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Research Article

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Social Media Classifications for Impactful Marketing in Khomas Region, Namibia

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Abstract

Marketers need to align their advertising content, consumer profiles, and social media applications for effective advertising, as social media usage and applications are increasing. However, the number and variety of social media applications increased proportionately, providing consumers and marketers with an infinite number of possibilities and causing complexity in the selection process. In order to categorise social media into three groups that marketers can utilise to better effectively target customers during social media marketing efforts, this study used factor analysis. Furthermore, the study recommended new, useful marketing strategies for social media marketers. The research philosophy used in this study was positivist. Specifically, this study used an empirical research methodological technique. The degree of internal consistency between the various assessments was assessed using the Cronbach alpha coefficient to test the reliability of the scales in the research instrument. A pilot study of the research instrument was conducted on a limited sample in order to further guarantee its dependability. To reach a sample of 230 customers, systematic random sampling was used. Data was gathered via a self-administered questionnaire. Regression analysis was performed using Structural Equation Modelling (SEM) to validate the study model. The results showed that there are three different kinds of social media: formal, casual, and entertaining. Both informal and entertainment social media have an impact on formal social media, which is the primary social media platform. Other unofficial social media sites include Facebook, Instagram, Twitter, WhatsApp, and more. Snapchat and YouTube are social media sites for entertainment. Both product and age-related social media marketing may be the subject of future studies. Future research can ascertain the links between product and social media type as well as the associations between age and social media type usage.

Keywords: Entertainment Social Media; Formal Social Media, Impactful Marketing, Informal Social Media, Social Media Types

1. Introduction

Marketers need to align their advertising content, consumer profiles, and social media applications for effective advertising, as social media usage and applications are increasing. However, the number and variety of social media applications increased proportionately, providing consumers and marketers with an infinite number of possibilities and causing complexity in the selection process. According to the 2018 International Telecommunications Union Report, the use of portable electronic communication devices—such as cell phones, digital music players, and portable Internet access devices—is skyrocketing worldwide, ushering in the social media era. Specifically, the quantity of these devices is increasing, as are the number of people subscribing to the services they provide. For instance, the global number of mobile subscribers increased at a compound annual rate of 24% between 2000 and 2016, reaching 4 billion in December 2017) [1].

One of the marketing methods with the quickest global growth is social media marketing (Berliner, 2016). With remarkable success, marketers are positioning and appealing to consumers through social media marketing. Marketers must make sure that advertising content, consumer profiles, and social media applications align for effective advertising, though, as the number of social media references and applications is growing.

In order to better target consumers during social media marketing initiatives, this study employed factor analysis to divide social media into three primary categories. The study also aims to offer new, useful suggestions for marketing professionals in the area of social media marketing.

2. Aim of the study

This study's primary goal was to employ factor analysis to divide social media into three categories that marketers in Namibia's Khomas Region might utilise to more precisely target customers during social media marketing efforts.

3. Literature Review

According to Kaplan & Haenlein , social media marketing is a subset of mobile marketing [2]. The modern concept of social media likely began in 1994 when Bruce and Susan Abelson established "Open Diary," an early social networking site that united online diary writers into a single community.

Srivastava makes a compelling case by implying that the growth of social media marketing caused mobile phone technology to advance significantly over the previous ten years, moving from phones that could only make calls and send short messages to more complex and sophisticated features like sending emails and making video calls. He summed up by saying that contemporary cell phones have become into essential "social objects" and a ubiquitous tool [3]. While both Kaplan and Haenlein and Srivastava concur that mobile phone technology has evolved, Srivastava summarises by emphasising the tremendous capabilities of mobile phones that emerged as a result of technological advancements. However, the need for increased communication and the creation of new software applications ultimately led to the evolution of social media.

Nowadays, a lot of customers' lives depend heavily on their mobile phones, especially those of young adults and teenagers [4]. Because they always have it with them and check it frequently for updates on major social media apps like Facebook, WhatsApp, Instagram, YouTube, LinkedIn, Pinterest, and Snapchat, to name a few, many people have an addiction to it [4]. Customers now utilise their mobile devices to communicate with friends, family, and the rest of the world through social media, rather than only for personal use. It now serves as a definition of personality, individualism, and prosperity. Marketers may access and serve customers at any time and from any location because to the widespread use of mobile phones [5].

