## BABEȘ-BOLYAI UNIVERSITY, CLUJ-NAPOCA FACULTY OF PSYCHOLOGY AND EDUCATION SCIENCES DOCTORAL SCHOOL "EDUCAȚIE, REFLECȚIE, DEZVOLTARE"

## Ph.D. Thesis Summary

Applying technology acceptance modeling to social networking.
A psychosocial extension and partial validation of existing theorie

Doctoral Supervisor,

Associate Professor Alina S. Rusu, PhD Habil.

Doctoral student,

PhD candidate Dorin Stanciu

Cluj-Napoca

2017

## **CONTENTS**

I. Part I. Theoretical Framework
I.1. From networking technologies to social digital networking
I.1.1. A short overview of the Internet and web technologies
I.1.2. A digitally connected society. Psychosocial aspects
I.1.2.1. The importance of social media in psychosocial functioning
I.1.2.2. Social networking and the case of Facebook
I.2. Academic approaches to the study of technology adoption and social networking
I.2.1. Information Systems-based approaches. Technology acceptance model
(TAMs) 4
I.2.2. The unified theory of acceptance and use of technology
I.2.3. The hedonic-motivation system adoption model
I.3. Additional constructs beneficial to understanding the adoption of social networking
technologies
I.3.1. A potential expansion of the underpinnings of existing TAMs based on
psychosocial theories
I.3.2. Self-objectification in online exposure
I.3.3. Social influences. Support and honesty
I.3.4. Honesty. The bridging reciprocity
I.4. Research objectives
II. Part II. Original Research1
II.1. Study 1. Modeling Facebook adoption
II.1.1. Introduction
II.1.1. Objectives
II.1.1.2. General hypothesis
II.1.1.3. Particular/individual hypotheses
II.1.2. Methodology
II.1.2.1. The proposed research design
II.1.2.2. Measures
II.1.2.3. Procedure
II.1.2.3.1. Scales translation and adaptation13

II.1.2.3.2. Data collection	14
II.1.2.3.3. Data processing	14
II.1.2.4. Participants	14
II.1.3. Results	18
II.1.4. Discussions and conclusions regarding Study 1	18
II.2. Study 2. Family and peer influences on Facebook adoption	21
II.2.1. Introduction	21
II.2.1.1. Objectives	21
II.2.1.2. Hypotheses	21
II.2.2. Methodology	21
II.2.2.1. The research design	21
II.2.2.2. Measures	22
II.2.2.3. Procedure	22
II.2.2.4. Participants	23
II.2.2.4.1. Demographic data for Parent-Child Dyads	23
II.2.2.4.2. Demographic data for Best-Friends Dyads	25
II.2.3. Results	26
II.2.4. Discussion and Conclusions regarding Study 2	27
II.3. Study 3. Enhancing Facebook adoption through social support. A pa	artial validation
of the conceptual framework	29
II.3.1. Introduction	29
II.3.1.1. Conceptual framework for the experimental intervention	29
II.3.1.2. Objectives	30
II.3.2. Methodology	31
II.3.2.1. Design.	31
II.3.2.2. Hypotheses	31
II.3.2.3. Procedure	32
II.3.2.4. Measures	33
II.3.2.5. Participants	33
II.3.3. Results	35
II.3.4. Discussion and conclusion regarding Study 3	37
III. Part III. Conclusions and Discussions	39
III.1. The importance of the research for the state of the art	39

Ι	II.2.	Current ac	chievements and future avenues of research	40
IV.	Re	ferences		43
V.	Anne	ex to the th	esis' summary	49
	V.	1.1.1. Origi	nal models	49
	,	V.1.1.1.1.	Models based on the original UTAUT2	49
	•	V.1.1.1.2.	Models based on the original HMSAM	51
	V.	1.1.2. Mode	els based on the adapted UTAUT2	53
	•	V.1.1.2.1.	Causal model A1 based on adapted UTAUT2	53
	,	V.1.1.2.2.	Causal model A2 based on adapted UTAUT2 (second order factors	s)-55
	,	V.1.1.2.3.	Causal model B based on the adapted UTAUT2	56
	,	V.1.1.2.4.	Causal model C based on adapted HMSAM	58
	,	V.1.1.2.5.	Causal model D based on HMSAM	60
	V.:	1.1.3. Mode	el M based in combined predictors from HMSAM and UTAUT2	62

## List of figures

Figure 1: Percentage of Internet users in the entire population (source Worldbank, 2017)2
Figure 2: Venkatesh and colleagues' acceptance and use of technology model (apud Venkatesh
et al., 2003, p. 447)5
Figure 3: Venkatesh and colleagues' UTAUT2 (UTAUT extended and updated, apud
Venkatesh, Thong, & Xu, 2012, p. 160)6
Figure 4: Van der Heijden's extended model (apud Lowry et al., 2012, p. 622)7
Figure 5: The final hedonic-motivation system acceptance model (apud Lowry et al., 2012, p.
633)
Figure 6: Mean age and standard deviation for participants in Study 1 (bars represent standard
deviations)15
Figure 7: Breakdown of participants in Study 1 per level of completed education16
Figure 8: Breakdown of participants in Study 1 per living environment16
Figure 9: Breakdown of participants in Study 12 per Frequency of FB Use for Communication
via Posting17
Figure 10: Breakdown of participants in Study 12 per Frequency of FB Use for Communication
via Chat/Messenger17
Figure 11: Mean age and standard deviation for Parent-Child Dyad participants in Study 2 (bars
represent standard deviations)24
Figure 12: Breakdown of Parent-Child Dyad participants in Study 2 per level of completed
studies and gender24
Figure 13: Mean age and standard deviation of age for Best-Friends Dyad participants in Study
2 (bars represent standard deviations)25
Figure 14: Breakdown of Best-Friend Dyad participants in Study 2 per level of completed
studies and gender
Figure 15: CBSEM predictive model of <i>social support</i> construed as a first order factor
comprised of informational and emotional support, impacting on behavioral intention to use
Figure 16: CBSEM predictive model of informational support impacting on behavioral
intention to use30
Figure 17: CBSEM predictive model of <i>emotional support</i> impacting on <i>behavioral intention</i>
to use30

Figure 18: Mean age and standard deviation for the participants' entire sample per gender
(Study 3)
Figure 19: Mean age and standard deviation for the participants in Study 3 per gender and
experimental group
Figure 20: Means boxplot for the scores at behavioral intention for the three experimental
groups by time of measurement
Figure 21: Plot of estimated marginal means for the behavioral intention to use per
experimental group and measurement time (Study 3)
Figure 22: Causal model based on original UTAUT2 model
Figure 23: PLS model for Facebook adoption based on original UTAUT2 model (pathways of
influence)
Figure 24: Causal model based on original HMSAM51
Figure 25: PLS model for Facebook adoption based on original HMSAM model (pathways of
influence)
Figure 26: The causal model A1 based on adapted UTAUT2 (1st order factors)53
Figure 27: PLS modeling of causal model A1 based on adapted UTAUT2 (the influence
pathways)
Figure 28: Causal model A2 based on adapted UTATU2 (reflexive 2 <sup>nd</sup> order factors)55
Figure 29: PLS modeling of causal mode A2 based on UTAUT2 (reflexive $2^{nd}$ order factors,
the influence pathways)
Figure 30: Causal model B based on adapted UTAUT2 model
Figure 31: PLS model based on adapted UTAUT2 model (pathways of influence)57
Figure 32: Causal model C for Facebook adoption based on adapted HMSAM58
Figure 33: PLS modeling of model C based on adapted HMSAM (influence pathways)59
Figure 34: Causal model PLS D based on adapted HMSAM
Figure 35: PLS modeling (model D) based on adapted HMSAM (strength of influence
pathways)61
Figure 36: Causal model based on combined predictors from HMSAM and UTAUT2 and
additional constructs
Figure 37: PLS modeling (model M) based on combined predictors (strength of influence
pathways)63
Notes: The remaining figures, up to Figure 116 are presented in the Thesis and in the Annexes
and are not referenced in text.

## I. Part I. Theoretical Framework

## I.1. From networking technologies to social digital networking

## I.1.1.A short overview of the Internet and web technologies

Technology is increasingly more prevalent in our everyday lives. We are talking nowadays about the very real phenomenon of 'techno-globalization' or the worldwide, global pervasiveness in generating and implementing technological knowledge and advances (Schuch, 2013). There is now a rather common perception that technology, in general, and the Internet, in particular, evolve and grow exponentially in complexity and capabilities. This assessment is supported by empirical observations which confirmed that the increase in processing power grows yearly by a factor of 10, a phenomena referred to as the Moore's Law, after the name of one of Intel's founders, Gordon Moore (Williams, 2007).

Web 2.0 designates a stage of the Web in which the users are able to generate content and become active players/actors in the dynamics of the Web, due to the advent of new technologies such as Ajax, XML, Open API, Microformats, Flash, etc. (O'Reilly, 2007). The most important characteristic of Web 2.0, which separates it from Web 1.0, is its ability to permit bi-directional transmission of information, from the user/client to the server/provider and vice versa, and the user-generated content (UCG), features of capabilities outside the reach of the former Web 1.0 (Kietzmann, Hermkens, McCarthy, & Silvestre, 2011; O'Reilly, 2007). Moreover, the most important characteristics of Web 2.0, sometimes referred to as 'principles', are openness, user participation and content sharing, by virtue of a plethora of tools which include podcasting, videoblogging or regular blogging, syndicated content, social bookmarking and tagging, social networking, wikis, and other collaborative features (Khan, 2015).

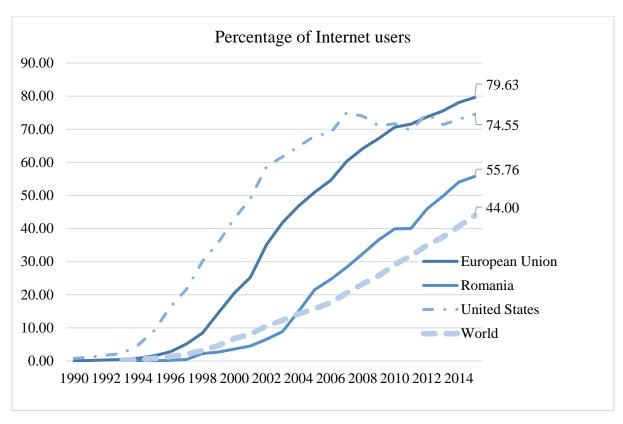


Figure 1: Percentage of Internet users in the entire population (source Worldbank, 2017)

## I.1.2.A digitally connected society. Psychosocial aspects

## I.1.2.1. The importance of social media in psychosocial functioning

The continued growth of the Internet and the development of social media technologies reached a point of such widespread popularity that they are often referred to as "democratized" technologies (*e.g.*, YouTube, Facebook, etc.) and the Internet is construed as a 'public sphere' (Reddick, 2010). These new meanings of the virtual space, as a 'people's public sphere' allowed for very important developments which shed new light on their importance. For instance, during the so-called "Arab Spring" in 2011, two very important social media, Twitter and Facebook, played an instrumental role in disseminating news and ideas, getting people together, helping them identify allies, providing virtual grounds for rallying, etc. (Khondker, 2011; Quinn, 2013). Stepping beyond peoples' use of social media, effects of more societal nature can be identified, such as: 1) social media was central to shaping political debates, 2) spikes in online revolutionary debates often predict major events on the ground, and 3) social media helped disseminating democratic ideas across international borders (Howard et al., 2011).

### I.1.2.2. Social networking and the case of Facebook

We are now witnessing the 'digital connectedness' of 'post-revolutionary times' invoked by Traub and Lipkin (1998), and foreseen as early as Vannevar Bush's memex (1946): "It is manifest in the advent of the digital computer and its accompanying methodologies, ways of working that stress relationships between bodies of knowledge and human minds and that utilize networks to create these relationships. The computer is valuable in its ability to allow us to reconceptualize our relation to knowledge and to organize it, rather than merely accumulate information" (Traub & Lipkin, 1998, p. 363).

Social networks, like Facebook, not only allow the creation of new relations between users or online befriending, but they can be used also to maintain pre-existing social relations or to solidify offline connections (Ellison, Steinfield, & Lampe, 2007). In their own words, "Facebook's mission is to give people the power to share and make the world more open and connected. People use Facebook to stay connected with friends and family, to discover what's going on in the world, and to share and express what matters to them" (Facebook, 2017).

Using social media and social networks is by no means restricted to the individual users, instead, there are example of companies whose initial focus was on facilitating social interaction are extending nowadays towards professional or work-related areas. Thus, increasingly more companies start to expand into social media and social networks to recruit candidates and promote their products, their events and even their specific corporate culture (Elmore, 2009). Meanwhile, 'classical' media began to acknowledge and even to recommend the use of social media for building and promoting professional profiles ("How social media will help you find a job," 2012; "What's out and in on the job-hunting front," 2009).

Facebook, the most popular social network, reached an impressive 1.7 billion users, which accounts for approximately one quarter of the world's entire population. (Elangovan & Agarwal, 2015; Facebook, 2016). More precise stats include: 1.23 billion daily active users on average for December 2016, 1.15 billion mobile daily active users on average for December 2016, 1.86 billion monthly active users as of December 31, 2016, and 1.74 billion mobile monthly active users as of December 31, 2016 (Facebook, 2017).

## I.2. Academic approaches to the study of technology adoption and social networking

## *I.2.1.Information Systems-based approaches. Technology acceptance models (TAMs)*

To date, the most prominent models with respect to technology acceptance (TAMs) are Venkatesh and colleagues' (2003) models, based on their *Unified Theory of Acceptance and Use of Technology* (Venkatesh et al., 2003), and Lowry and colleagues' (2012) *Hedonic-Motivation System Adoption Model* (Lowry et al., 2012). Both models have their most recent versions developed in the 2010s and both incorporate the most relevant theories and models until them. Similarly, both models attempt to explain and to predict users' utilization intentions of technological systems and, ultimately, the effective use of these systems, *i.e.*, the *technology adoption* (TA).

