	
	Relationship marketing: CRM & social CRM	
5. Social media type/ platform	Social networking sites	Facebook, Hi5, LinkedIn, Myspace
	Blogs	Blogspot, digg wordpress
	Microblogs	Twitter, twitxr, tweetpeek, plurk
	Content communities - Video sharing sites	Youtube, Flickr, Slideshare
	Forums - discussion	Phpbb. Phorum, skype, messenger, google talk

Having this classification as a base scheme we studied the articles again, this time in order to classify each one in one or more categories. Our scheme lacks of mutual exclusivity, since one article may belong to more than one category. Reviewed articles are classified into five categories and each of them is discussed as follows.

Studies follow different approaches related to the methodology used. This depends on the problem's nature and the research field (Noor, 2008). Diverse studies exclusively review the literature. Usually these studies are qualitative and theoretical. We detected 10 articles that perform reviews and/ or theoretical research. On the other hand; other studies perform quantitative research using questionnaires. Our study revealed 13 relative articles. The remaining articles do not use questionnaires and form the third category of Table 2.6 with 27 articles.

Table 2.6: Articles' classification concerning the methodology of research

Methodology of research	Articles	Percentage of articles/ total (n/52)
Literature review and/ or	Fan and Gordon (2014); Gayo-Avello et al. (2013);	19.2%

Methodology of research		Articles	Percentage of articles/ total (n/52)
Theoretical approach		Ghezzi, Gastaldi, Lettieri, Martini, and Corso (2016); Hanna, Rohm, and Crittenden (2011); Malthouse, Haenlein, Skiera, Wege, and Zhang (2013); Neirotti, Raguseo, and Paolucci (2016); Nettleton (2013); Praude and Skulme (2015); Stephen (2016); P. Yadav, Banwari, Parmar, and Maniar (2013)	
Survey	Questionnaire-based research	Carim and Warwick (2013); Fischer and Reuber (2011); Godey et al. (2016); Guesalaga (2016); A. J. Kim and Ko (2012); M. R. Lee, Yen, and Hsiao (2014); Michaelidou, Siamagka, and Christodoulides (2011); Nadeem, Andreini, Salo, and Laukkanen (2015); Paek, Hove, Jung, and Cole (2013); Panagiotopoulos, Shan, Barnett, Regan, and McConnon (2015); Praude and Skulme (2015); Sheth, Sisodia, and Sharma (2000); Tiago and Veríssimo (2014)	25%
	Non questionnaire-based research	Andrew, Mudd, Rich, and Bruich (2012); Asur and Huberman (2010); Bernabé-Moreno, Tejada-Lorente, Porcel, Fujita, and Herrera-Viedma (2015); Braojos-Gomez, Benitez-Amado, and Javier Llorens-Montes (2015); Castronovo and Huang (2012); Y.-L. Chen, Tang, Wu, and Jheng (2014); Geurin and Burch (2016); He et al. (2013); Jang, Sim, Lee, and Kwon (2013); Kavanaugh et	50%

Methodology of research	Articles	Percentage of articles/ total (n/52)
	al. (2012); Kelling, Kelling, and Lennon (2013); Kontopoulos, Berberidis, Dergiades, and Bassiliades (2013); Lau, Li, and Liao (2014); Lieberman (2014); Mostafa (2013); Pehlivan, Sarican, and Berthon (2011); Podobnik (2013); Qiu, Rui, and Whinston (2014); Ribarsky, Xiaoyu Wang, and Dou (2014); Rohm, Milne, and Kaltcheva (2012); Sabate, Berbegal-Mirabent, Cañabate, and Lebherz (2014); A. N. Smith, Fischer, and Yongjian (2012); Xiang, Schwartz, Gerdes Jr, and Uysal (2015); Xie et al. (2012); M. S. Yadav, de Valck, Hennig-Thurau, Hoffman, and Spann (2013); Yakushev and Mityagin (2014); Yu, Duan, and Cao (2013)	

The generic category of survey-related articles, both questionnaire-based and not, contributes more than 84% of papers. This can be explained by the fact that social media scientists prefer to contribute with primary research articles rather than review-based researches, since the field is quite new and presents a huge research development margin. Though this numeric conclusion can be evidenced by findings, we believe that theoretical approaches are still necessary and form a solid base for conducting primary research.

As S3M is a nascent developing model with challenges and opportunities for further research exploration, this Table is designed to assist researchers to obtain the basic knowledge but also to find gaps and limitations, not yet analyzed. The tendencies towards specific research can be revealed also from the next Table. As Gartner (2013) defines, social analytics include sentiment analysis, NLP, text analysis, predictive and content analysis. We enlarge this definition by

adding also statistical and behavioral analysis, as possible categories, in our taxonomy. Only one article performs effectuation analysis which is the process for entrepreneurial decision-making (Fischer & Reuber, 2011). These eight categories form the classification for Table 2.7.

Table 2.7: Articles' classification concerning the type of analysis

Type of analysis (primary data collection and/ or metric analysis)	Articles	Percentage of articles/ total (n/52)
Predictive analysis	Asur and Huberman (2010); Y.-L. Chen et al. (2014); Qiu et al. (2014)	5.8%
Natural Language Process (NLP) – Text analysis	Asur and Huberman (2010); He et al. (2013); Jang et al. (2013); Kontopoulos et al. (2013); Mostafa (2013); Xiang et al. (2015); Yakushev and Mityagin (2014); Yu et al. (2013)	15.3%
Effectuation analysis	Fischer and Reuber (2011)	1.9%
Statistical analysis	He et al. (2013); Podobnik (2013)	3.8%
Sentiment analysis	Y.-L. Chen et al. (2014); Jang et al. (2013); Kontopoulos et al. (2013); Lau et al. (2014); Mostafa (2013); Xiang et al. (2015); Yu et al. (2013)	13.4%
Behavioral analysis	Andrew et al. (2012); Mostafa (2013); Qiu et al. (2014); Xie et al. (2012)	7.7%
Social media activity analysis	Bernabé-Moreno et al. (2015); Guesalaga (2016); He et al. (2013); Lieberman (2014); Praude and Skulme (2015); Rohm et al. (2012); Sabate et al. (2014)	13.4%
Content analysis	Bernabé-Moreno et al. (2015); Geurin and Burch	15.4%

Type of analysis (primary data collection and/ or metric analysis)	Articles	Percentage of articles/ total (n/52)
	(2016); He et al. (2013); Jang et al. (2013); Neirotti et al. (2016); Panagiotopoulos et al. (2015); Ribarsky et al. (2014); A. N. Smith et al. (2012); Xiang et al. (2015)	

The dissertation’s propose model (S3M) is not yet fully standardized so it is normal that the different categories mix with each other. This is the reason why many papers fit more than one category. Nevertheless, even if classification is not yet fully clarified, we extract the next outcome by observing Table 2.7. NLP and text analysis, sentiment analysis, content and social media activity analysis are the dominant categories. This observation can be explained by the fact that data contain insights for customers and information for marketers so as to predict useful outcomes.

The present study ends up with 10 specific market fields of study. Only 18 articles clearly focus on specific fields of study, while the rest are generic. We list these fields in Table 2.8.

Table 2.8: Articles' classification concerning the field of study

Field of study	Articles	Percentage of articles/ total (n/52)
Banking	Ribarsky et al. (2014)	1.9%
Education	Kelling et al. (2013)	1.9%
Child welfare and advocacy	Paek et al. (2013)	1.9%
Tourism industry	Bernabé-Moreno et al. (2015); Kontopoulos et al. (2013); Mariani et al. (2016); Neirotti et al. (2016); Sabate et al. (2014); Xiang et al. (2015)	11.5%
Stock market	Yu et al. (2013)	1.9%
Entertainment (movies, sports)	Asur and Huberman (2010); Geurin and Burch (2016); Podobnik (2013)	5.7%
E-government	Kavanaugh et al. (2012)	1.9%
Food industry	He et al. (2013); Panagiotopoulos et al. (2015)	1.9%
Alternative marketing (viral, email, guerilla etc.)	Castronovo and Huang (2012)	1.9%
Clothing	Nadeem et al. (2015)	1.9%

As we notice, articles related to the tourism industry hold the largest percentage with six articles. In a total of 52 articles, this number represents the 11.5%, but among the 18 that focus on specific categories, the percentage rises in 33.3%. The fact that one third of the articles belong in the tourism industry was highly expected since tourism represents one of the most profitable industries worldwide, contributing to the global economy more than 48 trillion dollars for the same time span of our research, from 2010 to 2016 (Chung, Nam, & Koo, 2016). The same field has great potentials on following in-depth research and exporting main streams and sub-fields of study (Fouskas, Misirlis, Karanatsiou, & Vlachopoulou, 2018).

Business organizations create marketing programs, activities, and campaigns in order to move their current/ potential customers to the buyer's journey, designed to align marketing goals and sales activities. Several marketing objectives including specific actions were identified, such as brand awareness, engagement, marketing and especially customer research, behavioral targeting, e-WOM & promotion policy, relationship management & social CRM and social capital value including ROI questions /assessment.

Brand awareness means the exposure of the target audience to brand content and message, while engagement generates further actions taking into consideration the brand content/ offers. Marketing and customer research have been identified by marketers as important and common objectives related to the social media use, giving them valuable information regarding customers impressions, sentiment, satisfaction in order to estimate the conversion/purchase potential. Furthermore, the activation of customers' influence based on referrals, advocacy activities and evangelism inspiration for products/ services constitutes the marketing objective of a positive eWOM promotion policy. Relationship marketing objectives based on social CRM is the new concern in the marketing world, and with good reason (Hoffman & Fodor, 2010; Pentin, 2011). As social media explode among businesses and customers, monitoring, managing and exploiting the resulting data become essential tasks for almost any marketer. Companies are anxious to meet customers where they are in the social media realm looking for the tools to get involved and gain access. Social CRM software works in conjunction with traditional CRM systems to track customer behavior, as a tool that is part of a social media strategy.

The study of the articles revealed initially 7 marketing objectives supported by social media. Table 2.9 presents the articles based on each objective they serve.

Table 2.9: Articles' classification concerning the marketing objectives.

Marketing objectives	Articles	Percentage of articles/ total (n/52)
Awareness & Branding	Andrew et al. (2012); A. J. Kim and Ko (2012); Lieberman (2014); Mostafa (2013); Rohm et al. (2012); Sabate et al. (2014); A. N. Smith et al. (2012)	13.4%
Engagement	Fischer and Reuber (2011); Guesalaga (2016); Malthouse et al. (2013); Mariani et al. (2016); Osborne and Ballantyne (2012); Paek et al. (2013); Panagiotopoulos et al. (2015); Rohm et al. (2012); Sabate et al. (2014); Tiago and Veríssimo (2014)	19.2%
eWOM advertising & promotion	Y.-L. Chen et al. (2014); Stephen (2016)	1.9%
Predictive marketing research	Asur and Huberman (2010); Gayo-Avello et al. (2013); A. J. Kim and Ko (2012); Qiu et al. (2014); Yakushev and Mityagin (2014)	9.6%
Consumer behavior research	Bernabé-Moreno et al. (2015); Godey et al. (2016); Jang et al. (2013); Mostafa (2013); Nadeem et al. (2015); Ribarsky et al.	19.2%

Marketing objectives	Articles	Percentage of articles/ total (n/52)
	(2014); Rohm et al. (2012); Stephen (2016); Xiang et al. (2015); Xie et al. (2012)	
Social capital - Value (business, firm equity) - ROI	Braojos-Gomez et al. (2015); Fan and Gordon (2014); Godey et al. (2016); He et al. (2013); M. R. Lee et al. (2014); Neirotti et al. (2016); Pehlivan et al. (2011); Yu et al. (2013)	15.4%
Relationship marketing: CRM & social CRM	Geurin and Burch (2016); Malthouse et al. (2013); Nadeem et al. (2015); Osborne and Ballantyne (2012); M. S. Yadav et al. (2013)	9.6%

Engagement, consumer behavior research and relationship marketing represent the most dominant among the other categories with 10, 10 and 8 articles, respectively. All these three categories have the *consumer/customer* as a common factor. The consumer-centric marketing was presented as the upcoming trend a few years ago and the current literature and our findings demonstrate that tendency towards that direction (Osborne & Ballantyne, 2012; Sheth et al., 2000). Of the 47 articles related to some marketing objective, presented in Table 2.9, the 59.6% regards consumer-centric articles.

Table 2.10 represents the articles' distribution for the social media types or the platform used. In order to create this Table, we base our taxonomy on Kaplan and Haenlein (2010), Constantinides and Fountain (2008) and Mangold and Faulds (2009). A difference between these three articles is that the first two use the term *Content communities* for YouTube and the third one, *video sharing sites*.

Table 2.10: Articles' classification concerning the social media types/ platforms

Social media types/ platforms	Articles	Percentage of articles/ total (n/52)
Social Networking Sites (SNS)	Andrew et al. (2012); Carim and Warwick (2013); Y.-L. Chen et al. (2014); He et al. (2013); Kavanaugh et al. (2012); A. J. Kim and Ko (2012); M. R. Lee et al. (2014); Lieberman (2014); Mariani et al. (2016); Nadeem et al. (2015); Paek et al. (2013); Podobnik (2013); Ribarsky et al. (2014); Rohm et al. (2012); Sabate et al. (2014); Sheth et al. (2000); A. N. Smith et al. (2012); Tiago and Veríssimo (2014); Xie et al. (2012); M. S. Yadav et al. (2013)	38.5%
Blogs	Paek et al. (2013); Yakushev and Mityagin (2014); Yu et al. (2013)	5.8%
Microblogs	Asur and Huberman (2010); Bernabé-Moreno et al. (2015); Carim and Warwick (2013); Fischer and Reuber (2011); He et al. (2013); Kavanaugh et al. (2012); Kelling et al. (2013); A. J. Kim and Ko (2012); Kontopoulos et al. (2013); Lieberman (2014); Mostafa (2013); Paek et al. (2013); Ribarsky et al. (2014); Rohm et al. (2012); Sheth et	32.7%

Social media types/ platforms	Articles	Percentage of articles/ total (n/52)
	al. (2000); A. N. Smith et al. (2012); Yu et al. (2013)	
Content communities – Video sharing sites	Carim and Warwick (2013); Geurin and Burch (2016); Jang et al. (2013); Kavanaugh et al. (2012); A. N. Smith et al. (2012)	9.6%
Forums	Yu et al. (2013)	1.9%

In a total of 52 articles, 46 of them fit Table 2.10 with several articles studying multiple social media types or platforms. Articles related to Facebook and Twitter, dominate with 20 and 17 articles, and 38.5% and 32.7% respectively. These results were rather expected, given the fact that 1.86 billion Facebook users and 320 million Twitter users own an active account on these two most visited and diffused SNS and microblog platforms. In global scale, Facebook is used by 54% of global internet users, so it is expected that science will also be of interest for these two platforms.

Summarizing our findings, with respect to the corpus of all articles, we notice a peak on publications in 2013 followed by a decrease the next two years. An important finding is that 2016 represents a small but constant increase in the number of publications, showing an overall increase of interest in social media marketing analysis. Trends show the tourism industry, Facebook and Twitter as well as consumer-centric marketing to be the dominant categories, platforms and concepts behind social media marketing strategies. On the other hand though, these trends may bring to the surface gaps in other fields that need attention and research.

Regarding our specific outcomes, it becomes clear that primary data collection is the most used method on S3M and the data used for analysis, originate from primary metrics. Another useful outcome is the platform used. On today's social media research, Facebook and Twitter are the dominant platforms and so, the biggest part of the literature is focusing on these two platforms.

The above conclusions can help researchers to understand better the tendencies of the diverse field, but also reveal research gaps and lacks in the literature. We believe that the presented chapter presents potential for applications in many domains, ranging from marketing to academic or business research. By knowing how to effectively measure the social media value, companies and individuals can produce insights that allow improvement in promoting products and services.

2.2. Facebook data, actions and measurable activities

Over the last decade, Facebook has developed into the most popular social media platform, with 2.07 billion active users and an annual average increase of almost 16 per cent worldwide. Over 1.37 billion users log in on a daily basis (statista.com, 2018). In the United States only, 72% of the population uses Facebook daily (Duggan, 2015). Facebook delivers individuals with easy access to view personal information about friends, coworkers, even complete strangers (Christofides, Muise, & Desmarais, 2009). Over 96% of U.S. college students, have a Facebook account. In Greece, Facebook is by far the primary social network used by most of the population. Every second, 510000 comments, 293000 and 136000 photos are uploaded. This popularity of online social networking sites and in particular Facebook, provides a fertile ground for research as media users generate daily vast amounts of data and content. Analysts can extract useful insights, including among others the more elaborate aspects of users' personality. In order to fully understand, though, the potential of such data, it is firstly important to analyze in depth and comprehend the ecosystem of Facebook, the features and the metrics that can provide with data. Facebook contains facilities that help companies and users to promote, advise and advertise themselves. These Facebook Pages and Groups, although similar, have strict differences between them. A Facebook Page enables users and companies to publicly state their presence on the platform. Pages are visible to everyone by default, something that is not true on Profiles. Everyone who has an active account can be connected to these Pages, receive updates and interact with the administrators. On the other side, Facebook Groups are the feature of the platform dedicated to small group communication and for users who desire to share their

interests. Groups belong to the mentality of gathering around a common cause; increase the activism sentiment, organize people and share material, experience advices.

The next chapter focuses on Facebook data and users' measurable activities that can be used in order to extract useful insight regarding consumer behavior and especially personality traits. The survey we use is focused on the usage of advices from groups and pages related to well-being, in specific related to healthy diet and leisure activities, in correlation to users' personality. Further analysis of the survey and the related fields can be found on Chapter 5 and Chapter 6, where the methodology and the results are being analyzed.

References

- Aggarwal, C. (2011). An Introduction to Social Network Data Analytics. In C. C. Aggarwal (Ed.), *Social Network Data Analytics* (pp. 1-15): Springer US.
- Agner, S. C., Rosen, M. A., Englander, S., Tomaszewski, J. E., Feldman, M. D., Zhang, P., . . . Madabhushi, A. (2014). Computerized Image Analysis for Identifying Triple-Negative Breast Cancers and Differentiating Them from Other Molecular Subtypes of Breast Cancer on Dynamic Contrast-enhanced MR Images: A Feasibility Study. *Radiology*, 272(1), 91-99. doi: doi:10.1148/radiol.14121031
- Al-Debei, M. M., Al-Lozi, E., & Papazafeiropoulou, A. (2013). Why people keep coming back to Facebook: Explaining and predicting continuance participation from an extended theory of planned behaviour perspective. *Decision Support Systems*, 55(1), 43-54. doi: <http://dx.doi.org/10.1016/j.dss.2012.12.032>
- Amichai-Hamburger, Y., & Vinitzky, G. (2010). Social network use and personality. *Computers in Human Behavior*, 26(6), 1289-1295. doi: <http://dx.doi.org/10.1016/j.chb.2010.03.018>
- Amjad, N., & Wood, A. M. (2009). Identifying and changing the normative beliefs about aggression which lead young Muslim adults to join extremist anti-Semitic groups in Pakistan. *Aggressive behavior*, 35(6), 514-519.
- Andrew, L., Mudd, G., Rich, M., & Bruich, S. (2012). The Power of Like: How Brands Reach and Influence Fans Through Social Media Marketing. *Journal of Advertising Research*. doi: 10.2501/JAR-52-1-040-052
- Armitage, C. J. (2005). Can the theory of planned behavior predict the maintenance of physical activity? *Health psychology*, 24(3), 235.
- Asur, S., & Huberman, B. A. (2010). *Predicting the Future with Social Media*. Paper presented at the Proceedings of the 2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology - Volume 01.
- Awareness, I. (2012). Actionable Social Analytics: From Social Media Metrics to Business Insights Retrieved 14/12/2015, from <http://igo2group.com/wp-%C2%AD%E2%80%90content/uploads/2012/10/Actionable-%C2%AD%E2%80%90Social-%C2%AD%E2%80%90Analytics.pdf>
- Bailey, K. D. E. (1994). *Typologies and taxonomies: an introduction to classification techniques* (Vol. 102): Sage.

- Batrinca, B., & Treleaven, P. (2015). Social media analytics: a survey of techniques, tools and platforms. *AI & SOCIETY*, 30(1), 89-116. doi: 10.1007/s00146-014-0549-4
- Bello-Orgaz, G., Jung, J. J., & Camacho, D. (2016). Social big data: Recent achievements and new challenges. *Information Fusion*, 28, 45-59. doi: <http://dx.doi.org/10.1016/j.inffus.2015.08.005>
- Bernabé-Moreno, J., Tejada-Lorente, A., Porcel, C., Fujita, H., & Herrera-Viedma, E. (2015). CARESOME. *Know.-Based Syst.*, 80(C), 163-179. doi: 10.1016/j.knosys.2014.12.033
- Bishop, J. (2007). Increasing participation in online communities: A framework for human-computer interaction. *Computers in Human Behavior*, 23(4), 1881-1893. doi: <http://dx.doi.org/10.1016/j.chb.2005.11.004>
- Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, 2(1), 1-8. doi: <http://dx.doi.org/10.1016/j.jocs.2010.12.007>
- Bozionelos, G., & Bennett, P. (1999). The theory of planned behaviour as predictor of exercise: The moderating influence of beliefs and personality variables. *Journal of health psychology*, 4(4), 517-529.
- Braojos-Gomez, J., Benitez-Amado, J., & Javier Llorens-Montes, F. (2015). How do small firms learn to develop a social media competence? *International Journal of Information Management*, 35(4), 443-458. doi: <http://dx.doi.org/10.1016/j.ijinfomgt.2015.04.003>
- Carim, L., & Warwick, C. (2013). Use of social media for corporate communications by research-funding organisations in the UK. *Public Relations Review*, 39(5), 521-525. doi: <http://dx.doi.org/10.1016/j.pubrev.2013.08.006>
- Castronovo, C., & Huang, L. (2012). Social media in an alternative marketing communication model. *Journal of Marketing Development & Competitiveness*, 6(1), 117.
- Chang, C.-W., & Chen, G. M. (2014b). College students' disclosure of location-related information on Facebook. *Computers in Human Behavior*, 35, 33-38.
- Chen, Y.-L., Tang, K., Wu, C.-C., & Jheng, R.-Y. (2014). Predicting the influence of users' posted information for eWOM advertising in social networks. *Electronic Commerce Research and Applications*, 13(6), 431-439. doi: <http://dx.doi.org/10.1016/j.elerap.2014.10.001>

- Christofides, E., Muise, A., & Desmarais, S. (2009). Information disclosure and control on Facebook: Are they two sides of the same coin or two different processes? *Cyberpsychology & behavior*, *12*(3), 341-345.
- Chu, T.-H., & Chen, Y.-Y. (2016). With good we become good: Understanding e-learning adoption by theory of planned behavior and group influences. *Computers & Education*, *92*, 37-52.
- Chung, N., Nam, K., & Koo, C. (2016). Examining information sharing in social networking communities: Applying theories of social capital and attachment. *Telematics and Informatics*, *33*(1), 77-91. doi: <http://dx.doi.org/10.1016/j.tele.2015.05.005>
- Constantinides, E., & Fountain, S. J. (2008). Web 2.0: Conceptual foundations and marketing issues. *J Direct Data Digit Mark Pract*, *9*(3), 231-244.
- Daniel, Z., Hsinchun, C., Lusch, R., & Shu-Hsing, L. (2010). Social Media Analytics and Intelligence. *Intelligent Systems, IEEE*, *25*(6), 13-16. doi: 10.1109/mis.2010.151
- Duggan, M. (2015). Mobile messaging and social media. *Pew Research Center*. Retrieved from <http://www.pewinternet.org/2015/08/19/mobile-messaging-and-social-media-2015/>
- Fan, W., & Gordon, M. (2014). Unveiling the power of social media analytics. *Communications of ACM*.
- Fischer, E., & Reuber, A. R. (2011). Social interaction via new social media: (How) can interactions on Twitter affect effectual thinking and behavior? *Journal of Business Venturing*, *26*(1), 1-18. doi: <http://dx.doi.org/10.1016/j.jbusvent.2010.09.002>
- Fouskas, K., Misirlis, N., Karanatsiou, D., & Vlachopoulou, M. (2018). Big data analysis in Tourism and Hospitality: a mapping literature review. *6th International Conference on Contemporary Marketing Issues*.
- Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, *35*(2), 137-144. doi: <http://dx.doi.org/10.1016/j.ijinfomgt.2014.10.007>
- Gartner. (2013). Social Analytics, from <http://www.gartner.com/it-glossary/social-analytics>
- Gayo-Avello, P. T. M., Eni Mustafaraj, Markus Strohmaier, Harald Schoen, Peter Gloor, D., Schoen, H., Gayo-Avello, D., Takis Metaxas, P., Mustafaraj, E., . . . Gloor, P. (2013). The power of prediction with social media. *Internet Research*, *23*(5), 528-543. doi: doi:10.1108/IntR-06-2013-0115

- Geurin, A. N., & Burch, L. M. (2016). User-generated branding via social media: An examination of six running brands. *Sport Management Review*. doi: <http://dx.doi.org/10.1016/j.smr.2016.09.001>
- Ghezzi, A., Gastaldi, L., Lettieri, E., Martini, A., & Corso, M. (2016). A role for startups in unleashing the disruptive power of social media. *International Journal of Information Management*, 36(6, Part A), 1152-1159. doi: <http://dx.doi.org/10.1016/j.ijinfomgt.2016.04.007>
- 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. doi: <http://dx.doi.org/10.1016/j.jbusres.2016.04.181>
- Grubmüller, V., Götsch, K., & Krieger, B. (2013). Social media analytics for future oriented policy making. *European Journal of Futures Research*, 1(1), 1-9. doi: 10.1007/s40309-013-0020-7
- Guesalaga, R. (2016). The use of social media in sales: Individual and organizational antecedents, and the role of customer engagement in social media. *Industrial Marketing Management*, 54, 71-79. doi: <http://dx.doi.org/10.1016/j.indmarman.2015.12.002>
- Hajli, N., Shanmugam, M., Powell, P., & Love, P. E. (2015). A study on the continuance participation in on-line communities with social commerce perspective. *Technological Forecasting and Social Change*, 96, 232-241.
- Hanna, R., Rohm, A., & Crittenden, V. L. (2011). We're all connected: The power of the social media ecosystem. *Business Horizons*, 54(3), 265-273. doi: <http://dx.doi.org/10.1016/j.bushor.2011.01.007>
- He, W., Zha, S., & Li, L. (2013). Social media competitive analysis and text mining: A case study in the pizza industry. *International Journal of Information Management*, 33(3), 464-472. doi: <http://dx.doi.org/10.1016/j.ijinfomgt.2013.01.001>
- Hoffman, D., & Fodor, M. (2010). Can You Measure the ROI of Your Social Media Marketing? *MITSloan Management Review*, 52(1).
- Huang, T. K. (2015). Exploring the antecedents of screenshot-based interactions in the context of advanced computer software learning. *Computers & Education*, 80, 95-107.

