The Impact of Social Media on Brand Value Growth

MIHAELA IOANA GURĂU
PhD candidate Romanian Academy
School of Advanced Studies of the Romanian Academy
mihaela_gi@yahoo.com

IVONA STOICA (RĂPAN)
Assoc. Prof., PhD, Senior Researcher
Institute of National Economy, Romanian Academy
stradivonas@gmail.com

MARIANA GURĂU
Lecturer, Ph.D.
Faculty of Economics and Business Administration
„Nicolae Titulescu" University of Bucharest
marianagurau@univnt.ro

Abstract: The phenomenon of social media marketing (SMM) has only been developed in the last decade and focuses mainly on the impact that social networks have on consumer behavior. Despite the fact that each social media network has its own characteristics, the ubiquitous impact on economic life can create a chain of consequences that cause interactions between networks, ending up as one network exerts its influence on the others. The approach adopted in this research brings new perspectives for the literature by analyzing how an influencer *works on building their own* branding*, which helps him to be asked by other businesses for promotion and, why not, to help build other brands. We will therefore highlight how* influencers *can harness the potency of social networks and profit in favor of their own image.*

Keywords: brand value growth, social media marketing, branding, social media

1. Introduction

In recent years we have witnessed the rapid growth of social networks, which have become important centers of social activity and information pipelines. The identification of social influence in these social networks has become the center of information generation. The increasing amount of information circulating through online social networks is forcing the participants of these networks to fight for attention and influence through diversified social messages, by adopting economic, religious, sustainability and political opinions.

Consequently, identifying the influential users among them and quantifying their influence becomes an important problem with the application in viral marketing, in the dissemination of information, in the search and discovery of reliable information that will influence the prediction of rankings.

Social influence through online social networks (OSN) is very well exploited as a new and innovative marketing tool and is defined by (Senevirathna, et al. 2021) as "the ability of a user's action to affect the actions of other users. We refer to such events as relationships of social influence. However, in most cases these relationships are asymmetrical. A person who influences other users is called *an influencer*, and the person influenced is called influenced."

The influence of social media has been widely studied in many areas, including the fields of marketing, political science, human behavior and communication.

However, in the context of marketing on social networks, little is known about the somewhat cascading influence, or rather the snowball effect that social networks have on the "brand" that a good social media user (also known as *an influencer*) creates for himself, especially when he displays with the art of subtlety the products he promotes on a social network.

In analyzing the influence of social networks on users' decisions, one must take into account the specifics of the analyzed networks but also of the users' profile knowing that different users exert different influences in different ways, and the influence is correlated with the specific attributes of the user and the content. A content-related attribute could be to start a new post, contribute to a post, or share an existing post.

2. The role of social networks in increasing brand value

The dynamic and interactive functions of social networks make them an ideal channel for followers to engage in dialogue communication with opinion formers. Communicators can post messages designed to initiate conversational responses and get replies to messages from stakeholders interested in the topic, and thus encourage close ties with their followers. For example, on Facebook, Intagram, Youtube, Tik Tok you can initiate conversations in the comments section of each post. Also, by using @ can be evoked the person whose *username* is *denied*.

2.1. Theories of uses and satisfactions

Theories of uses and gratifications theory (UGT) (Katz, Blumler and Gurevitch, 1974) is a framework that explains how and why people actively search for certain types of media, theories that successfully apply to social media users. People receive satisfaction through social networks, they satisfy their informational, social and recreational needs.

In recent years, we have witnessed the rapid growth of online social networks, which have become important centers of social activity and information pipelines. Identifying social influence in these platforms can give us meaningful information to better understand the interaction behaviors between online users. However, it is difficult to quantitatively measure the influence among users, since many key factors cannot be noticed conveniently. More recent papers focus mainly on the development of theoretical models based on explicit causal knowledge. However, such knowledge is usually not available and often needs to be discovered.

The worldwide use of several social networks and the investments that companies make to promote their products and services through social networks have led researchers to study the interactions between these networks. (Phua, Jin and Kim 2017) have found that Instagram users have the biggest commitment compared to Facebook. Such a finding is also supported by the strategy of many economic entities to use Instagram as a "showcase" of presentation of the products or services offered.