The main difference between the two models consists in their underlying assumption. For instance, the *unified theory use and acceptance of technology model* (UTAUT) is representative for the so-called *utilitarian* models, which posit that the main driving factor in technology adoption is the systems' usefulness or their productive value. Moreover, from a historical perspective, the study of technology acceptance started with investigating predictions concerning the adoption of production systems, such as logistics, accounting, etc.

On the other hand, the hedonic component, or factor, involved in people's decision making regarding TA becomes increasingly more important and difficult to ignore, even for systems which were traditionally utilitarian in nature. For instance, with respect to learning communities, ranging from school learning to organizational learning, there is an increasing shift in emphasis from extrinsic to intrinsic motivation, including via the use of gamification elements (Cheong, Filippou, & Cheong, 2014; de-Marcos, Domínguez, Saenz-de-Navarrete, & Pagés, 2014; de-Marcos, Garcia-Lopez, & Garcia-Cabot, 2016; Elmore, 2009; "Gamification in Education and Libraries," 2015; Landers, 2014; Su & Cheng, 2015). Moreover, companies such as Apple make heavy use of the hedonic component in marketing their products, even though, originally, their products are utilitarian in nature. This may explain, at least in part, the success of products such as the iPad<sup>TM</sup> or the iPod<sup>TM</sup> (Lowry et al., 2012).

## *I.2.2.The unified theory of acceptance and use of technology*

The UTAUT model posits four main influencers (predictors/independent variables), directly significant for the acceptance and use of technology, *i.e.*, *performance expectations* (PE), *effort expectations* (EE), *social influences* (SI), and *facilitating conditions* (FC). It also

includes four main moderators or the pathways between the predictors and the outcomes behavioral intention and the use behavior: a) gender, b) age, c) experience, and d) voluntariness of use (see Figure 2, bellow, for details).

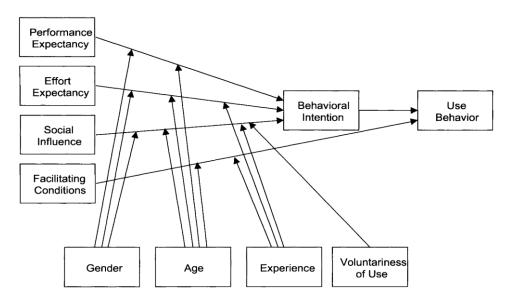


Figure 2: Venkatesh and colleagues' acceptance and use of technology model (apud Venkatesh et al., 2003, p. 447)

Table 1: Pathways of influence and their moderators in UTAUT

Predictors	N	Moderators		Outcome	
	Gender	Age	Experience '	Voluntariness	
				of use	_
Performance expectancy	Yes	Yes	No	No	Behavioral intention
Effort expectancy	Yes	Yes	Yes	No	Behavioral intention
Social influence	Yes	Yes	Yes	Yes	Behavioral intention
Facilitating conditions	No	Yes	Yes	No	Use behavior

In 2012, Venkatesh and colleagues extended and enhanced the UTAUT model, by incorporating new predictors—*i.e.*, *hedonic motivation*, *price value*, and *habit*—and by eliminating *voluntariness of use* from among the moderators (see the UTAUT2 model in Figure 3, bellow).

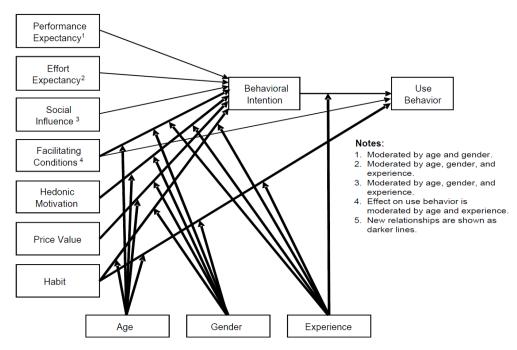


Figure 3: Venkatesh and colleagues' UTAUT2 (UTAUT extended and updated, apud Venkatesh, Thong, & Xu, 2012, p. 160)

Table 2: Old and new pathways of influence and their moderators in UTAUT2

Predictors		Moderators		Outcome
_	Gender	Age	Experience	
Performance expectancy	Yes	Yes	No	Behavioral intention
Effort expectancy	Yes	Yes	Yes	Behavioral intention
Social influence	Yes	Yes	Yes	Behavioral intention
Facilitating conditions*	Yes	Yes	Yes	Behavioral intention
Hedonic motivation*	Yes	Yes	Yes	Behavioral intention
Price value*	Yes	Yes	No	Behavioral intention
Habit*	Yes	Yes	Yes	Behavioral intention
Facilitating conditions*	No	Yes	Yes	Use behavior
Habit*	Yes	Yes	Yes	Use behavior
Behavioral intention**	No	No	Yes	Use behavior

Notes for Table 2: \* denotes a new pathway, \*\* denotes a modified pathway

## *I.2.3.The hedonic-motivation system adoption model*

As opposed to UTAUT and other utilitarian models, which focus on the external benefits that the system provides for the user, *i.e.*, extrinsic motivation (Venkatesh et al., 2003), HMSAM is fundamentally based on a composite construct of intrinsic motivation, while the extrinsic motivation is either discounted or subsumed to the intrinsic motivation (Lowry et al., 2012). Essentially, HMSAM is an extension of Van der Heijden's (2004) model, in which the construct of *joy* was incorporated by the larger construct of *cognitive absorption* (see the

originally proposed Van der Heijden's extended model in Figure 4, and the final HMSAM in Figure 5, bellow).

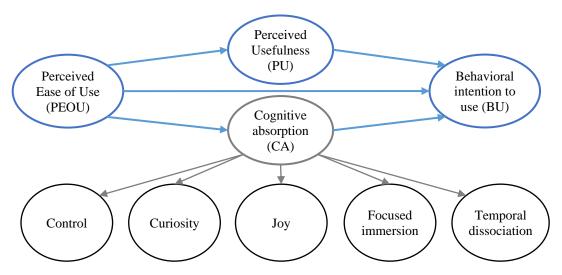


Figure 4: Van der Heijden's extended model (apud Lowry et al., 2012, p. 622)

The construct of *cognitive absorption* was introduced by Agarwal and Karahanna (2000). and designates a "state of deep involvement with software" (Agarwal & Karahanna, 2000, p. 665). In HMSAM, the *cognitive absorption* is a first order construct which subsumes five second order constructs, *i.e.*, *control*, *joy*, *curiosity*, *focused immersion* and *temporal dissociation* (Lowry et al., 2012).

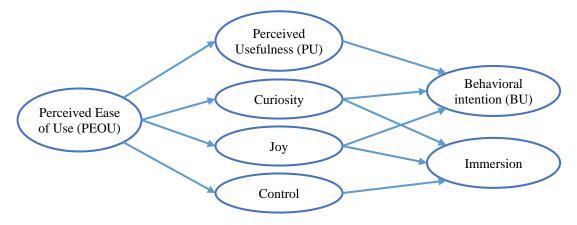


Figure 5: The final hedonic-motivation system acceptance model (apud Lowry et al., 2012, p. 633)

# I.3. Additional constructs beneficial to understanding the adoption of social networking technologies

# I.3.1.A potential expansion of the underpinnings of existing TAMs based on psychosocial theories

An important theoretical background, which can be employed more thoroughly to expand the explanatory perspectives on social media adoption, was pointed out by Kaplan and Haenlein (2010), in their 2010 article, *Users of the World, Unite! The Challenges and Opportunities of Social Media*. Kaplan and Haenlein (2010) identify two main dimensions of relevance for Social Media, *i.e.*, a media richness/social presence dimension, and a social dimension/self-presentation. While the first dimension or criterion, *i.e.*, media richness/social presence refers to the intensity, body, and quality of the communication, the second dimension takes into account the individuals' strategies for interacting with each other (Kaplan & Haenlein, 2010).

In SNS research, self-presentation is a central concept: "Like other online contexts in which individuals are consciously able to construct an online representation of self—such as online dating profiles and MUDS—SNSs constitute an important research context for scholars investigating processes of impression management, self-presentation, and friendship performance" (boyd & Ellison, 2007, p. 219).

Another body of research, relevant to our interests, came from social psychology and links self-presentation with a key construct in social psychology, namely, *self-objectification*. Social self-objectification designates one's propensity to regard oneself and to present oneself from the perspective of another, third person, focusing on observable bodily characteristics (*e.g.*, "how do I look"), rather than at the first person, focused on non-overt characteristics (*e.g.*, "what am I capable of?", "how do I feel?")" (Fredrickson, Roberts, Noll, Quinn, & Twenge, 1998; Noll & Fredrickson, 1998). Similarly, people employs selected self-presentation strategies with the goal of controlling other's impression of them (Goffman, 1978).

## I.3.2.Self-objectification in online exposure

In a previous research (Nistor & Stanciu, 2017), building on the aspects mentioned above, a scale was developed to measure Job Search Related Self-Objectification (SO), derived from ten guidelines found in ubiquitous job search guidebooks. Five statements addressed attributes we considered to be appearance-related (e.g. "describing your professional competence in fashionable terms"), further five competence-related (e.g. "showing impactful

results of your work"). The participants were asked to rate on a seven-point Likert scale from "absolutely unimportant" to "absolutely important". The resulting values were not aggregated as a mean value to a single dimension, but were first subjected to the exploratory and confirmatory analysis, which ultimately, yielded a 2-order composed construct.

The consequent analyses provided empirical evidence that *self-objectification* was positively associated with the *performance expectancy*, which, in turn, is one of the main pillars of the UTAUT model (*PE* significantly predicts *SO*,  $\beta = .31$ , p < .05), as well as with age, which is one of the main moderators for three main predictors on the model (*age* predicts *SO*,  $\beta = .14$ , p < .5) (Nistor & Stanciu, 2017).

## *I.3.3.Social influences. Support and honesty*

The *social influence* is a key component, posited as a direct influencer (*i.e.*, strictly technically, as predictor) in the utilitarian motivation models. Nevertheless, in other research, also related to the online behavior and Internet usage, social influences were investigated mostly as outcomes or predicted variables. Moreover, albeit conceptually, *the social support* is closely related to the *social influences*, *e.g.*, incorporated in UTAUT and UTAUT2, there are significant differences, which may prove to have explanatory/predictive value.

Social support is an important component of active participation in virtual communities. Research data suggest close positive associations between the perceived social support and the active implication in the virtual communities (Jang, Park, & Song, 2016; Taiminen, 2016). Another relevant feature of *social support* is its conceptual development as a super-ordinated construct, comprised of *informational* and *emotional support* (Huang, 2016). We hypothesize that the perceived social support will serve as a feedback mechanism which increases the users intrinsic motivation in their online and social network interactions.

## *I.3.4.Honesty. The bridging reciprocity*

Wilson, Gosling, and Graham (2012), identified three main area of relevance regarding the study of Facebook: a) the richness in behavioral data created by the users' activities; b) Facebook, and other SNSs, as well, not only reflect existing social processes, but also spawn new ones by ways in which hundreds of millions of people relate to each other and share information; and c) the need to carefully asses the negative and positive implication of using Facebook and other SNSs, such as privacy, intimacy, disclosure, etc. (Wilson et al., 2012).

Moreover, the degree in which an individual discloses information about him/herself in an online environment is closely related with the image that the individual wants to project in that particular digital environment, and, consequently, with self-objectification, as the manner of presentation, on the one hand, and with the desired outcome, as a strategic goal (see, also, above, about self-presentation). As Huang (2016) showed in his study regarding the use of Facebook, *self-disclosure*, in which *honesty* is an intrinsic component, and *social support* (construed bi-factorial as *emotional* and *informational* support) contribute greatly to the online wellbeing (explaining a significant 40% of the variance in online wellbeing), which, in turn, impacts on the continuance intention to use (Huang, 2016). In his study, Huang's design was able to explain almost 40% of the variance in the continuance intention to use Facebook (Huang, 2016).

## I.4. Research objectives

## Consequent and related **research questions** are:

- Can social networking be successfully studied (*i.e.*, modeled) using the same conceptual framework established for technology adoption, in general? And, if so,
- Which model is better for social networking, (*i.e.*, in our particular case, for Facebook adoption)?
- Can the models be improved (*i.e.*, is their predictive ability increased) by the addition of other, additional variables (suggested by existing research)?
- Can other constructs, more psychosocial in nature, be added to or combined with the existing models, in order to improve their adequacy to explaining Facebook adoption?
- Can behavioral intention as a dependent variable be influenced via the experimental manipulation of one the predictors?

## The main **research objectives** can be briefly summarized as follows:

- To identify the most suited model for social networks adoption (by using comparative analysis involving structural equation modeling), in the context of Romanian users.
- To improve the existing models via the addition of relevant constructs.
  - To identify relevant constructs with the potential to increase the models' predictive power;
- To partially validate the obtained models.

## II. Part II. Original Research

## II.1.Study 1. Modeling Facebook adoption

## II.1.1. Introduction

Based on the theoretical framework underpinning the technology acceptance models and results from research concerning the adoption of social networks, a design for studying the adoption of social networking in Romanian users was developed, taking into account new and relevant additional constructs, such as construct derived from the authors previous research *self-objectification* (Nistor & Stanciu, 2017), or from other research *social support, honesty*, and *online wellbeing* (Huang, 2016; Liang, Ho, Li, & Turban, 2011; C.-P. Lin, 2011; K.-Y. Lin & Lu, 2011).

