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Social Media Content Multimodality and the Level of User Interactions from the Perspective of Facebook and Instagram

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The article aimed to establish a simple methodology for examining the impact of message modality on user interactions. Using communication theory and content analysis methodology, 1,172 entries of selected recreational entities on Facebook (N=579) and Instagram (N=593) were analysed. The results suggest that higher modality levels positively influence user interactions, with a weak positive effect observed on Facebook and a moderate positive effect observed on Instagram. Practical implications include content marketing on social channels and the development of a theory of memetic content propagation. An innovative aspect of the research is an approach that consolidates the different levels of modality into one simple Post Modality Value (PMV). Research limitations include focusing only on two social media platforms, analysing fanpages associated with specific service industry entities, and disregarding the size of follower groups.

Keywords: *Facebook; Instagram; Content Multimodality; Multimodality Analysis; User Interactions; PMV Coefficient.*

Introduction

Social media stands out as one of the most prominent communication channels in contemporary society, boasting an estimated 62.3 % global penetration of social media platform accounts. Facebook, with over three billion users, dominates the landscape (Global Social Media Statistics, 2024).

The functionalities inherent in social media platforms provide users with a broad spectrum of options for content creation and dissemination on diverse topics. This content may take the form of User Generated Content (UGC), intricately linked to individual users and their unique experiences (Fu *et al.*, 2017), or Marketer Generated Content (MGC), either directly or indirectly associated with a brand or product (Qian *et al.*, 2022). In the realms of business and personal communication, the primary motivation behind content creation lies in the desire to reach a broad audience (Muller, J., & Christandl, 2019) and elicit a substantial number of reactions. The absence of reactions, particularly in UGC, can potentially heighten the stress levels of content creators (Haug *et al.*, 2024). For MGC, it may signify a lack of interest in the content (Kohli et al., 2015), indicating the ineffectiveness of brand marketing communication activities in social media channels.

Consequently, frequent analytical approaches have been developed, considering various aspects of content construction in predicting its popularity (Liu *et al.*, 2023). Popularity, in this context, is measured by the volume of interactions among message recipients and is defined by metrics such as likes, comments, and shares (Vandenbosch *et al.*, 2022). Cognitive, affective, and behavioural activities in the context of content consumption have been delineated by models such as AIDAT (Charlesworth, 2012) and COBRA (Muntinga, 2013).

Each shared post forms a semantic unity that lends itself to analysis through various approaches. In cognitive-affective terms, Swani et al. (2017) highlighted differences in interaction levels based on informational and emotional content in B2B and B2C relationships. However, a huge portion of research relies on natural language processing (NLP), incorporating machine learning (O'Halloran *et al.*, 2021), or deep learning methodologies (Chhabra & Vishwakarma, 2023). The modality of the message, encompassing semiotic perspectives, modes, and the meanings derived from them, plays a crucial role in these considerations. Meanings, in turn, arise from the interconnectedness of various modes: linguistic, visual, sound, gestural, and spatial (Kress, 2003), merging into a consistent message.

The study's objective was to explore the potential correlation between the multimodality of MGC-related messages (SNS posts) and their popularity, defined by diverse forms of user cognitive, emotional, and behavioural interactions and from the perspective of different social media platforms.

The paper consists of separate sections. The literature review offers an extensive overview of theories related to massage modalities, covering the distinctiveness of social media platforms and communication models. This section culminates in presenting research questions and outlining specific objectives. The methodological part provides detailed insights into the research methods employed and introduces the Post Modality Value (PMV) coefficient, along with its theoretical underpinnings. The results section presents the research findings. The subsequent section discusses the results and their practical and theoretical implications, particularly in the context of herd behaviour and memetic imitation theory. The need and areas for further research were also highlighted. The conclusion section discusses and summarizes the most important findings from the study and describes the examination limitations along with concluding explanations and remarks.

Literature Overview

Message Modality and Social Media Content

According to Bezemer and Jewitt (2011), meaning is inherently crafted through the utilization of diverse semiotic resources. These resources facilitate both the cognitive activity of recipients and the reciprocal communication between the source and the recipients of meaning contained in the message. The process of meaning-making involves the fusion of specific modes (Kress, 2003), namely the linguistic mode (comprising written and spoken language), the visual mode (focused on the perception of images, colours, and symbols constituting a semantic whole), the auditory mode (encompassing all sound stimuli such as music, spoken language, and ambient sounds), the gestural mode (related to body language and the conveyed emotions), and the spatial mode (connected to the role of physical space and the arrangement of aforementioned modes to convey a specific meaning).

Regarding the multimodality of messages, meanings are conveyed through various modes and synthesized into a specific message. These individual meanings complement each other to form a cohesive whole, fulfilling the fundamental metafunctions of the semiotic message, including the ideation metafunction (expressing current or desired reality), the textual metafunction (offering a synthetic description of the presented reality), and the interpersonal metafunction (reflecting the relationships between the source and the recipient of the message). These metafunctions serve as specific descriptors of the communication process (Lisowska-Magdziarz, 2018, based on Halliday, 1978).

Social media serves as a nexus connecting not only suppliers/manufacturers of products and services with their consumers (Zeng *et al.*, 2022) but also facilitating interactions among individual users (Kaplan and Haenlein, 2010). Stewart (2023) contends that the functionalities of social media platforms enable the creation of multimodal messages distinct from those in traditional forms of communication.

This distinction is particularly evident in digital media content (Magnusson & Godhe, 2019). In the context of social media, a diverse array of modes is observed in posts published on social media platforms (Lutkewitte, 2013). Content for social media can be generated either by individual users as User Generated Content (UGC) or directly by marketers associated with the product or brand as Marketer Generated Content (MGC) (Goh *et al.*, 2013).

