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Research Article

Consumers' social media engagement and online behavior: A structural equation modelling analysis

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ABSTRACT

In this work we expand on previous results, which were obtained by applying an exploratory factor analysis process. The analysis was carried out on a dataset constructed by means of a quantitative questionnaire regarding consumers' degree of engagement with social media and their respective online decisions and actions. Thus, the model under study here integrates these three derived constructs; "engagement", "decision", and "action" as its building blocks. The aim of this work is twofold: to validate model's fit leveraging a confirmatory factor analysis process and to investigate the relations between the three factors with structural equation modelling. With respect to the first objective, the measurement part of the model is verified, and its fit is tested and accepted under several heterogeneous indices. Secondly, the structural part of the model is validated against theoretical hypotheses regarding the relations between the three latent variables. Results show that both "engagement" and "decision" predict "action", with the former however being more important. To the best of our knowledge, the specific model built around these three constructs is not found elsewhere in literature and can prove to be a valuable source of information for e.g., marketers in their effort to apply an efficient marketing strategy.

Keywords: social media engagement, consumer behavior, communication, factor analysis, structural equation modelling

INTRODUCTION

Social media have dynamically entered and conquered our lives changing the ways that users communicate. Services and products are advertised quite differently from the past and consumers have easy access to information relevant to their needs. In this work we aim to analyze the online behavior of users as potential consumers, with respect to the products and services that are available on the web. These products and services appear frequently on their accounts while they engage with social media, even if they do not have an initial, clear intent for a purchase. In order to reach safe conclusions, the authors utilize previous results obtained with exploratory factor analysis (EFA) (Amanatidis et al., 2022) and proceed with confirmatory factor analysis (CFA) and development of a structural equation model (SEM).

User engagement with social networks essentially involves the creation of their profile, which may be public, private, or as a recent option, semi-private. A user's profile reveals the ways that this specific member of the online community relates and interacts with other participants (Lange, 2007). On the other hand, the profile of social media enables companies to use new interactive ways to reach and engage with their customers (Gallaugher & Ransbotham, 2010); they can generate online content rapidly and inexpensively, in order to support the development and establishment of a brand's presence (Ashley & Tuten, 2015). Kaplan and Haenlein (2010) classify social media by their characteristic into six different categories and give popular examples for each class. The six categories according to Kaplan and Haenlein (2010) refer to

(a) collaborative projects,

(b) blogs and micro blogs,

(c) content communities,

(d) social networking sites (SNS),

(e) virtual game worlds, and

(f) virtual communities.

Kaplan and Haenlein (2010) also arrange them on different levels according to media richness and self-presentation, starting from largely text-based; collaborative projects (Wikipedia) and blogs/microblogs (Twitter); to medium-rich level, content communities (YouTube) and SNS (Facebook); and high-level, virtual social (Second Life), and virtual game worlds (World of Warcraft).

To the best of our knowledge, in related literature, the term "consumer behavior" is mostly treated holistically and not as a series of distinct and consecutive steps. This study attempts to close this gap in literature by considering the three stages of the whole process: "engagement", "decision", and finally "action". In this context, this work is also trying to answer the following research questions:

RQ1. What are the ways that users online behave as consumers?

RQ2. Does the process that perspective consumers undergo depend upon their personal opinion as influenced by social media?

The next section provides a literature review of the concepts examined in this article and the hypotheses, which are proposed.

THEORETICAL FRAMEWORK & HYPOTHESES

Social Media & Consumer Behavior

Social media have become ubiquitous over the last years. Together with advances in technology they have dramatically altered the way that potential consumers, members of online communities, make decisions and act with respect to online products and services that they encounter on their daily web explorations. At the same time, enterprises have the ability to exploit social media platforms in order to expand the scope of their marketing strategies (Bharucha, 2018). The social media applications' interface is characterized by ease of use, which entails that the reach of customers is equally easy. This benefits users who can conveniently complete their seek for information, while at the same time they also tend to accept their friends' recommendations (Sema, 2022).

This exchange of information, desires and experiences, i.e., user interaction, is one of the most significant advantages of social media. A single, opinion sharing user can influence a perspective buyer as well, thereby not depending exclusively on businesses' source of information for brand communication (Ioanas, 2020). Social networks offer a great opportunity to consumers to increase interactivity with other users (Schivinski & Dabrowski, 2016). In a study concerning Microsoft employees (Efimova & Grudin, 2007), it is highlighted that leveraging blogs within a company's environment for either personal communication between employees or as a knowledge management tool, can be beneficiary to both staff and company. On a different context, Meshi et al. (2019) present results and argue that the excessive use of SNS may result in users' addiction and behavioral disorder, similar to substance use. Nevertheless, companies continuously put effort developing SNS features to make them even more attractive, showcasing their importance for their marketing strategies.