According to Persaud and Azhar , marketers have discovered ways to use mobile phones as marketing channels, even when customers use them to improve their social and private lives. According to Persaud and Azhar, these divergent viewpoints suggest that marketers need to make sure their mobile phone marketing tactics are not invasive. Additionally, this does not prove that consumers desire to see mobile ads on their mobile devices; rather, it indicates that further research is required to close the gap between the requirements of consumers and the objectives of marketers [6].

Customers can now easily and quickly shop across a variety of channels, including physical stores, web-based platforms, and mobile devices, with a significantly higher degree of convenience, flexibility, efficiency, and personalisation thanks to smartphones, which also have the potential to improve marketing value (Persaud and Azhar, 2012). The restricted features of typical mobile phones are voice calls, SMS, cameras, calendars, organisers, alarms, and reminders. Mobile web surfing, online apps, e-mail, instant messaging, photo messaging, video and audio playback, GPS, gaming, a video camera, picture and video editing, voice command, and many other features are among the many services that smartphones provide to their users [4].

Additionally, mobile phone carriers have made it easier for customers to stay online and use popular social networking sites continually by introducing considerably more affordable data packages (Basheer & Ibrahim, 2010). According to Johnson (2013), these offer marketers a huge chance to combine and broaden their mobile and social media marketing strategies.

Since smartphones and tablets are typically not shared with other members of the household, Berman (2016) argues that they have the capacity to send relevant, personalised messages and offers. As a result, marketers can customise messages for each individual customer based on their purchase history, social media usage, demographic information, and usage patterns obtained from the company's customer loyalty program. By incorporating Google filters like contacts, interests, and search queries, personalisation can be further improved. Based on information from the retailer's loyalty program, Nielsen Consumer Panel has created a predictive model that identifies the appropriate promotions for particular customers [7]. In a Nielsen Consumer Panel experiment carried out in the UK in 2015, a sample was divided into two groups: A control group of 10,000 consumers of the same retailer who did not register for the mobile app was compared to 10,000 app users who downloaded their loyalty card information through the app. The test group saw a 13% increase in coupon redemptions and a 37% increase in redemptions for product groupings when compared to the control group. Developing and executing successful mobile marketing campaigns for 433 household-new brands, as well as a 23% rise in redemptions for these products [7]. The creep factor is a significant personalisation trap. This happens when customers believe that marketers are monitoring their online transactions, website visits, and other private activities [8].

		Social presence/ Media richness		
		Low	Medium	High
Self-presentation/ Self-disclosure	High	Blogs	Social networking sites (e.g., Facebook)	Virtual social worlds (e.g., Second Life)
	Low	Collaborative projects (e.g., Wikipedia)	Content communities (e.g., YouTube)	Virtual game worlds (e.g., World of Warcraft)

Table 1: Classification of Social Media by Social Presence/Media Richness and Self-Presentation/Self-Disclosure

Source: [2]

In table 1 above, divide social media into six categories based on self-presentation/self-disclosure and presence/media richness. According to, the primary forms of social media are blogs, social networking sites, virtual social worlds, collaborative projects, content communities, and virtual worlds. There aren't any other classifications of social media in the literature except from the ones mentioned above by, although most authors have chosen to use these as the primary classifications [2].

Over time, social media has changed to give consumers and marketers more options. In order to fill the gap in the literature and enable purpose-driven social media marketing, this study will provide new social media categories for both consumers and marketers.

4. Methodology

4.1 Research Design

The research methodology used in this study was positivist. This study specifically employed a quantitative research methodological approach. The degree of internal consistency between the various measurements was assessed using the Cronbach alpha coefficient, which was used to test the reliability of the scales in the study instrument. A pilot study of the research instrument was conducted on a limited sample in order to further guarantee its dependability. To reach a sample of 230 customers, systematic random sampling was used. Data was gathered via a self-administered questionnaire. Multiple regression analysis was carried out using Structural Equation Modelling (SEM) for both hypothesis testing and research model validation.

4.2 Research Instrument

A standardised questionnaire that participants self-administered served as the study tool. Although they highly recommend the use of questioners in the survey research method, Saunders et al. (2012) clarify that questionnaires are excellent for case study and experiment strategies. A cover letter that assured respondents of their anonymity and gave a brief overview of the researcher, the study, and its goal was sent with the questionnaire.