With the rapid increase in the use of online social networks, social platforms now represent a large part of daily communication and play a major role in the dissemination of information throughout society. (Senevirathna, and others 2021) classifies the actions of social media users into three types:

(1) initiating a conversation or post ,
(2) contribution to an existing conversation or post, or
(3) sharing an existing post between conversations without changing the content.

Studies on the influence of social networks claim that the influence of a user is the same in all types of action. However, in reality, there are differences in how users influence others through initiation, contribution and sharing actions. Ignoring these differences in behavioral influence can prevent a comprehensive understanding of the real role of social influence in a wide variety of scenarios, including the propagation of information and maximization of influence, the transfer of knowledge in a community, and the development of projects such as online influence campaigns or online brand involvement at different stages of consumer purchasing decision.

For example, in online marketing campaigns, some users may create original content, some users may contribute to content created by others, and other users may spread the content to others through sharing. If a marketing firm is interested in controlling or interacting with this information shared, they may want to identify different users based on the role they play and how that user affects other users. Therefore, in this study, rather than modeling influence as a single entity, we modeled influence as its effect on the turnover of the business that an influncer has developed as a result of the promotion of products or services of companies in various fields of activity with the exploration of the cascading effects of social influence.

2.2. The role of social networks in increasing brand value

Currently, the evolution of *social media* platforms plays an important role in all areas of life, finding them deeply involved in issues of shaping tastes in consumer choices. Information circulates very quickly through Instagram, TikTok, Facebook, Twitter, vlogs, and events that affect any of the areas of economic and social life reach consumers in real time. In addition, the *social media* user generation is modern and open to everything new, with high tolerance and increased interest in making a better world.

The role of social networks in influencing the decisions of their followers, decisions related to choices, behavior, consumption, is one that is difficult to determine and absolutely uneven. (Saike, and others 2013) notes that "identifying influence in online social networks is difficult due to several confusing factors such as homophilia, unnoticed heterogeneity , simultaneity, factors that vary over time and other contextual effects. "

Studying the literature I did not find any study on *the branding* of a social media user who has a large number of followers – *influencer* – and who uses his influence in two senses: promoting products and services of other companies in an original way and working subtly on the development of his own brand. There are papers that analyze how some companies grow (Romao, and others 2019) as a result of using social networks for the purpose of promoting their own products. The article "aims to understand how interactions across multiple social networks influence the visibility of the most relevant social network of a luxury brand that acts as a showcase (Instagram)."

The approach adopted in this research brings new perspectives for the literature by analyzing how an *influencer* works on building their own *branding*, which helps him to be asked by other businesses for promotion and, why not, to help build other brands. We will therefore highlight how *influencers* can harness the potency of social networks and profit in favor of their own image.

Therefore, the following two research questions arise: (1) is there an influence of reciprocity between the development of one's own brand, reflected in the turnover, and the number of followers and their reactions to the posts of an influencer? (2) is it possible to reveal which characteristics contribute most to such an influence?

3. Case study “The impact of social networks on brand value growth”

In order to analyze the increase in the brand value of an economic entity whose object of activity is the provision of media representation services by promoting products and services (to some beneficiaries) through our own social networks, we have collected data on the evolution of the number of followers, the number of comments and the number of likes (likes) of the Instagram account that the company uses for media representation services.

We considered that these are the independent variables that influence the turnover of the firm, as a dependent variable. In order to be able to obtain relevant results, we used the monthly data on the listed elements, over a period of 41 months, which are relevant given the rapid increase in turnover, but also in the number of followers in a fairly short time that made there were big differences from month to month.

By analyzing these data, it is desired to identify the evolution trend of the turnover in the foreseeable future.

3.1. Purpose of the Study

This study aims at econometric modeling of social-media parameters, such as: the number of posts, the number of followers, the number of comments and the number of monthly likes, on the turnover from advertising services, as a dependent variable.