Users today have the tendency to search and retrieve information on products and services, as well as proceed with a purchase, utilizing social media platforms, blogs and other online communities. Consumers resort to internet technology not only if they intend to proceed with an actual online purchase, but also in cases, where they merely want to compare prices (pre-purchase) or find information regarding after sales services (post-purchase) (Komodromos et al., 2018). Marketers have reacted to this differential behavior by increasing the number of digital marketing channels, adjusted to suit users' different needs. Digital marketing influences, in several levels, the decision-making buying process of a customer (Gay et al., 2007). Social media marketing is termed as the empowering process to promote websites, products, services and respective websites by means of online social channels (Yazdanparast et al., 2016). Social media appear to be a significant tool for marketers; nevertheless, marketing executives should approach them through well-planned strategies and not hastily and superficially as many companies and organizations often do (Ahmed, 2015).

Gamboa and Goncalves (2014) stress that the vast majority of companies today participate in Web 2.0 applications via either a website, some type of blog or any other social networking platform, e.g., Facebook. Nevertheless, they also point out that companies do not fully exploit the potential given in order to achieve customer loyalty but merely see it as an opportunity to raise awareness of their brand. On the same track, Rust et al. (2010) claim that although many companies have access to technologies that could empower life-long user interest, cultivate their relationship with their customers and improve overall marketing by mining information available from users' interaction, little is done on this direction. Thus, it is of vital importance to examine the way that consumers behave in digital environments. A quite accurate definition of consumer behavior is given by Bennett (1995, p. 59), as "the dynamic interaction of affect and cognition, behavior, and the environment by which human beings conduct the exchange aspects of their lives".

Changes in consumer behavior when shopping online are determined by the purchase decision (Retnowati & Mardikaningsih, 2021). Successful marketing highly depends on consumer behavior especially since young users, driven by their need for socialization, make a shift towards a digital platform (Vinerean et al., 2013). Consumer decision-making refers to "behavior patterns of consumers, that precede, determine and follow on the decision process for the acquisition of need satisfying products, ideas or services" (du Plessis, 1990:11) and is closely related to consumer behavior and the product buying process as a whole. According to de Vries et al. (2012), the 'type' of a customer may be diverse; some may be identified as more 'loyal', ones that exhibit a strong preference over a certain brand and others are more social media oriented, looking to participate in digital activities and events sponsored by various brands. When users participate and interact, they actually reproduce and share as consumers concepts and values (Kim et al., 2012). This fact enables businesses to generate a word of mouth effect (Kwok & Yu, 2012).

Social Media & Consumer Engagement

Digital marketing experts in their effort to enhance their users' degree of engagement, must bring to focus and analyze the interactions, which are based on customer relationship (Tiago & Veríssimo, 2014). Customer engagement is defined by Brodie et al. (2011, p. 260) as "a psychological state that occurs by virtue of interactive, co-creative customer experiences with a focal agent/object (e.g., a brand)".

In this work engagement includes observing, following, endorsing, contributing, owning and leading (Rosenblatt, 2023). According to Calder et al. (2016), digital engagement stems from various forms of online experience and comprises three distinctive characteristics. The first characteristic has to do with experience and attempts to explain consumer-media interactions, which are closely related to the social media engagement. The second characteristic "allows for context-specific, instead of a one-size-fits-all measurement of engagement that can vary among social media platforms" (Voorveld et al., 2018, p. 50). The third characteristic is related to conceptualization of engagement (Davis-Mersey et al., 2010). This enriches our knowledge on how media engagement in general and more specifically social media engagement relates to advertising (Voorveld et al., 2018). The factors that drive social media engagement according to Jaakonmäki et al. (2017), can be distinguished in three different groups: the first one has to do with a post's creator, the second one with the post's context and the final one with certain features of the content, for example, textual content, visual content and audio content. Social media's technological nature encourages active participation of citizens in the public sphere, especially through likes, shares and comments (Karekla et al., 2022)

Social Media & Decision Making

New forms of peer pressure can be created through social media (Power & Philips-Wren, 2011). Lindsey-Mullikin and Borin (2017) segregate the consumer decision process into four stages; consideration, evaluation, purchase and post-purchase advocacy and argue that social media introduced the opportunity for users/consumers to gain control over the evaluation stage. Bulmer and di Mauro (2010) claim that social media have an impact on businesses and the decision-making process. The important of those key elements is that organizations differentiate the way they use social media, both internally and externally, mainly due to the existence of high levels of trust in information obtained from online networks

An example study (Dwityas & Briandana, 2017) reports on how social media can be used in decision making and refers to the traveling experience that includes:

(a) a pre-trip phase, which consists of demands/wants that have to do with gathering of information and evaluation on the basis of the product's image and related tourism activities,

(b) the trip phase, that involves the tourism experiences that the travelers are undergoing, and

(c) the post-trip phase, the phase when the travelers have returned back at home and evaluate their experiences.

In some cases, such as coastal tourism, the spatial information that is explicitly required by decision-makers has the effect of revealing the current state of the destination, with respect to a perspective visit (Kim et al., 2021).

Social Media & Public Relations

Kotler (2002, p. 768) stresses that "public relations is one of the most complex and uncommon elements of promotion. This element is an exceptional one because its results may be noticed only after a period of time". Gruning and Hunt (1984, p. 550) define public relations as "the function of management between any organization and its public". Breakenridge (2017) discusses a new way to practice public relations, namely PR 2.0. The novelty that PR 2.0 introduces is that it allows brands to talk directly and in real time with the consumers.