- IBM. (n.d.). What is big data Retrieved 15/12/2015, from www-01.ibm.com/software/in/data/bigdata/
- Jang, H.-J., Sim, J., Lee, Y., & Kwon, O. (2013). Deep sentiment analysis: Mining the causality between personality-value-attitude for analyzing business ads in social media. *Expert Systems with Applications*, 40(18), 7492-7503. doi: <http://dx.doi.org/10.1016/j.eswa.2013.06.069>
- Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons*, 53(1), 59-68. doi: <http://dx.doi.org/10.1016/j.bushor.2009.09.003>
- Kaptein, M., Markopoulos, P., de Ruyter, B., & Aarts, E. (2009). Can You Be Persuaded? Individual Differences in Susceptibility to Persuasion. In T. Gross, J. Gulliksen, P. Kotzé, L. Oestreicher, P. Palanque, R. Prates & M. Winckler (Eds.), *Human-Computer Interaction – INTERACT 2009* (Vol. 5726, pp. 115-118): Springer Berlin Heidelberg.
- Kavanaugh, A. L., Fox, E. A., Sheetz, S. D., Yang, S., Li, L. T., Shoemaker, D. J., . . . Xie, L. (2012). Social media use by government: From the routine to the critical. *Government Information Quarterly*, 29(4), 480-491. doi: <http://dx.doi.org/10.1016/j.giq.2012.06.002>
- Kelling, N. J., Kelling, A. S., & Lennon, J. F. (2013). The tweets that killed a university: A case study investigating the use of traditional and social media in the closure of a state university. *Computers in Human Behavior*, 29(6), 2656-2664. doi: <http://dx.doi.org/10.1016/j.chb.2013.06.044>
- Kim, A. J., & Ko, E. (2012). Do social media marketing activities enhance customer equity? An empirical study of luxury fashion brand. *Journal of Business Research*, 65(10), 1480-1486. doi: <http://dx.doi.org/10.1016/j.jbusres.2011.10.014>
- Kobielus, J. (2010). Social Media Analytics: You Will Still Need Actual Analysts In The Loop. Retrieved from http://blogs.forrester.com/james_kobielus/10-07-16-social_media_analytics_you_will_still_need_actual_analysts_loop
- Kontopoulos, E., Berberidis, C., Dergiades, T., & Bassiliades, N. (2013). Ontology-based sentiment analysis of twitter posts. *Expert Systems with Applications*, 40(10), 4065-4074. doi: <http://dx.doi.org/10.1016/j.eswa.2013.01.001>

- Koohikamali, M., Peak, D. A., & Prybutok, V. R. (2017). Beyond self-disclosure: Disclosure of information about others in social network sites. *Computers in Human Behavior*, *69*, 29-42.
- Lau, R. Y. K., Li, C., & Liao, S. S. Y. (2014). Social analytics: Learning fuzzy product ontologies for aspect-oriented sentiment analysis. *Decision Support Systems*, *65*(0), 80-94. doi: <http://dx.doi.org/10.1016/j.dss.2014.05.005>
- Lee, M. R., Yen, D. C., & Hsiao, C. Y. (2014). Understanding the perceived community value of Facebook users. *Computers in Human Behavior*, *35*(0), 350-358. doi: <http://dx.doi.org/10.1016/j.chb.2014.03.018>
- Leong, L.-Y., Ooi, K.-B., Chong, A. Y.-L., & Lin, B. (2013). Modeling the stimulators of the behavioral intention to use mobile entertainment: Does gender really matter? *Computers in Human Behavior*, *29*(5), 2109-2121.
- Lieberman, M. (2014). *Visualizing Big Data: Social Network Analysis*. Paper presented at the Digital Research Conference.
- Liu, F., & Lee, H. J. (2010). Use of social network information to enhance collaborative filtering performance. *Expert Systems with Applications*, *37*(7), 4772-4778. doi: <http://dx.doi.org/10.1016/j.eswa.2009.12.061>
- Malthouse, E. C., Haenlein, M., Skiera, B., Wege, E., & Zhang, M. (2013). Managing Customer Relationships in the Social Media Era: Introducing the Social CRM House. *Journal of Interactive Marketing*, *27*(4), 270-280. doi: <http://dx.doi.org/10.1016/j.intmar.2013.09.008>
- Mandilas, A., Karasavoglou, A., Nikolaidis, M., & Tsourgiannis, L. (2013). Predicting Consumer's Perceptions in On-line Shopping. *Procedia Technology*, *8*, 435-444.
- Mangold, W. G., & Faulds, D. J. (2009). Social media: The new hybrid element of the promotion mix. *Business Horizons*, *52*(4), 357-365. doi: <http://dx.doi.org/10.1016/j.bushor.2009.03.002>
- Mariani, M. M., Di Felice, M., & Mura, M. (2016). Facebook as a destination marketing tool: Evidence from Italian regional Destination Management Organizations. *Tourism Management*, *54*, 321-343. doi: <http://dx.doi.org/10.1016/j.tourman.2015.12.008>

- Mayeh, M., Scheepers, R., & Valos, M. (2012, 2012). *Understanding the role of social media monitoring in generating external intelligence*. Paper presented at the Australasian Conference on Information Systems (23rd : 2012 : Geelong, Victoria), Geelong, Victoria.
- Michaelidou, N., Siamagka, N. T., & Christodoulides, G. (2011). Usage, barriers and measurement of social media marketing: An exploratory investigation of small and medium B2B brands. *Industrial Marketing Management*, 40(7), 1153-1159. doi: <http://dx.doi.org/10.1016/j.indmarman.2011.09.009>
- Moore, K., & McElroy, J. C. (2012). The influence of personality on Facebook usage, wall postings, and regret. *Computers in Human Behavior*, 28(1), 267-274. doi: <http://dx.doi.org/10.1016/j.chb.2011.09.009>
- Mostafa, M. M. (2013). More than words: Social networks' text mining for consumer brand sentiments. *Expert Systems with Applications*, 40(10), 4241-4251. doi: <http://dx.doi.org/10.1016/j.eswa.2013.01.019>
- Nadeem, W., Andreini, D., Salo, J., & Laukkanen, T. (2015). Engaging consumers online through websites and social media: A gender study of Italian Generation Y clothing consumers. *International Journal of Information Management*, 35(4), 432-442. doi: <http://dx.doi.org/10.1016/j.ijinfomgt.2015.04.008>
- Neirotti, P., Raguseo, E., & Paolucci, E. (2016). Are customers' reviews creating value in the hospitality industry? Exploring the moderating effects of market positioning. *International Journal of Information Management*, 36(6, Part A), 1133-1143. doi: <http://dx.doi.org/10.1016/j.ijinfomgt.2016.02.010>
- Neti, S. (2011). Social media and its role in marketing. *International Journal of Enterprise Computing and Business Systems*, 1(2).
- Nettleton, D. F. (2013). Data mining of social networks represented as graphs. *Computer Science Review*, 7(0), 1-34. doi: <http://dx.doi.org/10.1016/j.cosrev.2012.12.001>
- Nielsen, J. K. (2012). Actionable Social Analytics: From Social Media Metrics to Business Insights (Vol. 2015).
- Noor, K. B. M. (2008). Case Study: A Strategic Research Methodology. *American Journal of Applied Science*, 5(11), 1602-1604.

- O'Connor, M. C., & Paunonen, S. V. (2007). Big Five personality predictors of post-secondary academic performance. *Personality and Individual Differences*, 43(5), 971-990. doi: <http://dx.doi.org/10.1016/j.paid.2007.03.017>
- Osborne, P., & Ballantyne, D. (2012). The paradigmatic pitfalls of customer-centric marketing. *Marketing Theory*, 12(2), 155-172. doi: doi:10.1177/1470593112441564
- Paek, H.-J., Hove, T., Jung, Y., & Cole, R. T. (2013). Engagement across three social media platforms: An exploratory study of a cause-related PR campaign. *Public Relations Review*, 39(5), 526-533. doi: <http://dx.doi.org/10.1016/j.pubrev.2013.09.013>
- Panagiotopoulos, P., Shan, L. C., Barnett, J., Regan, Á., & McConnon, Á. (2015). A framework of social media engagement: Case studies with food and consumer organisations in the UK and Ireland. *International Journal of Information Management*, 35(4), 394-402. doi: <http://dx.doi.org/10.1016/j.ijinfomgt.2015.02.006>
- Pehlivan, E., Sarican, F., & Berthon, P. (2011). Mining messages: Exploring consumer response to consumer- vs. firm-generated ads. *Journal of Consumer Behaviour*, 10(6), 313-321. doi: 10.1002/cb.379
- Pentin, R. (2011). A new framework for measuring social media activity. Internet Advertising Bureau.
- Podobnik, V. (2013, 26-28 June 2013). *An analysis of facebook social media marketing key performance indicators: The case of premier league brands*. Paper presented at the Telecommunications (ConTEL), 2013 12th International Conference on.
- Praude, V., & Skulme, R. (2015). Social Media Campaign Metrics in Latvia. *Procedia - Social and Behavioral Sciences*, 213, 628-634. doi: <http://dx.doi.org/10.1016/j.sbspro.2015.11.462>
- Qiu, L., Rui, H., & Whinston, A. B. (2014). Effects of Social Networks on Prediction Markets: Examination in a Controlled Experiment. *Journal of Management Information Systems*, 30(4), 235-268. doi: 10.2753/mis0742-1222300409
- Ribarsky, W., Xiaoyu Wang, D., & Dou, W. (2014). Social media analytics for competitive advantage. *Computers & Graphics*, 38(0), 328-331. doi: <http://dx.doi.org/10.1016/j.cag.2013.11.003>

- Rohm, A., Milne, G. R., & Kaltcheva, V. (2012). *The role of online social media in brand-consumer engagement*. Paper presented at the Direct/Interactive Marketing Research Summit Proceedings.
- Ryan, T., & Xenos, S. (2011). Who uses Facebook? An investigation into the relationship between the Big Five, shyness, narcissism, loneliness, and Facebook usage. *Computers in Human Behavior*, 27(5), 1658-1664. doi: <http://dx.doi.org/10.1016/j.chb.2011.02.004>
- Sabate, F., Berbegal-Mirabent, J., Cañabate, A., & Lebherz, P. R. (2014). Factors influencing popularity of branded content in Facebook fan pages. *European Management Journal*, 32(6), 1001-1011. doi: <http://dx.doi.org/10.1016/j.emj.2014.05.001>
- Sheth, J. N., Sisodia, R. S., & Sharma, A. (2000). The Antecedents and Consequences of Customer-Centric Marketing. *Journal of the Academy of Marketing Science*, 28(1), 55-66. doi: 10.1177/0092070300281006
- Smith, A., Pilecki, M., & McAdams, R. (2014). How To Make Social Media Data Actionable. Retrieved from <https://www.forrester.com/How+To+Make+Social+Media+Data+Actionable/fulltext/-/E-RES56563>
- Smith, A. N., Fischer, E., & Yongjian, C. (2012). How Does Brand-related User-generated Content Differ across YouTube, Facebook, and Twitter? *Journal of Interactive Marketing*, 26(2), 102-113. doi: <http://dx.doi.org/10.1016/j.intmar.2012.01.002>
- statista.com. (2018). Number of monthly active Facebook users worldwide as of 3rd quarter 2017 (in millions) Retrieved 01-29-2016, 2018, from Number of monthly active Facebook users worldwide as of 3rd quarter 2017 (in millions)
- Stephen, A. T. (2016). The role of digital and social media marketing in consumer behavior. *Current Opinion in Psychology*, 10, 17-21. doi: <http://dx.doi.org/10.1016/j.copsyc.2015.10.016>
- Sterne, J., & Scott, M. D. (2010). *Social Media Metrics: How to Measure and Optimize Your Marketing Investment*: Wiley.
- Syed, A. R., Gillela, K., & Venugopal, C. (2013). The future revolution on big data. *International Journal of Advanced Research in Computer and Communication Engineering*, 2(6).

- Taneja, A., Vitrano, J., & Gengo, N. J. (2014). Rationality-based beliefs affecting individual's attitude and intention to use privacy controls on Facebook: An empirical investigation. *Computers in Human Behavior*, 38, 159-173.
- Tang, J.-H., Chen, M.-C., Yang, C.-Y., Chung, T.-Y., & Lee, Y.-A. (2016). Personality traits, interpersonal relationships, online social support, and Facebook addiction. *Telematics and Informatics*, 33(1), 102-108.
- Tiago, M. T. P. M. B., & Verissimo, J. M. C. (2014). Digital marketing and social media: Why bother? *Business Horizons*, 57(6), 703-708. doi: <http://dx.doi.org/10.1016/j.bushor.2014.07.002>
- Valkanas, G., & Gunopulos, D. (2013). A UI Prototype for Emotion-Based Event Detection in the Live Web. In A. Holzinger & G. Pasi (Eds.), *Human-Computer Interaction and Knowledge Discovery in Complex, Unstructured, Big Data* (Vol. 7947, pp. 89-100): Springer Berlin Heidelberg.
- Xiang, Z., Schwartz, Z., Gerdes Jr, J. H., & Uysal, M. (2015). What can big data and text analytics tell us about hotel guest experience and satisfaction? *International Journal of Hospitality Management*, 44(0), 120-130. doi: <http://dx.doi.org/10.1016/j.ijhm.2014.10.013>
- Xie, Y., Cheng, Y., Honbo, D., Zhang, K., Agrawal, A., Choudhary, A., . . . Gou, J. (2012). *Probabilistic macro behavioral targeting*. Paper presented at the Proceedings of the 2012 workshop on Data-driven user behavioral modelling and mining from social media, Maui, Hawaii, USA.
- Yadav, M. S., de Valck, K., Hennig-Thurau, T., Hoffman, D. L., & Spann, M. (2013). Social Commerce: A Contingency Framework for Assessing Marketing Potential. *Journal of Interactive Marketing*, 27(4), 311-323. doi: <http://dx.doi.org/10.1016/j.intmar.2013.09.001>
- Yadav, P., Banwari, G., Parmar, C., & Maniar, R. (2013). Internet addiction and its correlates among high school students: A preliminary study from Ahmedabad, India. *Asian Journal of Psychiatry*, 6(6), 500-505. doi: <http://dx.doi.org/10.1016/j.ajp.2013.06.004>
- Yakushev, A., & Mityagin, S. (2014). Social Networks Mining for Analysis and Modeling Drugs Usage. *Procedia Computer Science*, 29(0), 2462-2471. doi: <http://dx.doi.org/10.1016/j.procs.2014.05.230>

- Yang, M., Kiang, M., Ku, Y., Chiu, C., & Li, Y. (2011). Social Media Analytics for Radical Opinion Mining in Hate Group Web Forums *Journal of Homeland Security and Emergency Management* (Vol. 8).
- Yu, Y., Duan, W., & Cao, Q. (2013). The impact of social and conventional media on firm equity value: A sentiment analysis approach. *Decision Support Systems*, 55(4), 919-926. doi: <http://dx.doi.org/10.1016/j.dss.2012.12.028>

Chapter 3.

Personality traits models on social media

Facebook represents the most used social medium with over 1,7 billion active users (statista.com, 2018). Only in the United States, 72% of the population make use of Facebook in a daily basis (Duggan, 2015). These users generate a huge amount of data and content, attracting scholars' interest. Some researchers focus on personality traits in combination with Facebook use, associating behaviors and measurement online activities (Amichai-Hamburger & Vinitzky, 2010; Wang, Jackson, Zhang, & Su, 2012). Many theories are used to explain the online behavior of users in combination with their personality (D. Gosling, Augustine, Vazire, Holtzman, & Gaddis, 2011; Hall & Pennington, 2013). One of them, the Five-Factor Model of personality (FFM), known as Big Five, represents the most commonly used model for researching and examining the relationships between personality traits and online users. The present chapter aims to present except the Big Five, also a comparison analysis of the most used models in order to facilitate future research focused on different fields.

3.1. Approach for each theory and model comparison

Literature refers to a plethora of personality models in order to extract the individuals' traits. Most of these models are originated and elaborated from the science of psychology. Social science, in which digital marketing belongs, makes use of these models, most of the times extended and adapted to the needs of each case. In the present paragraph we will provide with all the relevant information for the most used models on the literature. Next paragraph provides with a comparison analysis of these most used models and the last paragraph of the chapter analyzes the model used on our research.

3.1.2 The Sixteen Personality Factor Questionnaire (16PF)

This model was developed by Cattell R., Tatsuoka M. and Eber H. and it is mostly used by psychologists and psychiatrics as a clinical instrument for measuring disorders such as anxiety, adjustment, emotional stability and general behavioral issues. Diverse research from social science used the 16PF as an HR managers' instrument for career and occupational selection. The

creators of 16PF provided also with diverse extensions of the basic model, focused on specific demographics, mostly for different age ranges for pupils and students (Coan & Cattell, 1959; Lichtenstein, Dreger, & Cattell, 1986; Schuerger, 1995). Table 3.1 presents the 16 items of the model together with their descriptors (low range and high range) and the primary factor of the 16 items that belong.

Table 3.1: Primary factors, low and high range descriptors of 16PF

Primary factor	Descriptors of low range	Descriptors of high range
Warmth	Impersonal, distant, cool, reserved, detached, formal, aloof	Warm, outgoing, attentive to others, kindly, easy-going, participating, likes people
Reasoning	Concrete thinking, lower general mental capacity, less intelligent, unable to handle abstract problems	Abstract-thinking, more intelligent, bright, higher general mental capacity, fast learner
Emotional Stability	Reactive emotionally, changeable, affected by feelings, emotionally less stable, easily upset	Emotionally stable, adaptive, mature, faces reality calmly
Dominance	Deferential, cooperative, avoids conflict, submissive, humble, obedient, easily led, docile, accommodating	Dominant, forceful, assertive, aggressive, competitive, stubborn, bossy
Liveliness	Serious, restrained, prudent,	Lively, animated,

Primary factor	Descriptors of low range	Descriptors of high range
	taciturn, introspective, silent	spontaneous, enthusiastic, happy go lucky, cheerful, expressive, impulsive
Rule-Consciousness	Expedient, nonconforming, disregards rules, self-indulgent	Rule-conscious, dutiful, conscientious, conforming, moralistic, staid, rule bound
Social Boldness	Shy, threat-sensitive, timid, hesitant, intimidated	Socially bold, venturesome, thick skinned, uninhibited
Sensitivity	Utilitarian, objective, un sentimental, tough minded, self-reliant, no-nonsense, rough	Sensitive, aesthetic, sentimental, tender minded, intuitive, refined
Vigilance	Trusting, unsuspecting, accepting, unconditional, easy	Vigilant, suspicious, skeptical, distrustful, oppositional
Abstractedness	Grounded, practical, prosaic, solution oriented, steady, conventional	Abstract, imaginative, absent minded, impractical, absorbed in ideas
Privateness	Forthright, genuine, artless, open, guileless, naive, unpretentious, involved	Private, discreet, nondisclosing, shrewd, polished, worldly, astute,

Primary factor	Descriptors of low range	Descriptors of high range
		diplomatic
Apprehension	Self-Assured, unworried, complacent, secure, free of guilt, confident, self-satisfied	Apprehensive, self doubting, worried, guilt prone, insecure, worrying, self blaming
Openness to Change	Traditional, attached to familiar, conservative, respecting traditional ideas	Open to change, experimental, liberal, analytical, critical, free thinking, flexibility
Self-Reliance	Group-oriented, affiliative, a joiner and follower dependent	Self-reliant, solitary, resourceful, individualistic, self-sufficient
Perfectionism	Tolerates disorder, unexacting, flexible, undisciplined, lax, self-conflict, impulsive, careless of social rules, uncontrolled	Perfectionistic, organized, compulsive, self-disciplined, socially precise, exacting will power, control, self-sentimental
Tension	Relaxed, placid, tranquil, torpid, patient, composed low drive	Tense, high energy, impatient, driven, frustrated, over wrought, time driven.

On the present research we preferred the Big Five model due to a main and basic difference between 16PF and Big Five. Our proposed model does not permit the different traits to correlate with each other (social scientists call this technique orthogonal rotation), while on 16PF the different traits can correlate with each other (oblique rotation technique), making the statistical analysis impossible and difficult to understand (Costa Jr & McCrae, 1992). Since we consider the Big Five's variables independent, there was no need of inter-correlation among them, so the choice of 16PF was incorrect (Cattell & Mead, 2008; Karson & O'Dell, 1976).

3.1.2 The alternative five model of personality (ALT-FFM)

The model was firstly introduced by Zuckerman and colleagues (Zuckerman, 2002) and represents basically, an extension of Big Five, with the addendum of Aggression, Sociability and Activity as new variables - see Table 3.2 (Zuckerman, Kuhlman, Thornquist, & Kiers, 1991).

Table 3.2: Factor analysis and measurements of the alternative five model of personality (ALT-FFM)

Factor	Measurements
Neuroticism – anxiety	Measures anxiety, fear, general emotionality, psychasthenia, and inhibition of aggression. The factor is also associated with obsessive indecisiveness, lack of self-confidence, and sensitivity to criticism
Aggression–hostility vs. social desirability	Measures aggression, hostility, anger, lack of inhibitory control, and low social desirability. The factor is associated with rudeness, thoughtless and antisocial behavior, vengefulness, quick temper and impatience
Impulsive sensation-seeking	Measures low socialization, and

Factor	Measurements
	high psychoticism, impulsivity, and sensation-seeking. The impulsivity items assess lack of planfulness and a tendency to act without thinking. The sensation seeking items describe a liking for thrills and excitement, novelty and variety, and unpredictable situations and friends
Sociability	Measures affiliation, social participation, and extraversion. Assesses liking for big parties and interactions with many people, as well as a dislike of isolation in sociable people versus a liking for the same in unsociable people
Activity	Measures energetic behavior and persistence. This factor is associated with need to keep active and feelings of restlessness when there is nothing to do

Our proposed model, as it is analyzed on next chapter, includes Sociability and Activity as two new variables by using the Theory of Planned Behavior, which already contains Subjective Norms, Attitude and Intention to Behavior items. Furthermore, literature on the subject asserts that that FFM together with TPB are the most used and suitable for this dissertation's field of study (Aluja, García, & García, 2002).

3.1.3 The HEXACO personality model

This model is based again on previous work of Costa Jr and McCrae (1992), adding Honesty-Humility as a sixth variable. This variable can explain traits like narcissism and manipulateness that cannot be analyzed with FFM. Table 3.3 summarizes the model's factors, facets and adjectives.

Table 3.3: HEXACO’s factors, facets and its adjectives

Factor	Facets	Adjectives
Honesty-Humility	Sincerity, Fairness, Greed Avoidance, Modesty	Sincere, honest, faithful, loyal, modest/unassuming versus sly, deceitful, greedy, pretentious, hypocritical, boastful, pompous
Emotionality	Fearfulness, Anxiety, Dependence, Sentimentality	Adjectives: Emotional, oversensitive, sentimental, fearful, anxious, vulnerable versus brave, tough, independent, self- assured, stable
Extraversion	Social Self-Esteem, Social Boldness, Sociability, Liveliness	Outgoing, lively, extraverted, sociable, talkative, cheerful, active versus shy, passive, withdrawn, introverted, quiet, reserved
Agreeableness	Forgivingness, Gentleness, Flexibility, Patience	patient, tolerant, peaceful, mild, agreeable, lenient, gentle versus ill- tempered, quarrelsome, stubborn, choleric
Conscientiousness	Organization, Diligence, Perfectionism, Prudence	organized, disciplined, diligent, careful,

Factor	Facets	Adjectives
		thorough, precise versus sloppy, negligent, reckless, lazy, irresponsible, absent-minded
OpennesstoExperience	Aesthetic Appreciation, Inquisitiveness, Creativity, Unconventionality	intellectual, creative, unconventional, innovative, ironic versus shallow, unimaginative, conventional

The Big Five factors do not include an Honesty-Humility factor, but some of the characteristics belonging to Honesty-Humility are incorporated into the Big Five's Agreeableness factor (Kibeom Lee & Ashton, 2008; Saucier, 2009). Big Five and HEXACO have three factors in common which are Extraversion, Openness and Conscientiousness.

The inspirers of HEXACO (Ashton & Lee, 2009) have developed different versions of the basic model, as it occurs with most of the models studied in this chapter, like HEXACO-PI-R, that adds more traits to analyze, as altruism (K Lee & Ashton, 2004).