Every item, with the exception of demographics, was developed using the repatotory grid technique (Malhotra & Birks, 2006) and refined through a pilot study conducted before and after. Formal, casual, and entertainment social media—the last three verified social media categories were subsequently embraced. Additionally, a scale of questions ranging from 5 = Strongly Agree; 4 = Agree; 3 = Neutral; 2 = Disagree and 1 = Strongly Disagreewas used to gauge the respondents' degree of agreement with social media. Most marketing research uses Likert scale questions to measure attitudinal items (Malhotra & Birks, 2006). The factors, scales, and items used are listed in table 2 below.

Section A: Respondents' Demographic data		
Factors / Variables	**Description**	
Gender	Two items: Male, Female	
Age	Three items: 41 years +; 31 – 40 years; Less than 30 years	
SECTION B: FACEBOOK Rating scale: 5 = Strongly Agree; 4 = Agree; 3 = Neutral; 2 = Disagree and 1 = Strongly Disagree		
FACEBOOK	1	I feel that Facebook is a Formal social media platform
	2	I also use Facebook as an informal platform
	3	I find Facebook to be an entertaining application
SECTION C: TWEETER Rating scale: 5 = Strongly Agree; 4 = Agree; 3 = Neutral; 2 = Disagree and 1 = Strongly Disagree		
TWEETER	1	I feel that Tweeter is a Formal social media platform
	2	I also use Tweeter as an informal platform
	3	I find Tweeter to be an entertaining application
SECTION D: INSTAGRAM Rating scale: 5 = Strongly Agree; 4 = Agree; 3 = Neutral; 2 = Disagree and 1 = Strongly Disagree		
INSTAGRAM	1	I feel that Instagram is a Formal social media platform
	2	I also use Instagram as an informal platform
	3	I find Instagram to be an entertaining application

SECTION E: LINKED-IN **Rating scale: 5 = Strongly Agree; 4 = Agree; 3 = Neutral; 2 = Disagree and 1 = Strongly Disagree**		
LINKED-IN	1	I feel that Linked-In is a Formal social media platform
	2	I also use Linked-In as an informal platform
	3	I find Linked-In to be an entertaining application
SECTION F: SNAPCHAT **Rating scale: 5 = Strongly Agree; 4 = Agree; 3 = Neutral; 2 = Disagree and 1 = Strongly Disagree**		
SNAPCHAT	1	I feel that Snapchat is a Formal social media platform
	2	I also use Snapchap as an informal platform
	3	I find Snapchap to be an entertaining application
SECTION G: PINTEREST **Rating scale: 5 = Strongly Agree; 4 = Agree; 3 = Neutral; 2 = Disagree and 1 = Strongly Disagree**		
PINTEREST	1	I feel that Pinterest is a Formal social media platform
	2	I also use Pinterest as an informal platform
	3	I find Pinterest to be an entertaining application
SECTION H: YOU TUBE **Rating scale: 5 = Strongly Agree; 4 = Agree; 3 = Neutral; 2 = Disagree and 1 = Strongly Disagree**		
YOUTUBE	1	I feel that You Tube is a Formal social media platform
	2	I also use You Tube as an informal platform
	3	I find You Tube to be an entertaining application
SECTION I: OTHER **Rating scale: 5 = Strongly Agree; 4 = Agree; 3 = Neutral; 2 = Disagree and 1 = Strongly Disagree**		
OTHER	1	I feel that Other Formal social media platforms are more useful to me
	2	I also use Other social media informal platforms
	3	I find Other to be an entertaining application

Table 2: Measurement of Variables Factors

4.3 Description of demographic data

The sources of participant demographic data are shown in Table 3 below. Table 3 shows the demographic data collected from participants, which included age, gender, and subscription to social networking apps. The number of participants, mean, standard deviation, skewness, and kurtosis were the specific descriptive variables that were discussed.