Public relations were greatly enhanced with the advent of social media applications, which invite users to actively participate and generate content as well (Shirky, 2011), thereby acting as "prosumers" (Chandler, & Chen 2015). Moreover, digital tools have changed the nature of communication by making it more personal and more direct. The high level of interactivity has effectively driven PR from a stage of mere passive user exposure to a participatory process that allows users to create content and contribute with their perspectives (Lozano et al., 2020). Companies and organizations could take advantage of this transformed form of communication and exercise PR through the utilization of Web 2.0 related technologies (Mylona & Amanatidis, 2017).

Hypotheses Development

As Vinerean and Opreana (2021) mention, marketers must place a strong emphasis on customer engagement on digital settings and social media platforms as engaged customers have a greater predisposition of recommending products, services, brands and companies to other potential or existing customers through word-of-mouth, social media posts, social media comments/likes/shares and reviews on different sites. Tafesse and Wien (2018) link message strategies to consumer behavioral engagement, which is conceptualized in terms of consumer actions of liking and sharing brand posts. These actions represent an active form of brand engagement in which consumers take extra steps to interact with brand posts beyond mere exposure. Thus, the following hypothesis is proposed:

H1. Engagement and decision are positively related with action.

Engaged customers can contribute to "organizational innovation processes, create brand referrals and co-create experiences" (Rather, 2019, p. 2634). According to the congruity theory, we explore the role of self-brand image and value congruity on consumer engagement (Islam et al., 2018). Congruity theory suggests that customers express positive attitudes and behaviors, if they attain beliefs congruent with events or experiences (Lee & Jeong, 2014). When individuals exhibit commitment, they are much more likely to develop positive attitudes and behaviors towards that brand, leading to consumer engagement. The notion of a customer engagement cycle refers to awareness, consideration, inquiry, purchase, and retention stages, which appear to represent stages in the purchase process that customers use to decide the specific product (Sashi, 2012). Thus, the following hypothesis is proposed:

H2. Engagement has a positive impact on decision.

The above hypotheses will be examined in the context of the previously considered model (Amanatidis et al., 2022), which comprises three factors corresponding to related items, as described in the next section.

MATERIALS & METHODS

The quantitative research questionnaire, used in the research (Amanatidis et al., 2022), had been structured after a thorough literature survey and subsequent qualitative research, in order to ratify the appropriateness of the questions and was revisited here. It aimed to explore the online behavior of 200 Greek citizens with respect to social media use. For the sampling process, the convenience sampling method was chosen. Although the method of convenience sampling is non-random and consequently it does not allow for generalization, it is quite often the appropriate method, especially under strict time constraints (Mitchell & Jolley, 2012). The survey form consisted of 14 questions, where participants marked their responses regarding their level of agreement (or frequency of actions etc.) on a five-point Likert scale. The questionnaire items fell into one of two thematic classes, with the first concerning the users' general point of view about social media and the second being related to their online behavior. There were no questions on demographic data for this work.

In many cases, when measuring data and relationships between data variables, there may exist some underlying concepts, which are not directly observed (latent) and therefore it is not possible to quantify them directly. Instead, we resort to measuring different aspects of these latent variables and try to reason about their relationship or not with the underlying concept, in a process known as factor analysis, or EFA for the more traditional framework (Hoyle, 2023). EFA is a technique, which reduces the dimensionality of the dataset, similar to principal component analysis (PCA), in order to achieve parsimony (Field et al., 2012). EFA is very frequently leveraged as a first stage, initial analysis before engaging with other closely related stages, i.e., CFA and SEM (Kline, 2010). Whereas EFA deals only with observed variables and their relation with any possibly existing, underlying latent variables (factors), CFA's purpose is to validate the discovered, latent-to-observed, factor structure. Finally, SEM involves the process of developing models with the objective of analyzing possible relationships between latent variables only. SEM is not a single method but a family of related techniques and is actually a superset of both EFA and CFA. In this work we expanded on our previous results that had been obtained with EFA (Author et al., 2022), by employing CFA and SEM analysis, leveraging RStudio and the lavaan (latent variable analysis) package.

RESULTS

In this section we present the results from the factor analyzes and SEM processes.

Exploratory Factor Analysis

In Amanatidis et al. (2022), we had explored the various factors that can be deduced from users' attitude on social media platforms and drive their consumer behavior. Our aim here was to exploit the core strength of SEM, the combination of EFA and CFA. SEM, in general, is a linear statistical modelling process that analyzes variable relations and bears resemblance with other processes, e.g., analysis of variance, or PCA and multiple regression analysis. It has however a broader scope, with features that generalize, extend and integrate such models (Hoyle, 2023). Therefore, it cannot be considered as a single statistical method but as a family of related techniques instead.

