Annals of "Dunarea de Jos" University of Galati
Fascicle I. Economics and Applied Informatics
Years XXX – nº2/2024
ISSN-L 1584-0409 ISSN-Online 2344-441X
www.eia.feaa.ugal.ro

DOI https://doi.org/10.35219/eai15840409418

The Impact of Mobile Marketing Campaigns on Consumers

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A R T I C L E I N F O

Article history:
Accepted August 2024
Available online August 2024

JEL Classification
M31, O33, M21

Keywords:
mobile marketing, consumer behavior, SEM-PLS, Technological Change

A B S T R A C T

Understanding how the different components of mobile marketing influence consumer decisions can guide companies in developing more effective marketing strategies that lead to improved business outcomes. The complexity of consumer behavior and mobile marketing requires a rigorous and creative approach that combines theory with practice, analysis with synthesis, and data with interpretation. By gaining a deeper understanding of consumer behavior and the impact of mobile marketing, we can help shape a future in which technology and marketing are used in ways that benefit all stakeholders. We live in a technology-dominated era where mobile devices have become part of our everyday lives. In this digital cumulus, consumer behavior has undergone radical transformations, and understanding these changes is essential for any company that wants to remain competitive. Mobile marketing, in particular, has become an indispensable communication channel capable of reaching consumers in various, personalized and direct ways. Therefore, the study of the impact of these strategies on consumer behavior is not only relevant, but also necessary to successfully delve into the different situations and factors of the contemporary market. This research aims to develop and contribute to existing insights in the field by applying advanced analytical methods, such as SEM-PLS, to model and understand the complex relationships between mobile marketing and consumer behavior.

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1. Introduction

Mobile marketing has become an essential component in modern marketing strategies, having a significant impact on consumer behavior. Mobile marketing allows brands to interact directly with consumers through their personal devices. Mobile marketing campaigns such as push notifications, SMS messages and social media campaigns can generate a high level of engagement due to accessibility and customization (Xie W., 2024).

Mobile devices offer excellent opportunities for personalizing marketing messages. Demographic data, purchase history and browsing behavior allow the creation of highly relevant messages for consumers, which increases the likelihood that they will respond positively to marketing campaigns.

Mobile marketing directly influences consumer buying behavior. Quick access to product information, special offers and reviews contribute to more informed and faster purchase decisions (Kumar S., 2024). Also, promotions and discounts sent through mobile apps can encourage impulse purchases.

An essential aspect of mobile marketing is the user experience. Mobile apps and mobile-optimized websites offer a simplified and intuitive browsing experience. A positive experience can improve consumers' perception of the brand and lead to increased loyalty (Tong S. et al., 2020).

Mobile marketing gives consumers access to information and offers anywhere, anytime, thereby increasing accessibility and convenience. This contributes to overall consumer satisfaction and can positively influence the purchase decision. Another major advantage of mobile marketing is the ability to monitor and measure the effectiveness of campaigns in real time. This allows marketers to quickly adjust strategies and optimize campaigns to achieve better results. Despite the mentioned advantages, there are also concerns about data privacy and security. Consumers are increasingly aware of how their data is collected and used, and improper data management can lead to loss of trust and negative reactions from consumers (Kurtz OT et al., 2021).

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Mobile marketing campaigns have a profound impact on consumers by increasing engagement, personalization, influencing purchasing behavior and improving user experience. However, the success of these campaigns depends on how brands manage data privacy and security, as well as their ability to deliver real value to consumers.

2. Literature review

The advent of the Internet and communication technologies (ICT) has transformed direct marketing into what is known today as online marketing, which uses the Internet to communicate with potential customers (Hair, JF et al, 2017). Using the Internet as a marketing channel connects potential customers with sellers electronically. Direct marketing could be defined as any activity that creates and exploits a direct relationship between sellers and buyers on an individual level. To be successful in direct marketing you need to know how to direct the target audience to the proposed activity, although this can also be a weakness (Aaker DA, Moorman C., 2017). The ability of direct marketers to find the right audience for their product at the right time is crucial to business success (Cristache, N. et al, 2022). Direct marketing uses various types of channels to reach target customers. Some of these channels include direct selling, direct mail, telemarketing, telemedia, TV marketing, email marketing, social media marketing, and mobile marketing (Tiago MTPMB, Veríssimo JMC, 2014).

Mobile marketing emerged in the late 1990s with the sending of simple messages via Short Message Service (SMS). Strategies changed after the introduction of better technologies and the proliferation of smartphones, tablets and PCs where many other new mobile communication tools emerged (Chaffey, D. et al, 2016). Using various mobile operating systems such as Apple iOS, Google Android and others, many mobile network operators now offer a wide range of mobile applications and transaction/payment services in addition to information and entertainment services to their subscribers. Therefore, mobile marketing serves through phones as a useful technology in everyday life that can be used by both marketers and consumers (Xie W., et al, 2024).