3.2. Assumptions

The hypotheses studied are:

H1: There are significant causal relationships between the elements involved in the study;

H2: The equation of link between the evolution of turnover and the social media elements studied, estimated in the long term, is statistically significant.

3.3. Presentation of the data used

We analyzed the turnover of the company of a content creator and we used as data the evolution of the number of its followers, the evolution of the number of likes and comentaries, the number of postations per Instagram from January 2018 to December 2021. The data was taken from the internet (source: https://socialblade.com/youtube/c//monthly).

In order to test the long-term relationship between *turnover* (CA) and *Instagram / Month Posts* (POINS), *Instagram Followers* (UINST), respectively *The Number of Likes* (LIKE) and *Comments* (COMENT), we will start by testing the stationaryness of the data series used.

3.4. Stationary testing

Series: Turnover (CA)

The ADF and KPSS tests of the root drive are shown in the following tables:

Table 1. ADF drive root test for "Turnover" series

Null Hypothesis: CA has a unit root

Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.189228	0.0281
Test critical values:	1% level	-3.605593	
	5% level	-2.936942	
	10% level	-2.606857	

*MacKinnon (1996) one-sided p-values.

The probability attached to the null hypothesis (CA has a drive root) is 0.028, below the standard threshold of 5%. According to the ADF test, we accept the hypothesis that *the CA series is stationary*.

Table 2. KPSS drive root test for "Turnover" series
Null Hypothesis: CA is stationary
Exogenous: Constant
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.850853
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

The KPSS test *rejects the situation of stationaryness* (the statistics of the test, 0.8508, are greater than the value corresponding to the threshold of 5%, respectively, 0.463).

The ADF and KPSS therapies provide contradictory results (moreover, Ng-Perron tests reject the unit root hypothesis, and the ERS Point Optimal test does not support that hypothesis).

Conflicting results may be due to the small number of comments available (41).

Instead, all tests reject the unit root hypothesis for the series calculated in the first difference. In view of the previous analyses, we consider as a working hypothesis, that the Turnover series is non-existential, integrated by order I.

Series: Instagram Followers (UINST)

The ADF and KPSS tests of the root drive are shown in the following tables:

Table 3. ADF drive root test for the series "Followers on Instagram"
Null Hypothesis: UINST has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-2.914180	0.0526
Test critical values: 1% level	-3.605593	
5% level	-2.936942	
10% level	-2.606857	

*MacKinnon (1996) one-sided p-values.

According to the ADF test, the probability attached to the null hypothesis (CA has a drive root) is 0.0526 slightly above the standard threshold of 5%.

Table 4. KPSS drive root test for the series "Instagram Followers"

Null Hypothesis: UINST is stationary
Exogenous: Constant
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

	LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic	0.787896
Asymptotic critical values*: 1% level	0.739000
5% level	0.463000
10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

The KPSS test *rejects the stationary hypothesis* (the statistics of the test, 0.7879, is higher than the value corresponding to the threshold of 5%, respectively, 0.463).

All tests reject the unit root hypothesis for the series calculated in the first difference. We accept the hypothesis that *the UINST series is non-stationary*, integrated by the first order.

Series: Number of likes (LIKE)

The ADF and KPSS tests of the root drive are shown in the following tables:

Table 5. ADF drive root test for the series "Number of likes""

Null Hypothesis: LIKE has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-2.351894	0.1615
Test critical values: 1% level	-3.605593	

5% level	-2.936942	
10 % level	-2.606857	

*MacKinnon (1996) one-sided p-values.

According to the ADF test, the probability attached to the null hypothesis (CA?? or LIKE?? has a drive root is 0.1615, above the standard threshold of 5%. The test does not reject the assumption that *the LIKE series is non-stationary*. As the value of the statistic is slightly above the 10% threshold, we also apply the KPSS test.

Table 6. KPSS test of the root of the drive for the series "Number of likes"
Null Hypothesis: LIKE is stationary
Exogenous: Constant
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.413097
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

The KPSS test does not reject the hypothesis that *the LIKE series is stationary* (the value of the statistics is 0.413, lower than 5%). The results of the application of ADF and KPSS are contradictory, we have applied other tests: Phillips-Perron and Ng-Perron do not reject the unit root hypothesis.