The original dataset for our previous work had consisted of 14 questions (q1-q14). Data had been screened for missing values and outliers, accuracy, additivity, normality, linearity and homogeneity as well as correlation

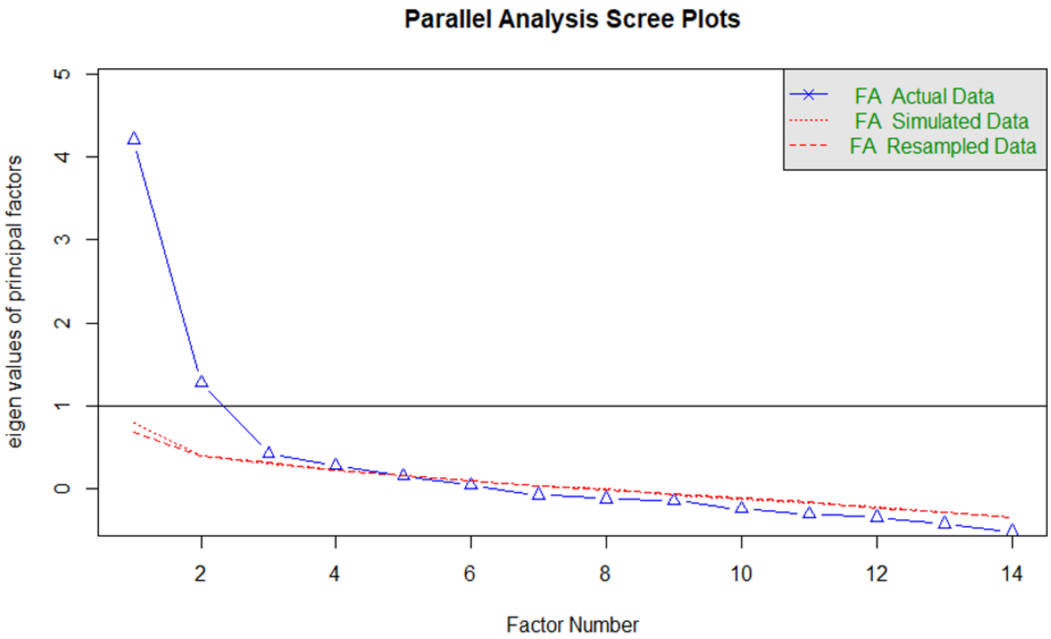

Figure 1. Suggested number of factors (Amanatidis et al., 2022)

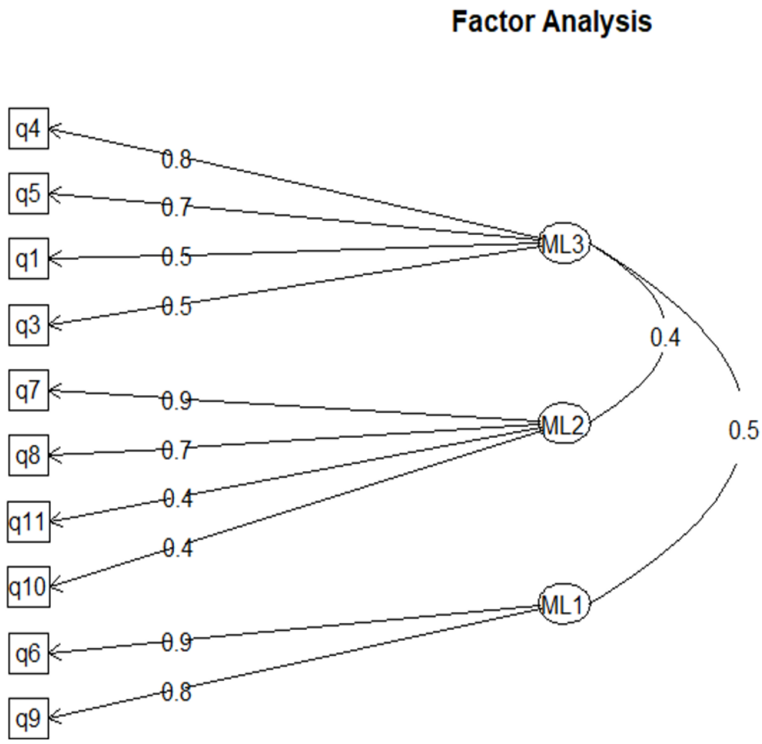

Figure 2. Factor loading matrices (Amanatidis et al., 2022)

and sampling adequacy. The process is deemed essential to ascertain that data is free from peculiarities that might lead to a non-positive definite matrix, which is a requirement for SEM (Kline, 2010). The number of factors (three) had been extracted with the aid of parallel analysis and scree plots, as visualized in **Figure 1**.

Factor loadings had been subsequently calculated and the process had suggested that four questions (q2, q12, q13, and q14) should be eliminated for not loading properly, i.e., for having an item-factor Pearson correlation less than .30 (Field et al., 2012). Factor analysis and satisfactory goodness of fit measure (RMSR=0.04; RMSEA=0.085 with [0.054, 0.118] as the 90% confidence interval; CFI=0.96; TLI=0.90) had led (Amanatidis et al., 2022) to model depicted in **Figure 2**, where questions loading on three factors “point of view” (ML1), “buying behavior” (ML2), and “personal engagement” (ML3) are shown along with factor correlations.