Respondent's Sex	Respondent's Age		FACEBOOK	TWEETER	INSTAGRAM	WHATSAPP	LINKEDIN	PINTEREST	SNAPCHAT	YOUTUBE	OTHER
Male	<30 years	N	115	115	115	115	115	115	115	115	115
		Mean	1.16	1.81	1.33	1.10	1.87	1.89	1.30	1.54	1.95
		Std. Deviation	.365	.395	.472	.307	.338	.318	.462	.501	.223
		Skewness	1.916	-1.590	.731	2.623	-2.224	-2.477	.862	-.159	-4.081
		Kurtosis	1.699	.539	-1.493	4.965	2.997	4.206	-1.280	-2.010	14.914
	31-40 years	N	5	5	5	5	5	5	5	5	5
		Mean	1.20	1.80	1.60	1.20	1.60	2.00	1.20	1.60	1.80
		Std. Deviation	.447	.447	.548	.447	.548	.000	.447	.548	.447
		Skewness	2.236	-2.236	-.609	2.236	-.609	.	2.236	-.609	-2.236
		Kurtosis	5.000	5.000	-3.333	5.000	-3.333	.	5.000	-3.333	5.000
	>40 years	N	5	5	5	5	5	5	5	5	5
		Mean	1.60	2.00	1.80	1.20	1.60	1.60	1.20	1.20	1.80
		Std. Deviation	.548	.000	.447	.447	.548	.548	.447	.447	.447
		Skewness	-.609	.	-2.236	2.236	-.609	-.609	2.236	2.236	-2.236
		Kurtosis	-3.333	.	5.000	5.000	-3.333	-3.333	5.000	5.000	5.000
	Total	N	125	125	125	125	125	125	125	125	125
		Mean	1.18	1.82	1.36	1.11	1.85	1.88	1.30	1.53	1.94
		Std. Deviation	.382	.389	.482	.317	.360	.326	.458	.501	.246
		Skewness	1.722	-1.651	.590	2.491	-1.962	-2.367	.905	-.114	-3.606
		Kurtosis	.982	.737	-1.678	4.271	1.880	3.662	-1.201	-2.020	11.183
Female	<30 years	N	194	194	194	194	194	194	194	194	194
		Mean	1.18	1.73	1.41	1.12	1.84	1.84	1.21	1.43	1.95
		Std. Deviation	.386	.444	.493	.330	.372	.372	.409	.496	.222
		Skewness	1.675	-1.056	.381	2.304	-1.820	-1.820	1.425	.294	-4.088
		Kurtosis	.815	-.895	-1.875	3.341	1.325	1.325	.031	-1.934	14.865
	31-40 years	N	24	24	24	24	24	24	24	24	24
		Mean	1.08	1.83	1.79	1.08	1.83	1.83	1.58	1.17	2.00
		Std. Deviation	.282	.381	.415	.282	.381	.381	.504	.381	.000
		Skewness	3.220	-1.910	-1.534	3.220	-1.910	-1.910	-.361	1.910	.
		Kurtosis	9.124	1.792	.377	9.124	1.792	1.792	-2.048	1.792	.
	>40 years	N	12	12	12	12	12	12	12	12	12
		Mean	1.33	1.75	2.00	1.25	2.00	1.75	1.33	1.25	2.00
		Std. Deviation	.492	.452	.000	.452	.000	.452	.492	.452	.000
		Skewness	.812	-1.327	.	1.327	.	-1.327	.812	1.327	.
		Kurtosis	-1.650	-.326	.	-.326	.	-.326	-1.650	-.326	.
	Total	N	230	230	230	230	230	230	230	230	230
		Mean	1.18	1.74	1.48	1.13	1.84	1.83	1.26	1.39	1.96
		Std. Deviation	.384	.438	.501	.333	.364	.376	.438	.489	.204
		Skewness	1.692	-1.122	.088	2.268	-1.903	-1.773	1.122	.448	-4.507
		Kurtosis	.871	-.747	-2.010	3.170	1.636	1.153	-.747	-1.815	18.471
Source: Authors (2022)											

Table 3: Case Summary of descriptive of demographics

Source: Authors (2022)

The data evaluated for each of the factors is summarised in table 3 above. For instance, the male age variable had 125 responses with ages ranging from less than 30, 31–40, and beyond 40. The largest percentage of participants, 115 (N), were under 30 years old, and the means for males ranged from 1.10 for WhatsApp to 1.95 for other social media. For the majority of people under 30, the Skewness and Kurtosis levels range. 2.623 for WhatsApp, 14.914 for Other Social Media, -731 for Twitter, and -1.280 for Snapchat.