Instead, all tests reject the unit root hypothesis for the series calculated in the first difference. We accept the hypothesis that *the LIKE series is non-stationary*, integrated by the first order.

Series: Comments (COMENT)

The ADF and KPSS tests of the root drive are shown in the following tables:

Table 7. ADF test of the root drive for series "Comments"
Null Hypothesis: COMENT has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.511746	0.1203
Test critical values:	-3.605593	-4.205004	
	-2.936942	-3.526609	
	-2.606857	-3.194611	

*MacKinnon (1996) one-sided p-values.

According to the ADF test, the probability attached to the null hypothesis (CA has a drive root) is 0.1203 above the standard threshold of 5%.

Table 8. KPSS test of the root drive for the series "Comments"

Null Hypothesis: LIKE is stationary
Exogenous: Constant
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.608296
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

The statistics of the KPSS test shall be above the value corresponding to the 5% threshold. I reject, the assumption that *the COMENT series is stationary*. All tests reject the unit root hypothesis for the series calculated in the first difference. Consequently, we accept the hypothesis that *the series "Comments" is non-stationary*, integrated by the first order.

Series: Instagram Posts / Moon (POINS)

The ADF test is shown in the following table:

Table 9. ADF drive root test for "Instagram Posts/ Month" series

Null Hypothesis: POINS has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.192091	0.0000
Test critical values:	1% level	-3.605593	
	5% level	-2.936942	
	10% level	-2.606857	

*MacKinnon (1996) one-sided p-values.

The probability attached to the null hypothesis (POINS has a drive root) is < 0.0001. According to the ADF test, we accept the hypothesis that *the POINS series is stationary*. We also apply the KPSS test:

Table 10. KPSS Drive Root Test for Instagram/Month Posts Series"

Null Hypothesis: LIKE is stationary
Exogenous: Constant

Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.277543
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

The statistics of the KPSS test are below the value corresponding to the threshold of 5%. We do not reject the hypothesis that *the series "Instagram Posts / Moon" is stationary*. Consequently, we accept the hypothesis that the series "Instagram Posts / Moon" is stationary.

3.5. Causation tests

Based on the results of the stationary analyses, we apply the Granger causation test for the d(CA), d(UINST), d(LIKE) d(COMENT) and POINS series. The results are as follows:

Table 11. Granger causation tests

Pairwise Granger Causality Tests
Sample: 2018M01 2021M12
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
D(UINST) does not Granger Cause D(CA)	38	0.44743	0.6431
D(CA) does not Granger Cause D(UINST)		1.50867	0.2361
D(LIKE) does not Granger Cause D(CA)	38	0.04064	0.9602
D(CA) does not Granger Cause D(LIKE)		0.31388	0.7328
D(COMENT) does not Granger Cause D(CA)	38	0.39468	0.6770
D(CA) does not Granger Cause D(COMENT)		0.08938	0.9147
POINS does not Granger Cause D(CA)	38	0.74954	0.4805
D(CA) does not Granger Cause POINS		2.22607	0.1239
D(LIKE) does not Granger Cause D(UINST)	38	0.97455	0.3880
D(UINST) does not Granger Cause D(LIKE)		0.05143	0.9499

D(COMENT) does not Granger Cause D(UINST)	38	1.83547	0.1755
D(UINST) does not Granger Cause D(COMENT)		0.41928	0.6610
POINS does not Granger Cause D(UINST)	38	0.77253	0.4700
D(UINST) does not Granger Cause POINS		0.13081	0.8778
D(COMENT) does not Granger Cause D(LIKE)	38	0.27740	0.7595
D(LIKE) does not Granger Cause D(COMENT)		0.82149	0.4486
POINS does not Granger Cause D(LIKE)	38	0.14403	0.8664
D(LIKE) does not Granger Cause POINS		3.06844	0.0600
POINS does not Granger Cause D(COMENT)	38	0.83183	0.4442
D(COMENT) does not Granger Cause POINS		0.70952	0.4992

The tests do not identify granger causal relationships between the change in the analyzed variables. In these conditions, we do not calculate models between stationary variables by differentiation, but we test the possibility of the existence of co-integration relations between the integrated variables of the first order.