Mobile marketing is defined as a set of practices that enable organizations to communicate and engage with their target audience in an interactive and engaging manner through any mobile device or network (Ryan D., Jones C., 2016). Mobile marketing connects businesses and each of their customers via mobile devices at the right time and place with the right message and requires the customer's explicit permission and/or active interaction. In addition, the emergence of mobile devices as a promotion channel has allowed marketers to improve the level of permission-based marketing (Strauss J., Frost R., 2016). The mobile channel is the best medium for permission-based marketing because it allows businesses to deal with each target customer as an individual. As a result, the concept of "value exchange" becomes the focal point of effective and successful permission-based mobile marketing, as consumers exchange their consent and sometimes personal demographic information and preferences in advance for a product, service or offer that they value. interest, relevant or valuable to them (Wang CL, 2023) (Gabor, M. R et al, 2020).

The popularity of mobile marketing has grown steadily in recent years among both businesses and consumers (Solomon, Michael R, 2019). The more consumers use smartphones and tablets to search for and purchase goods and services online, the more likely business owners are to find their niche, so they must constantly adapt and satisfy this increasing need for convenience for consumers (Hollensen S., 2020).

Mobile marketing allows relevant information to be delivered personalized and interactively to online customers (Alhidayatullah A., 2024). Mobile devices such as smartphones and tablets are widely used for web browsing, social networking, photo/video sharing, and online shopping, and in mobile marketing for making phone calls or sending text messages (Roy SK, 2023). Impact of SMS advertising on purchase intention for young consumers (Pricopoaia, O. et al, 2024). *International Journal of Financial, Accounting, and Management* , *4* (4), 427-447.. Nowadays, mobile marketing relies most, for the delivery of promotional information, on the phone messaging channel, on phone calls but also on the messaging of different social media channels such as WhatsApp, Viber, Signal or Telegram (Tarnanidis T., 2024).

3. Analysis and impact of mobile marketing components on consumers using SEM-PLS structural equation modeling

In the ever-expanding digital age, mobile marketing campaigns have become a fundamental element of organizations' strategies to reach and engage their target audiences. However, with such a dynamic and ever-changing environment, properly assessing the impact of these campaigns becomes critical to their effectiveness. In this context, the use of structural equations with the method of partial least squares (SEM-PLS) is used as a broad and flexible analytical tool, providing a comprehensive approach to modeling outcomes (Ringle, CM et al, 2015).

This research examines how SEM-PLS can be applied to analyze and evaluate the impact of mobile marketing campaigns. SEM-PLS is a structural modeling technique, it allows to analyze the complex relationships between the variables involved in the model and to estimate the direct and indirect effects, thus providing a comprehensive perspective on the interactions within the mobile marketing campaigns. We used this method because for each previously mentioned variable, with the role of predictor of the influence on the reputation of the brand, we identified specific indicators that form, respectively reflect, it.

Variables such as brand awareness and preferences, conversion and purchase rates, segmentation and variability in responses, brand retention and loyalty, impact on sales, interaction and engagement will be analyzed, with special attention given to the central core - influence on brand reputation.

Through this approach, we aim to highlight the significant benefits of SEM-PLS in unraveling the complexity of the impact of mobile marketing campaigns, thereby providing marketers with an analytical framework for understanding and improving their strategies.

The elaborated structural model is highlighted in figure no.1, highlighting the relationships between variables by means of six hypotheses.