3.2.Rationale behind the selected models in the present research and analysis

Five-Factor Model of personality (FFM), represents the most commonly used model for researching and examining the relationships between personality traits and online users. This taxonomy is one of the most reliable methods for exporting and monitoring personalities (McCrae & John, 1992; Moore & McElroy, 2012; Ryan & Xenos, 2011; Tan, 2012; Zywica & Danowski, 2008). Big Five is based on the notion that users' personality can be ranked on a five-axes model. Every axis represents a specific factor from: Openness to experience, Conscientiousness, Extraversion, Agreeableness and Neuroticism, defined as follows (John et al., 2008).

In literature each one of the five factors has been examined, showing associations with the way

users interact on social media. Furthermore, several of the measurable activities on social media are believed to be influenced by each of the five factor model, negatively or positively.

Some of them indicate which personalities use Facebook under certain conditions (Carpenter et al., 2011). Others (Amichai-Hamburger & Vinitzky, 2010; Ross et al., 2009) found that users with high neuroticism have accurate personal profile information or that users with high extraversion use frequently the internet. Other studies shown that high extraverted and open to new experiences users are less influential that it was though on past studies (Correa et al., 2010). Similar results can be found in more studies (Moore & McElroy, 2012; Ryan & Xenos, 2011). Moore and McElroy (2012) found that extraverted and sentimentally stable users (neuroticism's bipolar factor) are positively related to Facebook usage, but users with low agreeableness and conscientiousness are negatively related.

In their research on US adults, Correa et al. (2010) focus on three of the aforementioned personality traits (Extraversion, Openness and Neuroticism). They claim that Extraversion and Openness are positively related to Facebook usage but Neuroticism is negatively associated. Gender and age have been also associated to Facebook use. Men with increased emotional stability (low levels of Neuroticism), are more regular users as opposed to women. Extraversion and social media usage are associated, mostly among youngsters. On the other hand openness and social media usage are strongly associated among more mature users. A survey among undergraduate students indicated that Extraversion and Agreeableness are positively linked to social media usage, as opposed to Conscientiousness and emotional stability that are negatively associated (Moore and McElroy, 2012). This specific research is one of the first that actually followed the users' profiles, having the users' acceptance, of course, in order to measure the metrics that are related to social media usage. (Ross et al., 2009) claimed that most of the personality factors with the exception of Extraversion and Openness are not so influential, and that low levels on Extraversion and Agreeableness lead to lower number of friends on Facebook. Seidman (2013) in an online survey among 184 undergraduate students found that Agreeableness and Neuroticism form the best predictors of belongingness-related behaviors and motivation. Extraversion has also been associated to frequent Facebook use. Low levels of Conscientiousness and high levels of Neuroticism are positively related to self-presentations.

Mouakket (2017) on a study among university students in the United Arab Emirates associated the Big Five personality traits with user continuance intention towards Facebook.

Cimbaljević (2015) confirms an association between personality traits and decisions regarding the tertiary education. Mariani et al. (2016) developed a scale that measures Facebook intensity, including engagement measurements and integration with specific users' personality in daily life. Their study examines Facebook usage from a self-esteem perspective.

Other studies follow the same procedure, including self-esteem and Facebook intensity to their research (Błachnio et al., 2016; J.-E. R. Lee et al., 2012; Orosz et al., 2015; Skues et al., 2012; Wilson et al., 2010). In particular Skues et al. (2012) found that higher levels in openness are associated with more time spent on Facebook and high number of friends. Loneliness is also correlated to more friends on Facebook based on Skues et al. (2012), Ross et al. (2009) and Mariani (2016). Five studies, examine intentions' sincerity on Facebook in order to clarify if self-presentation on social media can be considered reliable (Back et al., 2010; S. D. Gosling et al., 2007; Hart et al., 2015; Nadkarni & Hofmann, 2012; Seidman, 2013). One study only examines the relationship among personality, Facebook use and leisure activities, finding that there is a positive relationship between time use on Facebook and recreation activities (Kuo & Tang, 2014). Furthermore, attachment theory examines how deep an emotional bond is between two persons. The theory sustains that attachment may not be reciprocal, so an individual may have an attachment with another person which is not shared (Godey et al., 2016). Our study revealed three articles that combine attachment theory with personality traits and Facebook usage. These studies extend the five factor model by adding anxiety and avoidance as complementary factors (Hart et al., 2015; Michael A. Jenkins-Guarnieri et al., 2012; Michael A Jenkins-Guarnieri et al., 2013). One study examines the association between Facebook usage and adolescents, finding that extraverted minors are positively related to Facebook use. In that study, authors associate teenagers, who tend to be influence by peer group pressure, with frequent Facebook usage (Vlachopoulou & Boutsouki, 2014). More analytically and for each trait separately, from the literature review, we obtain:

Openness measures peoples' originality and open-mindedness (Čukić & Bates, 2014). It also reflects the individuals' vividness of imagination. Open to new experience users are correlated with often status updates and participation to Facebook groups (Bachrach et al., 2012). Other

studies confirm that users with high openness tend to use other alternatives of communications rather than Facebook (Guadagno et al., 2008). Especially for Facebook, Amichai-Hamburger and Vinitzky (2010) found that users with high scores on openness tend to share more personal information, confirming a positive association with open to new experience users and social media usage.

Conscientiousness measures the constraint and the control of impulse. Such individuals are thinking before acting, delaying gratification, following rules and being organized. Individuals with high scores on conscientiousness are reliable and disciplined. Previous studies claim that, because of Facebook nature, conscientious users focus on their goals and try not to be distracted by the medium (Wehrli, 2008). Even if these individuals use Facebook, they do it only for academic purposes or self-improvement (Kuo & Tang, 2014; Mark & Ganzach, 2014). This exact type of personality implies that conscientious users are hesitant with "Like" button but not with photo uploads (Bachrach et al., 2012).

Extraversion measures a person's energy and enthusiasm. Usually extraverted individuals are social, optimistic, active and talkative (Moore & McElroy, 2012). Extravert individuals usually keep a positive way of thinking on their daily life (Augustine & Hemenover, 2008). Extraverted users are positively related to Facebook overall usage and hold a primary role on initiating relationships on Facebook (Michael A. Jenkins-Guarnieri et al. (2012); Vlachopoulou and Boutsouki (2014). An analysis of 133 Facebook profiles indicated that Extraversion is the most dominant trait for the profile accuracy (S. D. Gosling et al. (2007). This is further supported by Back et al. (2010). Their research on 236 German and USA users between 17 and 22 years old concluded that Accuracy was strongest for Extraversion personality trait.

Agreeableness measures a person's altruism and affection. Individuals with high score in agreeableness are more flexible, forgive easier, are kind and sympathetic. Usually they try to avoid conflicts, and that is why such individuals are likely possible not to reject an offer coming from a friend. Agreeableness may also refer to individuals who seek information on internet (J. Choi & Kim, 2014; Nadkarni & Hofmann, 2012; Seidman, 2013). Agreeableness is negatively correlated to Facebook usage on previous studies (Michael A. Jenkins-Guarnieri et al., 2012; Seidman, 2014).

Neuroticism measures a person's negative emotionality and nervousness (John et al., 2008; M.

M. Smith et al., 2014). Neuroticism refers to anxious and nervous by nature personalities. Neurotic individuals often hide some aspects of themselves, but they show them only online (Seidman, 2013). Neuroticism and emotional stability are inversely associated. More high scores on neuroticism an individual obtains, less emotional stability presents. Neurotic users use Internet more frequent, respect to extravert ones (Amichai-Hamburger & Vinitzky, 2010). Regarding social media, neurotic users tend to participate more, trying to create a more attractive profile (Wehrli, 2008).

Concluding, Big Five is the most used model in order to extract personality traits and correlate them with social media measurable activities. The model, though, by itself can only extract useful outcomes related to the personality of users, in this case, of Facebook. Our research is related not only to behaviors and personalities, but to behavioral intentions as well. That means that an effective but simple model like Big Five cannot export complete results if a behavioral model together with a personality trait model is used in combination with it. For that purpose, we will use the Theory of Planned Behavior, and together with Big Five we will create a new and extended model of behavioral predictions related to eHealth. Next, TPB is presented and analyzed to its factors. Furthermore we present the rationale behind the specific model's choice. The Theory of Planned Behavior introduces a new independent variable the Perceived Behavioral Control. PBC is determined by the availability of skills, resources, and opportunities, as well as the perceived importance of those skills, resources, and opportunities to achieve outcomes. Changing one of the three predictors of TPB model, the intention to use can be increased and as a result the actual behavior towards an action is increasing. Figure 3.1 presents the main framework of TPB and its internal variables' dependencies.

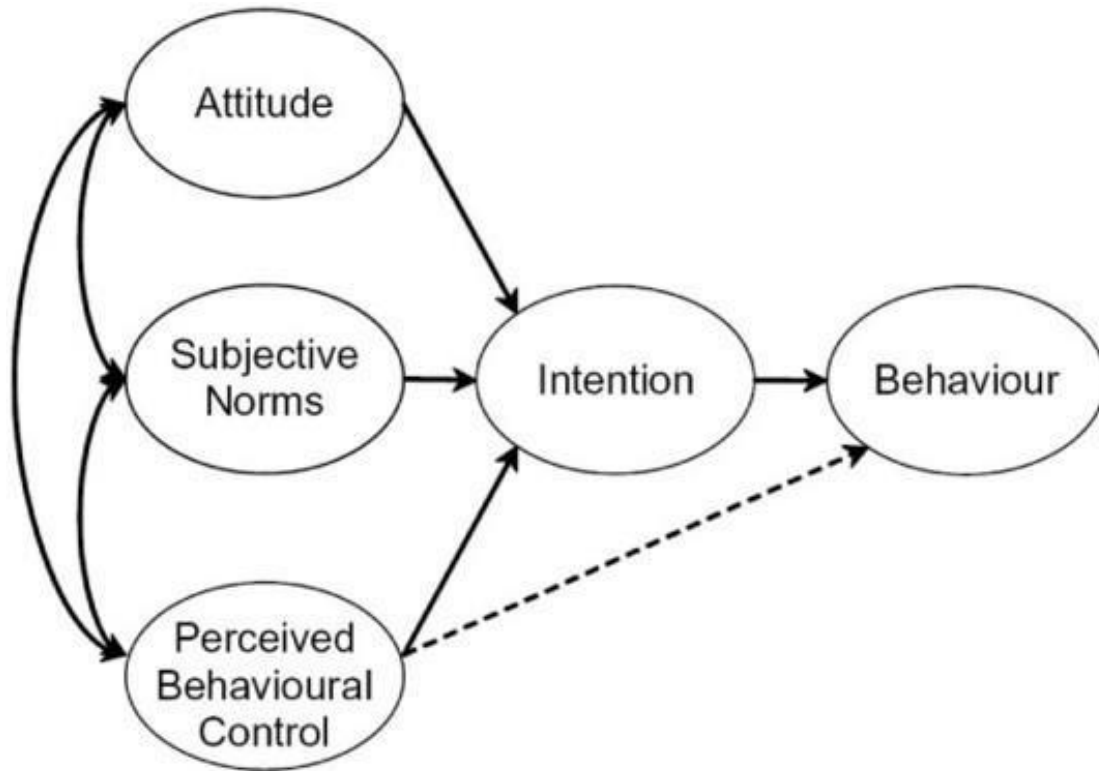


Figure 3.1: The Theory of Planned Behavior

TPB and has been the explicit theoretical basis for many studies over various contextual settings. The evolution of TPB is called Decomposed TPB and practically explores the dimensions of attitude belief, subjective norm (social influence) and perceived behavioral control by decomposing them into specific belief dimensions: perceived usefulness (PU), perceived ease of use (PEOU), and compatibility. These three factors have been found to be consistently related specifically to technology usage (Taylor & Todd, 1995).

The present research uses TPB for two main reasons: TPB has been widely used for health behavior predictions. Furthermore, the addition of the Big Five model as extra variables on TPB provides a more comprehensive theoretical perspective of the user's acceptance and final behavior in the context of eHealth features of Facebook (Branley & Covey, 2018). TPB derives from TRA and it was first developed by Ajzen (1985). In TPB the performance of a person's particular behavior can be predicted by three variables: the attitude of a person towards the behavior (ATT), the subjective norms (SN) and the perceived behavioral control (PBC). These three variables lead to the intention (I) towards a specific behavior (I), affecting finally the

individual's actual behavior. The model used for the present research needed to be extended and use a plethora of new independent variables, in specific the five components of the Big Five model. Among the theories/ models that use subjective norm as a variable (necessary to our research), TPB was the only one that, even extended, gave secure results, in comparison with the other models that include subjective norm. Over the next two chapters, we analyze the methodology used as well as the statistical analysis conducted on the research model, using structural equation modeling. Summarizing, the model used in the dissertation represents an extension of two models: Big Five and Theory of Planned Behavior. The resulting model is a combination of the two aforementioned models, where the Big Five factors are independent variables and the TPB both depended and independent ones, depending each time on the hypothesis.

Summarizing, the model used in the dissertation represents the combination of two models: Big Five and Theory of Planned Behavior, where the Big Five factors are independent variables and the TPB both depended and independent ones, depending each time on the hypothesis. The proposed model called "eHePeBe-SMA" is shown on Figure 3.2. The part of the Big Five model is called Pe, from the Personality traits and the TPB is called Be (Behavior). The field of research is eHealth (e-He) and our initial apply is occurred on social media users' behavior analysis (SMA).

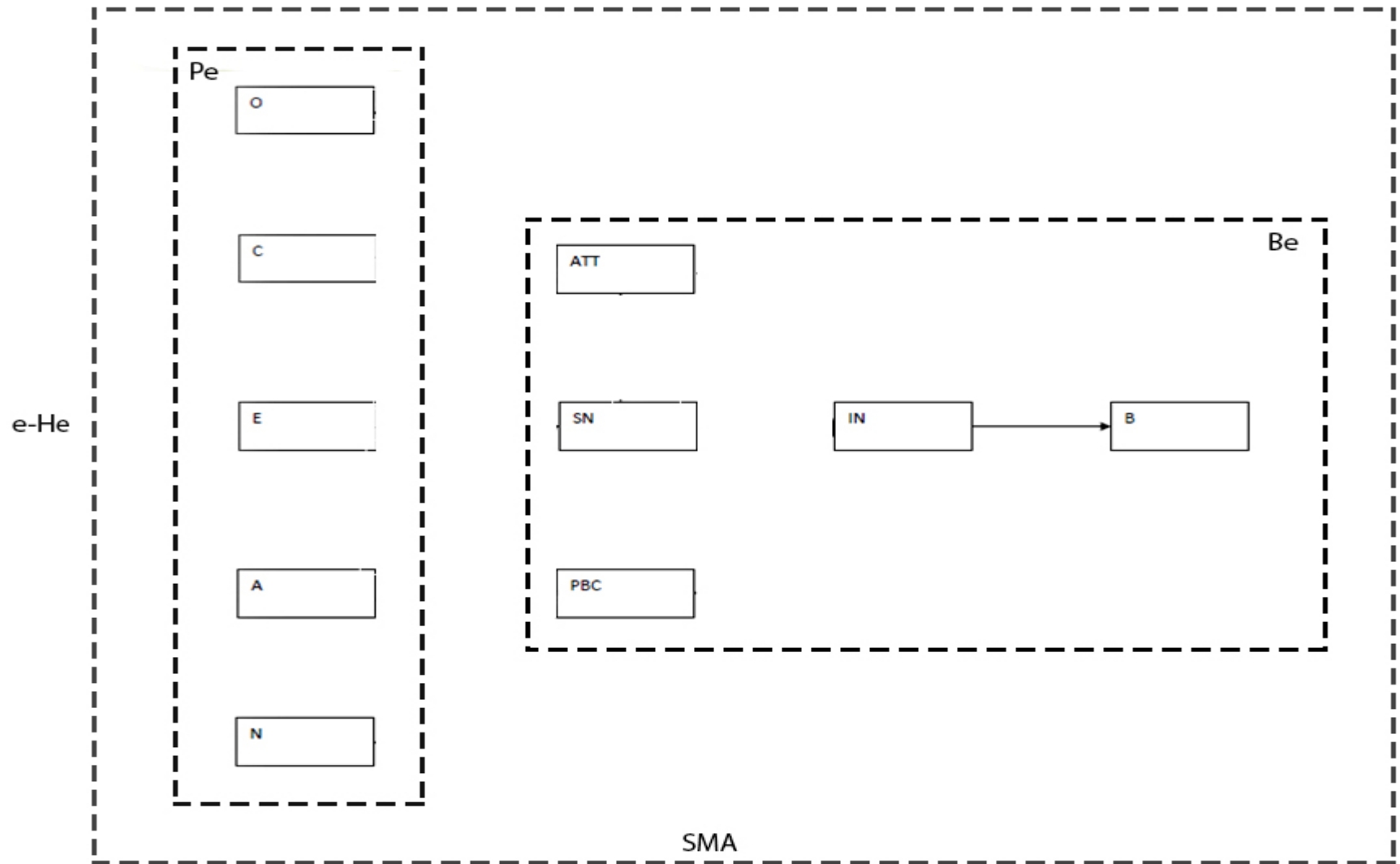


Figure 3.2: The 'e-HePeBe-SMA' proposed framework

References

- Aluja, A., García, Ó., & García, L. F. (2002). A comparative study of Zuckerman's three structural models for personality through the NEO-PI-R, ZKPQ-III-R, EPQ-RS and Goldberg's 50-bipolar adjectives. *Personality and Individual Differences, 33*(5), 713-725.
- Amichai-Hamburger, Y., & Vinitzky, G. (2010). Social network use and personality. *Computers in Human Behavior, 26*(6), 1289-1295. doi: <http://dx.doi.org/10.1016/j.chb.2010.03.018>
- Ashton, M. C., & Lee, K. (2009). The HEXACO-60: A short measure of the major dimensions of personality. *Journal of personality assessment, 91*(4), 340-345.
- Augustine, A. A., & Hemenover, S. H. (2008). Extraversion and the consequences of social interaction on affect repair. *Personality and Individual Differences, 44*(5), 1151-1161. doi: <http://dx.doi.org/10.1016/j.paid.2007.11.009>
- Bachrach, Y., Kosinski, M., Graepel, T., Kohli, P., & Stillwell, D. (2012). *Personality and patterns of Facebook usage*. Paper presented at the Proceedings of the 4th Annual ACM Web Science Conference, Evanston, Illinois.
- Back, M. D., Stopfer, J. M., Vazire, S., Gaddis, S., Schmukle, S. C., Egloff, B., & Gosling, S. D. (2010). Facebook profiles reflect actual personality, not self-idealization. *Psychological science*.
- Błachnio, A., Przepiorka, A., & Rudnicka, P. (2016). Narcissism and self-esteem as predictors of dimensions of Facebook use. *Personality and Individual Differences, 90*, 296-301.
- Carpenter, J. M., Green, M. C., & LaFlam, J. (2011). People or profiles: Individual differences in online social networking use. *Personality and Individual Differences, 50*(5), 538-541. doi: <http://dx.doi.org/10.1016/j.paid.2010.11.006>
- Cattell, H. E., & Mead, A. D. (2008). The sixteen personality factor questionnaire (16PF). *The SAGE handbook of personality theory and assessment, 2*, 135-178.
- Choi, J., & Kim, Y. (2014). The moderating effects of gender and number of friends on the relationship between self-presentation and brand-related word-of-mouth on Facebook. *Personality and Individual Differences, 68*(0), 1-5. doi: <http://dx.doi.org/10.1016/j.paid.2014.03.040>
- Coan, R. W., & Cattell, R. B. (1959). The development of the early school personality questionnaire. *The Journal of Experimental Education, 28*(2), 143-152.

- Correa, T., Hinsley, A. W., & de Zúñiga, H. G. (2010). Who interacts on the Web?: The intersection of users' personality and social media use. *Computers in Human Behavior*, 26(2), 247-253. doi: <http://dx.doi.org/10.1016/j.chb.2009.09.003>
- Costa Jr, P. T., & McCrae, R. R. (1992). The five-factor model of personality and its relevance to personality disorders. *Journal of Personality Disorders*, 6(4), 343.
- Čukić, I., & Bates, T. C. (2014). Openness to experience and aesthetic chills: Links to heart rate sympathetic activity. *Personality and Individual Differences*, 64(0), 152-156. doi: <http://dx.doi.org/10.1016/j.paid.2014.02.012>
- Duggan, M. (2015). Mobile messaging and social media. *Pew Research Center*. Retrieved from <http://www.pewinternet.org/2015/08/19/mobile-messaging-and-social-media-2015/>
- 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. doi: <http://dx.doi.org/10.1016/j.jbusres.2016.04.181>
- Gosling, D., Augustine, A., Vazire, S., Holtzman, N., & Gaddis, S. (2011). Manifestation of personality in online social networks: Self-reported facebook-related behaviors and observable profile information. *Cyberpsychology, behavior and social networking*, 14, 483-488.
- Gosling, S. D., Gaddis, S., & Vazire, S. (2007). Personality Impressions Based on Facebook Profiles. *ICWSM*, 7, 1-4.
- Guadagno, R. E., Okdie, B. M., & Eno, C. A. (2008). Who blogs? Personality predictors of blogging. *Computers in Human Behavior*, 24(5), 1993-2004. doi: <http://dx.doi.org/10.1016/j.chb.2007.09.001>
- Hall, J. A., & Pennington, N. (2013). Self-monitoring, honesty, and cue use on Facebook: The relationship with user extraversion and conscientiousness. *Computers in Human Behavior*, 29(4), 1556-1564. doi: <http://dx.doi.org/10.1016/j.chb.2013.01.001>
- Hart, J., Nailling, E., Bizer, G. Y., & Collins, C. K. (2015). Attachment theory as a framework for explaining engagement with Facebook. *Personality and Individual Differences*, 77, 33-40.
- Jenkins-Guarnieri, M. A., Wright, S. L., & Hudiburgh, L. M. (2012). The relationships among attachment style, personality traits, interpersonal competency, and Facebook use. *Journal*

- of *Applied Developmental Psychology*, 33(6), 294-301. doi: <http://dx.doi.org/10.1016/j.appdev.2012.08.001>
- Jenkins-Guarnieri, M. A., Wright, S. L., & Johnson, B. D. (2013). The interrelationships among attachment style, personality traits, interpersonal competency, and Facebook use. *Psychology of Popular Media Culture*, 2(2), 117.
- John, Naumann, L., & Soto, C. (2008). Paradigm Shift to the Integrative Big Five Trait Taxonomy: History, Measurement, and Conceptual Issues. In O. John, R. Robbins & L. Pervin (Eds.), *Handbook of Personality: Theory and Research* (pp. 114-156): Guilford.
- Karson, S., & O'Dell, J. W. (1976). A guide to the clinical use of the 16 PF.
- Kuo, T., & Tang, H.-L. (2014). Relationships among personality traits, Facebook usages, and leisure activities – A case of Taiwanese college students. *Computers in Human Behavior*, 31(0), 13-19. doi: <http://dx.doi.org/10.1016/j.chb.2013.10.019>
- Lee, J.-E. R., Moore, D. C., Park, E.-A., & Park, S. G. (2012). Who wants to be “friend-rich”? Social compensatory friending on Facebook and the moderating role of public self-consciousness. *Computers in Human Behavior*, 28(3), 1036-1043. doi: <http://dx.doi.org/10.1016/j.chb.2012.01.006>
- Lee, K., & Ashton, M. (2004). The HEXACO Personality Inventory: A new measure of the major dimensions of personality. *Multivariate Behavioral Research*, 39(2), 329-358.
- Lee, K., & Ashton, M. C. (2008). The HEXACO personality factors in the indigenous personality lexicons of English and 11 other languages. *Journal of Personality*, 76(5), 1001-1054.
- Lichtenstein, D., Dreger, R. M., & Cattell, R. B. (1986). Factor structure and standardization of the Preschool Personality Questionnaire. *Journal of Social Behavior and Personality*, 1(2), 165.
- Mariani, M. M., Di Felice, M., & Mura, M. (2016). Facebook as a destination marketing tool: Evidence from Italian regional Destination Management Organizations. *Tourism Management*, 54, 321-343. doi: <http://dx.doi.org/10.1016/j.tourman.2015.12.008>
- Mark, G., & Ganzach, Y. (2014). Personality and Internet usage: A large-scale representative study of young adults. *Computers in Human Behavior*, 36(0), 274-281. doi: <http://dx.doi.org/10.1016/j.chb.2014.03.060>