For the male majority age group under 30, negative skewness values for five social media platforms are predominant. Social media skew that is negative (scores that cluster to the right at the low values). (Page 80, Tabachnick & Fidell, 2007). For the male majority age group under 30, positive kurtosis values for six social media applications are prevalent, suggesting that the distribution of social media is rather peaked (clustered in the centre), with long, thin tails. A distribution that is generally flat (too many examples in the extremes) is indicated by kurtosis values less than 0 (Tabachnick & Fidell 2007, p. 80).

Age varied for females Of the 230 respondents, 194 (N) were under 30 years old, with averages for females ranging from 1.12 for WhatsApp to 1.95 for other social media. The respondents' ages ranged from <30 years to 31-40 years to >40 years. For the predominant age group under 30, the Skewness and Kurtosis levels range. 2.304 for WhatsApp, 14.865 for Other Social Media, and -4.088 and -.895 for Twitter, respectively.

For the female majority age group, negative skewness values for five social media platforms are prevalent. Scores clustered to the right at the low values imply negative social media skew. (Page 80, Tabachnick & Fidell, 2007). For the female majority age group under 30, positive kurtosis values for six social media applications are prevalent, suggesting that the distribution of social media is rather peaked (clustered in the centre), with long, thin tails. A distribution that is generally flat (too many examples in the extremes) is indicated by kurtosis values less than 0 (Tabachnick & Fidell 2007, p. 80). Skewness won't "make a substantive difference in the analysis" with samples that are sufficiently large (Tabachnick & Fidell 2007, p. 80). Kurtosis may cause the variation to be underestimated, however a high sample size (200+ instances; see Tabachnick & Fidell 2007, p. 80) also lowers this risk. Since the sample size in this instance is 355, neither the skewness nor the kurtosis values will have an impact.

4.4 Factor analysis

Factor analysis is a three-step process. Step 1 involves determining whether the data is appropriate for the factor. Examination The sample size (more than 150) and the degree of correlation between the variables (or items) are the two primary factors to take into account when evaluating whether a given data set is appropriate for factor analysis (Tabachnick and Fidell, 2007).

Step 2: Extraction of factors The process of factor extraction is figuring out how few factors can best capture the relationships between the variables in the collection. Finding (extracting) the number of underlying elements or dimensions can be done in a number of ways. primary components, primary factors, picture factoring, maximum probability factoring, alpha factoring, unweighted least squares, and generalised least squares are a few of the most often used extraction methods (Tabachnick and Fidell, 2007).

Step 3: Interpretation and rotation of factors: The next stage is to attempt to understand the components when their number has been established. The components are "rotated" to aid in this process. This exposes the loading pattern in an easier-to-understand way without altering the underlying solution. Rotation can be approached in two ways, leading to either oblique (correlated) or orthogonal (uncorrelated) factor solutions. Fidell and Tabachnick (2007).

The associations between various social media factors were investigated using exploratory factor analysis. Furthermore, the research model was validated and Standardised Regression Weights and Standardised Estimate Regression Weights were established using confirmatory factor analysis.

Factors	Item	Mean	Std	Skew	Kurt	Communalities	Loadings	Eigenvalue	% of variance	KMO
INFORMAL SOCIAL MEDIA	FACEBOOK	1.18	0.38	1.69	0.85	0.13	0.34	1.21	15.07	
	TWEETER	1.77	0.42	-1.28	-0.37	0.16	0.32			
	INSTAGRAM	1.44	0.50	0.26	-1.94	0.48	0.68			
FORMAL SOCIAL MEDIA	WHATSAPP	1.12	0.33	2.32	3.39	0.06		1.62	17.69	
	LINKEDIN	1.85	0.36	-1.91	1.64	0.59	0.73			
	PINTEREST	1.85	0.36	-1.94	1.75	0.21	0.44			
ENTERTAINMENT SOCIAL MEDIA	SNAPCHAT	1.27	0.45	1.03	-0.93	0.09	0.30	3.33	14.17	model explains 46.92% of variation
	YOUTUBE	1.44	0.50	0.24	1.94	0.42	0.64			
Total									46.93	

Table 4: EFA -CFA Analysis and Descriptive for new Social Media Factors

Using SPSS version 25, the eight social media posts were put via Principal Axis Factoring (PAF). The data's suitability for factor analysis was assessed before performing (PAF). The data was shown to be normal by the skewness and kurtosis. Upon examining the correlation matrix, several coefficients with values of.3 and higher were found. The appropriateness of the correlation was supported by the Kaiser-Meyer-Olkin and Bartlett's test for sample adequacy value, which was.62, above the suggested value of.6 (Kaiser, 1974). The selected variables were sufficiently correlated for a factor analysis, as indicated by the significant results of the KMO and Bartlett's test for sample adequacy and the communalities for each variable (all above 0.300 and the majority above 0.600). Three components with eigenvalues greater than one were identified by Principal Axis Factoring, and they explained 15.07%, 17.69%, and 14.17% of the variance, respectively.