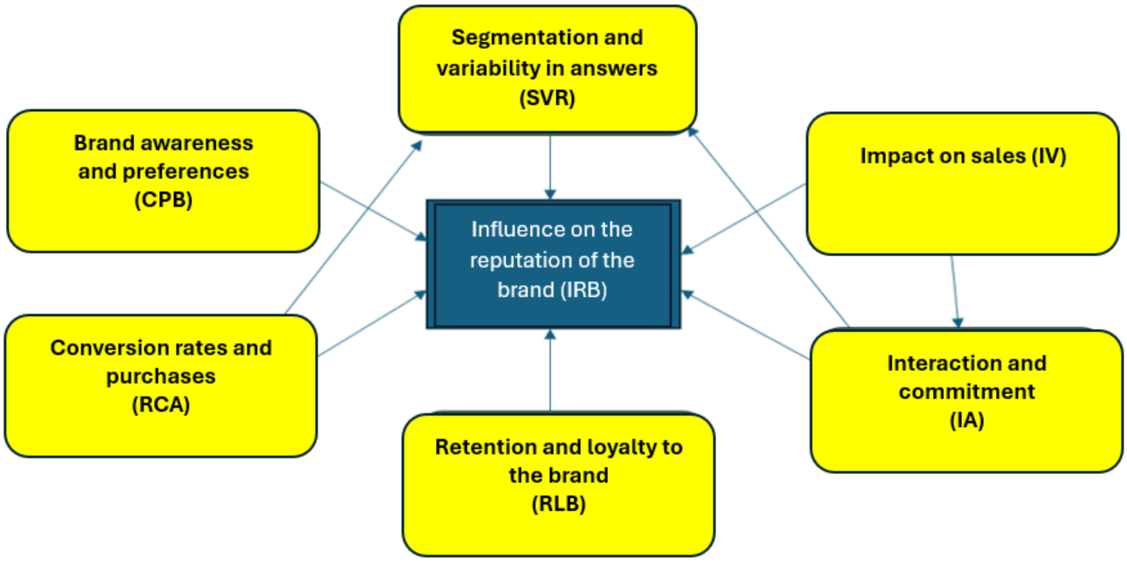

Figure 1. Conceptual model of research based on structural equation modeling

Source: processing authors

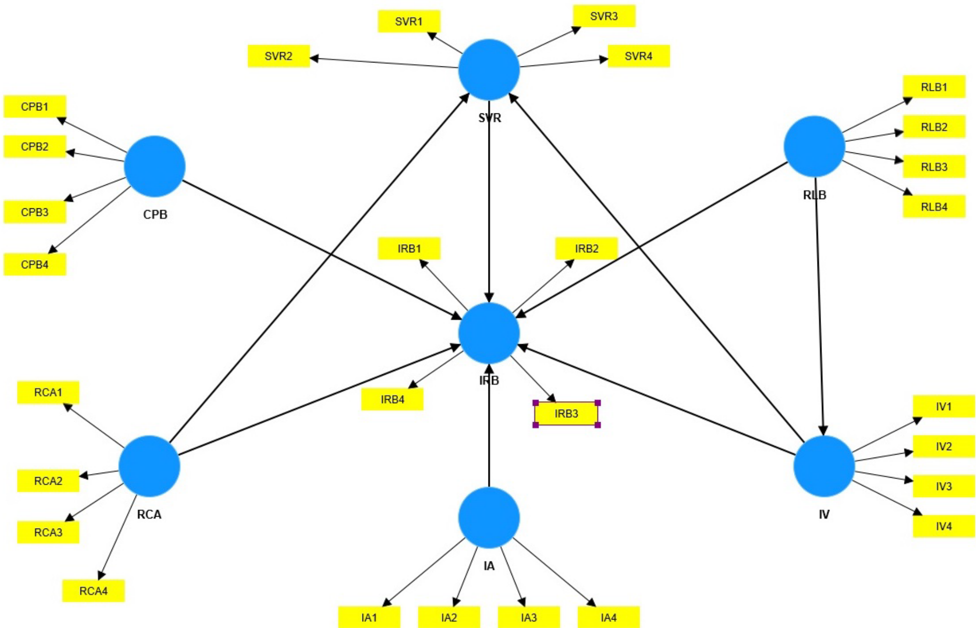

Figure 2. Conceptual research model and hypotheses

Source: processing authors

Hypothesis 1: Increased brand awareness and preference (CPB) is positively associated with higher conversion and acquisition rate (RCA), highlighting the direct influence of awareness on business performance.

Hypothesis 2: Effective segmentation and increased response variability (SVR) significantly contribute to increased brand awareness and preference (CPB), underscoring the importance of a diverse and segmented approach in marketing strategies.

Hypothesis 3: Greater interaction and engagement (IA) with mobile campaigns is associated with greater retention and brand loyalty (RLB), showing that ongoing engagement contributes to long-term loyalty.

Hypothesis 4: Increased engagement (IA) leads to increased brand awareness and preference (CPB), highlighting the crucial role of constant interaction in building the consumer's relationship with the brand.

Hypothesis 5: Greater brand awareness and preference (CPB) leads to increased sales impact (IV) with higher conversion and acquisition rate (RCA), underscoring the direct link between brand appeal and business performance.

Hypothesis 6: All variables - CPB, RCA, SVR, RLB, IA, IV - contribute positively to building and maintaining solid brand reputation (IRB), highlighting the complexity of interactions between different aspects of a mobile marketing campaign.

3.1 Analysis of research results based on structural equation modeling

Table no. 1 reflects the distribution of the indicators reflected by the items included in the questionnaire. The item with the highest mean is SVR3 (4,350) and the item with the lowest mean is IA2 (3,797). The standard deviations do not reveal very large differences between the indicators. The skewness index assesses the extent to which the distribution of a variable is symmetric. If the distribution of responses for a variable extends to the right or left extremes of the distribution, then the distribution is said to be skewed. The flattening index or the curvature coefficient (Kurtosis) is part of the indices for assessing the shape of a distribution. A high flattening index shows a distribution with the distribution of variables far from the mean. A general guideline for Skewness is that if the number is greater than +1 or less than –1, this is an indication of a substantially skewed distribution. For Kurtosis, the general indication is that if the value is greater than +1, the distribution is too skewed. Also, Kurtosis value less than –1 indicates too flat a distribution. In the case of the data collected in this research, we note normal data distributions on all the indicators associated with the latent variables in the conceptual model.