- McCrae, R. R., & John, O. P. (1992). An Introduction to the Five-Factor Model and Its Applications. *Journal of Personality*, 60(2), 175-215. doi: 10.1111/j.1467-6494.1992.tb00970.x
- Moore, K., & McElroy, J. C. (2012). The influence of personality on Facebook usage, wall postings, and regret. *Computers in Human Behavior*, 28(1), 267-274. doi: <http://dx.doi.org/10.1016/j.chb.2011.09.009>
- Mouakket, S. (2017). The role of personality traits in motivating users' continuance intention towards Facebook: Gender differences. *The Journal of High Technology Management Research*. doi: <https://doi.org/10.1016/j.hitech.2016.10.003>
- Nadkarni, A., & Hofmann, S. G. (2012). Why do people use Facebook? *Personality and Individual Differences*, 52(3), 243-249. doi: <http://dx.doi.org/10.1016/j.paid.2011.11.007>
- Orosz, G., Tóth-Király, I., & Bőthe, B. (2015). Four facets of Facebook intensity—The development of the Multidimensional Facebook Intensity Scale. *Personality and Individual Differences*.
- Ross, C., Orr, E. S., Sisic, M., Arseneault, J. M., Simmering, M. G., & Orr, R. R. (2009). Personality and motivations associated with Facebook use. *Computers in Human Behavior*, 25(2), 578-586. doi: <http://dx.doi.org/10.1016/j.chb.2008.12.024>
- Ryan, T., & Xenos, S. (2011). Who uses Facebook? An investigation into the relationship between the Big Five, shyness, narcissism, loneliness, and Facebook usage. *Computers in Human Behavior*, 27(5), 1658-1664. doi: <http://dx.doi.org/10.1016/j.chb.2011.02.004>
- Saucier, G. (2009). Recurrent personality dimensions in inclusive lexical studies: Indications for a Big Six structure. *Journal of Personality*, 77(5), 1577-1614.
- Schuerger, J. (1995). Career assessment and the sixteen personality factor questionnaire. *Journal of Career Assessment*, 3(2), 157-175.
- Seidman, G. (2013). Self-presentation and belonging on Facebook: How personality influences social media use and motivations. *Personality and Individual Differences*, 54(3), 402-407. doi: <http://dx.doi.org/10.1016/j.paid.2012.10.009>
- Seidman, G. (2014). Expressing the “True Self” on Facebook. *Computers in Human Behavior*, 31(0), 367-372. doi: <http://dx.doi.org/10.1016/j.chb.2013.10.052>

- Skues, J. L., Williams, B., & Wise, L. (2012). The effects of personality traits, self-esteem, loneliness, and narcissism on Facebook use among university students. *Computers in Human Behavior*, 28(6), 2414-2419. doi: <http://dx.doi.org/10.1016/j.chb.2012.07.012>
- Smith, M. M., Saklofske, D. H., & Nordstokke, D. W. (2014). The link between neuroticism and perfectionistic concerns: The mediating effect of trait emotional intelligence. *Personality and Individual Differences*, 61–62(0), 97-100. doi: <http://dx.doi.org/10.1016/j.paid.2013.12.013>
- statista.com. (2018). Number of monthly active Facebook users worldwide as of 3rd quarter 2017 (in millions) Retrieved 01-29-2016, 2018, from Number of monthly active Facebook users worldwide as of 3rd quarter 2017 (in millions)
- Tan, W., Yang, C. (2012). *Personality Traits Predictors of Usage of Internet Services*. Paper presented at the International Conference on Economics, Business Innovation, Singapore.
- Vlachopoulou, E., & Boutsouki, C. (2014). Facebook usage among teenagers—the effect of personality and peer group pressure; an exploratory study in Greece. *International Journal of Internet Marketing and Advertising*, 8(4), 285-299.
- Wang, J.-L., Jackson, L. A., Zhang, D.-J., & Su, Z.-Q. (2012). The relationships among the Big Five Personality factors, self-esteem, narcissism, and sensation-seeking to Chinese University students' uses of social networking sites (SNSs). *Computers in Human Behavior*, 28(6), 2313-2319. doi: <http://dx.doi.org/10.1016/j.chb.2012.07.001>
- Wehrli, S. (2008). Personality on social network sites: An application of the five factor model. *Zurich: ETH Sociology (Working Paper No. 7)*.
- Wilson, K., Fornasier, S., & White, K. M. (2010). Psychological predictors of young adults' use of social networking sites. *Cyberpsychology, Behavior, and Social Networking*, 13(2), 173-177.
- Zuckerman, M. (2002). Zuckerman-Kuhlman Personality Questionnaire (ZKPQ): an alternative five-factorial model. *Big five assessment*, 377-396.
- Zuckerman, M., Kuhlman, D. M., Thornquist, M., & Kiers, H. (1991). Five (or three) robust questionnaire scale factors of personality without culture. *Personality and Individual Differences*, 12(9), 929-941.
- Zywica, J., & Danowski, J. (2008). The Faces of Facebookers: Investigating Social Enhancement and Social Compensation Hypotheses; Predicting Facebook™ and Offline Popularity

- from Sociability and Self-Esteem, and Mapping the Meanings of Popularity with Semantic Networks. *Journal of Computer-Mediated Communication*, 14(1), 1-34. doi: 10.1111/j.1083-6101.2008.01429.x
- Ajzen, I. (1985). From Intentions to Actions: A Theory of Planned Behavior. In J. Kuhl & J. Beckmann (Eds.), *Action Control: From Cognition to Behavior* (pp. 11-39). Berlin, Heidelberg: Springer Berlin Heidelberg.
- Bandura, A. (2010). Modeling. *The Corsini encyclopedia of psychology*, 1-3.
- Benbasat, I., & Barki, H. (2007). Quo vadis TAM? *Journal of the association for information systems*, 8(4), 7.
- Bhattacharjee, A. (2001). Understanding information systems continuance: an expectation-confirmation model. *MIS Quarterly*, 351-370.
- Branley, D. B., & Covey, J. (2018). Risky behavior via social media: The role of reasoned and social reactive pathways. *Computers in Human Behavior*, 78(Supplement C), 183-191. doi: <https://doi.org/10.1016/j.chb.2017.09.036>
- Colley, A., & Comber, C. (2003). Age and gender differences in computer use and attitudes among secondary school students: what has changed? *Educational Research*, 45(2), 155-165.
- Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: a comparison of two theoretical models. *Management science*, 35(8), 982-1003.
- Eftekhari, A., Fullwood, C., & Morris, N. (2014). Capturing personality from Facebook photos and photo-related activities: How much exposure do you need? *Computers in Human Behavior*, 37(0), 162-170. doi: <http://dx.doi.org/10.1016/j.chb.2014.04.048>
- Fishbein, M. (2008). A reasoned action approach to health promotion. *Medical Decision Making*, 28(6), 834-844.
- Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behavior: An introduction to theory and research*.
- Geurin, A. N., & Burch, L. M. (2016). User-generated branding via social media: An examination of six running brands. *Sport Management Review*. doi: <http://dx.doi.org/10.1016/j.smr.2016.09.001>
- Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, 213-236.

- Kavanaugh, A. L., Fox, E. A., Sheetz, S. D., Yang, S., Li, L. T., Shoemaker, D. J., . . . Xie, L. (2012). Social media use by government: From the routine to the critical. *Government Information Quarterly*, 29(4), 480-491. doi: <http://dx.doi.org/10.1016/j.giq.2012.06.002>
- Losh, S. C. (2004). Gender, educational, and occupational digital gaps 1983-2002. *Social Science Computer Review*, 22(2), 152-166.
- Louho, R., Kallioja, M., & Oittinen, P. (2006). Factors affecting the use of hybrid media applications. *Graphic arts in Finland*, 35(3), 11-21.
- Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research*, 460-469.
- Oye, N., Iahad, N., & Rahim, N. A. (2014). The history of UTAUT model and its impact on ICT acceptance and usage by academicians. *Education and Information Technologies*, 19(1), 251-270.
- Rogers, E. M. (2002). Diffusion of preventive innovations. *Addictive Behaviors*, 27(6), 989-993.
- Rogers, E. M., & Shoemaker, F. F. (1971). *Communication of Innovations; A Cross-Cultural Approach*.
- Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. *Information Systems Research*, 6(2), 144-176.
- Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision sciences*, 39(2), 273-315.
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, 46(2), 186-204.
- Venkatesh, V., & Goyal, S. (2010). Expectation disconfirmation and technology adoption: polynomial modeling and response surface analysis. *MIS Quarterly*, 281-303.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425-478.

Chapter 4.

Social Media usage on the eHealth field

Social media represents today the most promising field on social science with the media platforms to have penetrated in every aspect of life and science. eHealth represents one of the most interesting fields of study, both for the importance and sensitivity of the data and the predictive capabilities. Behavioral analysis, as a sub-sector of social media analysis uses a plethora of tools, models and theories. Two of them are the Big Five Personality trait model and the Theory of Planned Behavior, for personality analysis and intentional behavior analysis, respectively. Furthermore, the hypotheses formulation is analyzed, after a short introduction to the two basic models used on the dissertation, the Big Five and the Theory of Planned Behavior. Conceptual definition of the research variables are given as well as the literature this study based for the research hypotheses. Finally the analytical definitions of the research hypotheses are provided.

4.1. Boolean research of the literature

Social media usage is penetrated in every field of science, rendering the Data Analysis one of the most promising sectors. In specific, eHealth represents one of the most interesting fields not only for the sensitivity of data but also for the importance of the insights that can be extracted from the analysis. Scientific literature contains thousands of articles related to social media. Analytically, from our literature research, we obtained the following results:

The first specified Boolean research on the most important libraries was containing the keywords Facebook, 'Theory of Planned Behavior' and eHealth. This result returned 43 results. Only three of them were somehow relative but none of them used Facebook as the primary platform or TPB as the basic intention theory (Bhattacharya et al., 2018; Freeman, Caldwell, Bennett, & Scott, 2018; Godino et al., 2016). The next Boolean research consisted on adding the term 'Big Five' on the research, returning 24 results. The fields of study vary in these results, fluctuating from public discussion fields (Dixit, Jyoti Badgaiyan, & Khare, 2017; Koban, Stein, Eckhardt, & Ohler, 2018), to gender differences studies (Mouakket, 2017), social media addictions (Tang,

Chen, Yang, Chung, & Lee, 2016), measurable activities on Facebook, such as posting, likes, friend requests etc. (Heirman et al., 2016; E. Kim, Lee, Sung, & Choi, 2016; S.-Y. Lee, Hansen, & Lee, 2016) and Web 2.0 technology acceptance and usage (Koohikamali, Peak, & Prybutok, 2017; Rauschnabel, Rossmann, & tom Dieck, 2017; Terzis, Moridis, & Economides, 2012; Xu, Frey, Fleisch, & Ilic, 2016). Once again, none of the aforementioned studies is similar to the present. The last Boolean research was conducting using the most specific keywords related to the present dissertation (Facebook AND (TPB OR 'Theory of Planned Behavior') AND 'Big Five' AND (eHealth OR wellbeing OR 'well being' OR 'leisure activities' OR 'healthy diet') returning 0 results.

To the best of our knowledge this is the first primary research on that combination of field. The originality of this research consists of correlating TPB and personality traits of Big Five model on the field of eHealth, in specific healthy diet and leisure activities that are suggested by relevant pages and/ or groups on Facebook.

4.2. Models used and hypotheses formulation

Our selected models (Big Five and Theory of Planned Behavior) are two of the most used methodologies in social science. Big Five classifies through percentages a user's personality among the five traits, namely Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism. Theory of Planned Behavior analyzes the intention to act in a certain way, taking into consideration 5 factors, namely Attitude (ATT), Subjective norms (SN), Perceived behavioral control (PBC), Intention to behavior (I) and actual Behavior (B).

Both Big Five and TPB are two of the most reliable methods for exporting and monitoring personalities and behaviors (McCrae & John, 1992; Moore & McElroy, 2012; Ryan & Xenos, 2011; Tan, 2012; Zywicki & Danowski, 2008).

In literature each one of the five factors has been examined, showing associations with the way users interact on social media. Furthermore, several of the measurable activities on social media are believed to be influenced by each of the five factor model, negatively or positively.

Some of them indicate which personalities use Facebook under certain conditions (Carpenter, Green, & LaFlam, 2011). Others (Amichai-Hamburger & Vinitzky, 2010; Ross et al., 2009) found that users with high neuroticism have accurate personal profile information or that users

with high extraversion use frequently the internet. Other studies shown that high extraverted and open to new experiences users are less influential that it was though on past studies (Correa, Hinsley, & de Zúñiga, 2010). Similar results can be found in more studies (Moore & McElroy, 2012; Ryan & Xenos, 2011). Moore and McElroy (2012) found that extraverted and sentimentally stable users (neuroticism's bipolar factor) are positively related to Facebook usage, but users with low agreeableness and conscientiousness are negatively related.

Cimbaljević (2015) confirms an association between personality traits and decisions regarding the tertiary education. Mariani, Di Felice, and Mura (2016) developed a scale that measures Facebook intensity, including engagement measurements and integration with specific users' personality in daily life. Their study examines Facebook usage from a self-esteem perspective.

Other studies follow the same procedure, including self-esteem and Facebook intensity to their research (Błachnio, Przepiorka, & Rudnicka, 2016; J.-E. R. Lee, Moore, Park, & Park, 2012; Orosz, Tóth-Király, & Bóthe, 2015; Skues, Williams, & Wise, 2012; Wilson, Fornasier, & White, 2010). In particular Skues et al. (2012) found that higher levels in openness are associated with more time spent on Facebook and high number of friends. Loneliness is also correlated to more friends on Facebook based on Skues et al. (2012), Ross et al. (2009) and Mariani et al. (2016). Five studies, examine intentions' sincerity on Facebook in order to clarify if self-presentation on social media can be considered reliable (Back et al., 2010; S. D. Gosling, Gaddis, & Vazire, 2007; Hart, Nailling, Bizer, & Collins, 2015; Nadkarni & Hofmann, 2012; Seidman, 2013). One study only examines the relationship among personality, Facebook use and leisure activities, finding that there is a positive relationship between time use on Facebook and recreation activities (Kuo & Tang, 2014). Furthermore, attachment theory examines how deep an emotional bond is between two persons. The theory sustains that attachment may not be reciprocal, so an individual may have an attachment with another person which is not shared (Godey et al., 2016). Our study revealed three articles that combine attachment theory with personality traits and Facebook usage. These studies extend the five factor model by adding anxiety and avoidance as complementary factors (Hart et al., 2015; Michael A. Jenkins-Guarnieri, Wright, & Hudiburgh, 2012; Michael A Jenkins-Guarnieri, Wright, & Johnson, 2013). Analytically, for each personality trait, we obtain the specific literature review.

Openness measures peoples' originality and open-mindedness (Čukić & Bates, 2014). It also reflects the individuals' vividness of imagination. Open to new experience users are correlated

with often status updates and participation to Facebook groups (Bachrach, Kosinski, Graepel, Kohli, & Stillwell, 2012). Other studies confirm that users with high openness tend to use other alternatives of communications rather than Facebook (Guadagno, Okdie, & Eno, 2008). Especially for Facebook, Amichai-Hamburger and Vinitzky (2010) found that users with high scores on openness tend to share more personal information, confirming a positive association with open to new experience users and social media usage.

Conscientiousness measures the constraint and the control of impulse. Such impulses are thinking before acting, delaying gratification, following rules and being organized. Individuals with high scores on conscientiousness are reliable and disciplined. Previous studies claim that, because of Facebook's nature, conscientious users focus on their goals and try not to be distracted by the medium (Wehrli, 2008). Even if these individuals use Facebook, they do it only for academic purposes or self-improvement (Kuo & Tang, 2014; Mark & Ganzach, 2014). This exact type of personality implies that conscientious users are hesitant with "Like" button but not with photo uploads (Bachrach et al., 2012).

Extraversion measures a person's energy and enthusiasm. Usually extraverted individuals are social, optimistic, active and talkative (Moore & McElroy, 2012). Extravert individuals usually keep a positive way of thinking on their daily life (Augustine & Hemenover, 2008). Vlachopoulou and Boutsouki (2014) and Michael A. Jenkins-Guarnieri et al. (2012) confirm that extraverted users are positively related to Facebook overall usage. Furthermore they find associations between extraversion and Facebook use intensity, explaining why extraversion holds a primary role on initiating relationships on Facebook.

Agreeableness measures a person's altruism and affection. Individuals with high score in agreeableness are more flexible, forgive easier, and are kind and sympathetic. Usually they try to avoid conflicts, and that is why such individuals are likely possible not to reject an offer coming from a friend. Agreeableness may also refer to individuals who seek information on internet (J. Choi & Kim, 2014; Nadkarni & Hofmann, 2012; Seidman, 2013). Agreeableness is negatively correlated to Facebook usage on previous studies (Michael A. Jenkins-Guarnieri et al., 2012; Seidman, 2014).

Neuroticism measures a person's negative emotionality and nervousness (John, Naumann, & Soto, 2008; M. M. Smith, Saklofske, & Nordstokke, 2014). Neuroticism refers to anxious and nervous by nature personalities. Neurotic individuals often hide some aspects of themselves, but

they show them only online (Seidman, 2013). Neuroticism and emotional stability are inversely associated. More high scores on neuroticism an individual obtains, less emotional stability presents. Neurotic users use Internet more frequent, respect to extravert ones (Amichai-Hamburger & Vinitzky, 2010). Regarding social media, neurotic users tend to participate more, trying to create a more attractive profile (Wehrli, 2008).

TBP is a theory that explains individuals' behavior. Basic concept of TBP is the fact that every individual has the intention of particular behaviors. These behaviors are determined by attitude (ATT), subjective norms (SN) and perceived behavioral control (PBC).

Attitude is defined as a person's demeanor towards a behavior that shapes the individual's behavioral intention and actual behavior. Aizen (1985) proposed that attitude is the main factor that develops the intention of using something. Other studies proved that attitude is also related to technology adoption. Several studies associate attitude with social media and technology usage, on the fields of e-Government (Ozkan & Kanat, 2011) or on specific platforms like Facebook (Al-Debei, Al-Lozi, & Papazafeiropoulou, 2013; Chang & Chen, 2014a; Pi, Chou, & Liao, 2013) or online communities (Hajli, Shanmugam, Powell, & Love, 2015). Thus, we propose the following hypotheses, regarding the association between ATT and diverse Big Five's personality traits as well as between ATT and TPB concepts:

Hypothesis #1: There is a positive correlation between Openness and Attitude towards the use of Facebook pages related to healthy diet and sport activities

Hypothesis #2: There is a positive correlation between Extraversion and Attitude towards the use of Facebook pages related to healthy diet and sport activities

Hypothesis #3: There is a positive correlation between Agreeableness and Attitude towards the use of Facebook pages related to healthy diet and sport activities

Hypothesis #4: There is a positive correlation between Attitude and Intention towards the use of Facebook pages related to healthy diet and sport activities

Subjective Norms refer to individuals' awareness of social influence from their narrow social circle to follow or not to follow a certain behavior (Ajzen, 1991). Ajzen's assumption was that individuals tend to behave in such a way as to be accepted by their important referents. Godin and Kok (1996) and Hagger, Chatzisarantis, and Biddle (2002) studied SN in relation to ATT and PBC, finding that SN in a weaker predictor for the Intention, respect to ATT and PBC. Lo, McKercher, Lo, Cheung, and Law (2011) found that SN, regarding Facebook users in specific, influence positively the intention to perform a certain behavior. Thus, we hypothesize the following positive relationship between SN and Big Five's personality traits as well as between SN and TPB components:

Hypothesis #5: There is a positive correlation between Extraversion and Subjective Norms towards the use of Facebook pages related to healthy diet and sport activities

Hypothesis #6: There is a positive correlation between Agreeableness and Subjective Norms towards the use of Facebook pages related to healthy diet and sport activities

Hypothesis #7: There is a positive correlation between Subjective Norms and Intention towards the use of Facebook pages related to healthy diet and sport activities

Hypothesis #8: There is a positive correlation between Subjective Norms and Attitude towards the use of Facebook pages related to healthy diet and sport activities

PBC refers to the amount of the control individuals possess on specific behaviors. In other words, PBC explains how easy or difficult is for a person to perform a certain behavior. Individuals without control over behavioral intentions tend not to perform the behavior, eventually (Trafimow, Sheeran, Conner, & Finlay, 2002). Rosen and Kluemper (2008) associate positively, extraversion and conscientiousness with PBC and negatively neuroticism and PBC. In specific, neuroticism represents a rather doubled-featured trait, since some authors associate neuroticism positively with Facebook usage (Correa et al., 2010; Mehdizadeh, 2010) but others, negatively (Amichai-Hamburger & Vinitzky, 2010). Furthermore, Al-Debei et al. (2013) assert that experienced Facebook users tend to be more frequent due to their abilities and that they will

continue participating on Facebook, leading to a higher intention to continue carrying out the behaviors. Next we present the hypotheses formulated regarding PBC and Big Five and TPB:

Hypothesis #9: There is a positive correlation between Conscientiousness and Perceived Behavioral Control towards the use of Facebook pages related to healthy diet and sport activities

Hypothesis #10: There is a positive correlation between Extraversion and Perceived Behavioral Control towards the use of Facebook pages related to healthy diet and sport activities

Hypothesis #11: There is a negative correlation between Neuroticism and Perceived Behavioral Control towards the use of Facebook pages related to healthy diet and sport activities

Hypothesis #12: There is a positive correlation between Perceived Behavioral Control and Intention towards the use of Facebook pages related to healthy diet and sport activities

Table 4.1 summarizes the references for each hypothesis formulated by the study and Table 4.2 provides the definitions, the descriptions of the research hypotheses and the paths for each hypothesis (H.-H. Chen & Chen, 2008; D. Lee, Chung, & Kim, 2013; Liang, Ling, Yeh, & Lin, 2013; Lin, Huang, Chang, & Jheng, 2013; Shih, 2011).

Table 4.1: The conceptual definitions of the research variables

Research Variables	Conceptual description	References
Openness (O)	Openness measures peoples' originality and open-mindedness. Openness to new experiences describes how original or complex an individual is in his life	Čukić and Bates (2014) D.-H. Choi and Shin (2017); D. Liu and Campbell (2017)
Conscientiousness (C)	Conscientiousness measures the constraint and the control of impulse. Such impulses are thinking before	J. Choi and Kim (2014); Nadkarni and Hofmann (2012); Seidman (2014)

Research Variables	Conceptual description	References
	acting, delaying gratification, following rules and being organized	
Extraversion (E)	Extraversion measures a person's energy and enthusiasm. Extravert individuals usually have positive way of thinking	Augustine and Hemenover (2008)
Agreeableness (A)	Agreeableness measures a person's altruism and affection. Agreeableness may also refer to individuals who seek information on internet	J. Choi and Kim (2014); Nadkarni and Hofmann (2012); Seidman (2013)
Neuroticism (N)	Neuroticism measures a person's negative emotionality and nervousness Neurotic individuals often hide some aspects of themselves, but they show them only online	John et al. (2008); M. M. Smith et al. (2014) Seidman (2013)
Attitude (ATT)	A person's attitude towards a specific behavior, that shapes the individual's behavioral intention and actual behavior	Al-Debei et al. (2013); Chang and Chen (2014a); Chu and Chen (2016); Hajli et al. (2015); Ozkan and Kanat (2011); Pi et al. (2013)
Subjective Norms (SN)	An individual's perception about a particular behavior, which is influenced by the judgment of significant others (parents, spouse, close friends, teachers)	Al-Debei et al. (2013); Amjad and Wood (2009); Chang and Chen (2014a); Chu and Chen (2016); Hajli et al. (2015); S.-Y. Lee, Hansen, and Lee (2016); Ozkan and Kanat (2011); Pi

Research Variables	Conceptual description	References
		et al. (2013)
Perceived Behavioral Control (PBC)	An individual's perceived ease (or difficulty) of performing a particular behavior. PBC is determined by the total set of accessible control beliefs. In general PBC adds to the effort a person will apply to a behavior. It is an independent variable that determines behavior as attitude and subjective norms remain constant	Al-Debei et al. (2013); Armitage (2005); Chang and Chen (2014a); Chu and Chen (2016); Hajli et al. (2015); Ozkan and Kanat (2011); Pi et al. (2013)
Intention (IN)	An indication of an individual's readiness to perform a given behavior. It is assumed to be an immediate antecedent of behavior. It is based on attitude towards the behavior, SN and PBC, with each predictor weighted for its importance in relation to the behavior and population of interest	Ahmad et al. (2014); Ajzen (2002); Bozionelos and Bennett (1999)
Behavior (B)	An individual's observable response in a given situation with respect to a given target. A behavior is a function of compatible intentions and perceptions of behavioral control, in that perceived behavioral control is expected to moderate the effect of intention on behavior, such that a favorable intention produces the behavior only when perceived behavioral control is strong	Ajzen (1991, 2002)

Each hypothesis was based on previous research that explained the field. Of course the research gap was such, so new definition of each hypothesis needed to be given and therefore to create the proposed model of the present dissertation. Table 4.2 provides with the main literature for each hypothesis analyzed in the present study.

Table 4.2: References for research hypotheses

Hypothesis	References
H1	Blackhart, Fitzpatrick, and Williamson (2014)
H2	R. Chen (2013)
H3	Xu et al. (2016)
H4	Al-Debei et al. (2013); Chang and Chen (2014a); Chu and Chen (2016); Hajli et al. (2015); Ozkan and Kanat (2011); Pi et al. (2013)
H5	Blackhart et al. (2014); Hoyt et al. (2009)
H6	Xu et al. (2016)
H7	Al-Debei et al. (2013); Chang and Chen (2014a); Chu and Chen (2016); Hajli et al. (2015); S.-Y. Lee et al. (2016); Ozkan and Kanat (2011); Pi et al. (2013)
H8	S.-Y. Lee et al. (2016); Pi et al. (2013)
H9	Hoyt, Rhodes, Hausenblas, and Giacobbi (2009)
H10	Blackhart et al. (2014); R. Chen (2013)
H11	Blackhart et al. (2014); R. Chen (2013); Rosen and Kluemper (2008)
H12	Al-Debei et al. (2013); Chang and Chen (2014a); Chu and Chen (2016); Hajli et al. (2015); Ozkan and Kanat (2011); Pi et al. (2013)

After studying the relevant literature, each hypothesis needs to be defined specifically for our research field. Table 4.3 summarizes these definitions, providing also the path for each hypothesis, noting with a “+” or “-”, whether we refer to positive or negative correlation between the examined variables.