3.6. Cointegration model

We built a model of cointegration between the non-stationary variables. The result is shown in the following table:

Table 12. Granger causation tests

Vector Error Correction Estimates
Sample (adjusted): 2018M03 2021M05
Included observations: 39 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
CA(-1)	1.000000
POINS(-1)	-1849.188
	(834.416)
	[-2.21615]
UINST(-1)	-0.931930
	(0.18893)
	[-4.93279]

LIKE(-1)	-2.499821
	(2.37961)
	[-1.05052]
COMENT(-1)	296.9825
	(105.484)
	[2.81541]
C	179863.1

Error Correction:	D(CA)	D(POINS)	D(UINST)	D(LIKE)	D(COMENT)
CointEq1	-0.905836	0.000151	0.030282	-0.008899	-0.000581
	(0.18187)	(6.9E-05)	(0.01359)	(0.01441)	(0.00043)
	[-4.98070]	[2.17132]	[2.22804]	[-0.61777]	[-1.35733]
D(CA(-1))	0.447559	2.86E-05	-0.010106	0.000793	0.000443
	(0.17691)	(6.8E-05)	(0.01322)	(0.01401)	(0.00042)
	[2.52988]	[0.42352]	[-0.76440]	[0.05660]	[1.06418]
D(POINS(-1))	-510.6003	-0.320146	9.747109	-11.79288	0.993904
	(395.706)	(0.15109)	(29.5718)	(31.3432)	(0.93082)
	[-1.29035]	[-2.11889]	[0.32961]	[-0.37625]	[1.06777]
D(UINST(-1))	2.988052	-0.000126	0.310086	0.081658	-0.000994
	(2.03332)	(0.00078)	(0.15195)	(0.16106)	(0.00478)
	[1.46955]	[-0.16291]	[2.04067]	[0.50702]	[-0.20788]
D(LIKE(-1))	0.711383	-0.000696	0.167912	-0.365247	0.006965
	(2.34180)	(0.00089)	(0.17501)	(0.18549)	(0.00551)
	[0.30378]	[-0.77825]	[0.95946]	[-1.96910]	[1.26443]
D(COMENT(-1))	77.94467	-0.034647	-3.794939	6.271766	-0.371883
	(79.7421)	(0.03045)	(5.95926)	(6.31623)	(0.18758)
	[0.97746]	[-1.13792]	[-0.63681]	[0.99296]	[-1.98255]
C	-7801.565	0.502709	1839.990	-120.7850	5.321064
	(6658.98)	(2.54258)	(497.636)	(527.446)	(15.6640)
	[-1.17159]	[0.19772]	[3.69746]	[-0.22900]	[0.33970]

R-squared	0.460644	0.449629	0.297545	0.123263	0.275386
Adj. R-squared	0.359515	0.346435	0.165835	-0.041125	0.139521
Sum sq. resids	1.26E+10	1840.439	70500935	79200134	69851.25
S.E. equation	19861.77	7.583780	1484.303	1573.215	46.72100
F-statistic	4.555011	4.357108	2.259089	0.749830	2.026909
Log likelihood	-437.4465	-130.4955	-336.2863	-338.5552	-201.4046
Akaike AIC	22.79213	7.051049	17.60443	17.72078	10.68741
Schwarz SC	23.09072	7.349637	17.90301	18.01937	10.98600
Mean dependent	1826.154	0.000000	2686.410	98.02564	2.948718
S.D. dependent	24817.82	9.380832	1625.161	1541.830	50.36652

Determinant resid covariance (dof adj.)	1.35E+26
Determinant resid covariance	5.01E+25
Log likelihood	-1430.641
Akaike information criterion	75.41749
Schwarz criterion	77.12371
Number of coefficients	40

4. Conclusions

Researchers increasingly address the subject of the influence of social networks on followers, a new current is about to make its way into their concerns, namely the concept of influence / passivity. A serious disadvantage of such an approach is the requirement of explicit causal knowledge, which is extremely rare in many scenarios and due to the fact that passivity also extends beyond the field of knowledge, that is, those users of social networks who are characterized by passivity, as a rule, are not receptive to scientific studies either and do not respond to questionnaires, the main study tools in the field.