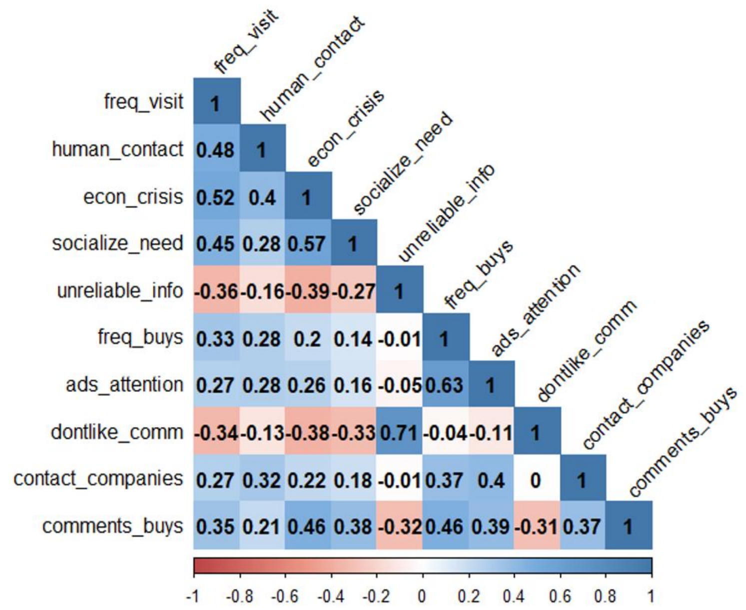

Figure 3. Correlation table (Source: Authors)

Confirmatory Factor Analysis

Thus, our final dataset consisted of 10 variables and 200 observations. With SEM in mind, which is generally considered a process that requires a large sample, our dataset here fulfilled the empirical n:q ratio rule, where n and q are the numbers of observations and parameters, respectively, as suggested by Jackson (2003). This sample to parameter ratio should ideally be 20 or more, with a value of 10 being a minimum. For CFA and SEM, computer-aided analysis utilized RStudio and the lavaan (latent variable analysis) package introduced in 2012 (Rosseel, 2012). 10 items, their original numbering and factor and new labels given here were:

1. q1–ML3: "How often do you visit SNS?" (freq_visit)
2. q3–ML3: "Social media tend to replace direct human contact." (human_contact)
3. q4–ML3: "Financial crisis has made me turn to social media as a means of leisure." (econ_crisis)
4. q5–ML3: "SNS fulfil my need for socialization." (socialize_need)
5. q6–ML1: "I believe that information found on social media platforms is not reliable." (unreliable_info)
6. q7–ML2: "How often do you buy products that you see on social media pages?" (freq_buys)
7. q8–ML2: "How often do you pay attention to products and services' advertisements on social media?" (ads_attention)
8. q9–ML1: "I do not like the specific way of communication with social media." (dontlike_comm)
9. q10–ML2: "How often do you contact companies in social media to seek information related to products?" (contact_companies)
10. q11–ML2: "Comments I read on social media have an effect on my buying decisions." (comments_buys)

The correlation table rounded to two decimal points is shown on **Figure 3**, where we can ascertain many correlation magnitudes above 0.30, which is considered a medium effect size (Field et al., 2012). At this point, there is a technical problem for CFA with a single factor-two item case, as in our EFA results with ML1 factor predicting original q6 (unreliable_info) and q9 (dontlike_comm) items. The problem, widely known as model identification, is the process of verifying that there exists a unique solution for all free parameters in CFA, i.e., the number of degrees of freedom is at least zero, indicating a just-identified or saturated model. With two items there are only three unique known values in the variance-covariance matrix. This is insufficient in order to compute the five free parameters, namely–in LISREL notation, introduced by Jöreskog (1970)–the two loadings $\lambda 1$ and $\lambda 2$, the factor variance $\psi 11$ and the two residual variances $\theta 1$ and $\theta 2$. One possible solution to overcome this is to use the variance standardization method, which restricts the two loadings to be equal and fixes the factor variance. With this method lavaan reports df=0.

Table 1. Item loadings for a single factor model

Latent variables: f=~	Estimate	SE	z-value	P(>z|)	SD lv	SD all
freq_visit	0.414	0.039	10.487	0.000	0.414	0.701
human_contact	0.410	0.057	7.209	0.000	0.410	0.517
econ_crisis	0.404	0.036	11.262	0.000	0.404	0.740
socialize_need	0.441	0.049	8.920	0.000	0.441	0.617
unreliable_info	-0.691	0.102	-6.767	0.000	-0.691	-0.489
freq_buys	0.511	0.085	6.036	0.000	0.511	0.442
ads_attention	0.543	0.088	6.183	0.000	0.543	0.452
dontlike_comm	-0.666	0.098	-6.812	0.000	-0.666	-0.492
contact_compns	0.431	0.080	5.379	0.000	0.431	0.398
comments_buys	0.461	0.051	9.068	0.000	0.461	0.626

Note. SE: Standard error & SD: Standard deviation

Table 2. Loadings for a two-factor model (orthogonal & variance standardization)