## II.1.1.1. Objectives

The **first main research objectives** in this stage was to adapt the existing technology acceptance models to the adoption of social networking in the Romanian socio-cultural context (operationalized via the use of Facebook, as the most representative social network), and to further refine the models in terms of bettering their explanatory power for the particular application to social networking. It is worth noting that improving a model involves taking into consideration both the total variance explained as well as improving the indices of fit (this caveat is presented in greater detail in the following sections).

The **second main objective** of this part of the research was to extend the models via the incorporation of the new additional constructs, which may have proven relevant in terms of explaining the adoption of social networking.

A set **of working hypotheses** was consequently developed, positing that, on the one hand, the existing models can be applied to the adoption of social networking, and, on the other hand, that the current models can benefit from encompassing new and relevant new additional constructs. However, because of the complexities of testing these working hypothesis, and because of the characteristics of the research methodology involved, two layers, of general and, respectively, particular, hypotheses, can be observed.

## II.1.1.2. General hypothesis

The general working hypothesis of the structural equation modeling followed closely the research objective. They can be summarized as:

- The models can be used to explain the Romanian respondents' adoption of Facebook.
- The models can be improved by adapting them according to results from EFA.
- The additional constructs mentioned in Objectives are relevant in explaining the users' intention to use Facebook.
- The additional constructs mentioned in Objectives can improve the explanatory power of the models.

## II.1.1.3. Particular/individual hypotheses

With respect to developing and testing the models for Facebook adoption, virtually every pathway of influence indicated in the original models (the final models are represented graphically section Theoretical Background,) represented a hypothesis that needed to be tested. The testing was done using confirmatory factor analysis in SEM, using the covariance-based method. From reasons of parsimony (there are hundreds of possible combinations between the possible predictors and the posited outcome, *i.e.*, the *behavioral intention to use*), not all hypotheses were listed here. However, all hypothesis were assessed and their confirmation or negation can be observed in the tables regarding the (significance of) pathways of influence and the indices of models' fit.

## II.1.2. Methodology

## II.1.2.1. The proposed research design

## The type of research design

The proposed research design was a one-time cross-sectional/transversal study. With respect to gathering the required information, it consisted in applying the measurement instruments (self-reported questionnaires) corresponding to the constructs/variables of interest (predictors/independent variables, mediators and moderators, and, respectively, predicted/outcome/dependent variables). With respect to its goals, Study 1 aimed at applying the models used for technology adoption to the case of social networking adoption.

### The choice of modeling methods

It is worth noticing that in their development and validation of UTAUT2, Venkatesh et al. (2012) used the partial least square method, based on Chin et al.'s (2003) recommendations for testing models with vast number of interactions between the terms, whereas Lowry et al.'s (2012) development and validation of HMSAM involved the use of covariance based structural equation modeling (CBSEM), mostly because this method allows the testing of model differences by comparing model fit indices, a decision which they based on Gefen et al.' (2011) recommendations (Gefen, Straub, & Rigdon, 2011).

### II.1.2.2. Measures

UTAUT2 is comprised of eight 7-point Likert scales, each containing between 3 and 4 items. Additional, a supplementary scale, *i.e. use behavior*, measuring the actual use, and which is open to modifications by the researcher, according the specificities of the research topic, can be introduced. Seven scales measure the predictor/independent variables, whereas the last two measure the predicted/dependent variables.

In turn, the final proposed HMSAM is comprised of seven 7-point Likert scales, six of these being predictor/independent variables and the seventh, *behavioral intention to use*, is, in fact, similar with *behavioral intention* from UTAUT2.

Additionally, in order to extend the models and aiming to improve the explained variance in the use intention (measured via *behavioral intention/behavioral intention to use*), based on theoretical reasons explained in the previous section, we used also scales for *self-objectification*, *honesty*, *social support* (comprised of *emotional support* and *informational support*), and *online social wellbeing*. All scales corresponding to the additional constructs were previously used by Huang (2016) in his research regarding Facebook adoption, with the exception of the *self-objectification* scale which was adapted from (Nistor & Stanciu, 2017).

## II.1.2.3. Procedure

## II.1.2.3.1. Scales translation and adaptation

The instruments (scales) used in our research were applied for the first time to the Romanian population. Therefore, the translation was handled independently by two translators (one was the author and the other was a published scientist with high proficiency in using English in various contexts). After completion of the blind translations, the divergent terms were discussed and the inter-rating matrix was constructed. For those items were the difference was

insignificant (*i.e.*, for synonyms or for differences in wording without change of meaning) the original differences rating were nullified. The initial inter-rater agreement was 83%, completely satisfactory to proceed with the translation, especially that an unforced consensual agreement was established on all items.

#### II.1.2.3.2. Data collection

In order to disseminate the measurement instruments, *i.e.*, the self-reported questionnaires, a web-based questionnaire was developed using Google Forms. The link to the final Google Form Questionnaire was disseminated to the participants via face-to-face school meetings, as well as in other web communities, such as Facebook groups, etc. Students enrolled in the Educational Psychology and in the Ergonomics courses at various departments of the Technical University of Cluj-Napoca were contacted first. Second, the students were instructed to disseminate the link to the questionnaire to any friend who may be a user of Facebook or other Social Media and to their parents, if they wanted to.

## II.1.2.3.3. Data processing

The data (participants' responses) was collected via an export from Google Spreadsheets to Microsoft Excel and further into IBM SPSS® ver. 24, IBM SPSS AMOS® and SmartPLS®. The structural equation modeling was done using IBM AMOS ver. 23 (for covariance based analyses) and SmartPLS ver. 3 (for variance based computations).

## II.1.2.4. Participants

The participation in the study was voluntary and open to any individual interested, age 14 or above. Most of the participants were students from the Technical University of Cluj-Napoca, enrolled in course of Psychology. However, the participation was made open to any willing individual, and the participants were asked to distribute the invite to the research to friends and families. The socio-demographic indicators collected referred to the participants included gender, and age (see, also, Table 3, below, for details). In total, 1256 individuals age between 14 and 62, and mean age  $M_{\text{age}} = 25.70$ ,  $SD_{\text{age}} = 11.13$ , took part on the research. Out of them, 676 participants were female ( $M_{\text{age female}} = 27.21$ ,  $SD_{\text{age female}} = 12.04$ ) and 580 were male ( $M_{\text{age male}} = 23.94$ ,  $SD_{\text{age male}} = 9.68$ )

Table 3: Demographic data for age for the participants in Study1

Gend	er	N	Mean Age	SD Age	Min Age	Max Age
	Female	676	27.21	12.04	14	62
	Male	580	23.94	9.68	13	59
Total		1256	25.70	11.13	13	62

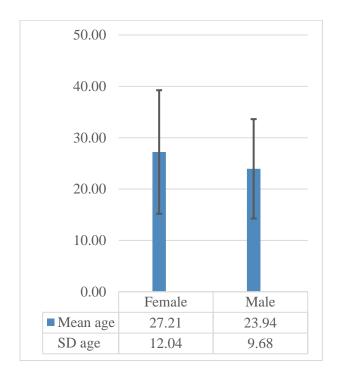


Figure 6: Mean age and standard deviation for participants in Study 1 (bars represent standard deviations)

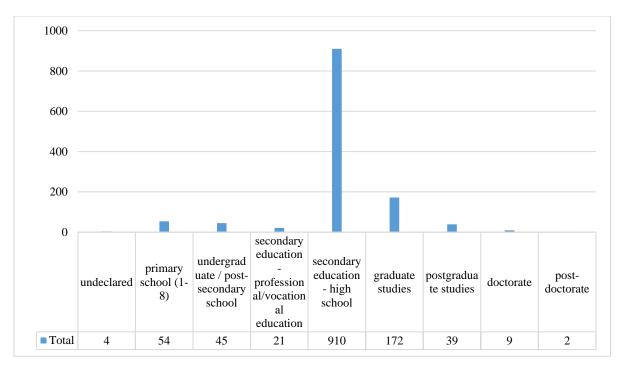


Figure 7: Breakdown of participants in Study 1 per level of completed education

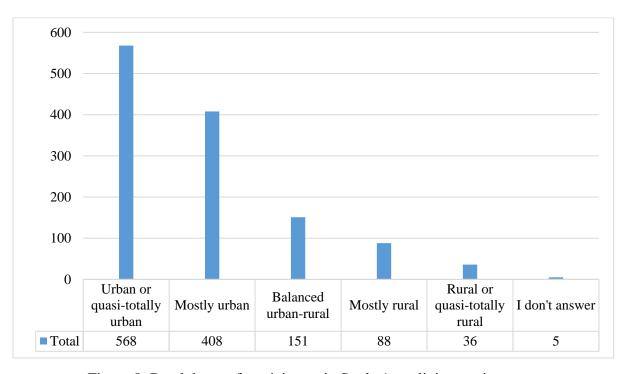


Figure 8: Breakdown of participants in Study 1 per living environment

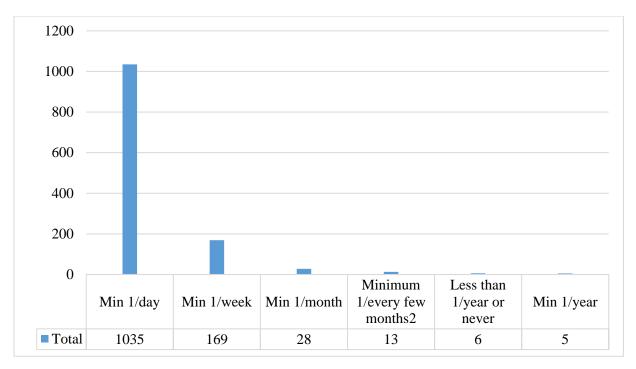


Figure 9: Breakdown of participants in Study 12 per Frequency of FB Use for Communication via Posting

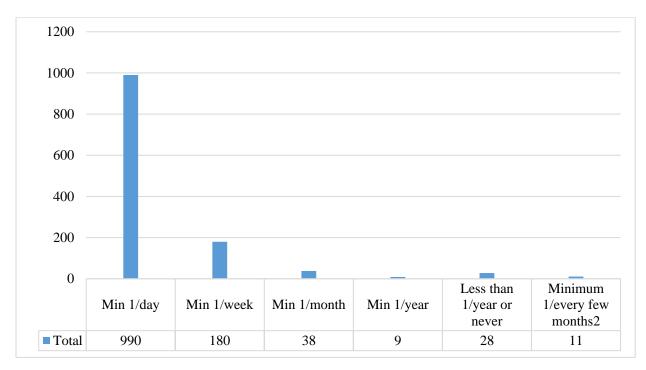


Figure 10: Breakdown of participants in Study 12 per Frequency of FB Use for Communication via Chat/Messenger

### II.1.3. Results

## II.1.4. Discussions and conclusions regarding Study 1

The results obtain from the above modeling processes showed a gradual improvement of the models, which came along with relaxing the criterion of replicating the models as close as possible, concomitantly with observing findings from EFA and the consequent structural analysis. Table 4, below, shows, in synthetic presentation, that the best fitted models where obtained for the adapted models, while the common latent factor models showed that good to great fit indices are characteristic for the models after accounting for the common-method bias.

Table 4: Summary of fit indices for the causal models

Table 4: Summary of 11t indices for the causal models								
Model Code				Fit indices				
_	df	CMIN/df	NFI	CFI	<b>RMSEA</b>	SRMR	PCLOSE	
Models based on original UTAUT2 and HMSAM								
M-U-u	247	9.764	.868	.879	.084	.074	.000	
M-U-c	237	7.997	.896	.907	.075	.064	.000	
CLF - U - c	222	6.5444	.920	.931	.066	.039	.000	
M-H-u	751	10.378	.767	.784	.086	.098	.000	
CLF - H - u	710	7.610	.838	.856	.073	.056	.000	
Models based on ad	lapted UT	AUT2 and H	MSAM					
M-U-c-A	196	4.505	.949	.960	.053	.037	.091	
C-U-c-A1	245	4.738	.947	.957	.055	.041	1.000	
C-U-c-A2	255	5.286	.938	.949	.058	.055	.000	
M-U-u-B	237	7.004	.929	.938	.069	.050	.000	
M-U-c-B	225	5.390	.948	.957	.059	.050	.000	
CLF - U - c - B	205	4.165	.963	.972	.050	.043	.050	
C-U-c-B	1125	3.814	.939	.955	.027	.041	1.000	
M-H-c-C	344	4.935	.932	.945	.056	.046	.000	
CLF - H - c - C	315	4.068	.948	.960	.049	.036	.622	
M-H-c-D	172	5.306	.950	.959	.059	.055	.000	
CLF - H - u - D	154	3.831	.968	.976	.047	.037	.841	
C-H-c-D	175	5.774	.945	.954	.062	.058	.000	
Model based on cor	nbined ex	tended and ac	dapted U	ΓAUT2 an	d HMSAM			
M-c-M	1179	3.625	.918	.939	.056	.047	1.000	
C - C - M	1171	3.403	.924	.945	.044	.043	1.000	
CLF - M - c	1120	3.049	.934	.955	.040	.037	1.000	

Note: Values in bold correspond to best fit models

Note on the model codes:

First letter (capital): M = measurement model, C = Causal, CLF = model with common latent factor.

Second letter (capital): U = UTAUT2, H = HMSAM,

Third letter (small): c = constrained, u = unconstrained,

Fourth letter (capital, if exists) = A, A1, A2, B, C, D, M (version of model; see the models name and/or the corresponding names in the figures' captions),

Best fitted models are shown in bold.