Table 1. Descriptive statistical indicators associated with the conceptual model

28 Indicators with 123 cases and 0 missing values Zoom (82%) Copy to Excel

Name	No.	Type	Missings	Mean	Median	Scale min	Scale max	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness
CPB1	1	MET	0	4.203	4.000	1.000	5.000	1.000	5.000	0.928	1.596	-1.222
CPB2	2	MET	0	4.008	4.000	1.000	5.000	1.000	5.000	0.992	0.112	-0.826
CPB3	3	MET	0	4.073	4.000	1.000	5.000	1.000	5.000	0.997	0.285	-0.945
CPB4	4	MET	0	3.911	4.000	1.000	5.000	1.000	5.000	1.119	-0.499	-0.703
RCA1	5	MET	0	3.967	4.000	1.000	5.000	1.000	5.000	1.051	0.329	-0.913
RCA2	6	MET	0	3.878	4.000	1.000	5.000	1.000	5.000	1.123	-0.069	-0.837
RCA3	7	MET	0	4.114	4.000	1.000	5.000	1.000	5.000	0.981	0.641	-1.068
RCA4	8	MET	0	3.984	4.000	1.000	5.000	1.000	5.000	1.044	0.557	-1.010
SVR1	9	MET	0	4.211	4.000	1.000	5.000	1.000	5.000	0.867	1.466	-1.108
SVR2	10	MET	0	4.041	4.000	1.000	5.000	1.000	5.000	1.023	0.586	-1.050
SVR3	11	MET	0	4.350	4.000	3.000	5.000	3.000	5.000	0.710	-0.812	-0.627
SVR4	12	MET	0	3.894	4.000	1.000	5.000	1.000	5.000	1.153	0.176	-0.949
RLB1	13	MET	0	3.854	4.000	1.000	5.000	1.000	5.000	1.208	-0.081	-0.920
RLB2	14	MET	0	3.984	4.000	1.000	5.000	1.000	5.000	1.051	0.218	-0.944
RLB3	15	MET	0	3.951	4.000	1.000	5.000	1.000	5.000	1.182	-0.002	-0.982
RLB4	16	MET	0	4.000	4.000	1.000	5.000	1.000	5.000	1.044	0.622	-1.042
IV1	17	MET	0	4.179	4.000	1.000	5.000	1.000	5.000	0.946	1.539	-1.242
IV2	18	MET	0	4.268	4.000	1.000	5.000	1.000	5.000	0.807	1.776	-1.187
IV3	19	MET	0	4.187	4.000	1.000	5.000	1.000	5.000	0.923	1.134	-1.138
IV4	20	MET	0	4.252	4.000	1.000	5.000	1.000	5.000	0.889	1.793	-1.294
IA1	21	MET	0	4.154	4.000	1.000	5.000	1.000	5.000	0.963	0.918	-1.146
IA2	22	MET	0	3.797	4.000	1.000	5.000	1.000	5.000	1.275	-0.465	-0.826
IA3	23	MET	0	4.041	4.000	1.000	5.000	1.000	5.000	0.958	0.510	-0.926
IA4	24	MET	0	3.935	4.000	1.000	5.000	1.000	5.000	1.117	0.316	-0.969
IRB1	25	MET	0	4.057	4.000	1.000	5.000	1.000	5.000	0.982	0.401	-0.950
IRB2	26	MET	0	4.236	4.000	1.000	5.000	1.000	5.000	0.807	1.614	-1.116
IRB3	27	MET	0	4.033	4.000	1.000	5.000	1.000	5.000	0.971	-0.151	-0.768
IRB4	28	MET	0	4.179	4.000	1.000	5.000	1.000	5.000	0.963	1.749	-1.363