Latent variables: f1=~	Estimate	SE	z-value	P(>z|)	SD lv	SD all
freq_visit	0.396	0.041	9.753	0.000	0.396	0.672
human_contact	0.434	0.057	7.580	0.000	0.434	0.546
econ_crisis	0.366	0.038	9.755	0.000	0.366	0.672
socialize_need	0.403	0.051	7.880	0.000	0.403	0.564
freq_buys	0.643	0.083	7.752	0.000	0.643	0.557
ads_attention	0.660	0.087	7.625	0.000	0.660	0.549
contact_compns	0.532	0.079	6.719	0.000	0.532	0.492
comments_buys	0.469	0.051	9.119	0.000	0.469	0.636
Latent variables: f2=~						
unreliable_info	1.168	0.071	16.426	0.000	1.168	0.827
dontlike_comm	1.168	0.071	16.426	0.000	1.168	0.863
Covariances: f1~~f2	0.000				0.000	0.000

Note. SE: Standard error & SD: Standard deviation

If we consider all ten items for a single factor model, the model is identified and the number of degrees of freedom is positive, df=35 in our case, indicating an over-identified model with plenty of room for improvement. Model identification also enables accessing the model fit via a number of metrics, either incremental fit indices (e.g., comparative fit index–CFI, or Tucker Lewis index–TLI, which compare the user model against a baseline model) or absolute fit indices (e.g., root mean square error of approximation–RMSEA, which compare the user model against the observed data). These metrics have come to complement the historically first method to access a model's fit, Chi-square model. In our case the test statistic was relatively large (298.311) and p-value (Chi-square) was zero, which indicates that we reject the null hypothesis. In CFA models the null hypothesis states that the covariance matrix as implied by the model is the same as the observed covariance matrix.

10 items loaded reasonably well for a single factor model, with q9 (contact_companies) loading the least (0.398) and q3 (econ_crisis) the greatest (0.740) (**Table 1**). Nevertheless, the fit indices were not that good (CFI=0.610, TLI=0.488, RMSEA=0.194) suggesting that more factors should be introduced in our CFA model, aided in essence by our previous EFA results.

When introducing more factors to a model, there is the option of restricting them to be uncorrelated (orthogonal) or allowing for some inter-factor correlation (oblique). In this context, a second orthogonal factor was introduced for items q6 and q9, where, as stated previously, variance standardization was utilized for this two-item factor. Results showed proper loadings and improved model fit (CFI=0.722, TLI=0.652, RMSEA=0.162) but was nevertheless still not satisfactory (**Table 2**).

With oblique factors (marker method) results were even better (CFI=0.766, TLI=0.691, RMSEA=0.152) with some loadings decreasing but remaining acceptable (**Table 3**).

Finally, introducing the third factor according to EFA results, as shown in **Figure 2**, the model fit was additionally improved (CFI=0.902, TLI=0.863, RMSEA=0.102), which is marginally acceptable. The Standardized Root Mean Square Residual (SRMR) metric was also reported as 0.081. Both RMSEA and SRMR are slightly above the cut-off values of 0.1 and 0.08, respectively. Respective loadings are depicted in **Table 4**.

Table 3. Loadings for a two-factor model (oblique & marker method)

Latent variables: f1=~	Estimate	SE	z-value	P(>z|)	SD lv	SD all
freq_visit	0.411	0.040	10.335	0.000	0.411	0.697
human_contact	0.427	0.057	7.496	0.000	0.427	0.537
econ_crisis	0.392	0.036	10.760	0.000	0.392	0.719
socialize_need	0.431	0.050	8.610	0.000	0.431	0.603
freq_buys	0.570	0.084	6.797	0.000	0.570	0.494
ads_attention	0.595	0.087	6.817	0.000	0.595	0.495
contact_compns	0.479	0.080	6.016	0.000	0.479	0.443
comments_buys	0.466	0.051	9.138	0.000	0.466	0.633
Latent variables: f2=~						
unreliable_info	1.186	0.113	10.470	0.000	1.186	0.840
dontlike_comm	1.150	0.109	10.565	0.000	1.150	0.850
Covariances: f1~~f2	-0.479	0.070	-6.857	0.000	-0.479	-0.479

Note. SE: Standard error & SD: Standard deviation

Table 4. Loadings for three-factor model

Latent variables: f1=~	Estimate	SE	z-value	P(>z|)	SD lv	SD all
freq_visit	0.431	0.040	10.817	0.000	0.431	0.730
human_contact	0.429	0.057	7.489	0.000	0.429	0.540
econ_crisis	0.421	0.036	11.599	0.000	0.421	0.771
socialize_need	0.463	0.050	9.341	0.000	0.463	0.649
Latent variables: f2=~						
freq_buys	0.900	0.079	11.449	0.000	0.900	0.779
ads_attention	0.906	0.082	11.010	0.000	0.906	0.754
contact_compns	0.574	0.079	7.266	0.000	0.574	0.531
comments_buys	0.447	0.053	8.492	0.000	0.447	0.606
Latent variables: f3=~						
unreliable_info	1.209	0.106	11.390	0.000	1.209	0.856
dontlike_comm	1.128	0.101	11.125	0.000	1.128	0.833
Covariances: f1~f2	0.533	0.070	7.569	0.000	0.533	0.533
Covariances: f1~f3	-0.545	0.067	-8.100	0.000	-0.545	-0.545
Covariances: f2~~f3	-0.151	0.085	-1.767	0.077	-0.151	-0.151