The initial attempts to model the acceptance of social networking by simply applying the models of technology acceptance proved unsuccessful. Even after accounting for the common method bias, the best fitted model (see Model CLF – U – c in Table 27, above) reached only a CMIN/df of 6.544, over the threshold of 5, suggested by Tabachnick and Fidell (2007), and, respectively, and a CFI of .920, under the threshold of .950 suggested by Hu and Bentler (1999).

However, all the models developed consequently showed good, and, thus, acceptable, fit indices, which prove an adequate correspondence between the models and the observed data. Moreover, the addition of new predictors proved that these were relevant for the behavioral intention of use, which contributed to the improvement of the existing conceptual/theoretical framework.

Therefore, Study 1 provided solid scientific arguments to conclude that the main objectives were fulfilled. The technology acceptance models can be successfully used to predict the adoption intention for social networking, albeit only in adapted form. Also, the additional of new psychological constructs brings new insights into the adoption of social networking.

It is important to be noted here that Study 1 had to observe two stringent and, somewhat conflicting, requirements. On the one hand, the conceptual framework, *i.e.*, the models, or the theory regarding the technology acceptance, for both the utilitarian and for the hedonic motivation approach, had to be respected as close as possible.

On the other hand, social networking is not just a technological system, *i.e.* a material object. The user receives feedback not only from the system, but from other users as well. In this respect, the system is a mere facilitator, albeit virtual, of the interaction between people. The 'adoption' of social networking is as much an adoption of social interaction as it is of the corresponding supporting technology.

Therefore, the introduction of new constructs (*i.e.*, *self-objectification*, *social support*, etc.) can be seen not only as potentially beneficial, but rather as a necessary exploratory process. Moreover, firstly, since the models were applied for the first time on the Romanian population, and, secondly, since the models' application to social networking is rather new, the results from exploratory analyses had to be considered as well. This led, in turn, to the need to adapt the models, accordingly.

In specific relation with the above remarks regarding the exploratory analyses, an important caveat must be observed here, in regard to the 'most adequate' models, or the most successful modeling of the observed data. Generally, the explanatory power of a model is

related to the percentage of explained variance in the outcome variables. However, the explained variance is also related to the number of constructs in the model, especially with the volume of observed data. Nevertheless, even if increasing the number of 'explanatory' predictors lead to an increase in the explained variance for the predicted variables, this doesn't guarantee a good fit.

Therefore, is situations such as these, the researcher has to balance the need or the objective to explain as much variance as possible in the outcome variables with the requirements to have an adequately well fitted model, which correspond as closely as possible to the variance in the entire observed data. Moreover, as the exploratory factor analyses showed, especially in the case of the combine model M, there may be situations in which certain predictors (for instance, *self-objectification*, *honesty*, or *social support*, in case of model M) are better in summarizing the variance than older ones (see, for instance, dropped constructs from model M, which were previously present in the original UTAUT2 and HAMSAM, such as *facilitating conditions*, or *immersion* etc.).

However, as the results presented above showed, both research objectives were successfully reached and a relevant conceptual framework was developed, which has not only good explanatory (predictive) power, but also has specific relevance for the social networking.

## II.2.Study 2. Family and peer influences on Facebook adoption

## II.2.1. Introduction

## II.2.1.1. Objectives

Peer influence on human behavior is well established for a variety of behaviors ranging from generic (Hollander, 1964) to risk behavior (Gardner & Steinberg, 2005; Maxwell, 2002). Similarly, family influences on child's behavior is also a well-established topic in psychology. Today, there is no real scientific debate that, leaving aside the magnitude of such influence, parental rearing influences the child's behavior. This third study, concerning family influences on Facebook adoption was closely related, conceptually, to the other two studies.

The main objective on this study was to observe if there is a significant association between the children's adoption of Facebook, on the one hand, and their parents, on the other hand. Secondly, I was interested in identifying if other constructs investigated this far, in the previous studies, were subject to such associations.

## II.2.1.2. Hypotheses

Based on the above mentioned research interest, a general working hypothesis was formulated, positing that the children's adoption of Facebook should be positively associated with their parents' adoption of Facebook, as well as with their friends'. Similarly, the same positive association hypothesis was extended to the other constructs as well.

In statistics terms, the corresponding null hypotheses stated that there were no statistically significant association between the parent-child pairs/dyads, on the one hand, and the best-friends pairs/dyads, on the other hand, with respect to the constructs of interest.

### II.2.2. Methodology

## II.2.2.1. The research design

Although using a regression or a general, or even a generalized, linear model might have been tempting, for this stage of the research I resorted to simple bivariate product-moment correlation between the variables/constructs which comprised the models.

The study of the acceptance models presented above showed that much more numerous causing factors are at play than simple dyadic influences, and, if such dyadic influences are present, it is more likely that a bidirectional feedback mechanisms is present, and not a unidirectional influence. As such, using regression would be just a mathematical artifact, without ecological validity and would only build on speculation.

Nevertheless, even the simple association as evidenced by correlation, would be beneficial to understand the dissemination of preferences towards the use of Facebook, within dyadic relations.

#### II.2.2.2. Measures

The variables of interest were the same as the ones used in the previous studies, *i.e.*, the constructs which comprise the original UTAUT2 and HMSAM models, together with the additional new constructs. As such, this stage of research included *performance expectancy*, *effort expectancy*, *facilitating conditions*, *social influence*, *hedonic motivation*, *price value*, and *behavioral intention* from UTAUT2 (Venkatesh et al., 2012), and *perceived ease of use*, *perceived usefulness*, *curiosity*, *joy*, *control*, *immersion* and *behavioral intention to use* from HMSAM (Lowry et al., 2012). The additional constructs included *self-objectification* (Nistor & Stanciu, 2017), *honesty*, *social (informational* and *emotional*) *support*, and *online social wellbeing* (Huang, 2016).

The scales were presented in detail in the Measurement section of Study 1, and their item structure and psychometric properties are presented in Annex I.

## II.2.2.3. Procedure

Data regarding the participants' opinions with respect to the measured constructs were gathered at the same time with data for Study 1. In fact, data used in this study is the same data as the data from Study 1, except that it contains only the responses of the paired participants (those participating in a dyad). During the instruments' dissemination phase, the participants were asked if they were willing to participate in the research in a dyad, *i.e.*, a pair, with a parent or with a best-friend. The participation was voluntary and informed consent was obtained from the participants. The participants had an option to declare their belonging to a parent-child or to a best-friend dyad during the completion of the web questionnaire.

## II.2.2.4. Participants

The participants were recruited from amongst those participants in Study 1 who expressed their willingness to participate in a dyad with a best friend and/or a parent. Consequent to their option of dyad, their data was allocated to the group of Parent-Child Dyads or the group of Best-Friends Dyads.

## II.2.2.4.1. Demographic data for Parent-Child Dyads

Three hundred and thirty four Romanian children and parents with  $M_{\rm age} = 23.90$  years of age and  $SD_{\rm age} = 13.73$  took part in this stage of the research (the complete breakdown of age data per type of participant in dyad and per gender is presented in Table 5, below, while Figure 11, below, present the mean age and standard deviation per type of participant in dyad).

Table 5: Age and gender data for Parent-Child Dyad participants in Study 2

Participant type in	N	M Age	$SD_{Age}$	Min Age	Max Age
Parent-Child Dyad	1.6	10.55	1 40	18	26
Child	167	19.57	1.48	17	26
Female	96	19.47	1.38	17	22
Male	71	19.70	1.61	18	26
Parent	167	46.23	4.32	37	59
Female	117	45.25	4.28	37	59
Male	50	48.52	3.52	42	57
Total	334	32.90	13.73	17	59

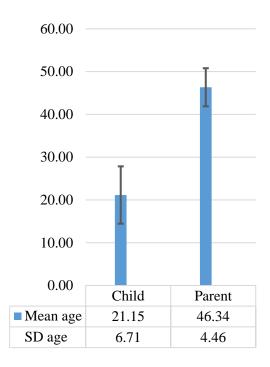


Figure 11: Mean age and standard deviation for Parent-Child Dyad participants in Study 2 (bars represent standard deviations)

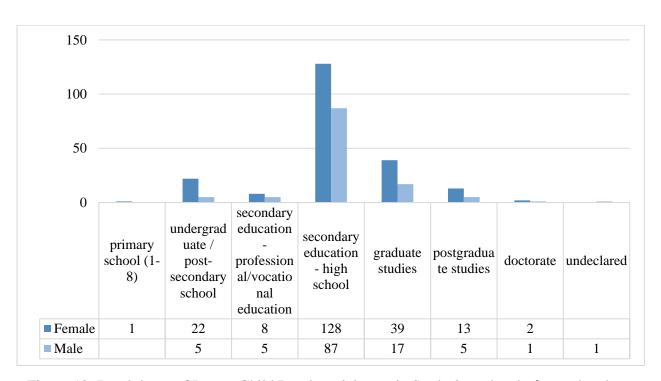


Figure 12: Breakdown of Parent-Child Dyad participants in Study 2 per level of completed studies and gender

## II.2.2.4.2. Demographic data for Best-Friends Dyads

Five hundred and seventy four best-friends with  $M_{\rm age} = 20.29$  years of age and  $SD_{\rm age} = 4.04$  were included in this research stage (the complete breakdown of age data per type of participant in dyad and per gender is presented in Table 6, below, while Figure 13, below, present the mean age and standard deviation per type of participant in dyad).

Table 6: Age and gender data for Best-Friends Dyads participants in Study 2

Participant type in	N	$M_{ m Age}$	$SD_{\mathrm{Age}}$	Min Age	Max Age
<b>Best-Friends Dyad</b>					
Female	292	20.01	4.44	14	48
Male	282	20.59	3.56	14	45
Total	574	20.29	4.04	14	48

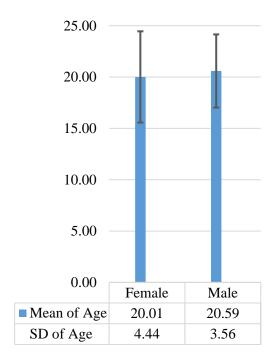


Figure 13: Mean age and standard deviation of age for Best-Friends Dyad participants in Study 2 (bars represent standard deviations)

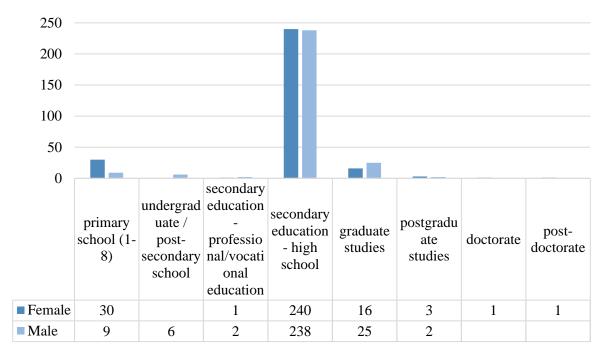


Figure 14: Breakdown of Best-Friend Dyad participants in Study 2 per level of completed studies and gender

### II.2.3. Results

The correlational analyses between the corresponding constructs for each group of participants in the Parent-Child dyads—for instance, the correlation between the *behavioral intention* to use (BI) for parents and the *behavioral intention* to use for children—showed positive significant associations between several of the constructs of interest: *curiosity* (r = .172, p < .05), *focused immersion* (r = .158, p < .05), *perceived usefulness*(r = .159, p < .05), *temporal dissociation* (r = .164, p < .05) and *self-objectification*(r = .187, p < .05). Albeit apparently small, considering also the number of participants in Parent-Child dyads, these associations have to be considered carefully.

For the Best-Friends dyads, no significant associations were found for any the variables of interest.

In order to account for the possibility of a method bias being responsible for obtaining the above mentioned correlations, a series of additional correlational analyses was performed, for both the Parent-Child dyads and the Best-Friends dyads, but replacing one member of the dyad with a random chosen partner. No significant association was observed after the randomization of partners for neither of the two dyadic groups, thus, excluding the possibility that the previously obtained association be the result of a method artifact.

A power calculation showed that a total sample of minimum 308 participants was necessary for  $\alpha$  (2-tailed) = .05,  $\beta$  = .2, at a correlation of r = .159, (Hulley, Cummings,

Browner, Grady, & Newman, 2013) where  $\alpha$  is the probability of rejecting the null hypothesis (the Type I error),  $\beta$  is the probability of failing to reject the null hypothesis under the alternative hypothesis (the Type II error), and r = .159 was the minimum significant correlation obtained between the variables of interest.

## II.2.4. Discussion and Conclusions regarding Study 2

A large number of participants (908; 334 in Parent-Child dyads and 574 in Best-Friends dyads) responded to this part of the research. As explained in the Methodology section for Study 2, a correlational analysis was employed, which could have been followed by a general linear model (multiple regression) if the obtained results suggested it. Nevertheless, the main objective, *i.e.*, to identify those constructs that may be subjected to familial or peer influences was reached.

While the results for the Parent-Child dyads suggest that four at least five constructs (i.e., self-objectification, curiosity, focused immersion, temporal dissociation, and perceived usefulness) positive and significant association between children's and parents' preferences exist, no significant association was observed for the Best-Friend dyads.

Three of the identified constructs (*curiosity*, *focused immersion* and *temporal dissociation*) belonged to HMSAM (Lowry et al., 2012), while one (*perceived usefulness*) belonged to UTAUT2 (Venkatesh et al., 2012) and one (*self-objectification*) was introduced based on Nistor and Stanciu's (2017) research.

This results suggest that the hedonic aspect may be more common to family members and more pervasive in its manifestation than the utilitarian aspects emphasized in UTAUT2. With respect to self-objectification, it also suggests that the way in which individuals present themselves, even in digital environments, may be significantly subjected to familial influences than.