Source: report generated by Smart PLS 3 software

Table 2. Correlations between variables

Correlations

	CPB1	CPB2	CPB3	CPB4	RCA1	RCA2	RCA3	RCA4	SVR1	SVR2	SVR3	SVR4	RLB1	RLB2	RLB3	RLB4	IV1	IV2	IV3	IV4	IA1	IA2	IA3	IA4	IRB1	IRB2	IRB3	IRB4
CPB1	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
CPB2	0.572	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
CPB3	0.502	0.493	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
CPB4	0.714	0.631	0.538	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
RCA1	0.565	0.585	0.623	0.675	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
RCA2	0.609	0.592	0.502	0.677	0.616	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
RCA3	0.448	0.567	0.689	0.520	0.682	0.581	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
RCA4	0.566	0.660	0.509	0.556	0.563	0.623	0.589	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SVR1	0.442	0.376	0.584	0.472	0.489	0.444	0.421	0.444	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SVR2	0.454	0.504	0.626	0.401	0.462	0.507	0.554	0.511	0.558	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SVR3	0.386	0.342	0.274	0.326	0.418	0.339	0.386	0.326	0.421	0.406	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SVR4	0.575	0.640	0.664	0.522	0.527	0.555	0.514	0.586	0.534	0.713	0.264	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
RLB1	0.636	0.598	0.535	0.604	0.579	0.700	0.556	0.566	0.488	0.577	0.363	0.625	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
RLB2	0.520	0.585	0.676	0.538	0.610	0.494	0.680	0.585	0.548	0.590	0.356	0.575	0.658	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
RLB3	0.491	0.562	0.589	0.569	0.647	0.633	0.559	0.533	0.391	0.593	0.272	0.670	0.662	0.641	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
RLB4	0.462	0.668	0.523	0.592	0.600	0.548	0.556	0.575	0.377	0.457	0.351	0.621	0.671	0.711	0.653	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
IV1	0.375	0.414	0.477	0.353	0.423	0.288	0.372	0.225	0.549	0.446	0.428	0.412	0.436	0.461	0.335	0.371	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
IV2	0.372	0.414	0.339	0.288	0.288	0.305	0.239	0.275	0.395	0.371	0.489	0.336	0.349	0.388	0.210	0.318	0.608	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
IV3	0.364	0.416	0.506	0.347	0.434	0.422	0.363	0.383	0.479	0.621	0.397	0.607	0.557	0.456	0.590	0.439	0.474	0.489	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
IV4	0.381	0.394	0.410	0.382	0.453	0.430	0.312	0.364	0.564	0.498	0.505	0.549	0.459	0.265	0.515	0.342	0.420	0.416	0.636	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
IA1	0.720	0.595	0.454	0.624	0.583	0.589	0.523	0.585	0.428	0.447	0.528	0.564	0.684	0.549	0.528	0.550	0.416	0.396	0.462	0.553	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
IA2	0.488	0.541	0.574	0.472	0.693	0.516	0.629	0.602	0.407	0.480	0.303	0.555	0.540	0.659	0.582	0.477	0.374	0.345	0.433	0.325	0.562	1.000	0.000	0.000	0.000	0.000	0.000	0.000
IA3	0.512	0.573	0.652	0.512	0.623	0.579	0.583	0.562	0.460	0.645	0.434	0.652	0.504	0.566	0.620	0.447	0.468	0.375	0.617	0.494	0.593	0.719	1.000	0.000	0.000	0.000	0.000	0.000
IA4	0.444	0.720	0.530	0.548	0.573	0.583	0.593	0.592	0.493	0.500	0.347	0.632	0.632	0.615	0.657	0.635	0.450	0.380	0.525	0.541	0.644	0.619	0.626	1.000	0.000	0.000	0.000	0.000
IRB1	0.505	0.417	0.494	0.545	0.514	0.463	0.576	0.358	0.396	0.427	0.473	0.357	0.508	0.497	0.367	0.389	0.453	0.288	0.329	0.365	0.558	0.425	0.499	0.441	1.000	0.000	0.000	0.000
IRB2	0.479	0.526	0.564	0.518	0.632	0.489	0.572	0.497	0.451	0.530	0.410	0.472	0.452	0.560	0.532	0.502	0.466	0.402	0.388	0.450	0.518	0.497	0.619	0.522	0.639	1.000	0.000	0.000
IRB3	0.489	0.557	0.501	0.572	0.655	0.548	0.483	0.522	0.465	0.482	0.361	0.562	0.538	0.502	0.625	0.538	0.445	0.269	0.529	0.528	0.534	0.538	0.655	0.632	0.518	0.654	1.000	0.000
IRB4	0.478	0.450	0.579	0.498	0.560	0.479	0.469	0.440	0.539	0.496	0.408	0.537	0.512	0.380	0.572	0.348	0.483	0.294	0.621	0.631	0.584	0.493	0.680	0.547	0.522	0.563	0.690	1.000

Source: report generated by Smart PLS 3 software

The Structural Equation Modeling partial least squares (SEM-PLS) correlation table provides a visual representation of the degree of association between the variables included in the model. This analysis allows observing the direction and intensity of relationships between key variables, providing insights into the complexity of the model's structure.

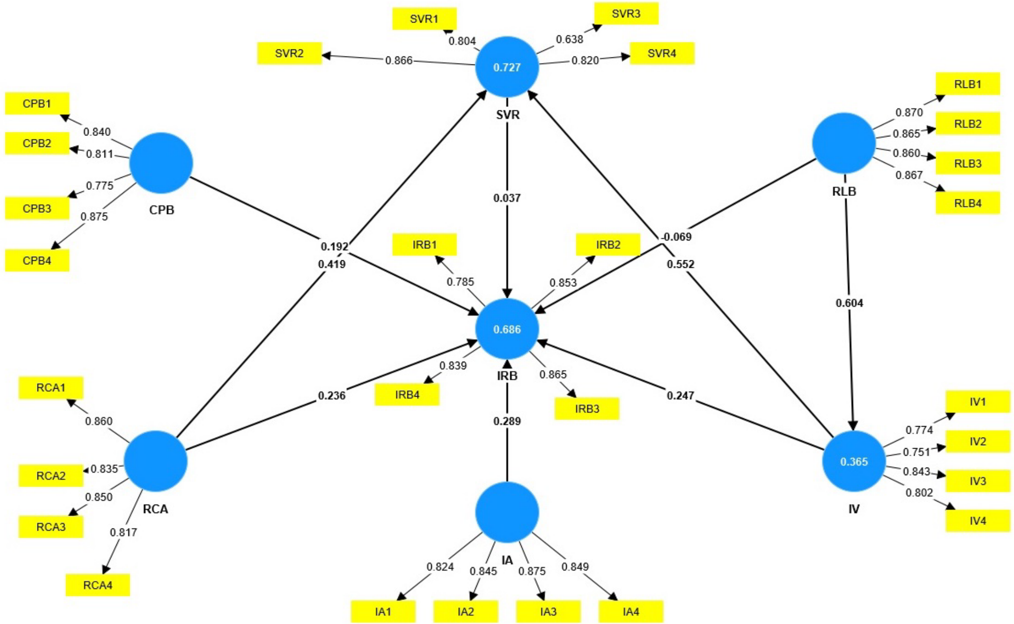

Figure 3. Determination of the effect coefficients, the contributions of the indicators to the reflective latent variables and the weights of the indicators to the formative latent variables