Note. SE: Standard error & SD: Standard deviation

At this point, in order to improve the fit of our model, we reviewed the factor loadings from our EFA results (Author et al., 2022)–which were all above the suggested value of .30–and opted to discard the three variables that loaded the least; q3 (human_contact), q10 (contact_companies) and q11 (comments_buys). With this modification, lavaan reported after 31 iterations (cut-off values as suggested by Hoyle, 2023): Chi-square test statistic 19.633 with df=11 and p-value=0.051 (non-significant at α=.05, retaining the null hypothesis); SRMR=0.038 (<0.08); CFI=0.981 (>0.95); TLI=0.964 (>0.95); RMSEA=0.063 (<0.1). The final accepted model is shown on **Table 5**.

CFA has thus validated EFA results. It has to be stated at this point that we have performed a first order analysis, i.e., we have not considered the possibility of factors predicting other factors (second order CFA). In such a case, factors are termed as endogenous or exogenous, according to whether a factor is being predicted by other factors or not. This however was explored later in the context of SEM.

Structural Equation Modelling

SEM is a generic framework that facilitates linear modelling between observed variables (e.g., simple, multiple or multivariate regression), between latent and observed variables (CFA) or exclusively between latent variables (structural regression). It also allows for path analysis, an extension to multivariate regression, where endogenous variables can possibly explain other endogenous variables. The first two cases are jointly referred to as the measurement part of the model, whereas the last case constitutes the structural part of the model. SEM is based on three main pillars (Bollen, 1989):

1. the path analysis,
2. the synthesis of latent variables and measurement models, and
3. methods that estimate the parameters of structural models.

Table 5. Accepted three-factor model

Latent variables: f1=~	Estimate	SE	z-value	P(>z|)	SD lv	SD all
freq_visit	0.402	0.041	9.724	0.000	0.402	0.682
econ_crisis	0.435	0.037	11.680	0.000	0.435	0.798
socialize_need	0.484	0.050	9.655	0.000	0.484	0.678
Latent variables: f2=~						
freq_buys	0.907	0.115	7.880	0.000	0.907	0.785
ads_attention	0.970	0.121	7.988	0.000	0.970	0.807
Latent variables: f3=~						
unreliable_info	1.201	0.104	11.534	0.000	1.201	0.850
dontlike_comm	1.135	0.100	11.391	0.000	1.135	0.839
Covariances: f1~f2	0.389	0.081	4.784	0.000	0.389	0.389
Covariances: f1~f3	-0.568	0.067	-8.530	0.000	-0.568	-0.568
Covariances: f2~~f3	-0.081	0.088	-0.921	0.357	-0.081	-0.081

Note. SE: Standard error & SD: Standard deviation

Generally, the objective with SEM is to approximate as closely as possible the population variance-covariance matrix Σ (as estimated by sample's matrix S) with a parameterized model's variance-covariance matrix Σ(θ). When initially employing SEM analysis it is suggested to start with the measurement part of the model and subsequently proceed with the structural part. The structural regression part allows for explanatory latent variables, which can be either exogenous or endogenous, depending on their relation. In our case, the measurement part of the model has been resolved due to the previous CFA (and EFA) analyzes. For the structural part we also had identified three factors, initially discovered in our previous work and confirmed in this paper. Three factors had originally been identified as "personal engagement", "point of view", and "buying behavior". We slightly altered their names here as "engagement", "decision", and "action", which intuitively correspond to major steps for a potential consumer, from intent, strong or not, to a final purchase.

With respect to the latent variables' relation, we first hypothesized that "engagement" and "decision" predict "action" (hypothesis **H1**), which led to a model M1 with one endogenous ("action") and two exogenous ("engagement" and "decision") latent variables. Implementation of M1 in lavaan was successful and the model is visualized (by means of the semPlot package) as a path diagram in **Figure 4** (left). In a SEM path diagram, latent variables appear as circles, observed variables as squares and single headed arrows represent their relation, e.g., factor "engagement" (eng) predicts item "freq_visit" (abbreviated as "frq_v" by the package). The width of the arrows denotes the strength of the relation, which is also displayed numerically. A negative association appears in red, as for example for the rather weak relation between "engagement" (eng) and "decision" (dcs), which is negative due to the fact that "decision" loads on items unreliable_info (un_) and dontlike_comm (dn_), which have a negative meaning and could have been reverse coded. This has indeed been tested with the arrow changing color. Double headed arrows represent variances, in the case of self-loops, or covariances, e.g., in the case of the arrow between "engagement" and "decision". Dashed lines represent scaling by fixing factor loadings (Epskamp, 2015).