Table 4.3: The definitions of the research hypotheses

Hypothesis	Description	Path**
H1	There is a positive correlation between Openness and Attitude *	$O \rightarrow ATT^+$
H2	There is a positive correlation between Extraversion and Attitude *	$E \rightarrow ATT^+$
H3	There is a positive correlation between Agreeableness and Attitude *	$A \rightarrow ATT^+$
H4	There is a positive correlation between Attitude and Intention *	$ATT \rightarrow IN^+$
H5	There is a positive correlation between Extraversion and Subjective Norms *	$E \rightarrow SN^+$
H6	There is a positive correlation between Agreeableness and Subjective Norms *	$A \rightarrow SN^+$
H7	There is a positive correlation between Subjective Norms and Intention *	$SN \rightarrow IN^+$
H8	There is a positive correlation between Subjective Norms and Attitude *	$SN \rightarrow ATT^+$
H9	There is a positive correlation between Conscientiousness and Perceived Behavioral Control *	$C \rightarrow PBC^+$
H10	There is a positive correlation between Extraversion and Perceived Behavioral Control *	$E \rightarrow PBC^+$
H11	There is a negative correlation between Neuroticism and Perceived Behavioral Control *	$N \rightarrow PBC^-$
H12	There is a positive correlation between Perceived Behavioral Control and Intention *	$PBC \rightarrow IN^+$

* Towards the use of Facebook pages related to healthy diet and sport activities

** Where '+' means positive correlation and '-' a negative one

The aforementioned hypotheses and factors, that work as observed and latent variables are summarized on Figure 4.1. The edges on the figure represent the association between variables,

noted by the number of hypothesis of Table 4.3. On chapter 7, these labels will be replaced by the structural equation modeling measurements, showing the weight for each association (Figure 7.1).

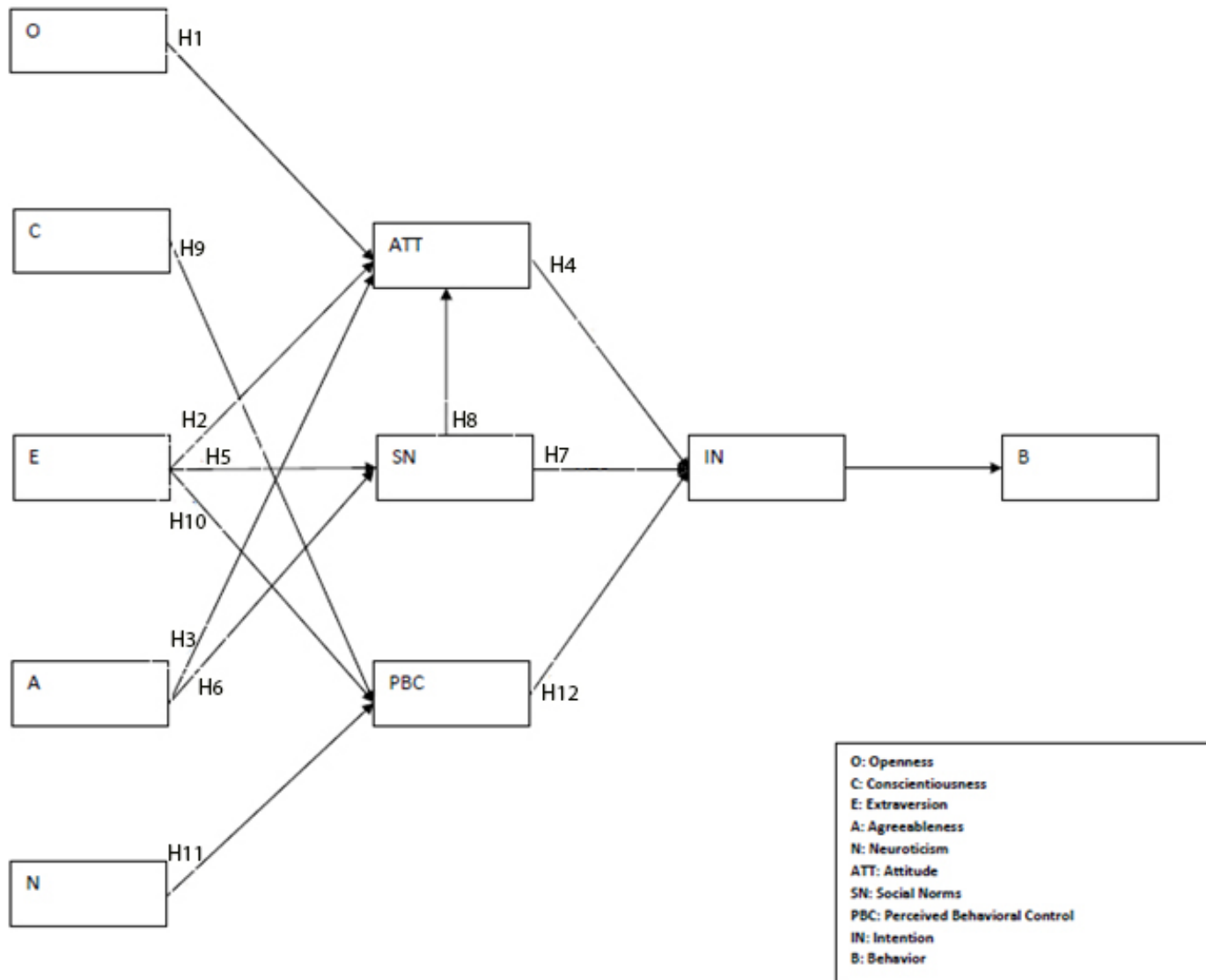


Figure 4.1: Initial conceptual model

References

- Ahmad, M. H., Shahar, S., Teng, N. I. M. F., Manaf, Z. A., Sakian, N. I. M., & Omar, B. (2014). Applying theory of planned behavior to predict exercise maintenance in sarcopenic elderly. *Clinical interventions in aging, 9*, 1551.
- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211.
- Ajzen, I. (2002). Perceived behavioral control, Self-Efficacy, locus of control, and the theory of planned Behavior1. *Journal of applied social psychology, 32*(4), 665-683.
- Al-Debei, M. M., Al-Lozi, E., & Papazafeiropoulou, A. (2013). Why people keep coming back to Facebook: Explaining and predicting continuance participation from an extended theory of planned behaviour perspective. *Decision Support Systems, 55*(1), 43-54. doi: <http://dx.doi.org/10.1016/j.dss.2012.12.032>
- Amichai-Hamburger, Y., & Vinitzky, G. (2010). Social network use and personality. *Computers in Human Behavior, 26*(6), 1289-1295. doi: <http://dx.doi.org/10.1016/j.chb.2010.03.018>
- Amjad, N., & Wood, A. M. (2009). Identifying and changing the normative beliefs about aggression which lead young Muslim adults to join extremist anti-Semitic groups in Pakistan. *Aggressive behavior, 35*(6), 514-519.
- Armitage, C. J. (2005). Can the theory of planned behavior predict the maintenance of physical activity? *Health psychology, 24*(3), 235.
- Augustine, A. A., & Hemenover, S. H. (2008). Extraversion and the consequences of social interaction on affect repair. *Personality and Individual Differences, 44*(5), 1151-1161. doi: <http://dx.doi.org/10.1016/j.paid.2007.11.009>
- Bachrach, Y., Kosinski, M., Graepel, T., Kohli, P., & Stillwell, D. (2012). *Personality and patterns of Facebook usage*. Paper presented at the Proceedings of the 4th Annual ACM Web Science Conference, Evanston, Illinois.
- Back, M. D., Stopfer, J. M., Vazire, S., Gaddis, S., Schmukle, S. C., Egloff, B., & Gosling, S. D. (2010). Facebook profiles reflect actual personality, not self-idealization. *Psychological science*.
- Błachnio, A., Przepiorka, A., & Rudnicka, P. (2016). Narcissism and self-esteem as predictors of dimensions of Facebook use. *Personality and Individual Differences, 90*, 296-301.

- Blackhart, G. C., Fitzpatrick, J., & Williamson, J. (2014). Dispositional factors predicting use of online dating sites and behaviors related to online dating. *Computers in Human Behavior*, 33(0), 113-118. doi: <http://dx.doi.org/10.1016/j.chb.2014.01.022>
- Bozionelos, G., & Bennett, P. (1999). The theory of planned behaviour as predictor of exercise: The moderating influence of beliefs and personality variables. *Journal of health psychology*, 4(4), 517-529.
- Carpenter, J. M., Green, M. C., & LaFlam, J. (2011). People or profiles: Individual differences in online social networking use. *Personality and Individual Differences*, 50(5), 538-541. doi: <http://dx.doi.org/10.1016/j.paid.2010.11.006>
- Chang, C.-W., & Chen, G. M. (2014a). College students' disclosure of location-related information on Facebook. *Computers in Human Behavior*, 35(0), 33-38. doi: <http://dx.doi.org/10.1016/j.chb.2014.02.028>
- Chen, H.-H., & Chen, S.-C. (2008). The empirical study of automotive telematics acceptance in Taiwan: Comparing three technology acceptance models. *International Journal of Mobile Communications*, 7(1), 50-65.
- Chen, R. (2013). Living a private life in public social networks: An exploration of member self-disclosure. *Decision Support Systems*, 55(3), 661-668. doi: <http://dx.doi.org/10.1016/j.dss.2012.12.003>
- Choi, D.-H., & Shin, D.-H. (2017). Exploring political compromise in the new media environment: The interaction effects of social media use and the Big Five personality traits. *Personality and Individual Differences*, 106(Supplement C), 163-171. doi: <https://doi.org/10.1016/j.paid.2016.11.022>
- Choi, J., & Kim, Y. (2014). The moderating effects of gender and number of friends on the relationship between self-presentation and brand-related word-of-mouth on Facebook. *Personality and Individual Differences*, 68(0), 1-5. doi: <http://dx.doi.org/10.1016/j.paid.2014.03.040>
- Chu, T.-H., & Chen, Y.-Y. (2016). With good we become good: Understanding e-learning adoption by theory of planned behavior and group influences. *Computers & Education*, 92, 37-52.
- Cimbaljević, M. (2015). Social media marketing in tourism and hospitality. *Annals of Tourism Research*, 54, 236-238. doi: <http://dx.doi.org/10.1016/j.annals.2015.05.006>

- Correa, T., Hinsley, A. W., & de Zúñiga, H. G. (2010). Who interacts on the Web?: The intersection of users' personality and social media use. *Computers in Human Behavior*, 26(2), 247-253. doi: <http://dx.doi.org/10.1016/j.chb.2009.09.003>
- Čukić, I., & Bates, T. C. (2014). Openness to experience and aesthetic chills: Links to heart rate sympathetic activity. *Personality and Individual Differences*, 64(0), 152-156. doi: <http://dx.doi.org/10.1016/j.paid.2014.02.012>
- 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. doi: <http://dx.doi.org/10.1016/j.jbusres.2016.04.181>
- Godin, G., & Kok, G. (1996). The theory of planned behavior: a review of its applications to health-related behaviors. *American journal of health promotion*, 11(2), 87-98.
- Gosling, S. D., Gaddis, S., & Vazire, S. (2007). Personality Impressions Based on Facebook Profiles. *ICWSM*, 7, 1-4.
- Guadagno, R. E., Okdie, B. M., & Eno, C. A. (2008). Who blogs? Personality predictors of blogging. *Computers in Human Behavior*, 24(5), 1993-2004. doi: <http://dx.doi.org/10.1016/j.chb.2007.09.001>
- Hagger, M. S., Chatzisarantis, N. L., & Biddle, S. J. (2002). The influence of autonomous and controlling motives on physical activity intentions within the Theory of Planned Behaviour. *British journal of health psychology*, 7(3), 283-297.
- Hajli, N., Shanmugam, M., Powell, P., & Love, P. E. (2015). A study on the continuance participation in on-line communities with social commerce perspective. *Technological Forecasting and Social Change*, 96, 232-241.
- Hart, J., Nailling, E., Bizer, G. Y., & Collins, C. K. (2015). Attachment theory as a framework for explaining engagement with Facebook. *Personality and Individual Differences*, 77, 33-40.
- Hoyt, A. L., Rhodes, R. E., Hausenblas, H. A., & Giacobbi, P. R. (2009). Integrating five-factor model facet-level traits with the theory of planned behavior and exercise. *Psychology of Sport and Exercise*, 10(5), 565-572.
- Jenkins-Guarnieri, M. A., Wright, S. L., & Hudiburgh, L. M. (2012). The relationships among attachment style, personality traits, interpersonal competency, and Facebook use. *Journal*

- of *Applied Developmental Psychology*, 33(6), 294-301. doi: <http://dx.doi.org/10.1016/j.appdev.2012.08.001>
- Jenkins-Guarnieri, M. A., Wright, S. L., & Johnson, B. D. (2013). The interrelationships among attachment style, personality traits, interpersonal competency, and Facebook use. *Psychology of Popular Media Culture*, 2(2), 117.
- John, Naumann, L., & Soto, C. (2008). Paradigm Shift to the Integrative Big Five Trait Taxonomy: History, Measurement, and Conceptual Issues. In O. John, R. Robbins & L. Pervin (Eds.), *Handbook of Personality: Theory and Research* (pp. 114-156): Guilford.
- Kuo, T., & Tang, H.-L. (2014). Relationships among personality traits, Facebook usages, and leisure activities – A case of Taiwanese college students. *Computers in Human Behavior*, 31(0), 13-19. doi: <http://dx.doi.org/10.1016/j.chb.2013.10.019>
- Lee, D., Chung, J. Y., & Kim, H. (2013). Text me when it becomes dangerous: Exploring the determinants of college students' adoption of mobile-based text alerts short message service. *Computers in Human Behavior*, 29(3), 563-569. doi: <http://dx.doi.org/10.1016/j.chb.2012.11.014>
- Lee, J.-E. R., Moore, D. C., Park, E.-A., & Park, S. G. (2012). Who wants to be “friend-rich”? Social compensatory friending on Facebook and the moderating role of public self-consciousness. *Computers in Human Behavior*, 28(3), 1036-1043. doi: <http://dx.doi.org/10.1016/j.chb.2012.01.006>
- Lee, S.-Y., Hansen, S. S., & Lee, J. K. (2016). What makes us click “like” on Facebook? Examining psychological, technological, and motivational factors on virtual endorsement. *Computer Communications*, 73, Part B, 332-341. doi: <https://doi.org/10.1016/j.comcom.2015.08.002>
- Liang, T.-P., Ling, Y.-L., Yeh, Y.-H., & Lin, B. (2013). Contextual factors and continuance intention of mobile services. *International Journal of Mobile Communications*, 11(4), 313-329.
- Lin, K. H., Huang, K. F., Chang, Y. Y., & Jheng, C. H. (2013). Potential consumers' intentions to use LBS in Taiwan. *International Journal of Mobile Communications*, 11(6), 636-655.
- Liu, D., & Campbell, W. K. (2017). The Big Five personality traits, Big Two metatraits and social media: A meta-analysis. *Journal of Research in Personality*, 70(Supplement C), 229-240. doi: <https://doi.org/10.1016/j.jrp.2017.08.004>

- Lo, I. S., McKercher, B., Lo, A., Cheung, C., & Law, R. (2011). Tourism and online photography. *Tourism Management*, 32(4), 725-731. doi: <http://dx.doi.org/10.1016/j.tourman.2010.06.001>
- Mariani, M. M., Di Felice, M., & Mura, M. (2016). Facebook as a destination marketing tool: Evidence from Italian regional Destination Management Organizations. *Tourism Management*, 54, 321-343. doi: <http://dx.doi.org/10.1016/j.tourman.2015.12.008>
- Mark, G., & Ganzach, Y. (2014). Personality and Internet usage: A large-scale representative study of young adults. *Computers in Human Behavior*, 36(0), 274-281. doi: <http://dx.doi.org/10.1016/j.chb.2014.03.060>
- McCrae, R. R., & John, O. P. (1992). An Introduction to the Five-Factor Model and Its Applications. *Journal of Personality*, 60(2), 175-215. doi: 10.1111/j.1467-6494.1992.tb00970.x
- Mehdizadeh, S. (2010). Self-presentation 2.0: Narcissism and self-esteem on Facebook. *Cyberpsychology, Behavior, and Social Networking*, 13(4), 357-364.
- Moore, K., & McElroy, J. C. (2012). The influence of personality on Facebook usage, wall postings, and regret. *Computers in Human Behavior*, 28(1), 267-274. doi: <http://dx.doi.org/10.1016/j.chb.2011.09.009>
- Nadkarni, A., & Hofmann, S. G. (2012). Why do people use Facebook? *Personality and Individual Differences*, 52(3), 243-249. doi: <http://dx.doi.org/10.1016/j.paid.2011.11.007>
- Orosz, G., Tóth-Király, I., & Bőthe, B. (2015). Four facets of Facebook intensity—The development of the Multidimensional Facebook Intensity Scale. *Personality and Individual Differences*.
- Ozkan, S., & Kanat, I. E. (2011). e-Government adoption model based on theory of planned behavior: Empirical validation. *Government Information Quarterly*, 28(4), 503-513. doi: <https://doi.org/10.1016/j.giq.2010.10.007>
- Pi, S.-M., Chou, C.-H., & Liao, H.-L. (2013). A study of Facebook Groups members' knowledge sharing. *Computers in Human Behavior*, 29(5), 1971-1979. doi: <http://dx.doi.org/10.1016/j.chb.2013.04.019>
- Rosen, P. A., & Kluemper, D. H. (2008). The impact of the big five personality traits on the acceptance of social networking website. *AMCIS 2008 proceedings*, 274.

- Ross, C., Orr, E. S., Sisic, M., Arseneault, J. M., Simmering, M. G., & Orr, R. R. (2009). Personality and motivations associated with Facebook use. *Computers in Human Behavior*, 25(2), 578-586. doi: <http://dx.doi.org/10.1016/j.chb.2008.12.024>
- Ryan, T., & Xenos, S. (2011). Who uses Facebook? An investigation into the relationship between the Big Five, shyness, narcissism, loneliness, and Facebook usage. *Computers in Human Behavior*, 27(5), 1658-1664. doi: <http://dx.doi.org/10.1016/j.chb.2011.02.004>
- Seidman, G. (2013). Self-presentation and belonging on Facebook: How personality influences social media use and motivations. *Personality and Individual Differences*, 54(3), 402-407. doi: <http://dx.doi.org/10.1016/j.paid.2012.10.009>
- Seidman, G. (2014). Expressing the “True Self” on Facebook. *Computers in Human Behavior*, 31(0), 367-372. doi: <http://dx.doi.org/10.1016/j.chb.2013.10.052>
- Shih, Y.-W. (2011). Facilitators and benefits of using Mobile Entertainment Services. *International Journal of Mobile Communications*, 9(5), 458-476.
- Skues, J. L., Williams, B., & Wise, L. (2012). The effects of personality traits, self-esteem, loneliness, and narcissism on Facebook use among university students. *Computers in Human Behavior*, 28(6), 2414-2419. doi: <http://dx.doi.org/10.1016/j.chb.2012.07.012>
- Smith, M. M., Saklofske, D. H., & Nordstokke, D. W. (2014). The link between neuroticism and perfectionistic concerns: The mediating effect of trait emotional intelligence. *Personality and Individual Differences*, 61–62(0), 97-100. doi: <http://dx.doi.org/10.1016/j.paid.2013.12.013>
- Tan, W., Yang, C. (2012). *Personality Traits Predictors of Usage of Internet Services*. Paper presented at the International Conference on Economics, Business Innovation, Singapore.
- Trafimow, D., Sheeran, P., Conner, M., & Finlay, K. A. (2002). Evidence that perceived behavioural control is a multidimensional construct: Perceived control and perceived difficulty. *British Journal of Social Psychology*, 41(1), 101-121.
- Vlachopoulou, E., & Boutsouki, C. (2014). Facebook usage among teenagers—the effect of personality and peer group pressure; an exploratory study in Greece. *International Journal of Internet Marketing and Advertising*, 8(4), 285-299.
- Wehrli, S. (2008). Personality on social network sites: An application of the five factor model. *Zurich: ETH Sociology (Working Paper No. 7)*.

- Wilson, K., Fornasier, S., & White, K. M. (2010). Psychological predictors of young adults' use of social networking sites. *Cyberpsychology, Behavior, and Social Networking*, *13*(2), 173-177.
- Xu, R., Frey, R. M., Fleisch, E., & Ilic, A. (2016). Understanding the impact of personality traits on mobile app adoption—Insights from a large-scale field study. *Computers in Human Behavior*, *62*, 244-256.
- Zywica, J., & Danowski, J. (2008). The Faces of Facebookers: Investigating Social Enhancement and Social Compensation Hypotheses; Predicting Facebook™ and Offline Popularity from Sociability and Self-Esteem, and Mapping the Meanings of Popularity with Semantic Networks. *Journal of Computer-Mediated Communication*, *14*(1), 1-34. doi: 10.1111/j.1083-6101.2008.01429.x

Chapter 5.

Research methodology

During the six-month period of data collection, 578 adults completed a 47-items questionnaire related to personality traits (24 items), intentional behavior (14 items) and some general demographic questions. In this chapter we provide with the analysis of the methodology used, the operational definitions of the study instruments and the sample characteristics and demographics. For each factor of the model, we analyze which item was used on the survey (Table 6.1). The aim of this chapter is to provide with the base knowledge, first for the present research and second for any future research that will use the same methodology, models and theories. Chapter 5, together with Chapter 6, which includes the results of the study form a solid background in which future academics can base their research and extend our findings or, based on the same methodology, explore other fields of study.

The objective of the primary research was to test and evaluate the proposed model ‘e-HePeBe-SMA’, examining the effects on individuals’ behavior towards healthy diet and sport activities in combination to Facebook pages and groups. A questionnaire of 47 items distributed online via Facebook messages and emails and 578 valid answers were obtained.

5.1. Operationalization of variables

Table 5.1 indicates the operational definitions of the study instruments. Each variable is measured through diverse items based on a 5-point Likert scale, ranking from 1 (completely disagree) to 5 (Completely agree). An extended 24-item Big Five Personality Trait Inventory was used for Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism. After reviewing the relevant literature, a 14-item inventory for TPB was created, customized for providing information about the adoption of healthy eating or sports tips suggested by various pages/ groups on Facebook.

Table 5.1: Operational definitions of the study instruments

Research Variables	Operational Definitions
Openness (O)	O1. I use a rich vocabulary O2. I have a vivid imagination O3. I often have great new ideas O4. I can easily understand difficult and new concepts
Conscientiousness (C)	C1. I am always prepared C2. I look at the details C3. I never leave pending C4. I like the order in my stuff C5. I always follow a program C6. I am demanding in my work
Extraversion (E)	E1. I am always the focus of interest in a celebration E2. I feel comfortable between people E3. I always start a conversation first E4. I usually talk to many people (e.g. at a party) E5. I do not mind being at the center of attention
Agreeableness (A)	A1. I am interested in the problems of others A2. I am interested for people's problems A3. I am a sensitive person A4. I enjoy my spare time for others A5. I understand the feelings of others A6. I make them around me feeling comfortable
Neuroticism (N)	N1. I rarely feel despondent and sad N2. I never get anxious N3. I am high tempered person
Attitude (ATT)	ATT1. I find it a good idea to follow healthy eating or sports tips that suggest various pages / groups on Facebook. ATT2. I would feel enjoyable if I follow healthy eating or sports tips that suggest various pages / groups on Facebook.

Research Variables	Operational Definitions
	ATT3. I would be very helpful to follow healthy eating or sports tips that suggest various pages / groups on Facebook.
Subjective Norms (SN)	<p>SN1. Most of my friends think I should be following healthy eating or sports tips that suggest different pages / groups on Facebook.</p> <p>SN2. People who are important to me consider that I should follow healthy eating or sports tips that suggest different pages / groups on Facebook.</p> <p>SN3. The people who influence me with their opinions believe that it would be good to follow healthy eating or sports tips that suggest various pages / groups on Facebook.</p>
Perceived Behavioral Control (PBC)	<p>PBC1. I plan carefully the daily schedule so I follow the healthy eating or sports tips suggested by various pages / groups on Facebook.</p> <p>PBC2. If I really want it, it is very easy for me to follow the healthy eating or sports tips suggested by various pages / groups on Facebook.</p> <p>PBC3. It only depends on me if I follow the healthy eating or sports tips that suggest various pages / groups on Facebook.</p>
Intention (IN)	<p>IN1. If I have already used such tips, I intend to reuse.</p> <p>IN2. I believe that in the future I will use Facebook pages that offer tips for healthy eating or sports.</p> <p>IN3. I'm aiming to visit Facebook pages that offer tips for healthy eating or sports.</p>
Behavior (B)	<p>B1. I already use Facebook pages or other social media that offer tips for healthy eating or sports.</p> <p>B2. I already follow pages on Facebook or other social media that offer tips for healthy eating or sports.</p>

5.2 Data collection and sample characteristics

A questionnaire was distributed online on 750 users, via e-mail, Facebook and LinkedIn posts and personal messages. Answers were collected for a 6-month period, specifically from May 2017 to November 2017. The questionnaire was based on previous surveys and therefore, the validity and the reliability were a priori approved. We conducted a pilot collection of answers (n=40) in order to identify any misunderstandings and lacks of clarity and accuracy. 578 users responded the questionnaire completely, obtaining a response rate equal to 77%. Table 5.2 presents the demographic profile of the participants. Sex is equally distributed. The vast majority belongs to the 18-24 age range (76.8%), making the research even more targeted of specific age groups. Considering that the range 18-27 occupies the 87.7% of the total sample, we can extract hyper focused outcomes regarding the aforementioned age decade. An ample majority of the respondents are undergraduate students (82%), living in big cities and urban areas (82.7%).