5. Findings

Despite not being included in the study's hypothesis, social media applications were determined to be highly important and linked with other items in the data set by the EFA, CFA, and structural equation modelling that were performed on all questionnaire questions. All social media elements were thus included in the SEM regression analysis, and the tables below show how they affected other mobile marketing adoption items in the model fit. Below is an illustration and discussion of the regression weights and Standardised Estimate Regression Weights table.

			Estimate	S.E.	C.R.	P
Informal_SM1	<---	Formal_SM2	0.428	0.145	2.947	0.003
Entern_SM	<---	Formal_SM2	0.239	0.117	2.041	0.041
SOCIALMEDIA3	<---	Informal_SM1	1			
SOCIALMEDIA2	<---	Informal_SM1	0.754	0.175	4.322	***
SOCIALMEDIA1	<---	Informal_SM1	0.535	0.135	3.959	***
SOCIALMEDIA4	<---	Informal_SM1	0.25	0.097	2.577	0.01
SOCIALMEDIA9	<---	Informal_SM1	0.116	0.062	1.855	0.064
SOCIALMEDIA5	<---	Formal_SM2	1			
SOCIALMEDIA6	<---	Formal_SM2	0.504	0.156	3.232	0.001
SOCIALMEDIA8	<---	Entern_SM	1			
SOCIALMEDIA7	<---	Entern_SM	0.45	0.384	1.171	0.242

Table 5: Social media Standardized Regression Weights

Source: Field Survey (2017)

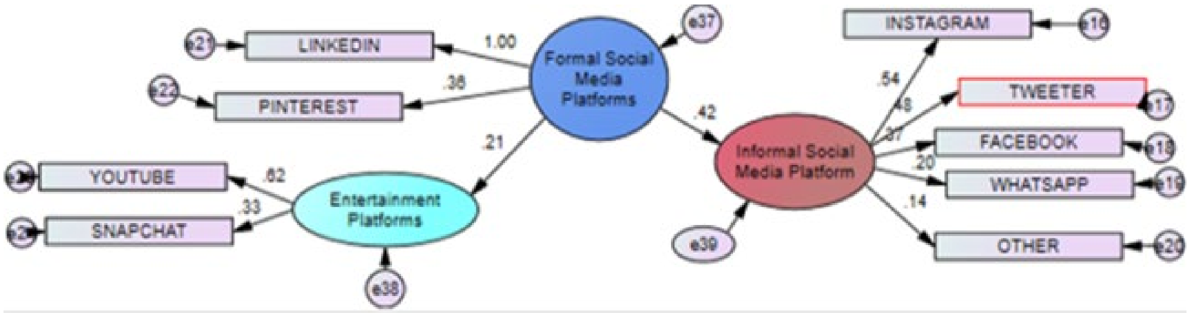
With the exception of social media 7 and 9, Table 5 shows that all crucial ratios are over the 1.96 threshold for directed path relations, with the exception of the two p-values for social media 7 and 9. Social media elements and new components (formal, informal, and entertainment social media) showed a significant directional route with high correlations, according to AMOS.

			Estimate
Informal_SM1	<--	Formal_SM2	0.491
Entern_SM	<--	Formal_SM2	0.232
SOCIALMEDIA3	<--	Informal_SM1	0.538
SOCIALMEDIA2	<--	Informal_SM1	0.478
SOCIALMEDIA1	<--	Informal_SM1	0.374
SOCIALMEDIA4	<--	Informal_SM1	0.204
SOCIALMEDIA9	<--	Informal_SM1	0.141
SOCIALMEDIA5	<--	Formal_SM2	0.846
SOCIALMEDIA6	<--	Formal_SM2	0.429
SOCIALMEDIA8	<--	Entern_SM	0.634
SOCIALMEDIA7	<--	Entern_SM	0.319

Table 6: Social Media Standardized Estimate Regression Weights

Source: Field Survey (2017)

The contribution of social media factors to the new components (formal, informal, and entertainment social media) is shown in Table 6 of the Standardised Regression Weights.Significant elements' contributions range from 20% on social media 4 to 63% on social media 8.