Source: Smart PLS 3 software processing

Figure no. 3 highlights the relationships between the latent variables included in the research model, indicated by arrows pointing from the exogenous latent variable considered a predictor to the dependent (endogenous) latent variable. Also, the diagram illustrates the variables that can be measured through a formative approach (IA - **Interaction and Engagement,** CPB - Brand Awareness and Preferences, RLB - Brand Retention and Loyalty and IRB - Influence on Brand Reputation, RCA - Conversion Rates and Purchases), where the arrows point from indicators to variables), respectively the variables that can be measured through a reflective approach (IV - **Impact on Sales**, SVR - Segmentation and Variability in Responses).

Cronbach Alpha is a measure of the internal consistency or reliability of a variable's measurement, reflecting how correlated the variables within the structural model are. The minimum accepted threshold for this indicator is 0.7. The values for Cronbach Alpha are assigned in Table no. 3 only to the reflective variables (IV and SRV), both exceeding the threshold of 0.7.

Table 3. Evaluation of internal consistency and convergent validity in the case of the reflective measurement model

Construct reliability and validity - Overview

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
CPB	0.844	0.845	0.896	0.682
IA	0.871	0.876	0.911	0.720
IRB	0.856	0.860	0.903	0.699
IV	0.805	0.816	0.871	0.629
RCA	0.862	0.864	0.906	0.707
RLB	0.889	0.891	0.923	0.749
SVR	0.789	0.799	0.865	0.618

Source: Smart PLS 3 software processing

The composite confidence level (CR) is obtained by combining all the variances and covariances of the true score from the composite of the indicators within the latent variables and dividing their sum by the total variance in the composite. Like Cronbach Alpha, CR is a reliability indicator; if Cronbach Alpha assumes that the factor loadings are the same for all indicators, CR considers the variable loadings of the indicators. Acceptable CR values are generally considered above the threshold of 0.7 and in the case of this research we note that this indicator exceeds the minimum recommended threshold for the two reflective variables (IV and SRV).

Spearman's rank correlation coefficient (Rho) is a non-parametric test used to measure the strength of association between two variables, where the value r = 1 means a perfect positive correlation and the value r = -1 means a perfect negative correlation. We note in the case of the four reflective variables (IV and SRV) a positive correlation.

Table 4. Evaluation of the statistical collinearity test

Collinearity statistics (VIF)

	VIF
CPB1	2.204
CPB2	1.820
CPB3	1.526
CPB4	2.509
IA1	1.932
IA2	2.331
IA3	2.435
IA4	2.146
IRB1	1.814
IRB2	2.249
IRB3	2.383
IRB4	2.071
IV1	1.719
IV2	1.741
IV3	1.921
IV4	1.745
RCA1	2.206
RCA2	2.016
RCA3	2.166
RCA4	1.908
RLB1	2.302
RLB2	2.422
RLB3	2.181
RLB4	2.524
SVR1	1.662
SVR2	2.377
SVR3	1.297
SVR4	2.178

The variance inflation factor (VIF) is a measure of multicollinearity between a set of variables in a multiple regression. Values greater than 5 indicate high multicollinearity.

Multicollinearity occurs when a group of independent variables are highly correlated with each other.

The variance inflation factor (VIF) appears in the definition of the variance of the estimated coefficients and measures how many times the variance of the coefficients is overestimated due to multicollinearity compared to the situation when there would be no collinearity within the structural model.

We note that Smart PLS 3 software generates variance inflation factor (VIF) values for both formative and reflective variables. The RLB4 reflective indicator has the highest level of variance inflation, while the SVR3 reflective indicator has the lowest level of variance inflation. All VIF values are below the threshold of 5.00 (Table 3.6) and we can conclude that collinearity does not reach critical levels for any of the formative or reflective variables and implicitly does not create problems in the estimation of the analyzed structural model.

Source: Smart PLS 3 software processing

The convergent validity of the model is assessed by the average variance extracted (AVE), which measures the variance that is captured by a variable relative to the variance due to measurement error. In general, an AVE value of at least 0.5 or higher is expected, otherwise the error variance is greater than the explained variance. We note that the two variables (IV and SRV) have AVE above the recommended threshold.

In the case of discriminant validity, the Fornell-Larcker criterion compares the square root of the average variance extracted (AVE) with the correlation of the latent variables. A latent variable should better explain the variance of its own indicators than the variance of other latent variables.