Subsequently, we explored the possibility of a second endogenous variable, "decision", being predicted by "engagement" (hypothesis **H2**), while these two factors jointly predict "action" as before. This model, M2, is visualized in **Figure 4** (right).

As the two models share the same measurement part, they fit the same (SRMR=0.038, CFI=0.981, TLI=0.964, RMSEA=0.063), which is acceptable. They differ only in their structural part and their role here is to serve as a demonstration of how hypothesized theory can be verified with SEM and lavaan. In the context of this work, it is evident that the engagement factor is in both models quite important for the prediction of consumer behavior, from intent to final action.

CONCLUSIONS

Dissemination of information across users and online societies has radically been transformed by the advent and ubiquitous presence of social media applications. Users nowadays generate content online very quickly while at the same time they receive, process and share a great amount of information either from organizations or their peers. In a previous work (Amanatidis et al., 2022) we aimed to explore the ways that

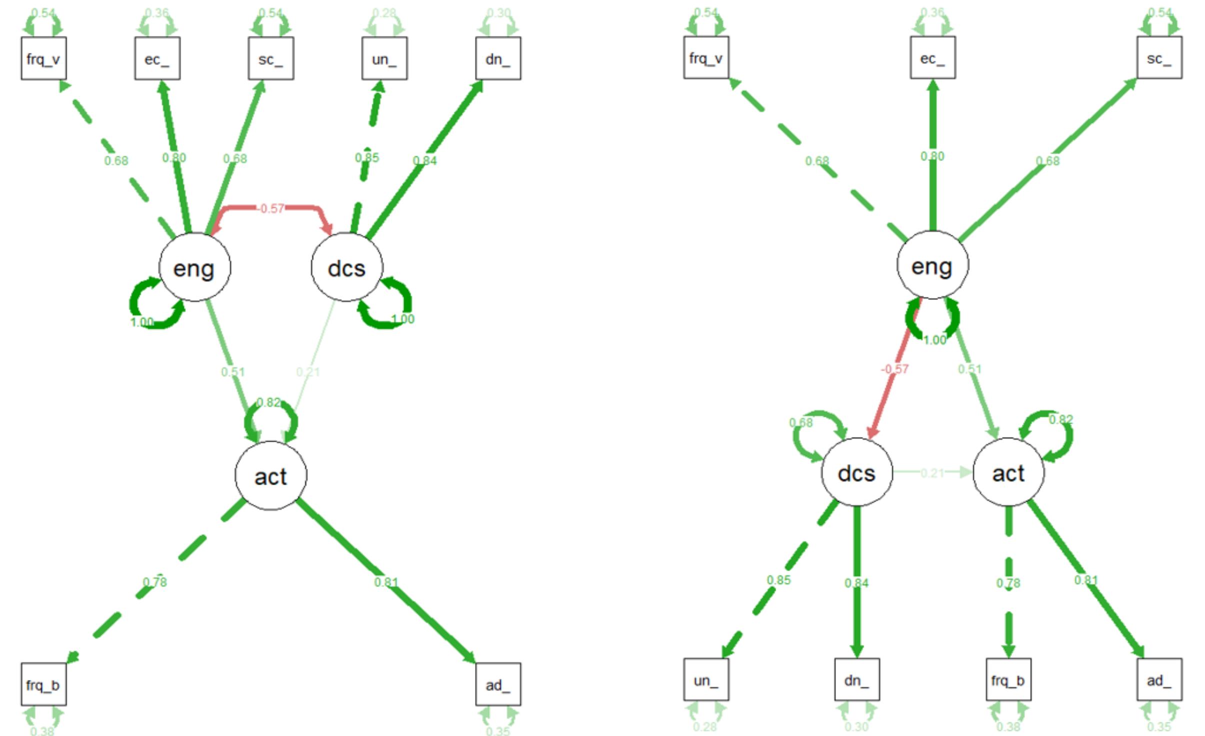

Figure 4. SEMs: M1: one endogenous variable (left) & M2: two endogenous variables (right) (Source: Authors)

users' online behavior as consumers and the possible purchase process they undergo can be driven by their personal opinion towards social media use and their degree of engagement. In this work, we have expanded on these EFA results. CFA has verified the measurement part of the model and different theoretical hypotheses have been tested with respect to the structural part of the model. All factor loadings are accepted, and the model fits quite well (SRMR=0.038, CFI=0.981, TLI=0.964, RMSEA=0.063). Results also show that both factors "engagement" and "decision" substantially predict "action", with the former however being more important. To the best of our knowledge, the specific model built around these three constructs is not found elsewhere in literature and the model developed can prove to be a valuable source of information for e.g., marketers in their effort to apply an efficient marketing strategy.

It is important for marketers to find new ways to exploit social media as according to our validated model engagement and decision predict action. Engagement has also an impact on decision as the intermediate step in the behavior cycle from awareness, consideration, inquiry, purchase, and retention stages (Sashi, 2012). The proposed model can be adopted and implemented by managers and marketers as an aid in designing their digital marketing strategies. Marketers and managers can focus on the items corresponding to the most important factor i.e., engagement so as to consider the users' opinion and attitude and take them into account for a successful marketing plan.

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