The lack of associations for the case of the Best-Friends dyads may indicate that there many more and much more powerful factors that influence a person's choice of behavior in relation to the use of a social network (as measured via the analyzed constructs), than the peer influence.

While no conclusion can be derived specifically as to the 'inherited' nature or any other mechanism of 'familial transference' with respect to *self-objectification*, *perceived usefulness*, *temporal dissociation*, *focused immersion* and *curiosity*, speculative hypotheses may be

formulated as to the way the members of a family learn from each other to explore new sources of information (*curiosity*), are accustomed to present themselves to others (*self-objectification*), and attribute value to the tools that they use (*perceived usefulness*). However, further and much more rigorous analyses and research are necessary in order to clarify the underlying mechanisms of the observed associations.

# II.3.Study 3. Enhancing Facebook adoption through social support. A partial validation of the conceptual framework

#### II.3.1. Introduction

#### II.3.1.1. Conceptual framework for the experimental intervention

The conceptual framework developed during the modeling stage showed that it is plausible to construe *social support*, in both its forms, *i.e.*, *emotional*, and, *respectively*, informational, as an influencer for the *behavioral intention of use*, as the outcome variable. The structural equation modeling can be used to understand or to depict analysis performed within the general linear model (Graham, 2008).

Based on the combined model M presented above, I constructed three structural equation models (see Figure 15, Figure 16, and Figure 17, below) which presented *social support*, *informational* support, and, respectively, *emotional support*, as influencers for the *behavioral intention to use* (DV).

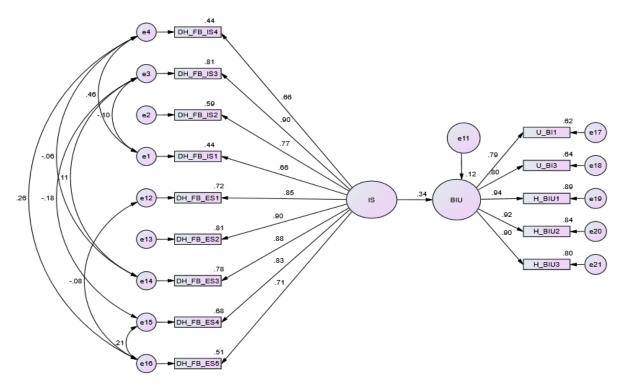


Figure 15: CBSEM predictive model of *social support* construed as a first order factor comprised of *informational* and *emotional* support, impacting on *behavioral intention to use* 

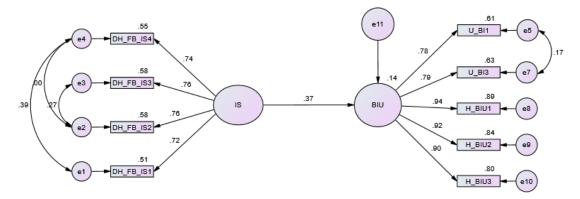


Figure 16: CBSEM predictive model of *informational support* impacting on *behavioral intention to use* 

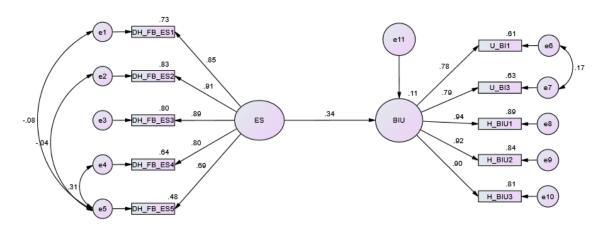


Figure 17: CBSEM predictive model of *emotional support* impacting on *behavioral intention* to use

#### II.3.1.2. Objectives

The research objectives for this study were to determine if modifications at the level of the dependent variable *behavioral intention of use* can be obtained by modifying the levels of social support that the users receive during their use of Facebook.

The consequent research question for this situation was if the (potential) modifications in the outcome (behavioral intention to use) were induced by the intentional (experimental) manipulations of the social support received by users.

The specific working and null hypotheses are presented after the Design section, because they are dependent (particular to) the methodology used, and this is particularly important when analysis of variance (ANOVA) is employed, since the question *which groups* are compared is of the outmost importance when using ANOVA.

#### II.3.2. Methodology

#### II.3.2.1. Design

A repeated measures (pre-test – post-test) quasi-experimental design, with convenience sampling (without randomization) and with control group was used to test the working hypothesis. The independent variable was *social support*, with two modalities, *informational support* (IS), and, respectively, *emotional support* (ES). The dependent variable was *behavioral intention of use* (BI), measured twice. The pre-test measurement collected data regarding the participants' levels of BI before the intervention, while the post-test measurement collected data regarding the participant's levels of BI after the intervention. Consequently, the null hypotheses formulated in terms of negating the working hypotheses, *i.e.*, we tested the probability that no difference be recorded with respect to BI as DV before and after the manipulation of either of the IV's modalities.

Table 7: Synthetic representation of the experimental design for Study 3

Type of Experimental Group	Task	Measurement Pre-Test	Intervention	Measurement Post-Test	Expected outcome
Informational Support Group	Receive informational support	Yes	Yes Informational support	Yes	Levels of BI higher than for ES and C groups
Emotional Support Group	Receive emotional support	Yes	Yes Emotional support	Yes	Levels of BI higher than for C group but lower than for ES group
Control Group	Provide baseline comparison	Yes	No	Yes	Levels of BI lower than for ES and IS groups

### II.3.2.2. Hypotheses

Considering the previously observed association between *social support* as predictor for the *behavioral intention of use*, the general working hypothesis that an increase in social support would lead to an increase in the participants' willingness to use Facebook was formulated.

Specifically, the working hypotheses for each form of social support stated that either form of social support (informational, and, respectively, emotional) would lead to an increase in behavioral intention to use.

Additionally, based on the results from the structural equation modeling presented in Introduction, and after a brief exploratory correlation analysis of the association between the IS and ES, on the one hand, and the BI, on the other hand, revealed that both IS and BI, and ES and BI are positively associated with medium strength (.322, p < .01, and, respectively, .317, p < .01), a specific hypothesis was formulated with respect to the prevalence of the influence of the two forms of social support on the *intention to use*.

As such, based on the correlations observed, the specific working hypothesis stated that providing emotional support was expected to be less efficient than providing informational support in determining positive changes in BI. Consequently, three experimental groups of participants were formed. The duration of the experimental intervention was set to two months, between mid-November 2016 and mid-January 2017.

The corresponding null hypotheses negate the influence of the intentional (experimental intervention) and attributes the potentially observed differences to chance.

#### II.3.2.3. Procedure

In order to analyze the effect of the social support as the independent variable (IV) with its two modalities ( $IV1 = emotional \ support$  and  $IV2 = informational \ support$ ) on the behavioral intention to use as the outcome or dependent variable (DV), two groups of participants were tasked with providing emotional, and, respectively,  $informational \ support$  to their participating parents. The third group was kept as control, and was asked only to provide a repeated measurement for the outcome variable after the intervention done by the first two groups was concluded.

Both groups of students were also asked to express their emotional support, or, respectively, willingness to help with information and/or advice on using Facebook, whenever their parents were active on Facebook, without becoming intrusive or to press them in any way and without going against their own values. The entire duration of the intervention was of two months, at the end of the first semester of study.

#### II.3.2.4. Measures

The same three items scale for BI extracted from Venkatesh et al.'s (2012) UTAUT2 which was previously used in the modeling part of the research, was also used to measure the pre-test and post-test levels of BI. The final score for BI was obtained by direct sum of item scores.

## II.3.2.5. Participants

The participant-students' allocation to their experimental groups was done randomly, by allocating them an identification ID and consequently using a random number selector to choose split the sample into two experimental groups. Consequently, the responding parents were also randomly allocated to their intervention modalities. The participants' initial sample included 185 pairs of students-parents. However, only 135 pairs completed the intervention and 126 pairs were kept in the research, after balancing the number of participants in each research group. The demographic data regarding the participants' age and the corresponding breakdown per gender and experimental group is presented in Table 8, and Figure 18 and Figure 19, below.

Table 8: Number and age data for the participants in Study 3 per gender and experimental group

Participants' type	N	Mean age	SD age
(per gender and group)			
Female	83	44.29	3.46
Control	26	44.58	3.29
<b>Emotional Support</b>	29	43.79	3.36
<b>Informational Support</b>	28	44.54	3.77
Male	43	49.56	3.84
Control	16	49.44	3.56
<b>Emotional Support</b>	13	50.38	3.78
<b>Informational Support</b>	14	48.93	4.32
Total	126	46.09	4.37

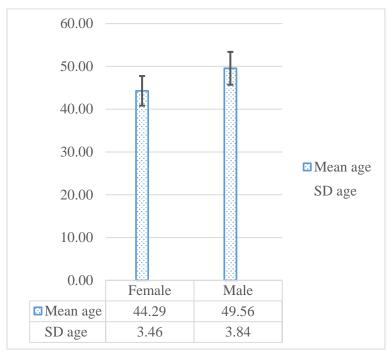


Figure 18: Mean age and standard deviation for the participants' entire sample per gender (Study 3)

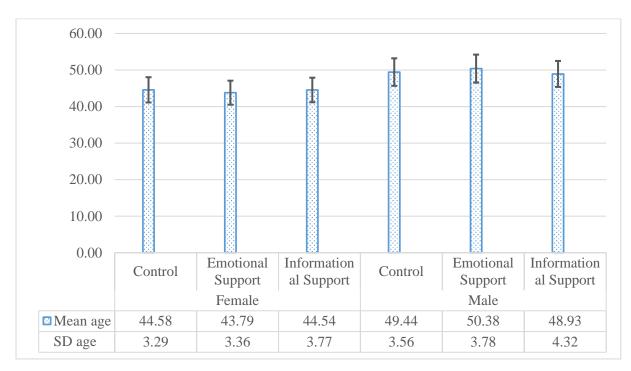


Figure 19: Mean age and standard deviation for the participants in Study 3 per gender and experimental group

#### II.3.3. Results

Prior to analyzing the effects of the intervention, the three experimental groups (the control group, the 'emotional support' group, and, respectively, the 'informational support' group) were compared to see if significant differences existed between them in terms of level of the outcome variable, *i.e. behavioral intention to use*. A one-way analysis of variance (ANOVA) with the type of experimental group as between-subjects factor was conducted.

A brief visual inspection of the means box plot revealed that the two experimental groups subjected to their interventions expressed higher post-test levels in *behavioral intention* as compared with the pre-test measurement, whereas the increase in mean scores at *behavioral intention* (BI) for the control group appeared insignificant (see Figure 20, below). More specifically, the group that received informational support showed a slightly higher increase in BI levels (a mean difference of 1.74, from M pretest IS = 15.88, SD pretest IS = 3.23 to M posttest IS = 18.69, SD posttest IS = 2.21, as compared with a mean difference of 1.59, from M pretest ES = 15.52, SD pretest ES = 3.16, to M posttest ES = 17.38, SD posttest ES = 2.39, for the emotional support group, or as compared with the control group, which presented a mean difference of .17, from M pretest C = 15.40, SD pretest C = 3.25, to M posttest C = 15.57, SD posttest C = 3.25.

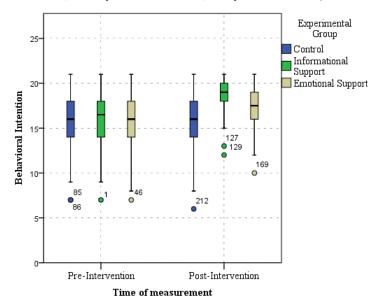


Figure 20: Means boxplot for the scores at behavioral intention for the three experimental groups by time of measurement

However, in order to assess the statistical significance of this increases in post-test scores in *behavioral intention* as compared with the pre-test scores, across the thee groups, a mixed between-within subjects ANOVA with repeated measure was conducted. The within-subject factor was the moment of measurement, named 'MeasurementTime'. Since all

experimental groups were measured the same way, once before the intervention and once after, and because the measurements were done in similar fashion, the within-subjects factor was named, conveniently, time, and had two levels, *i.e.*, one corresponding to the pre-intervention measurements and one corresponding to the post-intervention measurements. Also, since each intervention group was subjected to a different type of intervention, *i.e.*, each group received either emotional, or informational support, the between-subjects factor was the type of intervention, or lack thereof for the control (*i.e.*, the independent variable).

The examination of the MeasurementTime\*Group interaction effect, showed by the tests of within-subjects effects, revealed that there was a significant effect of the interaction between the intervention and the type of group:  $F_{\text{MeasurementTime*Group}}(2, 123) = 156.25, p < .001$ , partial  $\eta^2 = .369$ . The test of between-subjects effects also showed significant differences between the experimental groups, albeit at a significance level greater than 0.01:  $F_{\text{Between Groups}}(2, 123) = 4.157, p = .018$ .

The multiple comparisons post-hoc tests (Tukey HSD) showed that only the control group differed significantly from the other two groups, *i.e.*, the informational, and the emotional support group. The pairwise comparisons between the groups at the pre-test, and, respectively post-test stages, showed that at the pre-test moment of measurement neither group different significantly from any of the others.

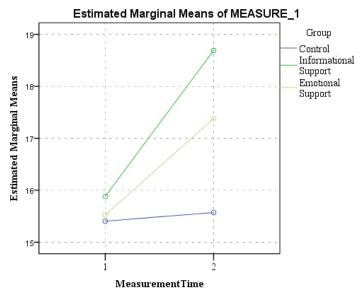


Figure 21: Plot of estimated marginal means for the behavioral intention to use per experimental group and measurement time (Study 3)

#### II.3.4. Discussion and conclusion regarding Study 3

The conceptual framework regarding the adoption of social networking posited that behavioral intention to use, as indicator of adoption, was influenced by several major factors, including the social support that the user receives. Consequently, the main objective of Study 3 was to determine if intentional (experimental) modifications can be induced at the level of the posited (hypothesized) predictor, i.e., behavioral intention to use. If that was the case, than the conceptual framework was partially validated, holding true at least for the direction of influence between the two constructs, social support as independent variable, and behavioral intention as dependent variable.