Method SEM-PLS does not take into account that the data are normally distributed, which implies that significance tests cannot be applied to test whether coefficients such as weights, outlier loadings, and relationship coefficients are significant. In contrast, SEM-PLS relies on a nonparametric bootstrap procedure to test the significance of the relationship coefficients estimated in SEM-PLS. In the bootstrapping procedure, subsamples are created with observations drawn randomly from the original data set (by replacement). The subsample is then used to estimate the structural model. This process is repeated until a large number of random data samples, approximately 5,000, have been created. Parameter estimates (weights, outlier loadings, and relationship coefficients estimated from subsamples) are used to obtain standard errors for the estimates. With this information, T-test values and asymptotic significances (p-values) are calculated to assess the significance of each estimate and validate or reject the research hypotheses.

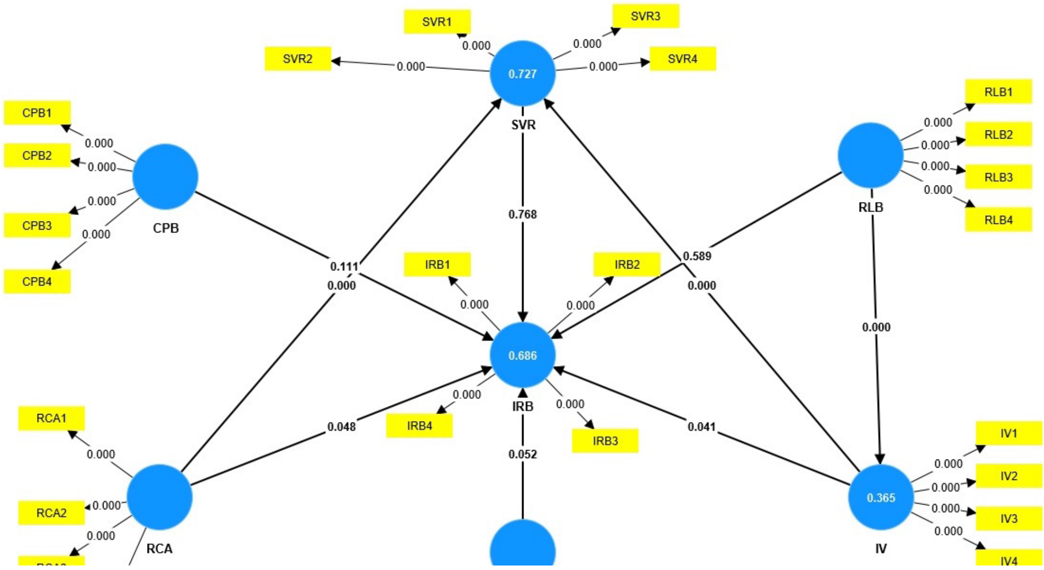

Figure 4. Determination of p-values associated with the relationships between the variables of the model, after applying the bootstrap procedure

Source: Smart PLS 3 software processing

Figure no. 4 reflects the structural model generated after applying the bootstrap procedure, in which the asymptotic significance values (p-value) are highlighted on the connection relations between the latent variables. The data reflected in Table no. 5 are useful for validating/rejecting the hypotheses from the analyzed structural model.

Table 5. The values of the asymptotic significance p and the T test for the 6 hypotheses in the structural model

Total effects - Mean, STDEV, T values, p values   Zoom (100%)   Copy to Excel   Copy to R

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
CPB -> IRB	0.192	0.192	0.121	1.593	0.111
IA -> IRB	0.289	0.284	0.149	1.944	0.052
IV -> IRB	0.267	0.273	0.110	2.439	0.015
IV -> SVR	0.552	0.552	0.059	9.371	0.000
RCA -> IRB	0.251	0.247	0.122	2.065	0.039
RCA -> SVR	0.419	0.420	0.060	6.935	0.000
RLB -> IRB	0.092	0.105	0.131	0.703	0.482
RLB -> IV	0.604	0.612	0.061	9.859	0.000
RLB -> SVR	0.333	0.338	0.047	7.132	0.000
SVR -> IRB	0.037	0.035	0.125	0.295	0.768

Source: Smart PLS 3 software processing

Not all hypotheses are validated, as the p-values exceed the maximum allowed significance level of 0.05 in some cases. The T-test shows us the magnitude of the correlation between the latent variables in this structural model. Thus, **brand retention and loyalty (RLB)** has the strongest effect in terms of **impact on sales** (T-test = 9.859, p-value tends to zero), while segmentation and variability in responses (SVR) has the lower impact on **segmentation and response variability (SVR)** (T-test = 0.295, p-value = 0.768).

In the research, 123 valid responses were collected through a questionnaire distributed online. The questionnaire was completed by respondents with various demographic characteristics, their distribution being presented in Table 3.1 and illustrated in Figures 3.3, 3.4 and 3.5. The majority of respondents come from the urban environment (77.2%), and in terms of occupation, most are employees (39.8%) or students (33.3%).