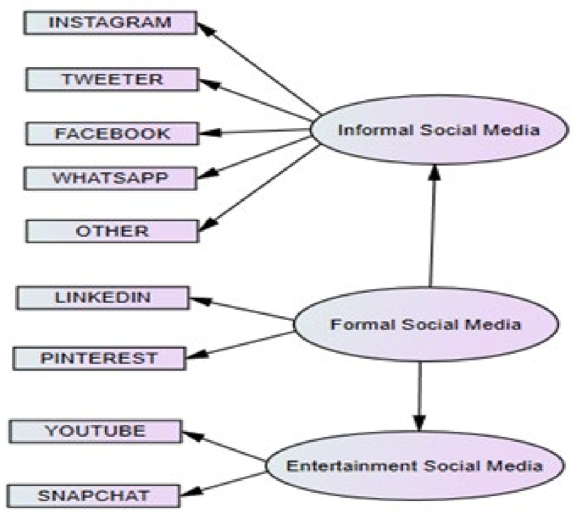
Measure	Estimate	Threshold	Interpretation
CMIN	971.148	--	--
DF	454	--	--
CMIN/DF	2.139	Between 1 and 3	Excellent
CFI	0.767	>0.95	Need More DF
SRMR	0.078	<0.08	Excellent
RMSEA	0.057	<0.06	Excellent
PClose	0.013	>0.05	Acceptable

Source: Field Survey (2017)

Chi-square's sensitivity to sample size makes it difficult to infer a reliable sense of model fit from its value. Thus, in addition to the Goodness-of-Fit Index (GFI), Comparative Fit Index (CFI), Standardised Root Mean Squared Residual (SRMR), and Root Mean Square Error of Approximation (RMSEA), other model fit indices must also be assessed. A strong overall degree of fit is indicated by a Goodness of Fit Index (GFI) of better than 0.9; values below 0.90 essentially suggest that the model may be improved. Additionally, a value of 0.90 or higher is deemed acceptable by the Comparative Fit Index (CFI) for a well-fitting model. An acceptable RMSEA (Root Mean Square Error of Approximation) is less than.08. A well-fitting model is indicated by a PClose or P-value more than 0.05 and a standardised summary of the average covariance residuals (SRMR, Standardised Root Mean Squared Residual) less than.10 (Kline, 2005; Hatcher, 2005; Hu & Bentler, 2012). The results showed a good fit for the structural model, which was followed by measurement models, according to the specified threshold values for the test statistics. The results of Model 1 demonstrate excellent fit based on the Chi-square (CMIN/DF = 2.139), comparative fit index (CFI =.77), root mean square error of approximation (RMSEA =.057), Standardised Root Mean Squared Residual (SMSR = 0.078), and P Value (Close = 0.013).

5.2 Final proposed framework: Social media types

The model was created to conceptualise social media kinds and explain the relationships between variables. In order to validate the final proposed framework, the framework was developed after standardised total effects weights, unstandardised regression weights, and the study measurement framework were examined. The last result of the suggested framework is Model 2, which will be covered in this section.



Model 2: Final proposed framework

Source: Field Survey (2018)
YouTube, Pinterest, and LinkedIn are examples of formal social media. Finally, WhatsApp has an impact on informal social media. Instagram, Twitter, and Facebook

6. Discussion of findings

The results showed that there are three different kinds of social media: formal, casual, and entertaining. Both informal and entertainment social media have an impact on formal social media, which is the primary social media platform. Other unofficial social media sites include Facebook, Instagram, Twitter, WhatsApp, and more. Snapchat and YouTube are social media sites for entertainment.

Nowadays, a lot of customers' lives depend heavily on their mobile phones, especially those of young adults and teenagers (Roach 2009, p. 149). Because they always have it with them and check it frequently for updates on popular social media apps like Facebook, WhatsApp, Instagram, YouTube, LinkedIn, Pinterest, and Snapchat, to name a few, it is an addiction for many people (Johnson, 2013). Customers now utilise their mobile devices to communicate with friends, family, and the rest of the world through social media, rather than only for personal use (Johnson, 2013). It now serves as a definition of personality, individualism, and prosperity. Marketers may access and serve customers at any time and from any location because to the widespread use of mobile phones (Roach 2009, p. 149). The results of this study further categorise social media into three primary groups, expanding on the discussion by Johnson (2013) and Roach (2009), p. 149.