The research design used in Study 3 allowed the testing of the hypotheses that both *emotional support* and *informational support* influence *behavioral intention to use*, and that *informational support* is more effective than *emotional support* in producing modifications in the *behavioral intention to use*. The results of the mixed between-within ANOVA presented above confirmed both working hypothesis (rejected the null hypotheses that the corresponding difference can be attributed to chance alone).

However, a few remarks with respect to the limitations and the drawbacks of our methodology have to be observed here. First, it is important to note that this was not a randomized study. The participants were assigned randomly to their research groups, but their overall implication in the study was based on voluntary consent of those participants who accepted to complete the questionnaires in a dyad with their children.

Second, the experimenter's bias cannot be excluded; it rather was intrinsic to this study because of the composition of the research groups and the allocation of tasks. For instance, it is entirely possible that the parents' answer have been affected by a particular form of social desirability, since they responded in relation with their own children's interventions. It is conceivable that a parent feels, and consequently, reports, the support that he/she receives from a child, differently than the way in which that parent would report the support received from a stranger.

Third, there was no measurement of the initial training or skillfulness of the parents in using the Facebook, and no measure of use was included as covariate in the design. This would have complicated the interpretation of the interaction effects, and would not have served to reaching this study's main research objective. Therefore, there is no way of knowing how the influence of social support, in either of its forms, *i.e.*, emotional vs. informational, affects people more or less skilled in using Facebook.

Fourth, similarly with the lack of measurement of parents' skillfulness levels in using Facebook, there was no measurement of how much they need the offered support (*i.e.*, the support that the children were tasked to offer to their parents).

Fifth, using children to provide support to their parents implies an enormous volume of variability or heterogeneity in the levels in which this support is provided. It is reasonable to assume that some participant-students were more skilled and/or more willing to provide support to their parents, than other participant-students.

The actual 'windows' of opportunity to provide support was another factor that had the potential to affect the influence of the provided support on the receiving parents' intention to use Facebook. Also, the duration of the intervention is another factor which was not considered. A lengthier duration of the intervention would have allowed an increase number of repeated measures, which, in turn, could have provided more insight on the mechanisms (how) the intervention affects the behavioral intention to use.

Nevertheless, while considering all limitations described above, Study 3 reached its main objective and provided empirical evidence that manipulating the social support has an authentic impact on the users' adoption of social networking, as measured by their intention to use Facebook.

This results, in turn, opens the door for two main avenues. On the one hand, it provides an advance into the validation of the underlying theory (*i.e.*, the models), which eases the path to proving other influencers' validation and provides experimental scenarios which can be used to test the models predictive power on various population groups (*i.e.*, according to age, gender, etc.).

On the other hand, Study 3 showed that people may be reluctant to use social networking, and, consequently, may resort to avoiding strategies, because they lack the required social support. Applicative programs can be envisioned where people with lesser social skills and lesser levels of self-confidence in using the digital tools of social networking can be helped to overcome their fear of use. These types of programs can benefit older people, those with alienation issues, and provide support groups for them, as well as sensitivity trainings for those in the support circles.

#### III. Part III. Conclusions and Discussions

#### III.1. The importance of the research for the state of the art

The need for our research was crucially linked to: 1) the impact of extremely rapid evolution of technologies, 2) the increasing importance of digitally mediated social interactions and their roles in the individual's life. Using the Internet, for instance, is no longer limited to desktop computers, as it was done initially. Instead, a huge variety of personal devices and gadgets are now connected to the Internet, such as laptops, tablet computers, smartphones, smartwatches, and even wearable technologies.

To date, with notable exceptions, there are few clear cut studies, able to provide a comparison of the utilitarian versus hedonic models in terms of their predictive power for social networks adoption. For instance, although HMSAM's authors assert that it is fundamentally different from the utilitarian systems (Lowry et al., 2012), recent 'upgrades' to UTAUT, leading to UTUAT2, which incorporates the hedonic aspect (Venkatesh, Thong, & Xin, 2016), brings again into focus the question of what is the most adequate (powerful) model.

This thesis included a literature review up to date and exposes constructs that, while not explicitly included in, or taken into consideration by the above-mentioned models, were revealed as having a good potential in explaining the technology acceptance and even to expand the explanatory power of the currently preeminent models. Although a study of social presence/media richness in itself was outside the coverage of our study, we expanded the theoretical basis of the current models with a view to the social dimension, or, more specifically, the self-presentation. For instance, disclosure, honesty, perceived social (informational and emotional) support, and the perceived wellbeing (Huang, 2016), as well as personal strategies such as self-objectification (Nistor & Stanciu, 2017), were shown to influence the person's online behaviors, in general, and one's adoption of a specific online environment, in particular.

Moreover, such a research, has never been conducted before in Romania. Neither the topic, albeit important due to its actuality and potential implications (*e.g.*, marketing of social networks, effects upon the users, etc.), nor the models themselves, have never been thoroughly investigated on Romanian participants. Even more so, there are active calls in today's research arena asking for more in-depth and related comparative studies, with a specific focus on age as one of the important moderators (Niehaves & Plattfaut, 2014).

## III.2. Current achievements and future avenues of research Current achievements

With respect to their predictive power, i.e., the explained variance, in most situations UTAUT2 was better than HMSAM. For instance, the models developed based on the original UTAUT2 and HMSAM explained 78% and, respectively, 57% of the behavioral intention to use. However, as explained in the section regarding the structural equation modeling, the models based on originals presented fit indices under the acceptable thresholds, which required an iterative process of modeling, aiming gradually to the best fitted models, while maintaining as much as possible from the original factor structure, or, in other words, staying true to the original theories. The same trend continued during the following stages of modeling, with models based on the adapted UTAUT2 explaining 55% of variance in BI (model A1), 59% (model A2, with second order factors), with a lowest of 53% (model B), whereas models based on HMSAM achieved 57% (model C) and, respectively 37% (model D). However, while the models were adapted, their fit indices improved dramatically. This requirement of achieving the best possible fit, while it meant sacrificing the explanatory value of the models, goes beyond satisficing theoretical or methodological criteria. It is intrinsically related to the parsimony of the model, which, along with the ability to best predict the variations in the observed data, is one of the most important tenets in structural equation modeling.

With respect to this research regarding the adoption of Facebook, UTAUT2 'performed' slightly better than HMSAM, in the sense that it allowed more flexibility and more dissociation between its constituting constructs. In this context, it may be worth mentioning that UTAUT2 has almost a decade of empirical testing ahead its 'younger' counterpart, HMSAM, which may have contributed to a better selection of constructs. The advantage of time did bring a definite advantage to UTAUT2 in terms of replication and validation attempts, as compared with HMSAM. In conclusion, with respect to the adaptation and utilization of both UTAUT2 and HMSAM to digital/online social networking, the main objective of this thesis was achieved.

Moreover, when the additional constructs (i.e., self-objectification, honesty, social support, etc.), which were far more psychological in nature than constructs such as facilitating intentions or behavioral observation scales such as focused immersion, they factored much better in predicting the behavioral intention to use than the predictors from the original models,

with the notable exception of *perceived ease of use* and, somewhat oddly (considering that it was discarded from the final HMSAM), *temporal dissociation*. However, it should be noted that the adoption of Facebook, or any other social network for that matter, is intrinsically different from the adoption of an inanimate technological system, regardless how immersive and/or interactive it may be. Social networks imply, ultimately, interacting with people, even if that interaction is mediated and channeled by technology. As such, in terms of explaining as well as possible, the adoption of Facebook measured via the *behavioral intention to use*, within our starting theoretical framework, this thesis' second main objective was also achieved. As the final model (model M, based on all combined hypothesized predictors) showed, psychological constructs, such as self-objectification, social support, and honesty, should be considered in the study of people's intention to use online communities.

Finally, our third objective was to provide as much evidence as possible, if possible, for the validation of the models. The brief experiment which allowed for the manipulation of social support as influencer for behavioral intention, albeit flawed, provided some support in this matter. Admittedly, it is much easier to manipulate *social support*, than completely extrinsic conditions, such as factors, entire groups of people, such as *social influences*, or completely intrinsic factors, such as *curiosity*. However, this doesn't diminish the value of scientific proof towards a partial validation of the model, with respect to the pathway of influence between social support and behavioral intention.

#### Future directions of action and research

Concluding all of the above observations, this research investigated a new and relevant topic, *i.e.*, the adoption of social networks, provided the translation and adaptation of the measurement instruments, and contributed significantly to proving causality within the underlying conceptual framework. Future studies can make use of the current achievements (including the translation, adaptation, and factor analyses of the instruments), and can benefit from the benchmark that this research provides with respect to the adoption of social networking for Romanian users.

However, more refined invariance computations and comparison can be designed and conducted, to contrast various groups of users, *i.e.*, male vs females, high education vs. lower education, high income vs. low income, specific IT instruction vs. non-specific IT knowledge, young vs. old, etc., which further studies can address. Also, as the exploratory correlational analyses from Study 2 showed, various mechanisms of family influences can be considered between at least five of the main constructs (*self-objectification, curiosity, focused immersion*,

temporal dissociation, and perceived usefulness). Specifically designed studied could contrast these factors between children and parents, and perhaps, extend their study for civil partner couples as well.

The experimental intervention provided not only empirical validation, albeit partial, for one of the developed models, thus contributing to strengthening the underlying theory, but it also opens the door for possible support interventions for those in need. As Logue and Effken (2012) observed, "Technology overload due to perceived lack of knowledge mediates the relationship between perceived ease of use and intention to use according to Pennington et al (Pennington, Kelton, & DeVries, 2006). Training has been shown to increase the acceptance of technology by improving a person's computer self-efficacy (Bedard, Jackson, Ettredge, & Johnstone, 2003)" (Logue & Effken, 2012, p. 165).

For instance, some people that may be reluctant to use social networking, and, consequently, may resort to avoiding strategies, because they lack the required social support. Applicative programs can be envisioned where people with lesser social skills and lesser levels of self-confidence in using the digital tools of social networking can be helped to overcome their fear of use. These types of programs can benefit older people, those with alienation issues, and provide support groups for them, as well as sensitivity trainings for those in the support circles.

When considering the obtained results, two main avenues for future research appear to be both promising and necessary. On the one hand, there is a clear need to provide empirical evidence from systematic and well-designed experimental intervention in order to clarify the nature of the hypothesized influence pathways. While SEM is an extremely powerful exploratory technique, it lacks the power of proving causality by itself. The second main direction, with specific respect to the adoption of social networking, in particular, and to the online behavior, in general, is identifying and measuring the most relevant psychological constructs, which bear relevance for the use intention.

#### **IV.** References

- Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *MIS Quarterly*, 24(4), 665-694.
- Bedard, J. C., Jackson, C., Ettredge, M. L., & Johnstone, K. M. (2003). The effect of training on auditors' acceptance of an electronic work system. *International Journal of Accounting Information Systems*, 4(4), 227-250.
- boyd, d. m., & Ellison, N. B. (2007). Social network sites: Definition, history, and scholarship. *Journal of Computer-Mediated Communication*, 13(1), 210-230.
- Bush, V. (1946). Endless horizons. Washington, D.C.: Public Affairs Press.
- Cheong, C., Filippou, J., & Cheong, F. (2014). Towards the Gamification of Learning: Investigating Student Perceptions of Game Elements. *Journal of Information Systems Education*, 25(3), 233-244.
- Chin, W. W., Marcolin, B. L., & Newsted, P. R. (2003). A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Information Systems Research*, 14(2), 189-217.
- de-Marcos, L., Domínguez, A., Saenz-de-Navarrete, J., & Pagés, C. (2014). An empirical study comparing gamification and social networking on e-learning. *Computers & Education*, 75, 82-91. doi:10.1016/j.compedu.2014.01.012
- de-Marcos, L., Garcia-Lopez, E., & Garcia-Cabot, A. (2016). On the effectiveness of game-like and social approaches in learning: Comparing educational gaming, gamification & social networking. *Computers* & *Education*, 95, 99-113. doi:10.1016/j.compedu.2015.12.008
- Elangovan, N., & Agarwal, P. (2015). Factors Influencing User Perception on Mobile Social Networking Apps. *Sumedha Journal of Management*, 4(2), 27.
- Ellison, N., Steinfield, C., & Lampe, C. (2007). Te benefits of Facebook "friends": Exploring the relationship between college students' use of online social networks and social capital. *Journal of Computer-Mediated Communication*, 12(3).
- Elmore, B. (2009). Social networking strategies. *Baylor Business Review*, 28(1), 25-27.
- Facebook. (2016). Company Info | Facebook Newsroom. Retrieved from <a href="http://newsroom.fb.com/company-info/">http://newsroom.fb.com/company-info/</a>