Starting with the descriptive analysis, table no. 5 presents the descriptive statistical indicators for the latent variables in the conceptual model. Indicators are measured by items rated on a Likert scale from 1 to 5, where 1 means "Strongly Disagree" and 5 means "Strongly Agree". Average values and standard deviations do not show significant differences between the indicators. For example, item SVR3 has the highest mean (4.350), while IA2 has the lowest mean (3.797). Skewness and Kurtosis indices indicate that the distributions of the variables are normal, without substantial distortions.

The correlations between the variables are analyzed and presented in table 3.3, providing a visual representation of the degree of association between them. Figure no. 4 highlights the relationships between the latent variables, indicating the formative variables (IA, CPB, RLB, IRB, RCA) and the reflective variables (IV, SVR). Predictive relationships between variables are represented by one-way arrows, demonstrating the complexity of interactions.

The internal consistency and convergent validity of the reflective variables (IV and SRV) are assessed by Cronbach Alpha and the composite confidence level (CR). The Cronbach Alpha and CR values for the reflective variables are above the threshold of 0.7, which indicates a good reliability of the measurements. Convergent validity is assessed by the average variance extracted (AVE), which has values above the threshold of 0.5 for the reflective variables, thus confirming the validity of the model.

1) The Collinearity Test and the Bootstrap Procedure

To assess the significance of the relationship coefficients, the bootstrap procedure was applied. In this procedure, subsamples of observations drawn randomly from the original data set are used to estimate the structural model. The obtained parameter estimates and standard errors are used to calculate T-test values and asymptotic significances (p-values). Figure no. 5 shows the structural model generated after applying the bootstrap procedure, highlighting the p-values for the relationships between the latent variables.

Validation of Hypotheses

Table no. 5 shows the T-test values and p-values for the six hypotheses formulated in the structural model. Not all hypotheses are validated, as p-values exceed the maximum accepted significance level of 0.05 in some cases. For example, the hypothesis that effective segmentation and increased response variability (SVR) significantly contribute to increased brand awareness and preferences (CPB) is not validated (T-test = 0.295, p-value = 0.768). In contrast, retention and brand loyalty (RLB) have the strongest effect on sales impact (T-test = 9.859, p-value tends to zero).

4. Conclusions

The research looked at variables such as brand awareness and preference (CPB), conversion and acquisition rates (RCA), segmentation and response variability (SVR), brand retention and loyalty (RLB), sales impact (IV), and interaction and engagement (IA). Each of these variables was measured by specific indicators, reflecting various aspects of mobile marketing campaigns. The developed structural model allowed the verification of the hypotheses regarding the mutual influences between these variables.

Research findings have shown that interaction and engagement (AI) play a critical role in building brand awareness and brand preference (CPB). This relationship underscores the importance of active consumer engagement in mobile marketing campaigns. Constant engagement with mobile campaigns not only boosts brand awareness, but also influences consumer preferences, thereby increasing the chances of conversions and purchases. Therefore, marketers need to focus on creating interactive and engaging campaigns to maximize the impact on CPB.

Segmentation and Response Variability (SVR) have been found to be another significant factor contributing to increased brand awareness and preference. A segmented and personalized approach to mobile marketing campaigns allows for effective targeting of different demographic and psychographic groups, leading to greater campaign relevance and effectiveness. This aspect is very important for marketers, as a well-targeted strategy can maximize the impact of marketing messages and generate a higher response rate.

On the other hand, retention and brand loyalty (RLB) were positively associated with interaction and engagement (IA). Long-term loyalty is cultivated through ongoing engagement and strong consumer relationships. Mobile marketing campaigns that succeed in maintaining a high level of engagement can reduce churn and encourage repeat purchases, thereby building brand loyalty.

Sales impact (IV) is influenced by brand awareness and preference (CPB), as well as conversion and acquisition rates (RCA). This relationship highlights the direct link between brand appeal and recognition and business performance. Mobile marketing campaigns that increase CPB have a positive effect on IV, proving that an effective marketing strategy not only increases brand visibility, but also drives sales.

By applying SEM-PLS, this research was able to demonstrate the complexity of the interactions between the variables involved in mobile marketing campaigns. The elaborated structural model showed that all variables - CPB, RCA, SVR, RLB, IA, IV - contribute positively to building and maintaining solid brand reputation

(IRB). This highlights the fact that the success of a mobile marketing campaign depends on multiple interconnected aspects that must be managed simultaneously.

For marketers, these results provide vital insights into optimizing mobile marketing strategies. Continuous consumer engagement and effective segmentation are critical factors that must be integrated into campaign planning. The structural model developed and validated through SEM-PLS provides a robust analytical framework that can be used to continuously evaluate and improve mobile marketing strategies. In this way, organizations can ensure the long-term success of their campaigns, maximizing the impact on brand awareness, consumer loyalty and business performance.

Acknowledgements

The present research was carried out within the internal grants Dunarea de Jos University of Galati - 2024:

1. Sustainable development of the European economy from the perspective of the transition to climate neutrality, Contract no. RF 2464/31.05.2024.

2.Strategies for promoting ecotourism destinations through Web3 technologies and augmented reality (AR), Contract no. RF 2465/31.05.2024.

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