Table 5.2: Demographic characteristics of the respondents

Demographics		Frequency	Percent
Gender	Male	286	49.5%
	Female	292	50.5%
Age	18-21	288	49.8%
	22-24	156	27.0%
	25-27	63	10.9%
	28-30	37	6.4%
	30+	34	5.9%
Education	UG student	474	82%
	PG student	97	16.8%
	PhD candidate	5	0.9%
	PhD+ education	2	0.3%
Residence	Urban area	478	82.7%
	Suburban area	72	12.5%
	Rural area	28	5.8%

It is also interesting to present the most used social media platforms. The top three social media in the list, with a significant difference from the fourth, are: Facebook, where the overwhelming 99.3% has an active account, Instagram with 72% active users from our sample and Twitter with 41.2% of the participants responding to possess an active account. An important finding is that even in times of great economic crisis in the country where the research was conducted; only 3.3% of respondents have an account on the largest professional social medium, to wit, LinkedIn. Table 5.3 presents the percentage of users with active accounts, among our sample.

Table 5.3: Social media platforms' with active accounts

Social Media Platform	Frequency	Percentage
Facebook	574	99.3%
Instagram	416	72%
Twitter	238	41.2%
LinkedIn	19	3.3%
Pinterest	11	1.9%
Viber	6	1%
Snapchat	5	<1%
YouTube channel	4	<1%
Reddit	2	<1%
Tumblr	1	<1%
Github	1	<1%
Tinder	1	<1%
Discord	1	<1%

The proposed model with the hypotheses was tested with Structural Equation Modeling (SEM), using maximum likelihood estimation. The techniques SEM uses, examine the covariance structure and the relationships between and among latent variables, including the effects of direct, indirect, reciprocal and misleading causal relationships (Zarmpou, Saprikis, Markos, & Vlachopoulou, 2012). A main difference between SEM and other similar models is that SEM assumes that variables cannot be measured with precision, so it includes an error on its

measurements. Two models are created in SEM, the measurement and the structural. The first one represents the construction on the measured variables, while the structural model presents the various associations between constructs. The measurement model proves that the latent variables measured the intended constructs. This technique is known as the Confirmatory Factor Analysis (CFA). CFA verifies the factor structure of the set of our observed variables. With CFA researchers can assume that a relationship between observed variables and their underlying latent constructs exists. After the CFA technique application, we confirmed that all constructs meet the measurement standards. This confirmation leads to the second test of the structural model in order to investigate the relationships among the theoretical constructs, thus confirming or not, the hypotheses model. Final purpose in order to confirm the theoretical model is an insignificant difference between measurement and structural model. SPSS 21 and SPSS AMOS 21 were used in this study to determine measurement and structural models.

5.3 Measurement model

The constructs are represented by the measured variables of our model. In order to test the measurement model, CFA was used. The model used 38 items that describe the 10 latent constructs, analytically: Openness (O), Conscientiousness (C), Extraversion (E), Agreeableness (A), Neuroticism (N), Attitude (ATT), Subjective Norms (SN), Perceived Behavioral Control (PBC), Intention to use (IN) and Behavior (B). Su and Chan (2017) recommend a list of fit indices from different classes, such as absolute fit, incremental fit and comparative fit. The following combination of fit measures was used: $\chi^2/d.f.$, non-norm fit index (NNFI), the root mean square error of approximation (RMSEA), the adjusted goodness of fit index (AGFI), the goodness of fit index (GFI), the comparative fit index (CFI) and the root mean square residual (RMR). For every index a threshold is given, together with the model's data, to set the goodness of fit. As it is shown on Table 5.4, the proposed model fits well with the data collected. As a result, reliability and validity (convergent and discriminant) could be calculated and evaluated. Before presenting the values found from the analysis, a short presentation of the statistical definitions is necessary in order to better understand why the proposed model has a good fit. Fit refers to the ability of a model to reproduce the data. A good-fitting model is one that is reasonably consistent with the data and so does not necessarily require re-specification, or adding

new paths on the measurement model. A good-fitting measurement model is required before interpreting the causal paths of the structural model.

It should be noted that a good-fitting model is not necessarily a valid model. For instance, a model all of whose estimated parameters are not significantly different from zero is a "good-fitting" model. Conversely, it should be noted that a model all of whose parameters are statistically significant can be from a poor fitting model. Additionally, models with nonsensical results (e.g., paths that are clearly the wrong sign) and models with poor discriminant validity can be "good-fitting" models. Parameter estimates must be carefully examined to determine if one has a reasonable model. Also it is important to realize that one might obtain a good-fitting model, yet it is still possible to improve the model and remove specification error. Finally, having a good-fitting model does not prove that the model is correctly specified.

There is considerable controversy about fit indices. Some researchers do not believe that fit indices add anything to the analysis (Barrett, 2007) and only the chi square should be interpreted. The worry is that fit indices allow researchers to claim that a miss-specified model is not a bad model. Others (Hayduk, Cummings, Boadu, Pazderka-Robinson, & Boulianne, 2007) argue that cutoffs for a fit index can be misleading and subject to misuse. Most analysts believe in the value of fit indices, but caution against strict reliance on cutoffs.

Table 5.4: The model's fit indices

Fit Indices	Recommended value	Measurement model	Structural model
$\chi^2 / \text{d.f.}$	≤ 3.00	2.17	2.16
NNFI	≥ 0.90	0.96	0.96
RMSEA	≤ 0.09	0.050	0.049
AGFI	≥ 0.80	0.90	0.88
GFI	≥ 0.90	0.91	0.91
CFI	≥ 0.90	0.96	.096
RMR	≤ 0.05	0.049	0.049

Next, we analyze the results of the study and answer to the initial hypotheses of the research. The measurement model of this paragraph extracted good values so the statistical analysis which follows to be statistically correct. Together with the tools of the structural equation modeling, we will provide with the reliability measurements and the final structural model that answers the aforementioned hypotheses.

References

- Barrett, P. (2007). Structural equation modelling: Adjudging model fit. *Personality and Individual Differences, 42*(5), 815-824.
- Hayduk, L., Cummings, G., Boadu, K., Pazderka-Robinson, H., & Boulianne, S. (2007). Testing! testing! one, two, three—Testing the theory in structural equation models! *Personality and Individual Differences, 42*(5), 841-850.
- Su, C. C., & Chan, N. K. (2017). Predicting social capital on Facebook: The implications of use intensity, perceived content desirability, and Facebook-enabled communication practices. *Computers in Human Behavior, 72*, 259-268. doi: <http://dx.doi.org/10.1016/j.chb.2017.02.058>
- Zarpou, T., Saprikis, V., Markos, A., & Vlachopoulou, M. (2012). Modeling users' acceptance of mobile services. [journal article]. *Electronic Commerce Research, 12*(2), 225-248. doi: 10.1007/s10660-012-9092-x

Chapter 6.

Findings and Results' Presentation

The present chapter, summarizes the results of the study in four tables including the factor loadings for each item of the questionnaire, the construct reliability (CR) of the results, the average variance extracted (AVE) and finally, the structural model with the paths the coefficients and the t-values, for each hypothesis. The aim of this chapter is to present and explain each result and table before proceeding with the explanation of each result in the next chapter. Definitions and explanations are provided for each table as well as an overall summary, before the in-depth analysis on the next chapter.

Table 6.1 presents the complete list of the factor loadings for every item of our research's questionnaire. In literature there is a plethora of thresholds and rules for accepted values and ranges, mostly depending on the sample size needed for significance. Hair, Black, Babin, and Anderson (2010) set the factor loading threshold, respect to our sample ($n=578$) at 0.30. On the other side Field (2013) suggests that a factor is reliable if it has four or more loadings at a minimum of 0.6 and Stevens (2012) sets the limit at 0.4, irrespective of the sample size. Tabachnick and Fidel (2007), based on Comrey and Lee (1992), being more strict with their cut-offs, set the limits to 0.32 for poor, 0.45 for fair, 0.55 for good, 0.63 for very good and 0.71 for excellent factor loadings. Finally, MacCallum, Widaman, Preacher, and Hong (2001) assert that all items must have communalities of over 0.60 or an average communality of 0.7, especially in research with small sample size. In our case, considering the sample size and the relevant literature, only the item ope2 falls just below the 0.6 but no item falls below the 0.5 rule of thumb of Hair's et al. (2010).

Table 6.1: Factor Loadings for survey's items

Survey Item	Factor Loading (> 0.6)	Survey Item	Factor Loading (> 0.6)
ext1	0.753	neu3	0.701
ext2	0.665	ope1	0.605
ext3	0.701	ope2	0.598
ext4	0.729	ope3	0.637
ext5	0.721	ope4	0.624
agr1	0.698	att1	0.736
agr2	0.711	att2	0.734
agr3	0.728	att3	0.759
agr4	0.651	sn1	0.732
agr5	0.757	sn2	0.803
agr6	0.667	sn3	0.797
cos1	0.760	pbc1	0.714
cos2	0.744	pbc2	0.739
cos3	0.764	pbc3	0.651
cos4	0.792	int1	0.764
cos5	0.685	int2	0.718
cos6	0.76	int3	0.697
neu1	0.775	b1	0.851
neu2	0.791	b2	0.831

The internal consistency was estimated through the Construct Reliability (CR) on Table 6.2, together with the Average Variance Extracted (AVE). CR is greater than 0.7, or close to 0.7 in only two cases, rendering all variables acceptable, and indicating also high internal consistency.

Table 6.2: Construct Reliability (CR) and Average Variance Extracted (AVE)

Big Five's Variables	CR	AVE
Extraversion	0.761	0.51
Agreeableness	0.780	0.49
Conscientiousness	0.789	0.55
Neuroticism	0.614	0.57
Openness	0.710	0.59
TPB Variables	CR	AVE
Attitude	0.787	0.55
Subjective Norms	0.821	0.60
Perceived Behavioral Control	0.669	0.49
Intention	0.735	0.53
Behavior	0.829	0.70

AVE's lowest value is 0.49 for Agreeableness and PBC, all values though are greater than the squared correlation estimates on Table 6.3 (see the values below the diagonal). As a result, the test does not show problems with the discriminant validity and no new path was included in order to improve the fit of the model, therefore, next paragraph analyzes the results of our structural model.

Table 6.3: Discriminant Validity

Variables	1	2	3	4	5	6	7	8	9	10
E	1.000									
A	.270	1.000								
C	.088	.155	1.000							
N	.018	.122	.036	1.000						
O	.263	.223	.247	.061	1.000					
ATT	.060	.025	.092	.122	.007	1.000				
SN	.175	.104	.036	.117	.083	.516	1.000			
PBC	.033	.155	.212	-.010	.107	.476	.382	1.000		
I	.125	.127	.094	.056	.063	.587	.401	.428	1.000	
B	.133	.070	.044	.002	.039	.554	.362	.419	.545	1.000

6.1. Structural Model

The next step consists of estimating the structural model in order to empirically measure the relationships among variables and constructs. Table 6.4 presented the comparison between the values calculated for the measurement and the structural model. The structural model presented similar estimates to the measurement model, suggesting an overall good model fit. Table 6.4 presents the coefficients for each hypothesis and the t-value calculation based on Bonsón and Flores (2011), posing the t-critical cutoff on 1.69. By these measurements, 4 hypotheses are not significant (H1, H2, H6, H11). In conclusion, given that 8 out of 12 estimates are consistent with the initial hypotheses, the results support the theoretical model, therefore, our SEM model (Figure 7.1), explains the data equally well with the CFA model.

Table 6.4: Hypotheses' paths, coefficients and t-values

Hypothesis	Path	Coefficient (β)	t-value (t)	p-value (p)
H1	O→ATT	-0.04	-0.96	> 0.05
H2	E→ATT	-0.02	-0.48	> 0.05
H3	A→ATT	0.33	8.43	<0.01
H4	ATT→IN	0.44	11.8	<0.01
H5	E→SN	0.19	4.67	<0.05
H6	A→SN	0.02	0.48	> 0.05
H7	SN→IN	0.11	2.67	<0.05
H8	SN→ATT	0.57	16.73	<0.01
H9	C→PBC	0.25	6.23	<0.05
H10	E→PBC	0.10	2.42	<0.05
H11	N→PBC	-0.02	-0.48	> 0.05
H12	PBC→IN	0.19	4.67	<0.05

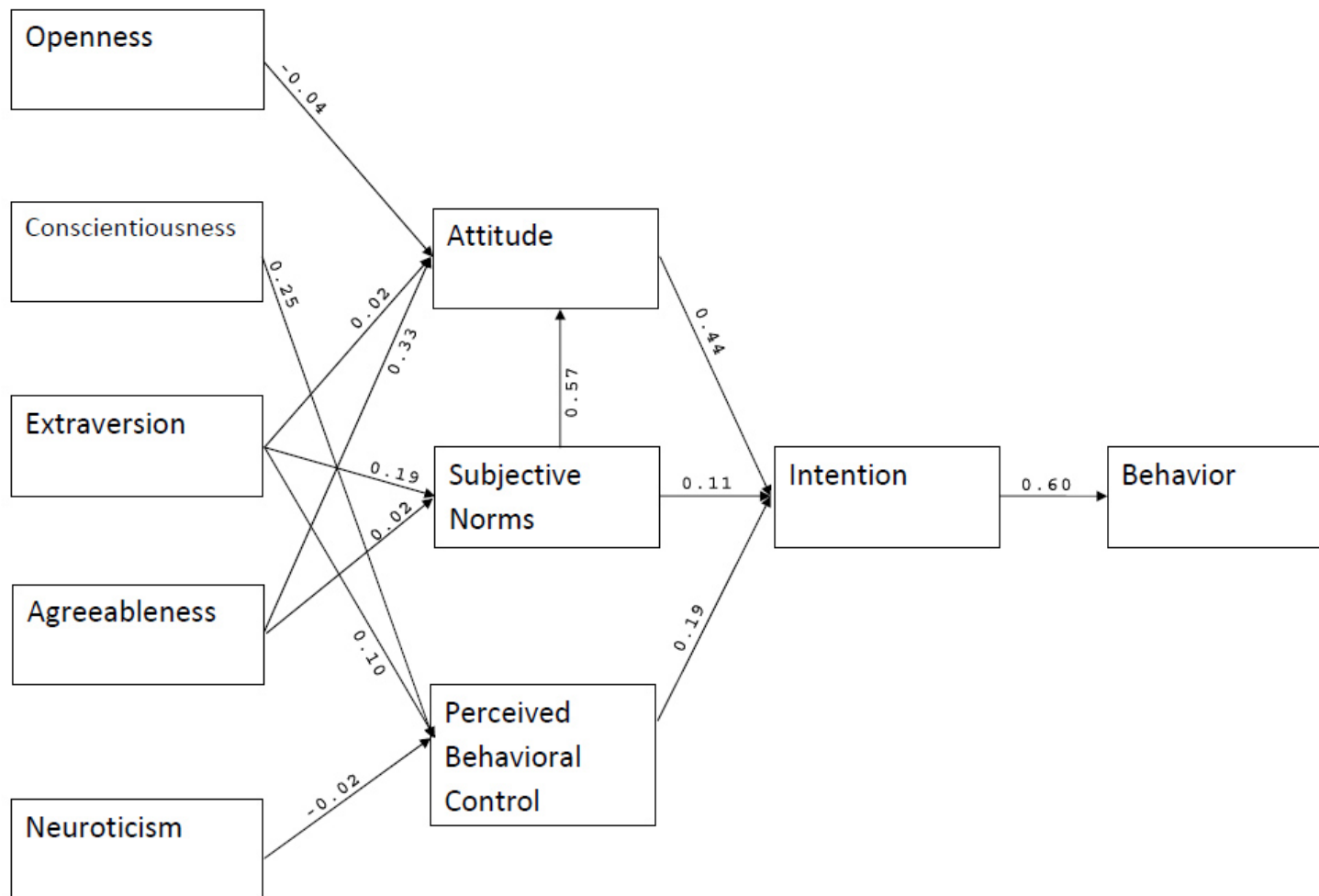


Figure 6.1: SEM results for the proposed model

Summarizing, the factor loadings of the model respect the literature's thresholds, placing the value at 0.3. Even if increasing the limit to 0.6, only one variable has lower value with a 0.002 difference. These thresholds lead us to confirm that the values on our variables are accepted. Furthermore, the construct reliability is greater than 0.7 in all cases, except two. This fact confirms acceptable variables with high internal consistency. In addition, all AVE values are greater than CR^2 , so no problems with the discriminant validity was occurred and no new path on the model was included in order to improve the fit of the model. As a result, we proceed to the structural model, where the comparison with the measurement model leads to similar estimations, obtaining a good model fit. Concluding, 8 out of 12 hypotheses were valid. In-depth analysis will follow on next Chapter 7.

References

Bonsón, E., & Flores, F. (2011). Social media and corporate dialogue: the response of global financial institutions. *Online Information Review*, 35(1), 34-49. doi:doi:10.1108/14684521111113579

Chapter 7.

Conclusions

Social media have been claimed as the present and next continuously increasing channel for communications, information and business implementation. The vast majority of people today uses social media and possesses active accounts on them so the traditional techniques from social sciences are becoming less and less important. The present chapter aims to conclude the entire previous research by analyzing the results regarding the hypotheses, interpret the statistical analysis of the previous chapters, and provide with the managerial implications of the study, the limitations and guides for future research on the field, starting from summarizing the research presenting the main findings that satisfy the needs of each of the research objective. The results of the analysis have important meaning, considering also the cultural characteristics of the research and great managerial implications for practitioners and academics.

7.1. Research overview and findings

The research presented in this dissertation is aimed at providing a prediction of behavior of social media users regarding eHealth-related pages and groups, in correlation with their personalities. The accomplishment of this aim is regarded to be helpful with the scheduling and developing of such pages and groups from digital marketing academics and practitioners. The author has structured the dissertation in seven chapters. Table 7.1 shows how the various steps that were established on Chapter 1 are satisfied throughout the dissertation.

Table 7.1: Accomplishments of the research steps

Research Steps	Accomplishments
Step 1. Explain the research motivation, paradigm, method and techniques that fit the current research objectives and lead to valid	Step 1 has been accomplished on Chapter 1, where the main details of the research background and the context were provided and explained.

Research Steps	Accomplishments
research results	
<p>Step 2. Analyze the fields, the objectives, the types of analysis and the social media platform environment</p>	<p>Step 2 has been accomplished on Chapter 2. A complete base for understanding and describing social media, social media metrics and social media analytics related to digital marketing strategy, policy and research, by reviewing the relevant literature, was provided. The main objective of this chapter was an extensive review of articles related to social media metrics and analytics in marketing, creating a mapping review/ systematic map of the relevant material.</p>
<p>Step 3. Provide a new typology and framework for the aforementioned research objectives and focus on eHealth field, behavioral analysis (personality traits and theories of planned behavior) and Social Networking Sites (Facebook)</p>	<p>Step 3 has been accomplished on Chapter 2. The primary goal in this chapter was also to create, among others, a conceptual classification scheme (named S3M) for the extant literature by using five distinct dimensions/ criteria of classification, such as: Methodology of research, Type of analysis, Field of study, Marketing objectives, and Social media types/ platforms.</p>
<p>Step 4. Develop the theoretical framework for the behavioral theories of Facebook users regarding the individuals' planned behavior over Facebook pages and groups related to eHealth activities</p>	<p>Step 4 has been accomplished on Chapter 3. This chapter aimed to present and analyze the diverse personality traits together with their extensions, focusing on the Big Five model. A comparison analysis of the most used models in order to facilitate future research focused on different fields was provided.</p>

Research Steps	Accomplishments
<p>Step 5. Identify the research gap on the field</p>	<p>Step 5 has been accomplished on Chapter 4, where the research gap was explained. Furthermore this chapter was focused on the eHealth field, analyzing the specific sector in-depth. The hypotheses formulation is were analyzed on this chapter too, after a short introduction to the two basic models used on the dissertation, the Big Five and the Theory of Planned Behavior. Conceptual definition of the research variables were given as well as the literature this study based for the research hypotheses. Finally the analytical definitions of the research hypotheses were provided</p>
<p>Step 6. Explain the research methodology that fits the testing of the theoretical model and leads to the final artifact of this research</p>	<p>Step 6 has been accomplished on Chapter 5. The methodology used on the research was presented as well as its analysis, the operational definitions of the study instruments and the sample characteristics and demographics. Each item used on the survey was analyzed. The aim of this chapter was to provide with the base knowledge, first for the present research and second for any future research that will use the same methodology, models and theories.</p>
<p>Step 7. Provide with the statistical analysis of the proposed model in order to test the theoretical frameworks</p>	<p>Step 7 has been accomplished on Chapter 6. Results of the study in four tables including the factor loadings for each item of the questionnaire, the construct reliability (CR) of the results, the average variance extracted (AVE) and finally, the structural model with the paths the coefficients and the t-values, for each hypothesis were analyzed. The aim of this chapter was to present and explain each result of the</p>

Research Steps	Accomplishments
	provided tables before proceeding with the explanation of each result in the next chapter. Definitions and explanations were provided for each table as well as an overall summary, before the in-depth analysis of the next chapter.
<p>Step 8. Evaluate the research conclusions in terms of their significance to theory and practice and identify future research directions that are important to continue refining this important area of research.</p>	<p>Step 8 has been accomplished on Chapter 7. This chapter aimed to conclude the entire previous research by analyzing the results regarding the hypotheses, interpret the statistical analysis of the previous chapters, and provide with the managerial implications of the study, the limitations and guides for future research on the field.</p>

As we notice, all the established objectives were accomplished and analyzed. Each chapter separately presented the findings of the research with validated data, frameworks and models. Next, the results are interpreted using the findings from the structural equation modeling analysis.

7.2. Interpretation of results

The present study examined how behavioral intentions, attitude, PBC, SN and the five factors of Big Five can predict the actual behavior of users regarding the use of social media platforms related to eHealth and well-being. The findings offer strong evidence in support of the proposed research model. Analytically, beginning from the demographics and the simple descriptive statistics:

The data from the sample, as it is already analyzed on Chapter 5 and 6, confirm good model fit, elevate response rate, and equally distributed values among demographic data. Furthermore, the data sample is focused on specific age range (something that was not scheduled initially, but it can be useful in order to extract outcomes for hyper-focused ages

and social order). In details, almost 77% of the sample belongs to 18-24 age-group with 82% of them being university students, living in urban areas.

Considering the measurement and the structural model, the diverse indices are close to each other, making safe to claim that the structural model is correct. In specific, all fit indices of both measurement and structural models are less than the appropriate values (with exception the NNFI, AGFI, GFI and CFI that have to be greater), as these are defined from the literature (Barrett, 2007; Bentler & Bonett, 1980; Bentler & Chou, 1987; Hayduk et al., 2007).

Regarding the factors loading, a specific reference needs to be done to the ope2 factor. This factor, related to the item that refers to “openness to new experience” factor from Big Five, is the only one that is less than 0.6 by 0.002. This imperceptible difference could remain unexplained due to its insignificant difference with the threshold (it would be acceptable if we limited the threshold to 0.3 as the literature indicates). Every other item has a factor loading greater than 0.6. From factor analysis' aspect, factor loading is the correlation between the observed score and the latent score. Generally, the higher the better since the square of factor loading can be directly translated as item reliability. From Rasch model's aspect (Rasch, 1960), factor loading is a discrimination parameter (i.e. how well an item can discriminate an individual from another). In both cases our survey is reliable (considering also the CR and AVE indices where all AVE values were greater than CR^2 , without the need of adding new paths on the model in order to improve the fit of the model and the discriminant validity).

The most important part of the analysis is the result we obtain from the structural equation modeling procedure, regarding our structural model. Eight out of twelve hypotheses are confirmed, leaving outside the boundaries of statistics, only 4 hypotheses, a quite acceptable number. The first hypothesis that is not confirmed is H1 ($H1; \beta = 0.04; t = -0.96; p > 0.05$), meaning that it is not confirmed the fact that there is a positive correlation between Openness and Attitude towards the use of Facebook pages related to healthy diet and sport activities, on our model and on our sample. Non confirmation we obtain also from the H2, H6 and H11 hypotheses, related to Extraversions and Attitude ($H2; \beta = -0.02; t = -0.48; p > 0.05$), Agreeableness and Subjective Norm ($H6; \beta = 0.02; t = 0.48; p > 0.05$), and Neuroticism and Perceived Behavioral Control ($H11; \beta = -0.02; t = -0.48; p > 0.05$), respectively.

On the other side 8 hypotheses of our initial model are confirmed. Immediate positive correlations from the Big Five to TPB factors were expected such as the Conscientiousness to

PBC ($H9$; $\beta = 0.25$; $t = 6.23$; $p < 0.05$), the Extraversion to Subjective Norm and PBC ($H5$; $\beta = 0.19$; $t = 4.67$; $p < 0.05$, $H10$; $\beta = 0.10$; $t = 2.42$; $p < 0.05$) and the Agreeableness to Attitude ($H3$; $\beta = 0.33$; $t = 8.43$; $p < 0.01$). Furthermore, Attitude and Subjective norm were found to have a strong positive impact on intention to behavior ($H4$; $\beta = 0.44$; $t = 11.8$; $p < 0.01$, $H7$; $\beta = 0.11$; $t = 2.67$; $p < 0.05$), supporting our hypotheses. PBC was found to have positive impact on intention to behavior ($H12$; $\beta = 0.19$; $t = 4.67$; $p < 0.05$). Last, but not least, a very strong positive impact is noted on Subjective norm to Attitude ($H8$; $\beta = 0.57$; $t = 16.73$; $p < 0.01$). This last correlation is the only one between internal factors of the same model, in this case TPB. Figure 6.1 and Table 6.4 of the previous chapter summarize the aforementioned findings.

Even if the study found that SN influence less the intention to use Facebook groups and pages related to healthy diet and sport activities, this can be done through ATT, considering the path $SN \rightarrow ATT \rightarrow IN$. Furthermore, Conscientiousness via PBC and Agreeableness via ATT can affect more the intention to use, and therefore the final behavior of usage. TPB literature can be contributed strongly by the verification of the hypotheses of our mode, so as social science.