Customers can now easily and quickly shop across a variety of channels, including physical stores, web-based platforms, and mobile devices, with a significantly higher degree of convenience, flexibility, efficiency, and personalisation thanks to social media applications. Smartphones can also change consumers' shopping experiences and add marketing value (Persaud and Azhar, 2012). By focussing on online buyers according to the social media platform they use most frequently, the study's findings can further improve these buying experiences.

Mobile web surfing, online apps, e-mail, instant messaging, photo messaging, video and audio playback, GPS, gaming, a video camera, picture and video editing, voice command, and many other functions are among the many services that users may enjoy with smartphones (Johnson, 2013). Additionally, mobile phone carriers have made it easier for customers to stay online and use popular social networking sites continually by introducing considerably more affordable data packages (Basheer & Ibrahim, 2010). According to Johnson (2013), these offer marketers a huge chance to combine and broaden their mobile and social media marketing strategies. Because marketers can leverage the primary social media platforms identified in this study to create consumer-specific tactics, the study's findings will help them create more successful plans.
Lastly, the three social media platforms identified by this study can help marketers create marketing plans tailored to particular products. Products can be categorised according to the primary social media platforms and promoted on the appropriate social media platform. Marketing plans for different customer age groups can also be developed via social media platforms.

7. Conclusion and future research avenues

In order to better target customers during social media marketing initiatives, the study's goal was to use factor analysis to divide social media into three major categories. Furthermore, the goal of the study was to offer new, useful suggestions for social media marketing practitioners. The results showed that there are three different kinds of social media: formal, casual, and entertaining. The primary social media platform is formal, which is impacted by informal and entertainment social media. Other unofficial social media sites include Facebook, Instagram, Twitter, WhatsApp, and more. Snapchat and YouTube are social media sites for entertainment.

By focussing on online buyers according to the social media platform they use most frequently, the study's findings can further improve these buying experiences. Because marketers can leverage the primary social media platforms identified in this study to create consumer-specific tactics, the study's findings will help them create more successful plans. Lastly, based on social media type classifications, the three social media types identified by this study can help marketers create product-specific marketing strategies that can help with the effective marketing of products. Both product and age-related social media marketing may be the subject of future studies. Future research can ascertain the links between product and social media type as well as the associations between age and social media type usage [10-13].

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References

1. Al-alak, B. A., & Alnawas, I. A. (2011). Measuring the acceptance and adoption of e-learning by academic staff. *Knowledge management & E-learning, 3*(2), 201.
2. Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business horizons, 53*(1), 59-68.
3. Srivastava, L. (2005). Mobile phones and the evolution of social behaviour. *Behaviour & information technology, 24*(2), 111-129.
4. Johnson, P., & Clark, M. eds. (2013). Business & management research methodologies. New Delhi. Sage.
5. Roach, G. (2009). Consumer perceptions of mobile phone marketing: a direct marketing innovation. *Direct marketing: an international journal, 3*(2), 124-138.
6. Persaud, A., & Azhar, I. (2012). Innovative mobile marketing via smartphones: Are consumers ready?. *Marketing intelligence & planning, 30*(4), 418-443.
7. Cameron, D., Gregory, C., & Battaglia, D. (2012). Nielsen personalizes the mobile shopping app: if you build the technology, they will come. *Journal of Advertising Research, 52*(3), 333-338.
8. Berman, S. J. (2012). Digital transformation: opportunities to create new businessss models. *Strategy & leadership, 40*(2), 16-24.
9. Tabachnick, B. G., Fidell, L. S., & Ullman, J. B. (2007). Using multivariate statistics (Vol. 5): pearson Boston.
10. Haghirian, P., & Dickinger, A. (2005). Identifying success factors of mobile marketing. ACR Asia-Pacific Advances.
11. International Telecommunications Union, 2008. Worldwide mobile cellular subscribers to reach 4 billion-mark late 2018.
12. Berliner, T. (2016). Mobile marketing: a scoping study of the literature and issues for future research. Information Development, 32(3), 527-553.
13. Saunders, M. (2014). Research Methods for Business Students (6th edn.

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