- Facebook. (2017). Company Info. Retrieved from <a href="https://newsroom.fb.com/company-info/">https://newsroom.fb.com/company-info/</a>
- Fredrickson, B. L., Roberts, T.-A., Noll, S. M., Quinn, D. M., & Twenge, J. M. (1998). That swimsuit becomes you: sex differences in self-objectification, restrained eating, and math performance. *Journal of Personality and Social Psychology*, 75(1), 269.
- Gamification in Education and Libraries. (2015). *Library Technology Reports*, 51(2), 20-28.
- Gardner, M., & Steinberg, L. (2005). Peer influence on risk taking, risk preference, and risky decision making in adolescence and adulthood: an experimental study. *Developmental Psychology*, 41(4), 625.
- Gefen, D., Straub, D. W., & Rigdon, E. E. (2011). An update and extension to SEM guidelines for admnistrative and social science research. *Management Information Systems Quarterly*, 35(2), iii-xiv.
- Goffman, E. (1978). The presentation of self in everyday life: Harmondsworth.
- Graham, J. M. (2008). The general linear model as structural equation modeling. *Journal of Educational and Behavioral Statistics*, 33(4), 485-506.
- Hollander, E. P. (1964). Leaders, groups, and influence.
- How social media will help you find a job. (2012). Public Relations Tactics, 19(3), 13-13.
- Howard, P. N., Duffy, A., Freelon, D., Hussain, M. M., Mari, W., & Maziad, M. (2011). Opening closed regimes: what was the role of social media during the Arab Spring?
- Hu, L. t., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis:
   Conventional criteria versus new alternatives. Structural Equation Modeling: A
   Multidisciplinary Journal, 6(1), 1-55. doi:10.1080/10705519909540118
- Huang, H.-Y. (2016). Examining the beneficial effects of individual's self-disclosure on the social network site. *Computers in human behavior*, 57, 122-132. doi:10.1016/j.chb.2015.12.030
- Hulley, S. B., Cummings, S. R., Browner, W. S., Grady, D. G., & Newman, T. B. (2013).
  Designing Clinical Research. Philadelphia: Wolters Kluwer/Lippincott Williams & Wilkins.
- Jang, K., Park, N., & Song, H. (2016). Social comparison on Facebook: Its antecedents and psychological outcomes. *Computers in human behavior*, 62, 147-154. doi:10.1016/j.chb.2016.03.082
- Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons*, 53(1), 59-68.
- Khan, G. F. (2015). Social Media-based Government Explained: Utilization Model, Implementation Scenarios, and Relationships. In I. Boughzala, M. Janssen, & S. Assar

- (Eds.), Case Studies in e-Government 2.0: Changing Citizen Relationships (pp. 15-28). Cham: Springer International Publishing.
- Khondker, H. H. (2011). Role of the New Media in the Arab Spring. *Globalizations*, 8(5), 675-679. doi:10.1080/14747731.2011.621287
- Kietzmann, J. H., Hermkens, K., McCarthy, I. P., & Silvestre, B. S. (2011). Social media? Get serious! Understanding the functional building blocks of social media. *Business Horizons*, 54(3), 241-251.
- Landers, R. N. (2014). Developing a Theory of Gamified Learning: Linking Serious Games and Gamification of Learning. *Simulation & Gaming*, 45(6), 752-768. doi:10.1177/1046878114563660
- Liang, T.-P., Ho, Y.-T., Li, Y.-W., & Turban, E. (2011). What Drives Social Commerce: The Role of Social Support and Relationship Quality. *International Journal of Electronic Commerce*, *16*(2), 69-90. doi:10.2753/JEC1086-4415160204
- Lin, C.-P. (2011). Assessing the mediating role of online social capital between social support and instant messaging usage. *Electronic Commerce Research and Applications*, 10(1), 105-114. doi:http://dx.doi.org/10.1016/j.elerap.2010.08.003
- Lin, K.-Y., & Lu, H.-P. (2011). Why people use social networking sites: An empirical study integrating network externalities and motivation theory. *Computers in human behavior*, 27(3), 1152-1161. doi:http://dx.doi.org/10.1016/j.chb.2010.12.009
- Logue, M. D., & Effken, J. A. (2012). An exploratory study of the personal health records adoption model in the older adult with chronic illness. *Informatics in Primary Care*, 20(3), 151-169.
- Lowry, P. B., Gaskin, J., Twyman, N., Hammer, B., & Roberts, T. (2012). Taking 'fun and games' seriously: Proposing the hedonic-motivation system adoption model (HMSAM). *Journal of the Association for Information Systems*, *14*(11), 617-671.
- Maxwell, K. A. (2002). Friends: The role of peer influence across adolescent risk behaviors. *Journal of Youth and Adolescence*, 31(4), 267-277.
- Niehaves, B., & Plattfaut, R. (2014). Internet adoption by the elderly: employing IS technology acceptance theories for understanding the age-related digital divide. *European Journal of Information Systems*, 23(6), 708-726.
- Nistor, N., & Stanciu, I.-D. (2017). "Being sexy" and the labor market: Self-objectification in job search related social networks. *Computers in human behavior*, 69, 43-53. doi:http://dx.doi.org/10.1016/j.chb.2016.12.005

- Noll, S. M., & Fredrickson, B. L. (1998). A mediational model linking self-objectification, body shame, and disordered eating. *Psychology of Women Quarterly*, 22(4), 623-636.
- O'Reilly, T. (2007). What is Web 2.0: Design patterns and business models for the next generation of software. . *Communication & Strategies*, 65(1), 17-37.
- Pennington, R. R., Kelton, A. S., & DeVries, D. D. (2006). The effects of qualitative overload on technology acceptance. *Journal of Information Systems*, 20(2), 25-36.
- Quinn, M. J. (2013). *Ethics for the information age*. Upper Saddle River, N.J.: Pearson Education/Addison-Wesley.
- Reddick, C. G. (2010). Comparative e-government.
- Schuch, K. (2013). Techno-Globalization and Innovation. *Encyclopedia of Creativity*, *Invention, Innovation and Entrepreneurship*, 1774-1781.
- Su, C. H., & Cheng, C. H. (2015). A mobile gamification learning system for improving the learning motivation and achievements. *Journal of Computer Assisted Learning*, 31(3), 268-286. doi:10.1111/jcal.12088
- Tabachnick, B. G., & Fidell, L. S. (2007). *Using multivariate statistics*. Boston, MA: Pearson : Allyn and Bacon.
- Taiminen, H. (2016). How do online communities matter? Comparison between active and non-active participants in an online behavioral weight loss program. *Computers in human behavior*, 63, 787-795. doi:10.1016/j.chb.2016.06.002
- Traub, C. H., & Lipkin, J. (1998). If We Are Digital: Crossing the Boundaries, 363.
- Van der Heijden, H. (2004). User acceptance of hedonic information systems. *MIS Quarterly*, 695-704.
- Venkatesh, V., Morris, M. G., Gordon, B. D., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425-478.
- Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157-178.
- Venkatesh, V., Thong, J. Y. L., & Xin, X. (2016). Unified Theory of Acceptance and Use of Technology: A Synthesis and the Road Ahead. *Journal of the Association for Information Systems*, 17(5), 328-376.
- What's out and in on the job-hunting front. (2009). Public Relations Tactics, 16(5), 23-23.
- Williams, R. S. (2007). The evolution of technology for electronic materials over the last 50 years. *JOM*, 59(2), 58-62. doi:10.1007/s11837-007-0023-6

- Wilson, R. E., Gosling, S. D., & Graham, L. T. (2012). A review of Facebook research in the social sciences. *Perspectives on Psychological Science*, 7(3), 203-220.
- Worldbank. (2017, 2017). Internet users (per 100 people). Retrieved from <a href="http://data.worldbank.org/indicator/IT.NET.USER.P2?cid=GPD\_44">http://data.worldbank.org/indicator/IT.NET.USER.P2?cid=GPD\_44</a>

# V. Annex to the thesis' summary

## V.1.1.1. Original models

## V.1.1.1.1. Models based on the original UTAUT2

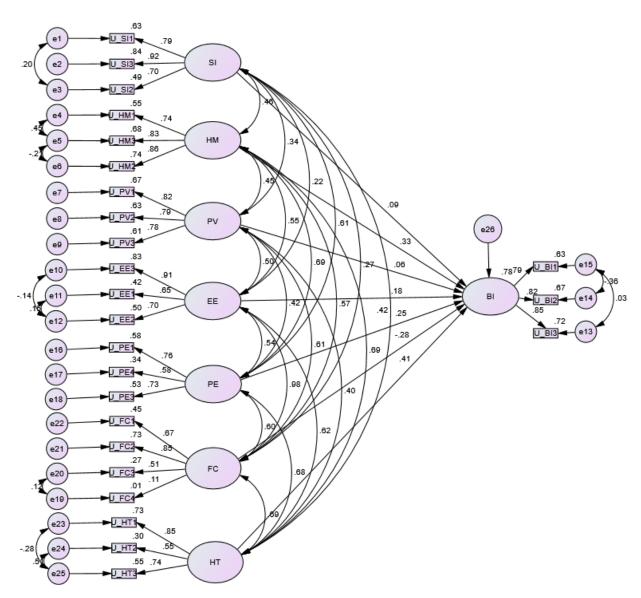


Figure 22: Causal model based on original UTAUT2 model

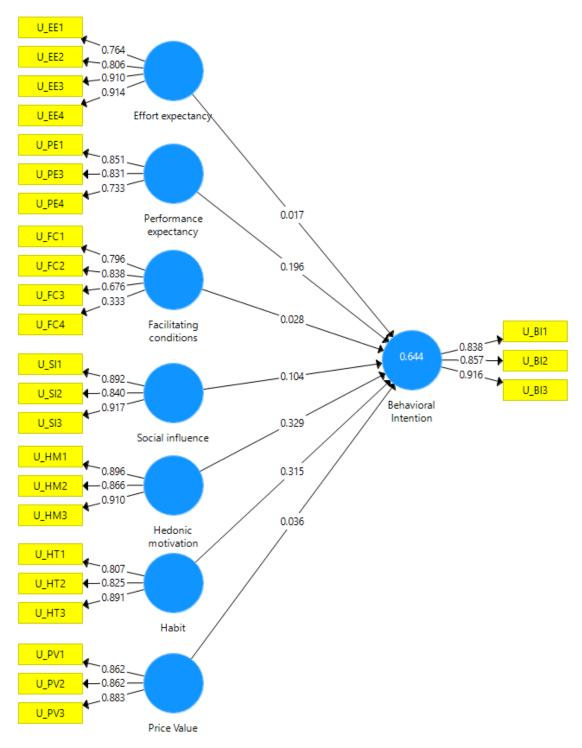


Figure 23: PLS model for Facebook adoption based on original UTAUT2 model (pathways of influence)

## V.1.1.1.2. Models based on the original HMSAM

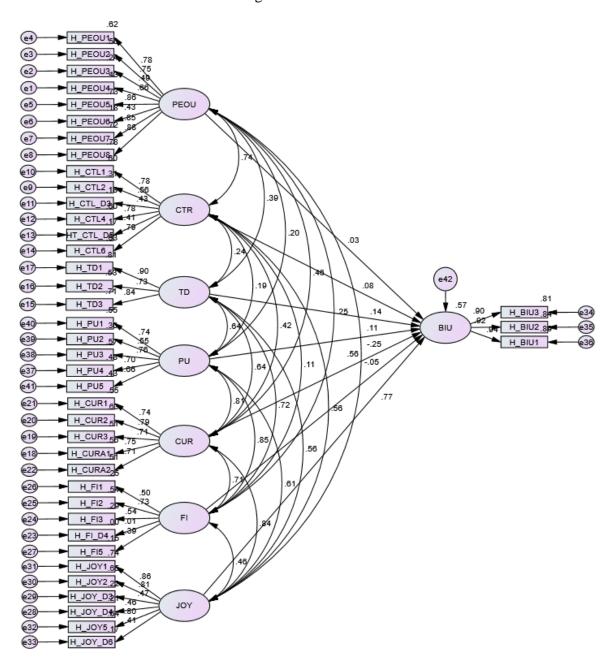


Figure 24: Causal model based on original HMSAM

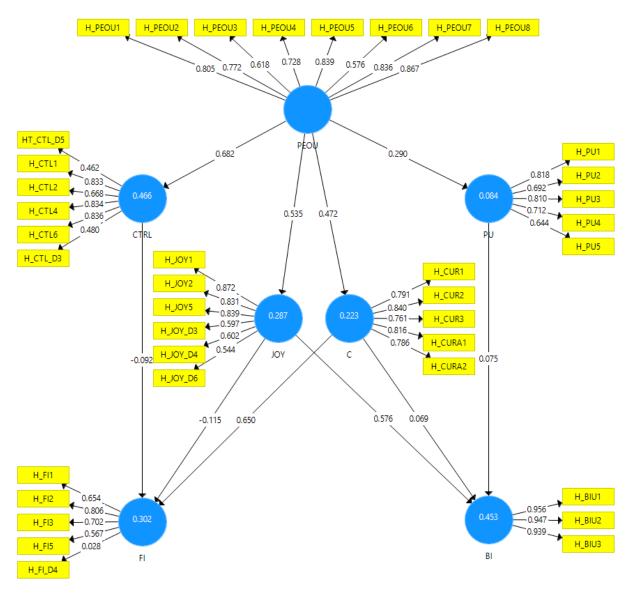


Figure 25: PLS model for Facebook adoption based on original HMSAM model (pathways of influence)

## V.1.1.2. Models based on the adapted UTAUT2

## V.1.1.2.1. Causal model A1 based on adapted UTAUT2

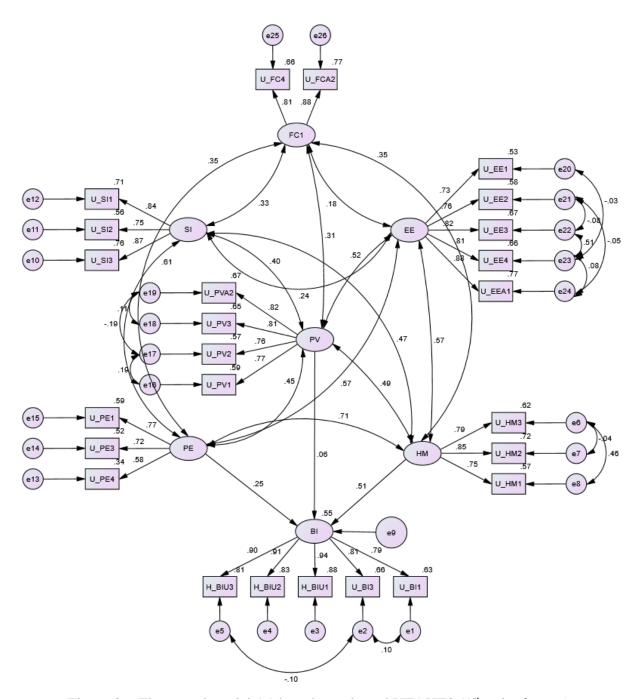


Figure 26: The causal model A1 based on adapted UTAUT2 (1st order factors)