7.3. Implications and contributions

Understanding and predicting consumers' behavior has been of particular interest to researchers for many years. Moreover, the assumption that knowledge of attitudes, and norms and will help in the task of predicting the actual behavior has formed the basis for much consumer and social research. Attitudes, subjective norms and behavioral control are assumed to play an important role in behavioral theory as the crucial link between what people think and what they do.

The conclusions of the present study can contribute to practitioners by helping them assess their marketing decisions based on the knowledge of which combination of personalities and planned behavior influence more the use of social media pages and groups related to healthy diet and sport activities. Companies involved in such activities can modify their strategies in order to communicate their products to a wider audience, maximizing reach and engagement. Furthermore, international brands can take into consideration that the Greek market presents particularities that maybe other regions do not, altering, thus, their planning and approaches. Consumers' behavior prediction is crucial not only on managerial level but for almost all fields of science. When marketers can target specific customers with the specific marketing

actions likely to have the most desirable impact, every marketing campaign and retention action will be more successful. The return of investment of up-sell, cross-sell and retention campaigns will be greater. Additionally, customers will feel the greater relevance of the company's communication with them, resulting in greater satisfaction, brand loyalty and word-of-mouth referrals.

Regarding the theoretical model (S3M), it regards to a continuously growing model, where new literature and upcoming fields can be added, year by year. Although S3M model represents a solid base for scientists, the social media analysis field is vivid and continuously expanding. New techniques and tools, marketing objectives, fields of study and platforms are adding constantly, growing the necessity of new literature reviews and frameworks. S3M model, therefore, represents a starting point where scientists can build on and create new subcategories on the already existing.

7.4 Limitations – Future research

Despite the fact that previous results show important implications for practitioners and academics, the research can be further improved by taking into consideration some of the limitations. While literature confirms all of our hypotheses, in our study only 8 out of 12 are finally confirmed. The difference between the present model and literature findings can be located on the different cultural dimensions among the different studies. The present research is focused on the Greek region with all the participants to be Greeks. This location-based limitation could be surpassed by conducting the same research on different geographical regions and then confront the outcomes. Similar studies can be conducted in the future in other countries, taking also into consideration the various cultural differences and conducting a cross-cultural study for multiethnic environments. Furthermore, considering a wider sample from the same region could add to the research with a more depictive view of the social media services penetration. Another limitation and future implication for further analysis is the fact that this study focused on the eHealth field, so different fields may lead to different results, considering that eHealth is a quite sensitive field of study, even in terms of 'light' matters such as the well-being.

Regarding the practical model of the dissertation, the e-HePeBe-SMA can be, if slightly alternate, used in many other fields of study. Here it is applied in the eHealth field,

but researchers can moderate the basic items of the survey (the ones that refer to ATT, PBC and SN) applying the same methodology to different fields of science. Except the TBP related items, future research can be conducted to different fields by changing the behavioral methodology used. Instead of the TPB model, researchers can use for example the TAM, asking for the acceptance among users and not the actual behavior, as this study does. Together with the behavioral model, researchers can add personality traits to the existing ones and expand even more the knowledge. For example, the Dark Triad personality trait which consist of studying the human personality based on Machiavellianism (a manipulative attitude), narcissism (excessive self-love), and psychopathy (lack of empathy) can be added on the existing Big Five model and discover even more aspects of users' personality. The same technique can be applied for traits that present grate interest among researchers today, such as loneliness, anxiety and depression.

References

- Barrett, P. (2007). Structural equation modelling: Adjudging model fit. *Personality and Individual Differences, 42*(5), 815-824.
- Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological bulletin, 88*(3), 588.
- Bentler, P. M., & Chou, C.-P. (1987). Practical issues in structural modeling. *Sociological Methods & Research, 16*(1), 78-117.
- Hayduk, L., Cummings, G., Boadu, K., Pazderka-Robinson, H., & Boulianne, S. (2007). Testing! testing! one, two, three—Testing the theory in structural equation models! *Personality and Individual Differences, 42*(5), 841-850.
- Rasch, G. (1960). Studies in mathematical psychology: I. Probabilistic models for some intelligence and attainment tests.

References

- Aggarwal, C. (2011). An Introduction to Social Network Data Analytics. In C. C. Aggarwal (Ed.), *Social Network Data Analytics* (pp. 1-15): Springer US.
- Agner, S. C., Rosen, M. A., Englander, S., Tomaszewski, J. E., Feldman, M. D., Zhang, P., . . . Madabhushi, A. (2014). Computerized Image Analysis for Identifying Triple-Negative Breast Cancers and Differentiating Them from Other Molecular Subtypes of Breast Cancer on Dynamic Contrast-enhanced MR Images: A Feasibility Study. *Radiology*, *272*(1), 91-99. doi: doi:10.1148/radiol.14121031
- Ajzen, I. (1985). From Intentions to Actions: A Theory of Planned Behavior. In J. Kuhl & J. Beckmann (Eds.), *Action Control: From Cognition to Behavior* (pp. 11-39). Berlin, Heidelberg: Springer Berlin Heidelberg.
- Al-Debei, M. M., Al-Lozi, E., & Papazafeiropoulou, A. (2013). Why people keep coming back to Facebook: Explaining and predicting continuance participation from an extended theory of planned behaviour perspective. *Decision Support Systems*, *55*(1), 43-54.
- Aluja, A., García, Ó., & García, L. F. (2002). A comparative study of Zuckerman's three structural models for personality through the NEO-PI-R, ZKPQ-III-R, EPQ-RS and Goldberg's 50-bipolar adjectives. *Personality and Individual Differences*, *33*(5), 713-725.
- Amichai-Hamburger, Y., & Vinitzky, G. (2010). Social network use and personality. *Computers in Human Behavior*, *26*(6), 1289-1295. doi: <http://dx.doi.org/10.1016/j.chb.2010.03.018>
- Amjad, N., & Wood, A. M. (2009). Identifying and changing the normative beliefs about aggression which lead young Muslim adults to join extremist anti-Semitic groups in Pakistan. *Aggressive behavior*, *35*(6), 514-519.
- Andrew, L., Mudd, G., Rich, M., & Bruich, S. (2012). The Power of Like: How Brands Reach and Influence Fans Through Social Media Marketing. *Journal of Advertising Research*. doi: 10.2501/JAR-52-1-040-052
- Armitage, C. J. (2005). Can the theory of planned behavior predict the maintenance of physical activity? *Health psychology*, *24*(3), 235.
- Ashton, M. C., & Lee, K. (2009). The HEXACO-60: A short measure of the major dimensions of personality. *Journal of personality assessment*, *91*(4), 340-345.

- Asur, S., & Huberman, B. A. (2010). *Predicting the Future with Social Media*. Paper presented at the Proceedings of the 2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology - Volume 01.
- Augustine, A. A., & Hemenover, S. H. (2008). Extraversion and the consequences of social interaction on affect repair. *Personality and Individual Differences, 44*(5), 1151-1161. doi: <http://dx.doi.org/10.1016/j.paid.2007.11.009>
- Awareness, I. (2012). Actionable Social Analytics: From Social Media Metrics to Business Insights Retrieved 14/12/2015, from <http://igo2group.com/wp-content/uploads/2012/10/Actionable-%C2%AD%E2%80%90content/uploads/2012/10/Actionable-%C2%AD%E2%80%90Social-%C2%AD%E2%80%90Analytics.pdf>
- Bachrach, Y., Kosinski, M., Graepel, T., Kohli, P., & Stillwell, D. (2012). *Personality and patterns of Facebook usage*. Paper presented at the Proceedings of the 4th Annual ACM Web Science Conference, Evanston, Illinois.
- Back, M. D., Stopfer, J. M., Vazire, S., Gaddis, S., Schmukle, S. C., Egloff, B., & Gosling, S. D. (2010). Facebook profiles reflect actual personality, not self-idealization. *Psychological science*.
- Bailey, K. D. E. (1994). *Typologies and taxonomies: an introduction to classification techniques* (Vol. 102): Sage.
- Bandura, A. (2010). Modeling. *The Corsini encyclopedia of psychology*, 1-3.
- Batrinca, B., & Treleaven, P. (2015). Social media analytics: a survey of techniques, tools and platforms. *AI & SOCIETY, 30*(1), 89-116. doi: 10.1007/s00146-014-0549-4
- Bello-Organ, G., Jung, J. J., & Camacho, D. (2016). Social big data: Recent achievements and new challenges. *Information Fusion, 28*, 45-59. doi: <http://dx.doi.org/10.1016/j.inffus.2015.08.005>
- Benbasat, I., & Barki, H. (2007). Quo vadis TAM? *Journal of the association for information systems, 8*(4), 7.
- Bernabé-Moreno, J., Tejada-Lorente, A., Porcel, C., Fujita, H., & Herrera-Viedma, E. (2015). CARESOME. *Know.-Based Syst., 80*(C), 163-179. doi: 10.1016/j.knosys.2014.12.033
- Bhattacharjee, A. (2001). Understanding information systems continuance: an expectation-confirmation model. *MIS Quarterly, 351-370*.
- Bishop, J. (2007). Increasing participation in online communities: A framework for human-computer interaction. *Computers in Human Behavior, 23*(4), 1881-1893. doi: <http://dx.doi.org/10.1016/j.chb.2005.11.004>

- Błachnio, A., Przepiorka, A., & Rudnicka, P. (2016). Narcissism and self-esteem as predictors of dimensions of Facebook use. *Personality and Individual Differences, 90*, 296-301.
- Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science, 2*(1), 1-8. doi: <http://dx.doi.org/10.1016/j.jocs.2010.12.007>
- Bonsón, E., & Flores, F. (2011). Social media and corporate dialogue: the response of global financial institutions. *Online Information Review, 35*(1), 34-49. doi: doi:10.1108/14684521111113579
- Bozionelos, G., & Bennett, P. (1999). The theory of planned behaviour as predictor of exercise: The moderating influence of beliefs and personality variables. *Journal of health psychology, 4*(4), 517-529.
- Branley, D. B., & Covey, J. (2018). Risky behavior via social media: The role of reasoned and social reactive pathways. *Computers in Human Behavior, 78*(Supplement C), 183-191. doi: <https://doi.org/10.1016/j.chb.2017.09.036>
- Braojos-Gomez, J., Benitez-Amado, J., & Javier Llorens-Montes, F. (2015). How do small firms learn to develop a social media competence? *International Journal of Information Management, 35*(4), 443-458. doi: <http://dx.doi.org/10.1016/j.ijinfomgt.2015.04.003>
- Bullinger, A. C., Hallerstedte, S. H., Renken, U., Soeldnet, J.-H., & Moeslein, K. M. (2010). *Towards Research Collaboration – a Taxonomy of Social Research Network Sites*. Paper presented at the AMCIS 2010 Proceedings.
- Carim, L., & Warwick, C. (2013). Use of social media for corporate communications by research-funding organisations in the UK. *Public Relations Review, 39*(5), 521-525. doi: <http://dx.doi.org/10.1016/j.pubrev.2013.08.006>
- Carpenter, J. M., Green, M. C., & LaFlam, J. (2011). People or profiles: Individual differences in online social networking use. *Personality and Individual Differences, 50*(5), 538-541. doi: <http://dx.doi.org/10.1016/j.paid.2010.11.006>
- Castronovo, C., & Huang, L. (2012). Social media in an alternative marketing communication model. *Journal of Marketing Development & Competitiveness, 6*(1), 117.
- Cattell, H. E., & Mead, A. D. (2008). The sixteen personality factor questionnaire (16PF). *The SAGE handbook of personality theory and assessment, 2*, 135-178.

- Chang, C.-W., & Chen, G. M. (2014). College students' disclosure of location-related information on Facebook. *Computers in Human Behavior*, *35*, 33-38.
- Chen, Y.-L., Tang, K., Wu, C.-C., & Jheng, R.-Y. (2014). Predicting the influence of users' posted information for eWOM advertising in social networks. *Electronic Commerce Research and Applications*, *13*(6), 431-439. doi: <http://dx.doi.org/10.1016/j.elerap.2014.10.001>
- Choi, J., & Kim, Y. (2014). The moderating effects of gender and number of friends on the relationship between self-presentation and brand-related word-of-mouth on Facebook. *Personality and Individual Differences*, *68*(0), 1-5. doi: <http://dx.doi.org/10.1016/j.paid.2014.03.040>
- Christofides, E., Muise, A., & Desmarais, S. (2009). Information disclosure and control on Facebook: Are they two sides of the same coin or two different processes? *Cyberpsychology & behavior*, *12*(3), 341-345.
- Chu, T.-H., & Chen, Y.-Y. (2016). With good we become good: Understanding e-learning adoption by theory of planned behavior and group influences. *Computers & Education*, *92*, 37-52.
- Chung, N., Nam, K., & Koo, C. (2016). Examining information sharing in social networking communities: Applying theories of social capital and attachment. *Telematics and Informatics*, *33*(1), 77-91. doi: <http://dx.doi.org/10.1016/j.tele.2015.05.005>
- Coan, R. W., & Cattell, R. B. (1959). The development of the early school personality questionnaire. *The Journal of Experimental Education*, *28*(2), 143-152.
- Colley, A., & Comber, C. (2003). Age and gender differences in computer use and attitudes among secondary school students: what has changed? *Educational Research*, *45*(2), 155-165.
- Comrey, A., & Lee, H. (1992). *A First Course in Factor Analysis* (2nd edn.) Lawrence Earlbaum Associates. Hillsdale, NJ.
- Constantinides, E., & Fountain, S. J. (2008). Web 2.0: Conceptual foundations and marketing issues. *J Direct Data Digit Mark Pract*, *9*(3), 231-244.
- Correa, T., Hinsley, A. W., & de Zúñiga, H. G. (2010). Who interacts on the Web?: The intersection of users' personality and social media use. *Computers in Human Behavior*, *26*(2), 247-253. doi: <http://dx.doi.org/10.1016/j.chb.2009.09.003>
- Costa Jr, P. T., & McCrae, R. R. (1992). The five-factor model of personality and its relevance to personality disorders. *Journal of Personality Disorders*, *6*(4), 343.

- Čukić, I., & Bates, T. C. (2014). Openness to experience and aesthetic chills: Links to heart rate sympathetic activity. *Personality and Individual Differences*, 64(0), 152-156. doi: <http://dx.doi.org/10.1016/j.paid.2014.02.012>
- Daniel, Z., Hsinchun, C., Lusch, R., & Shu-Hsing, L. (2010). Social Media Analytics and Intelligence. *Intelligent Systems, IEEE*, 25(6), 13-16. doi: 10.1109/mis.2010.151
- Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: a comparison of two theoretical models. *Management science*, 35(8), 982-1003.
- Duggan, M. (2015). Mobile messaging and social media. *Pew Research Center*. Retrieved from <http://www.pewinternet.org/2015/08/19/mobile-messaging-and-social-media-2015/>
- Eftekhar, A., Fullwood, C., & Morris, N. (2014). Capturing personality from Facebook photos and photo-related activities: How much exposure do you need? *Computers in Human Behavior*, 37(0), 162-170. doi: <http://dx.doi.org/10.1016/j.chb.2014.04.048>
- Fan, W., & Gordon, M. (2014). Unveiling the power of social media analytics. *Communications of ACM*.
- Field, A. (2013). *Discovering statistics using IBM SPSS statistics*: Sage.
- Fischer, E., & Reuber, A. R. (2011). Social interaction via new social media: (How) can interactions on Twitter affect effectual thinking and behavior? *Journal of Business Venturing*, 26(1), 1-18. doi: <http://dx.doi.org/10.1016/j.jbusvent.2010.09.002>
- Fishbein, M. (2008). A reasoned action approach to health promotion. *Medical Decision Making*, 28(6), 834-844.
- Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behavior: An introduction to theory and research*.
- Fouskas, K., Misirlis, N., Karanatsiou, D., & Vlachopoulou, M. (2018). Big data analysis in Tourism and Hospitality: a mapping literature review. *6th International Conference on Contemporary Marketing Issues*.
- Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, 35(2), 137-144. doi: <http://dx.doi.org/10.1016/j.ijinfomgt.2014.10.007>
- Gartner. (2013). Social Analytics, from <http://www.gartner.com/it-glossary/social-analytics>
- Gayo-Avello, P. T. M., Eni Mustafaraj, Markus Strohmaier, Harald Schoen, Peter Gloor, D., Schoen, H., Gayo-Avello, D., Takis Metaxas, P., Mustafaraj, E., . . . Gloor, P. (2013).

- The power of prediction with social media. *Internet Research*, 23(5), 528-543. doi: doi:10.1108/IntR-06-2013-0115
- Geurin, A. N., & Burch, L. M. (2016). User-generated branding via social media: An examination of six running brands. *Sport Management Review*. doi: <http://dx.doi.org/10.1016/j.smr.2016.09.001>
- Ghezzi, A., Gastaldi, L., Lettieri, E., Martini, A., & Corso, M. (2016). A role for startups in unleashing the disruptive power of social media. *International Journal of Information Management*, 36(6, Part A), 1152-1159. doi: <http://dx.doi.org/10.1016/j.ijinfomgt.2016.04.007>
- 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. doi: <http://dx.doi.org/10.1016/j.jbusres.2016.04.181>
- Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, 213-236.
- Gosling, D., Augustine, A., Vazire, S., Holtzman, N., & Gaddis, S. (2011). Manifestation of personality in online social networks: Self-reported facebook-related behaviors and observable profile information. *Cyberpsychology, behavior and social networking*, 14, 483-488.
- Gosling, S. D., Gaddis, S., & Vazire, S. (2007). Personality Impressions Based on Facebook Profiles. *ICWSM*, 7, 1-4.
- Grubmüller, V., Götsch, K., & Krieger, B. (2013). Social media analytics for future oriented policy making. *European Journal of Futures Research*, 1(1), 1-9. doi: 10.1007/s40309-013-0020-7
- Guadagno, R. E., Okdie, B. M., & Eno, C. A. (2008). Who blogs? Personality predictors of blogging. *Computers in Human Behavior*, 24(5), 1993-2004. doi: <http://dx.doi.org/10.1016/j.chb.2007.09.001>
- Guesalaga, R. (2016). The use of social media in sales: Individual and organizational antecedents, and the role of customer engagement in social media. *Industrial Marketing Management*, 54, 71-79. doi: <http://dx.doi.org/10.1016/j.indmarman.2015.12.002>
- Hair, J., Black, W., Babin, B., & Anderson, R. (2010). *Multivariate Data Analysis Seventh Edition* Prentice Hall.

- Hajli, N., Shanmugam, M., Powell, P., & Love, P. E. (2015). A study on the continuance participation in on-line communities with social commerce perspective. *Technological Forecasting and Social Change*, *96*, 232-241.
- Hall, J. A., & Pennington, N. (2013). Self-monitoring, honesty, and cue use on Facebook: The relationship with user extraversion and conscientiousness. *Computers in Human Behavior*, *29*(4), 1556-1564. doi: <http://dx.doi.org/10.1016/j.chb.2013.01.001>
- Hanna, R., Rohm, A., & Crittenden, V. L. (2011). We're all connected: The power of the social media ecosystem. *Business Horizons*, *54*(3), 265-273. doi: <http://dx.doi.org/10.1016/j.bushor.2011.01.007>
- Hart, J., Nailling, E., Bizer, G. Y., & Collins, C. K. (2015). Attachment theory as a framework for explaining engagement with Facebook. *Personality and Individual Differences*, *77*, 33-40.
- He, W., Zha, S., & Li, L. (2013). Social media competitive analysis and text mining: A case study in the pizza industry. *International Journal of Information Management*, *33*(3), 464-472. doi: <http://dx.doi.org/10.1016/j.ijinfomgt.2013.01.001>
- Hoffman, D., & Fodor, M. (2010). Can You Measure the ROI of Your Social Media Marketing? *MIT Sloan Management Review*, *52*(1).
- Huang, T. K. (2015). Exploring the antecedents of screenshot-based interactions in the context of advanced computer software learning. *Computers & Education*, *80*, 95-107.
- IBM. (n.d.). What is big data Retrieved 15/12/2015, from www-01.ibm.com/software/in/data/bigdata/
- Jang, H.-J., Sim, J., Lee, Y., & Kwon, O. (2013). Deep sentiment analysis: Mining the causality between personality-value-attitude for analyzing business ads in social media. *Expert Systems with Applications*, *40*(18), 7492-7503. doi: <http://dx.doi.org/10.1016/j.eswa.2013.06.069>
- Jenkins-Guarnieri, M. A., Wright, S. L., & Hudiburgh, L. M. (2012). The relationships among attachment style, personality traits, interpersonal competency, and Facebook use. *Journal of Applied Developmental Psychology*, *33*(6), 294-301. doi: <http://dx.doi.org/10.1016/j.appdev.2012.08.001>
- Jenkins-Guarnieri, M. A., Wright, S. L., & Johnson, B. D. (2013). The interrelationships among attachment style, personality traits, interpersonal competency, and Facebook use. *Psychology of Popular Media Culture*, *2*(2), 117.

- John, O., Naumann, L., & Soto, C. (2008). Paradigm Shift to the Integrative Big Five Trait Taxonomy: History, Measurement, and Conceptual Issues. In O. John, R. Robbins & L. Pervin (Eds.), *Handbook of Personality: Theory and Research* (pp. 114-156): Guilford.
- Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons*, 53(1), 59-68. doi: <http://dx.doi.org/10.1016/j.bushor.2009.09.003>
- Kaptein, M., Markopoulos, P., de Ruyter, B., & Aarts, E. (2009). Can You Be Persuaded? Individual Differences in Susceptibility to Persuasion. In T. Gross, J. Gulliksen, P. Kotzé, L. Oestreicher, P. Palanque, R. Prates & M. Winckler (Eds.), *Human-Computer Interaction – INTERACT 2009* (Vol. 5726, pp. 115-118): Springer Berlin Heidelberg.
- Karson, S., & O'Dell, J. W. (1976). A guide to the clinical use of the 16 PF.
- Kavanaugh, A. L., Fox, E. A., Sheetz, S. D., Yang, S., Li, L. T., Shoemaker, D. J., . . . Xie, L. (2012). Social media use by government: From the routine to the critical. *Government Information Quarterly*, 29(4), 480-491. doi: <http://dx.doi.org/10.1016/j.giq.2012.06.002>
- Kelling, N. J., Kelling, A. S., & Lennon, J. F. (2013). The tweets that killed a university: A case study investigating the use of traditional and social media in the closure of a state university. *Computers in Human Behavior*, 29(6), 2656-2664. doi: <http://dx.doi.org/10.1016/j.chb.2013.06.044>
- Kim, A. J., & Ko, E. (2012). Do social media marketing activities enhance customer equity? An empirical study of luxury fashion brand. *Journal of Business Research*, 65(10), 1480-1486. doi: <http://dx.doi.org/10.1016/j.jbusres.2011.10.014>
- Kobielus, J. (2010). Social Media Analytics: You Will Still Need Actual Analysts In The Loop. Retrieved from http://blogs.forrester.com/james_kobielus/10-07-16-social_media_analytics_you_will_still_need_actual_analysts_loop
- Kontopoulos, E., Berberidis, C., Dergiades, T., & Bassiliades, N. (2013). Ontology-based sentiment analysis of twitter posts. *Expert Systems with Applications*, 40(10), 4065-4074. doi: <http://dx.doi.org/10.1016/j.eswa.2013.01.001>
- Koohikamali, M., Peak, D. A., & Prybutok, V. R. (2017). Beyond self-disclosure: Disclosure of information about others in social network sites. *Computers in Human Behavior*, 69, 29-42.

- Kuo, T., & Tang, H.-L. (2014). Relationships among personality traits, Facebook usages, and leisure activities – A case of Taiwanese college students. *Computers in Human Behavior*, 31(0), 13-19. doi: <http://dx.doi.org/10.1016/j.chb.2013.10.019>
- Lau, R. Y. K., Li, C., & Liao, S. S. Y. (2014). Social analytics: Learning fuzzy product ontologies for aspect-oriented sentiment analysis. *Decision Support Systems*, 65(0), 80-94. doi: <http://dx.doi.org/10.1016/j.dss.2014.05.005>
- Lee, J.-E. R., Moore, D. C., Park, E.-A., & Park, S. G. (2012). Who wants to be “friend-rich”? Social compensatory friending on Facebook and the moderating role of public self-consciousness. *Computers in Human Behavior*, 28(3), 1036-1043. doi: <http://dx.doi.org/10.1016/j.chb.2012.01.006>
- Lee, K., & Ashton, M. (2004). The HEXACO Personality Inventory: A new measure of the major dimensions of personality. *Multivariate Behavioral Research*, 39(2), 329-358.
- Lee, K., & Ashton, M. C. (2008). The HEXACO personality factors in the indigenous personality lexicons of English and 11 other languages. *Journal of Personality*, 76(5), 1001-1054.
- Lee, M. R., Yen, D. C., & Hsiao, C. Y. (2014). Understanding the perceived community value of Facebook users. *Computers in Human Behavior*, 35(0), 350-358. doi: <http://dx.doi.org/10.1016/j.chb.2014.03.018>
- Leong, L.-Y., Ooi, K.-B., Chong, A. Y.-L., & Lin, B. (2013). Modeling the stimulators of the behavioral intention to use mobile entertainment: Does gender really matter? *Computers in Human Behavior*, 29(5), 2109-2121.
- Lichtenstein, D., Dreger, R. M., & Cattell, R. B. (1986). Factor structure and standardization of the Preschool Personality Questionnaire. *Journal of Social Behavior and Personality*, 1(2), 165.
- Lieberman, M. (2014). *Visualizing Big Data: Social Network Analysis*. Paper presented at the Digital Research Conference.
- Liu, F., & Lee, H. J. (2010). Use of social network information to enhance collaborative filtering performance. *Expert Systems with Applications*, 37(7), 4772-4778. doi: <http://dx.doi.org/10.1016/j.eswa.2009.12.061>
- Losh, S. C. (2004). Gender, educational, and occupational digital gaps 1983-2002. *Social Science Computer Review*, 22(2), 152-166.
- Louho, R., Kallioja, M., & Oittinen, P. (2006). Factors affecting the use of hybrid media applications. *Graphic arts in Finland*, 35(3), 11-21.