The analysis of these data identified the trend of evolution of the turnover in the foreseeable future. In order to analyze the increase in the brand value of an economic entity whose object of activity is the provision of media representation services by promoting products and services (to some beneficiaries) through our own social networks, we have collected data on the evolution of the number of followers, the number of comments and the number of likes (likes) of the Instagram account that the company uses for media representation services, considering that these are the independent variables that influence the turnover of the firm as a dependent variable.

Starting from the results of the stationary analysis, and as a result of the application of the Granger type causal test for the series d(CA), d(UINST), d(LIKE) d(COMENT) and POINS, we have reached the result that shows us that the co-integration coefficient is negative (-0.905836) and is significantly different from zero, which means that the co-integration equation is stable in the long term. The long-term relationship is: CA = 1848.188· POINS + 0.93163· UINST + 2.49982· LIKE – – 296.9825· COMMENT – 179863.1 This means that, in the long run, there is a stable positive relationship between turnover (CF) and Instagram / Month Posts (POINS), Instagram followers (UINST), respectively The number of likes (LIKEs) and a negative relationship between turnover (CF) and Comments (COMENT).

References:

[1] Jula, Dorin. 2020 - 2021. *Econometrie în EViews. Note de curs, Centrul de Modelare macroeconomică, .* INCE-SCOSAAR, București.

[2] Jula, Dorin, și Nicolae Marius Jula. 2020. *Econometrie (ediția a 3-a).* Bucuresti: Mustang.

[3] Katz, E, J. G. Blumler, și Gurevitch, M. 1974. „Utilization of Mass Communication by the Individual.” *The Uses of Mass Communications: Current Perspectives on Gratifications Research; Beverly Hills: Sage Publications.* 19-31.
[4] Krause, Amanda, A North, și Brody Heritage. 2014. „The uses and gratifications of using Facebook music listening applications.” *Computers in Human Behavior 39* 71 - 77.
[5] Lovejoy, Kristen, și Gregory D. Saxton. 2012. *Information, Community, and Action: How Nonprofit Organizations Use Social Media.* Journal of Computer-Mediated Communication.
[6] Phua, Joe, Seunga Jin, și Jihoon (Jay) Kim. 2017. „Uses and gratifications of social networking sites for bridging and bonding social capital: A comparison of Facebook, Twitter, Instagram, and Snapchat.” *Computers in Human Behavior, 72* 115 - 122.
[7] Porter, Lance V., Kaye D Sweetser, Deborah S. Chung, și Eunseong Kim. 2007. „Blog power: Examining the effects of practitioner blog use on power in public relations.” 92-95. Public Relations Review.
[8] Romao, Maria Tereza, Sergio Moro, Paulo Rita, și Pedro Ramos. 2019. „Leveraging a luxury fashion brand through social media.” *European Research on Management and Business Economics 25* 15 - 22.
[9] Romero, Daniel, Wojciech Galuba, Sitaram Asur, și Bernardo Huberman. 2011. „Influence and Passivity in Social Media.” *Machine Learning and Knowledge Discovery in Databases. ECML PKDD* 18 - 33.
[10] Saike, He, Xiaolong Zheng, Daniel Zeng, Kainan Cui, Zhu Zhang, și Chuan Luo. 2013. „Identifying Peer Influence in Online Social Networks.” *Intelligence and Security Informatics* 47 - 61.
[11] Senevirathna, Chathurani, Chathika Gunaratne, William Rand, Chathura Jayalath, și Ivan Garibay. 2021. „Influence Cascades: Entropy-Based Characterization of Behavioral Influence Patterns in Social Media.” *Microsoft Academic, Volume: 23, Issue: 2,* 160.