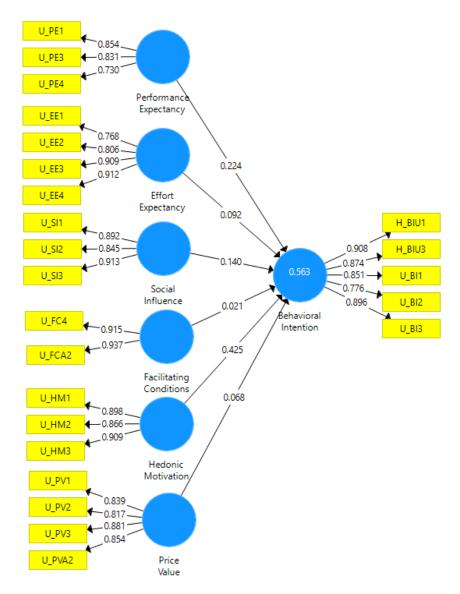


Figure 27: PLS modeling of causal model A1 based on adapted UTAUT2 (the influence pathways)

## V.1.1.2.2. Causal model A2 based on adapted UTAUT2 (second order factors)

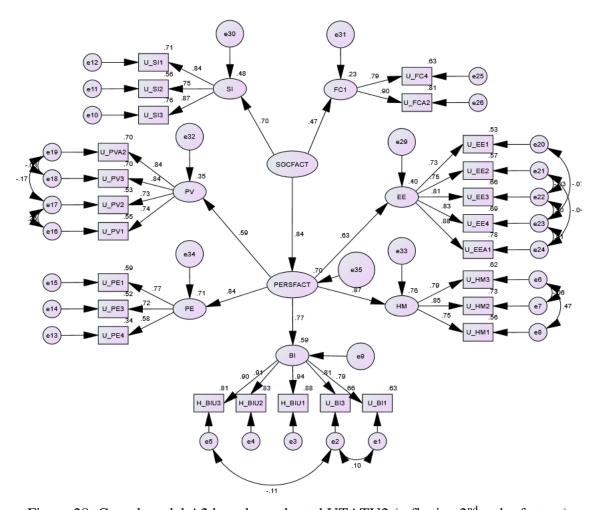


Figure 28: Causal model A2 based on adapted UTATU2 (reflexive 2<sup>nd</sup> order factors)

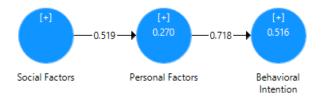


Figure 29: PLS modeling of causal mode A2 based on UTAUT2 (reflexive 2<sup>nd</sup> order factors, the influence pathways)

# V.1.1.2.3. Causal model B based on the adapted UTAUT2

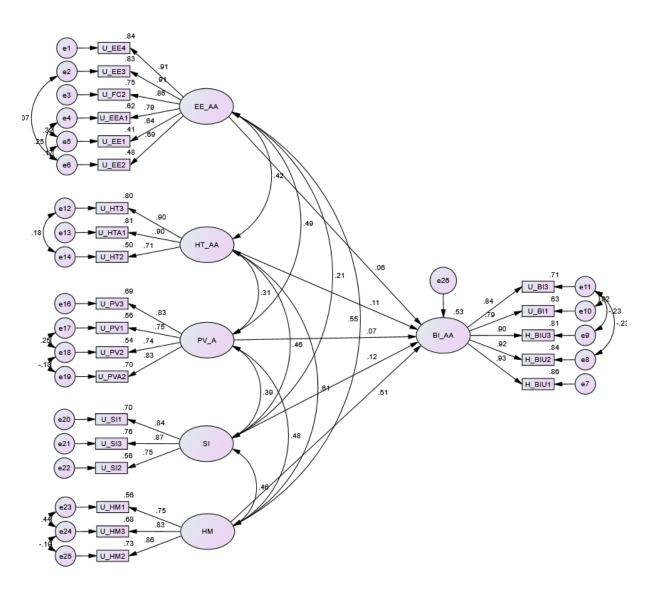


Figure 30: Causal model B based on adapted UTAUT2 model

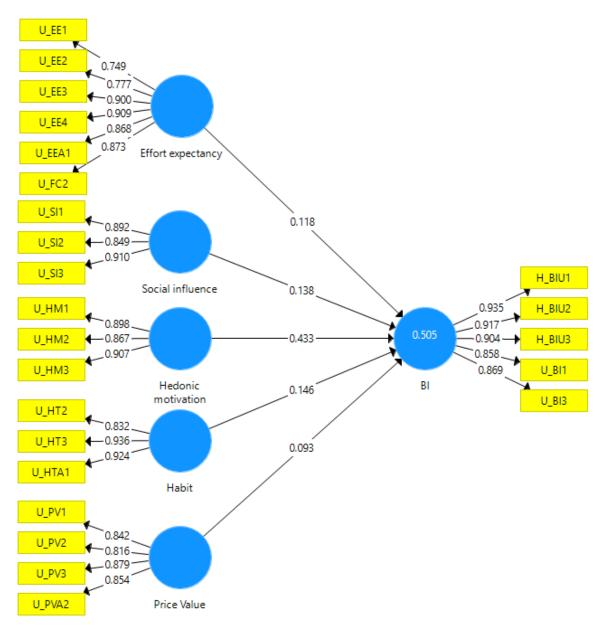


Figure 31: PLS model based on adapted UTAUT2 model (pathways of influence)

# V.1.1.2.4. Causal model C based on adapted HMSAM

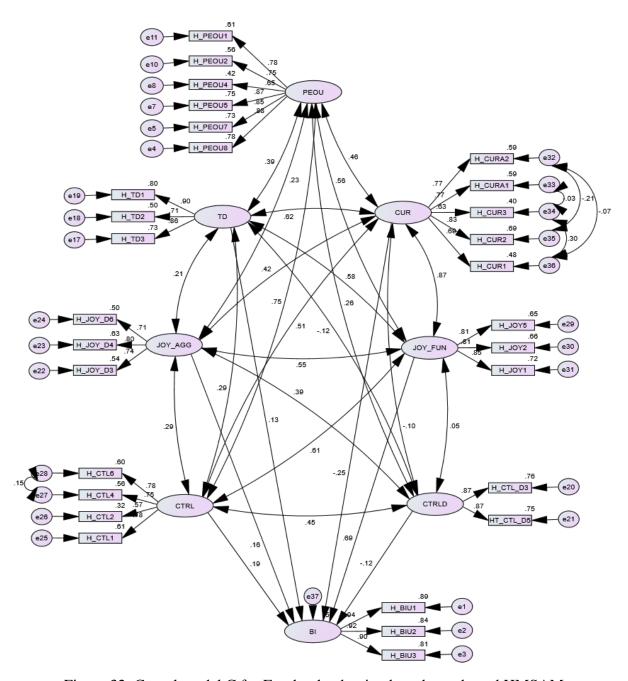


Figure 32: Causal model C for Facebook adoption based on adapted HMSAM

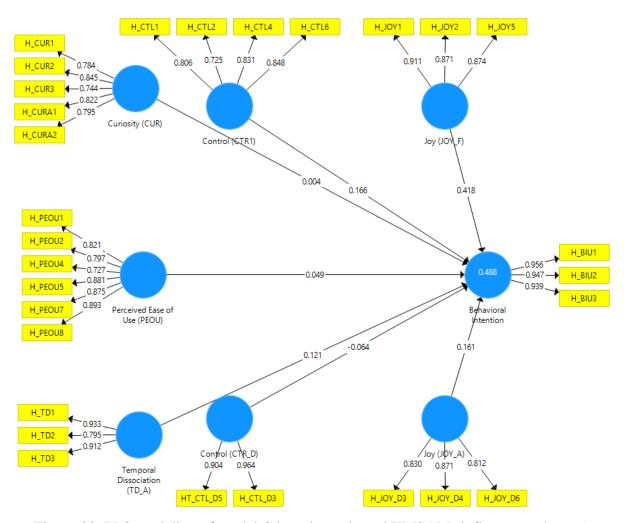
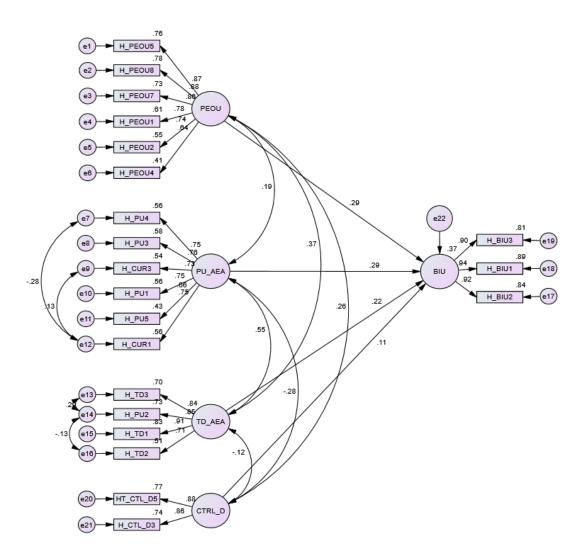


Figure 33: PLS modeling of model C based on adapted HMSAM (influence pathways)

## V.1.1.2.5. Causal model D based on HMSAM.



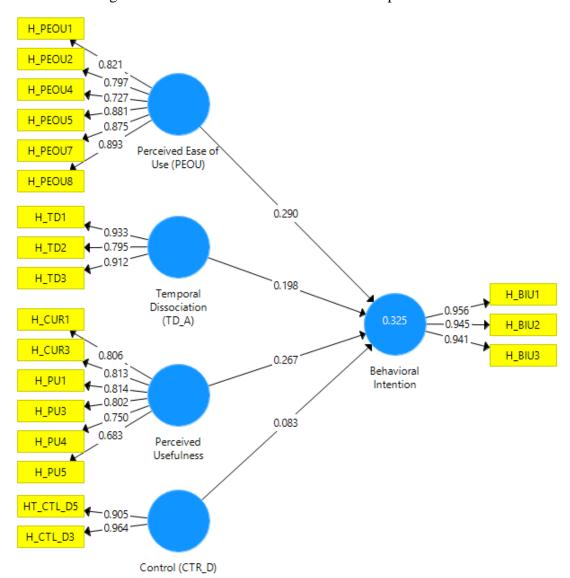


Figure 34: Causal model PLS D based on adapted HMSAM

Figure 35: PLS modeling (model D) based on adapted HMSAM (strength of influence pathways)

## V.1.1.3. Model M based in combined predictors from HMSAM and UTAUT2

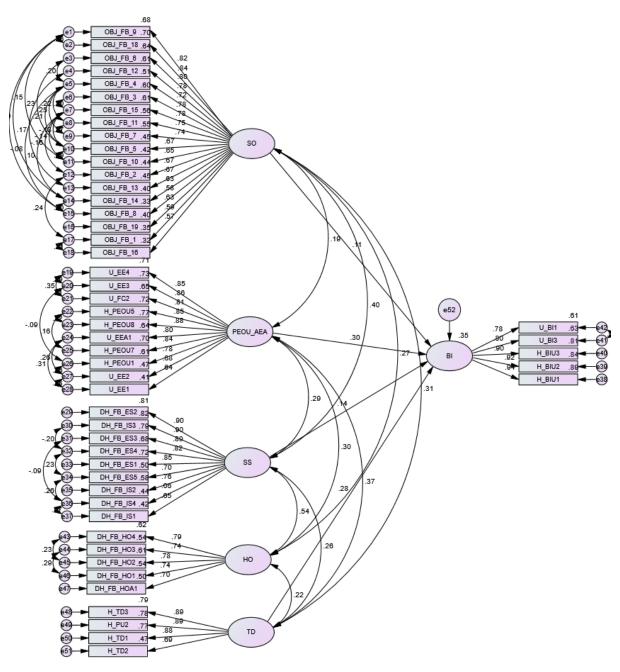


Figure 36: Causal model based on combined predictors from HMSAM and UTAUT2 and additional constructs

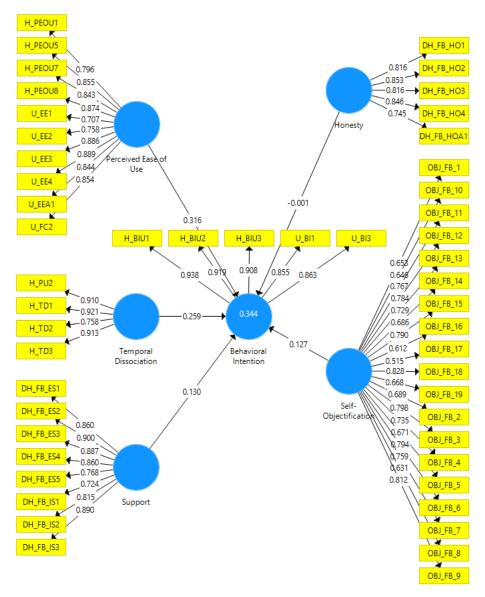


Figure 37: PLS modeling (model M) based on combined predictors (strength of influence pathways)