- MacCallum, R. C., Widaman, K. F., Preacher, K. J., & Hong, S. (2001). Sample size in factor analysis: The role of model error. *Multivariate Behavioral Research*, 36(4), 611-637.
- Malthouse, E. C., Haenlein, M., Skiera, B., Wege, E., & Zhang, M. (2013). Managing Customer Relationships in the Social Media Era: Introducing the Social CRM House. *Journal of Interactive Marketing*, 27(4), 270-280. doi: <http://dx.doi.org/10.1016/j.intmar.2013.09.008>
- Mandilas, A., Karasavoglou, A., Nikolaidis, M., & Tsourgiannis, L. (2013). Predicting Consumer's Perceptions in On-line Shopping. *Procedia Technology*, 8, 435-444.
- Mangold, W. G., & Faulds, D. J. (2009). Social media: The new hybrid element of the promotion mix. *Business Horizons*, 52(4), 357-365. doi: <http://dx.doi.org/10.1016/j.bushor.2009.03.002>
- Mariani, M. M., Di Felice, M., & Mura, M. (2016). Facebook as a destination marketing tool: Evidence from Italian regional Destination Management Organizations. *Tourism Management*, 54, 321-343. doi: <http://dx.doi.org/10.1016/j.tourman.2015.12.008>
- Mark, G., & Ganzach, Y. (2014). Personality and Internet usage: A large-scale representative study of young adults. *Computers in Human Behavior*, 36(0), 274-281. doi: <http://dx.doi.org/10.1016/j.chb.2014.03.060>
- Mayeh, M., Scheepers, R., & Valos, M. (2012, 2012). *Understanding the role of social media monitoring in generating external intelligence*. Paper presented at the Australasian Conference on Information Systems (23rd : 2012 : Geelong, Victoria), Geelong, Victoria.
- McCrae, R. R., & John, O. P. (1992). An Introduction to the Five-Factor Model and Its Applications. *Journal of Personality*, 60(2), 175-215. doi: 10.1111/j.1467-6494.1992.tb00970.x
- Michaelidou, N., Siamagka, N. T., & Christodoulides, G. (2011). Usage, barriers and measurement of social media marketing: An exploratory investigation of small and medium B2B brands. *Industrial Marketing Management*, 40(7), 1153-1159. doi: <http://dx.doi.org/10.1016/j.indmarman.2011.09.009>
- Misirlis, N., & Vlachopoulou, M. (2018). Social media metrics and analytics in marketing – S3M: A mapping literature review. *International Journal of Information Management*, 38(1), 270-276.

- Moore, K., & McElroy, J. C. (2012). The influence of personality on Facebook usage, wall postings, and regret. *Computers in Human Behavior*, 28(1), 267-274. doi: <http://dx.doi.org/10.1016/j.chb.2011.09.009>
- Mostafa, M. M. (2013). More than words: Social networks' text mining for consumer brand sentiments. *Expert Systems with Applications*, 40(10), 4241-4251. doi: <http://dx.doi.org/10.1016/j.eswa.2013.01.019>
- Mouakket, S. (2017). The role of personality traits in motivating users' continuance intention towards Facebook: Gender differences. *The Journal of High Technology Management Research*. doi: <https://doi.org/10.1016/j.hitech.2016.10.003>
- Nadeem, W., Andreini, D., Salo, J., & Laukkanen, T. (2015). Engaging consumers online through websites and social media: A gender study of Italian Generation Y clothing consumers. *International Journal of Information Management*, 35(4), 432-442. doi: <http://dx.doi.org/10.1016/j.ijinfomgt.2015.04.008>
- Nadkarni, A., & Hofmann, S. G. (2012). Why do people use Facebook? *Personality and Individual Differences*, 52(3), 243-249. doi: <http://dx.doi.org/10.1016/j.paid.2011.11.007>
- Nanos, I., Misirlis, N., & Manthou, V. (2017). *Cloud Computing Adoption and E-government*. Paper presented at the 6th International Symposium and 28th National Conference on Operational Research, At Thessaloniki, Greece.
- Neirotti, P., Raguseo, E., & Paolucci, E. (2016). Are customers' reviews creating value in the hospitality industry? Exploring the moderating effects of market positioning. *International Journal of Information Management*, 36(6, Part A), 1133-1143. doi: <http://dx.doi.org/10.1016/j.ijinfomgt.2016.02.010>
- Neti, S. (2011). Social media and its role in marketing. *International Journal of Enterprise Computing and Business Systems*, 1(2).
- Nettleton, D. F. (2013). Data mining of social networks represented as graphs. *Computer Science Review*, 7(0), 1-34. doi: <http://dx.doi.org/10.1016/j.cosrev.2012.12.001>
- Nielsen, J. K. (2012). Actionable Social Analytics: From Social Media Metrics to Business Insights (Vol. 2015).
- Noor, K. B. M. (2008). Case Study: A Strategic Research Methodology. *American Journal of Applied Science*, 5(11), 1602-1604.

- O'Connor, M. C., & Paunonen, S. V. (2007). Big Five personality predictors of post-secondary academic performance. *Personality and Individual Differences*, 43(5), 971-990. doi: <http://dx.doi.org/10.1016/j.paid.2007.03.017>
- Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research*, 460-469.
- Orosz, G., Tóth-Király, I., & Bőthe, B. (2015). Four facets of Facebook intensity—The development of the Multidimensional Facebook Intensity Scale. *Personality and Individual Differences*.
- Osborne, P., & Ballantyne, D. (2012). The paradigmatic pitfalls of customer-centric marketing. *Marketing Theory*, 12(2), 155-172. doi: doi:10.1177/1470593112441564
- Oye, N., Iahad, N., & Rahim, N. A. (2014). The history of UTAUT model and its impact on ICT acceptance and usage by academicians. *Education and Information Technologies*, 19(1), 251-270.
- Paek, H.-J., Hove, T., Jung, Y., & Cole, R. T. (2013). Engagement across three social media platforms: An exploratory study of a cause-related PR campaign. *Public Relations Review*, 39(5), 526-533. doi: <http://dx.doi.org/10.1016/j.pubrev.2013.09.013>
- Panagiotopoulos, P., Shan, L. C., Barnett, J., Regan, Á., & McConnon, Á. (2015). A framework of social media engagement: Case studies with food and consumer organisations in the UK and Ireland. *International Journal of Information Management*, 35(4), 394-402. doi: <http://dx.doi.org/10.1016/j.ijinfomgt.2015.02.006>
- Pehlivan, E., Sarican, F., & Berthon, P. (2011). Mining messages: Exploring consumer response to consumer- vs. firm-generated ads. *Journal of Consumer Behaviour*, 10(6), 313-321. doi: 10.1002/cb.379
- Pentin, R. (2011). A new framework for measuring social media activity. Internet Advertising Bureau.
- Podobnik, V. (2013, 26-28 June 2013). *An analysis of facebook social media marketing key performance indicators: The case of premier league brands*. Paper presented at the Telecommunications (ConTEL), 2013 12th International Conference on.
- Praude, V., & Skulme, R. (2015). Social Media Campaign Metrics in Latvia. *Procedia - Social and Behavioral Sciences*, 213, 628-634. doi: <http://dx.doi.org/10.1016/j.sbspro.2015.11.462>

- Qiu, L., Rui, H., & Whinston, A. B. (2014). Effects of Social Networks on Prediction Markets: Examination in a Controlled Experiment. *Journal of Management Information Systems*, 30(4), 235-268. doi: 10.2753/mis0742-1222300409
- Ribarsky, W., Xiaoyu Wang, D., & Dou, W. (2014). Social media analytics for competitive advantage. *Computers & Graphics*, 38(0), 328-331. doi: <http://dx.doi.org/10.1016/j.cag.2013.11.003>
- Rogers, E. M. (2002). Diffusion of preventive innovations. *Addictive Behaviors*, 27(6), 989-993.
- Rogers, E. M., & Shoemaker, F. F. (1971). *Communication of Innovations; A Cross-Cultural Approach*.
- Rohm, A., Milne, G. R., & Kaltcheva, V. (2012). *The role of online social media in brand-consumer engagement*. Paper presented at the Direct/Interactive Marketing Research Summit Proceedings.
- Ross, C., Orr, E. S., Sisic, M., Arseneault, J. M., Simmering, M. G., & Orr, R. R. (2009). Personality and motivations associated with Facebook use. *Computers in Human Behavior*, 25(2), 578-586. doi: <http://dx.doi.org/10.1016/j.chb.2008.12.024>
- Ryan, T., & Xenos, S. (2011). Who uses Facebook? An investigation into the relationship between the Big Five, shyness, narcissism, loneliness, and Facebook usage. *Computers in Human Behavior*, 27(5), 1658-1664. doi: <http://dx.doi.org/10.1016/j.chb.2011.02.004>
- Sabate, F., Berbegal-Mirabent, J., Cañabate, A., & Lebherz, P. R. (2014). Factors influencing popularity of branded content in Facebook fan pages. *European Management Journal*, 32(6), 1001-1011. doi: <http://dx.doi.org/10.1016/j.emj.2014.05.001>
- Saucier, G. (2009). Recurrent personality dimensions in inclusive lexical studies: Indications for a Big Six structure. *Journal of Personality*, 77(5), 1577-1614.
- Schuerger, J. (1995). Career assessment and the sixteen personality factor questionnaire. *Journal of Career Assessment*, 3(2), 157-175.
- Seidman, G. (2013). Self-presentation and belonging on Facebook: How personality influences social media use and motivations. *Personality and Individual Differences*, 54(3), 402-407. doi: <http://dx.doi.org/10.1016/j.paid.2012.10.009>
- Seidman, G. (2014). Expressing the “True Self” on Facebook. *Computers in Human Behavior*, 31(0), 367-372. doi: <http://dx.doi.org/10.1016/j.chb.2013.10.052>

- Sheth, J. N., Sisodia, R. S., & Sharma, A. (2000). The Antecedents and Consequences of Customer-Centric Marketing. *Journal of the Academy of Marketing Science*, 28(1), 55-66. doi: doi:10.1177/0092070300281006
- Skues, J. L., Williams, B., & Wise, L. (2012). The effects of personality traits, self-esteem, loneliness, and narcissism on Facebook use among university students. *Computers in Human Behavior*, 28(6), 2414-2419. doi: <http://dx.doi.org/10.1016/j.chb.2012.07.012>
- Smith, A., Pilecki, M., & McAdams, R. (2014). How To Make Social Media Data Actionable. Retrieved from <https://www.forrester.com/How+To+Make+Social+Media+Data+Actionable/fulltext/-/E-RES56563>
- Smith, A. N., Fischer, E., & Yongjian, C. (2012). How Does Brand-related User-generated Content Differ across YouTube, Facebook, and Twitter? *Journal of Interactive Marketing*, 26(2), 102-113. doi: <http://dx.doi.org/10.1016/j.intmar.2012.01.002>
- Smith, M. M., Saklofske, D. H., & Nordstokke, D. W. (2014). The link between neuroticism and perfectionistic concerns: The mediating effect of trait emotional intelligence. *Personality and Individual Differences*, 61–62(0), 97-100. doi: <http://dx.doi.org/10.1016/j.paid.2013.12.013>
- statista.com. (2018). Number of monthly active Facebook users worldwide as of 3rd quarter 2017 (in millions) Retrieved 01-29-2016, 2018, from Number of monthly active Facebook users worldwide as of 3rd quarter 2017 (in millions)
- Stephen, A. T. (2016). The role of digital and social media marketing in consumer behavior. *Current Opinion in Psychology*, 10, 17-21. doi: <http://dx.doi.org/10.1016/j.copsyc.2015.10.016>
- Sterne, J., & Scott, M. D. (2010). *Social Media Metrics: How to Measure and Optimize Your Marketing Investment*: Wiley.
- Stevens, J. P. (2012). *Applied multivariate statistics for the social sciences*: Routledge.
- Su, C. C., & Chan, N. K. (2017). Predicting social capital on Facebook: The implications of use intensity, perceived content desirability, and Facebook-enabled communication practices. *Computers in Human Behavior*, 72, 259-268. doi: <http://dx.doi.org/10.1016/j.chb.2017.02.058>
- Syed, A. R., Gillela, K., & Venugopal, C. (2013). The future revolution on big data. *International Journal of Advanced Research in Computer and Communication Engineering*, 2(6).

- Tabachnick, B., & Fidel, L. (2007). *Using multivariate statistics*: Boston: Pearson, Allyn and Bacon.
- Tan, W., Yang, C. (2012). *Personality Traits Predictors of Usage of Internet Services*. Paper presented at the International Conference on Economics, Business Innovation, Singapore.
- Taneja, A., Vitrano, J., & Gengo, N. J. (2014). Rationality-based beliefs affecting individual's attitude and intention to use privacy controls on Facebook: An empirical investigation. *Computers in Human Behavior*, 38, 159-173.
- Tang, J.-H., Chen, M.-C., Yang, C.-Y., Chung, T.-Y., & Lee, Y.-A. (2016). Personality traits, interpersonal relationships, online social support, and Facebook addiction. *Telematics and Informatics*, 33(1), 102-108.
- Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. *Information Systems Research*, 6(2), 144-176.
- Tiago, M. T. P. M. B., & Veríssimo, J. M. C. (2014). Digital marketing and social media: Why bother? *Business Horizons*, 57(6), 703-708. doi: <http://dx.doi.org/10.1016/j.bushor.2014.07.002>
- Valkanas, G., & Gunopulos, D. (2013). A UI Prototype for Emotion-Based Event Detection in the Live Web. In A. Holzinger & G. Pasi (Eds.), *Human-Computer Interaction and Knowledge Discovery in Complex, Unstructured, Big Data* (Vol. 7947, pp. 89-100): Springer Berlin Heidelberg.
- Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision sciences*, 39(2), 273-315.
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, 46(2), 186-204.
- Venkatesh, V., & Goyal, S. (2010). Expectation disconfirmation and technology adoption: polynomial modeling and response surface analysis. *MIS Quarterly*, 281-303.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425-478.
- Vlachopoulou, E., & Boutsouki, C. (2014). Facebook usage among teenagers—the effect of personality and peer group pressure; an exploratory study in Greece. *International Journal of Internet Marketing and Advertising*, 8(4), 285-299.
- Wang, J.-L., Jackson, L. A., Zhang, D.-J., & Su, Z.-Q. (2012). The relationships among the Big Five Personality factors, self-esteem, narcissism, and sensation-seeking to

- Chinese University students' uses of social networking sites (SNSs). *Computers in Human Behavior*, 28(6), 2313-2319. doi: <http://dx.doi.org/10.1016/j.chb.2012.07.001>
- Wehrli, S. (2008). Personality on social network sites: An application of the five factor model. *Zurich: ETH Sociology (Working Paper No. 7)*.
- Wilson, K., Fornasier, S., & White, K. M. (2010). Psychological predictors of young adults' use of social networking sites. *Cyberpsychology, Behavior, and Social Networking*, 13(2), 173-177.
- Xiang, Z., Schwartz, Z., Gerdes Jr, J. H., & Uysal, M. (2015). What can big data and text analytics tell us about hotel guest experience and satisfaction? *International Journal of Hospitality Management*, 44(0), 120-130. doi: <http://dx.doi.org/10.1016/j.ijhm.2014.10.013>
- Xie, Y., Cheng, Y., Honbo, D., Zhang, K., Agrawal, A., Choudhary, A., . . . Gou, J. (2012). *Probabilistic macro behavioral targeting*. Paper presented at the Proceedings of the 2012 workshop on Data-driven user behavioral modelling and mining from social media, Maui, Hawaii, USA.
- Yadav, M. S., de Valck, K., Hennig-Thurau, T., Hoffman, D. L., & Spann, M. (2013). Social Commerce: A Contingency Framework for Assessing Marketing Potential. *Journal of Interactive Marketing*, 27(4), 311-323. doi: <http://dx.doi.org/10.1016/j.intmar.2013.09.001>
- Yadav, P., Banwari, G., Parmar, C., & Maniar, R. (2013). Internet addiction and its correlates among high school students: A preliminary study from Ahmedabad, India. *Asian Journal of Psychiatry*, 6(6), 500-505. doi: <http://dx.doi.org/10.1016/j.ajp.2013.06.004>
- Yakushev, A., & Mityagin, S. (2014). Social Networks Mining for Analysis and Modeling Drugs Usage. *Procedia Computer Science*, 29(0), 2462-2471. doi: <http://dx.doi.org/10.1016/j.procs.2014.05.230>
- Yang, M., Kiang, M., Ku, Y., Chiu, C., & Li, Y. (2011). Social Media Analytics for Radical Opinion Mining in Hate Group Web Forums *Journal of Homeland Security and Emergency Management* (Vol. 8).
- Yu, Y., Duan, W., & Cao, Q. (2013). The impact of social and conventional media on firm equity value: A sentiment analysis approach. *Decision Support Systems*, 55(4), 919-926. doi: <http://dx.doi.org/10.1016/j.dss.2012.12.028>

- Zarpou, T., Saprikis, V., Markos, A., & Vlachopoulou, M. (2012). Modeling users' acceptance of mobile services. [journal article]. *Electronic Commerce Research*, 12(2), 225-248. doi: 10.1007/s10660-012-9092-x
- Zuckerman, M. (2002). Zuckerman-Kuhlman Personality Questionnaire (ZKPQ): an alternative five-factorial model. *Big five assessment*, 377-396.
- Zuckerman, M., Kuhlman, D. M., Thornquist, M., & Kiers, H. (1991). Five (or three) robust questionnaire scale factors of personality without culture. *Personality and Individual Differences*, 12(9), 929-941.
- Zywica, J., & Danowski, J. (2008). The Faces of Facebookers: Investigating Social Enhancement and Social Compensation Hypotheses; Predicting Facebook™ and Offline Popularity from Sociability and Self-Esteem, and Mapping the Meanings of Popularity with Semantic Networks. *Journal of Computer-Mediated Communication*, 14(1), 1-34. doi: 10.1111/j.1083-6101.2008.01429.x

Appendix

Questionnaire

Demographics		
Sex	Male:	Female:
Age		
Studies	Undergraduate student	
	Postgraduate student	
	PhD researcher	
	PhD	
Habitant	Urban	
	Semi-urban	
	Village	

Personality traits-related questions					
	Never	Rarely	Often	Very often	Always
I use a rich vocabulary					
I have a vivid imagination					
I often have great new ideas					
I can easily understand difficult and new concepts					
I am always prepared					
I look at the details					
I never leave pending					
I like the order in my stuff					
I always follow a program					
I am demanding in my work					
I am always the focus of interest in a celebration					
I feel comfortable between people					

Personality traits-related questions					
	Never	Rarely	Often	Very often	Always
I always start a conversation first					
I usually talk to many people (e.g. at a party)					
I do not mind being at the center of attention					
I am interested in the problems of others					
I am interested for people's problems					
I am a sensitive person					
I enjoy my spare time for others					
I understand the feelings of others					
I make them around me feeling comfortable					
I rarely feel despondent and sad					
I never get anxious					
I am high tempered person					

Regarding healthy diet and leisure activities					
	Irrelevant	Almost irrelevant	Neutral	Relevant	Very relevant
Most of my friends think I should be following healthy eating or sports tips that suggest different pages / groups on Facebook.					
I plan carefully the daily schedule so I follow the healthy eating or sports tips suggested by various pages / groups on Facebook.					
People who are important to me consider that I should follow healthy eating or sports tips that suggest					

Regarding healthy diet and leisure activities					
	Irrelevant	Almost irrelevant	Neutral	Relevant	Very relevant
different pages / groups on Facebook.					
It only depends on me if I follow the healthy eating or sports tips that suggest various pages / groups on Facebook.					
If I really want it, it is very easy for me to follow the healthy eating or sports tips suggested by various pages / groups on Facebook					
I find it a good idea to follow healthy eating or sports tips that suggest various pages / groups on Facebook.					
I would feel enjoyable if I follow healthy eating or sports tips that suggest various pages / groups on Facebook.					
The people who influence me with their opinions believe that it would be good to follow healthy eating or sports tips that suggest various pages / groups on Facebook.					
I would be very helpful to follow healthy eating or sports tips that suggest various pages / groups on Facebook.					
If I have already used such tips, I intend to reuse.					
I already follow pages on Facebook or other social media that offer tips for healthy eating or sports.					

Regarding healthy diet and leisure activities					
	Irrelevant	Almost irrelevant	Neutral	Relevant	Very relevant
I believe that in the future I will use Facebook pages that offer tips for healthy eating or sports					
I'm aiming to visit Facebook pages that offer tips for healthy eating or sports.					
I already use Facebook pages or other social media that offer tips for healthy eating or sports.					

I have an active account on the following social media:

Facebook

Blog

Twitter

Other: _____

Instagram

Publication list

Articles

- A9** Karanatsiou Dimitra., **Misirlis Nikolaos**, Yihao Li, Arvanitou Elvira Maria, W. Eric Wong (2019). An Assessment of Software Engineering Scholars and Institutions: In the Rise of the Decade (2010-2017). *Journal of systems and software*, 147(1), pp.246-261.
- A8** **Misiris N.**, Karanatsiou D., Vlachopoulou, M. (2019). *Do Academics Use Bibliometrics, Altmetrics and Social Media: Why, How, When?* *Journal of Altmetrics*. **Submitted (24.11.2018)**
- A7** **Misirlis N.**, Fouskas, K., Karanatsiou D., Vlachopoulou, M. (2019). A 5-year long Mapping Literature Review on Big Data Analytics in Tourism and Hospitality. *International Journal of Retail & Distribution Management*. **Minor Revision(10.12.2018)**
- A6** **Misirlis, Nikolaos**; Vlachopoulou, Maro (2019). Modeling Facebook users' behavior towards the use of Facebook pages related to healthy diet and sport activities. *Health and Technology*. **Submitted (18.09.2018)**
- A5** **Misirlis N.**, Vlachopoulou M. (2019) A Unified Framework for Decision-Making Process on Social Media Analytics. In: Sifaleras A., Petridis K. (eds) *Operational Research in the Digital Era – ICT Challenges*. Springer Proceedings in Business and Economics. Springer, Cham
- A4** **Misirlis, Nikolaos**; Lekakos, George; Vlachopoulou, Maro (2018). Associating Facebook Measurable Activities with Personality Traits: a Fuzzy Sets Approach. *Journal of Tourism, Heritage & Services Marketing*, 4(2).

- A3** Chatzithomas, Leonidas; **Misirlis, Nikolaos**; Boutsouki, Christina; Vlachopoulou, Maro (2018). Understanding the Role of Personality Traits on Facebook Intensity. *International Journal of Internet Marketing and Advertising*. **To appear**
(<http://www.inderscience.com/info/ingeneral/forthcoming.php?jcode=ijima>)
- A2** **Misirlis, N.**, Vlachopoulou M. (2018). Social media metrics and analytics in marketing - S3M A mapping literature review. *International Journal of Information Management*, 38 (1), pp. 270-276.
- A1** Karanatsiou, D., **Misirlis, N.**, Vlachopoulou, M. (2017). Bibliometrics and altmetrics literature review: Performance indicators and comparison analysis. *Performance Measurement and Metrics*, 18(1), pp.16-27.

Conferences (proceedings with full articles)

- C5** Fouskas, Konstantinos; **Misirlis, Nikolaos**; Karanatsiou, Dimitra; Vlachopoulou, Maro (2018). Big data analysis in Tourism and Hospitality: a mapping literature review. 6th International Conference on Contemporary Marketing Issues ICCMI 2018, June 25-27, 2018, Athens, Greece.
- C4** Hatzithomas, L., **Misirlis, N.**, Boutsouki, C., & Vlachopoulou, M. (2017). Effects of Personality Traits on Facebook Use. In 5th International Conference on Contemporary Marketing Issues ICCMI June 21-23, 2017 Thessaloniki, Greece (p. 422).
- C3** **Misirlis, Nikolaos**; Nanos, Ioannis; Vlachopoulou, Maro (2017). A Roadmap to Social Media Analytics. 6th International Symposium on Operational Research, June 8th, Thessaloniki, Greece.

- C2** Nanos, Ioannis; **Misirlis, Nikolaos**; Mathou, Vicky (2017). Cloud Computing Adoption and E-government. 6th International Symposium Operational Research, June 8th, Thessaloniki, Greece.
- C1** Chatzipavlou, Ioannis; **Misirlis, Nikolaos**; and Vlachopoulou, Maro, (2015). "Smartphone Medical App Use: A survey among Medical Students at Aristotle University of Thessaloniki". 5th Mediterranean Conference on Information Systems, Samos, Greece.

White Papers

- WP1** Kartsiotis, George; Hristu-Varsakelis, Dimitrios; **Misirlis, Nikolaos**; Vlahopoulos, Apostolos; Ziakis, Christos, (2016). New Agriculture for a New Generation: Recharging Greek Youth to Revitalize the Agriculture and Food Sector of the Greek Economy. Available from: http://mosaic.njaes.rutgers.edu/rty_reports/common_files/pdfs/afs/E-Commerce.pdf, 1-93, 2016, Stavros Niarchos Foundation.