Within the model of communication - the main theoretical framework of the study (Laswell, 1948; Osgood-Schramm, 1954 Berlo, 1960), meanings/messages, as synthesized modes, are encoded, transmitted, and decoded between the source and the receiver. This transmission occurs through a specific channel, yielding distinct cognitive, affective, and behavioural effects (Charlesworth, 2012; Muntinga, 2013), referred to as user engagement. User engagement, as defined by Hollebeek and Others (2016), involves "a psychologically justified desire to invest resources (time, emotions, behaviors, declared attitudes, etc.) in interacting with a specific object of engagement". Li et al. (2023) equates "interaction" and "engagement," stating that "engagement refers to the interaction with social media messages." Engagement is thus measured through activities related to MGC consumption, such as likes, comments, shares, and parasocial interactions - a concept denoting an illusory sense of social bond with media personalities and entities (Jia *et al.*, 2024; Labrecque, 2014).

As emphasized by Mehmet et al. (2014), "…each new social media platform utilizes combinations of these media modalities; language may be combined with visual, auditory, and kinetic resources, to construct very complex texts over time". Published posts are, therefore, a synthesis of individual modes aimed at conveying assigned meanings and eliciting specific effects. In line with communication theory, each message is emitted by the source through a chosen communication channel, received by the recipient, and produces cognitive and/or emotional and/or behavioural effects defined by interactions - such as liking, commenting, sharing, and parasocial interactions. Additionally, social media behaviours related to content creation and response are influenced by users' personality traits, as defined by the Big Five Personality Model, encompassing openness, conscientiousness, extroversion, agreeableness, and neuroticism (Yang *et al.*, 2023).

The visual mode, acting as a carrier of specific realism, simultaneously exerts a considerable influence on the emotions of the audience. Due to the inherent trust placed in visual content by recipients, it is perceived as the most credible (Sundar, 2008). Furthermore, visual content enables a more precise presentation and perception of reality, encompassing both its contextual and intangible components (Bakri *et al.*, 2020).

Consequently, high-modal content, incorporating multiple modes, provides deeper and more precise contextual signals of the presented reality, thereby enhancing its credibility (Kress & Van Leeuwen, 2021). This enhanced credibility can, in turn, have a more profound impact on the holistic effects of the communication process, encompassing the cognitive, affective, and behavioural activities of recipients. Simultaneously, according to Moon et al. (2018), visual content significantly aids in the proper processing, interpretation, and understanding of textual messages. The utilization of multiple modes in crafting messages for social media underscores the importance of appropriate content classification, particularly given its potential influence on the cognitive, affective, and behavioural activities of content recipients. It is crucial to note that not only the content itself but also the platform on which it is disseminated may be pivotal in shaping the expected effects of its release. Individual social media platforms attract users with varying demographics, notably in terms of age. This divergence is particularly evident when considering platforms like Facebook and Instagram. Analysing available statistical data reveals that Facebook (Statista, 2023a) tends to be more popular among older users, while Instagram is predominantly favoured by younger demographics (Statista, 2023b). This dichotomy presents intriguing research implications.

In the context of User Generated Content (UGC), Marketer Generated Content (MGC), and their respective modalities, it is pertinent to introduce the concept of social content management. Glazkov (2005) defined this as "a set of concepts, methodologies, and standards that enable and facilitate the creation, organization, and maintenance of content through the social interaction of individuals online."

Conversely, Aladwani (2014) posited that social content, originating from a broad spectrum of social media, is generated, and utilized not only by individual users but also by various business entities. Managing MGC and UGC, as defined in this context, essentially involves constructing a specific message aimed at achieving desired effects related to relationship building and maintenance, ultimately aligning with communication goals. Establishing and maintaining relationships in this context may be intricately tied to the acquisition of interactions, manifesting in the form of likes, comments, and shares.

Classification of Multimodal Content

Xu et al. (2024) applied the theory of message multimodality to detect and analyse misinformation spreading on social media, utilizing Weibo and X platforms as examples. They highlighted issues related to single-modality (text-only content) and multi-modality (posts built from multiple modes). Similarly, Wang et al. (2023) employed multimodality analysis of posts to predict their popularity based on information diffusion, determined by the number of audience interactions. The authors emphasized the significance of interaction levels in analysing and predicting trends related to content popularity. Afyouni et al. (2022) utilized multimodality as one perspective to detect social events within content shared in Social Networking Sites (SNS), identifying, and establishing relationships between text and image. Imran et al. (2020) discussed issues related to the multimodality of content in the context of crisis informatics, focusing on information activities for crisis management and the use of AI tools.

An & Wan Zainon (2023) demonstrated the role of colours and their impact on the emotional context of shared multimodal content, encompassing both visual and textual modes. O'Halloran et al. (2021) highlighted, based on the Multimodal Analysis Platform (MAP), new possibilities for data acquisition and analysis, including Big Data, from content with diverse modalities, including linguistic and visual modes. The assumptions for classifying weak and high-modal content in terms of deep learning and AI were developed by Liu et al. (2018). They also highlighted that the presence of multiple complementary modes somehow strengthens and authenticates the message. From a Marketer Generated Content (MGC) perspective, the modality of text-image posts is identified as one of the key elements influencing its popularity (Quian *et al.*, 2022).

From the perspectives outlined above, a two-area approach to the analysis of content within SNS emerges: single-modal, primarily involving the language mode, and multi-modal, which includes the synthesis of other modes with the language mode. However, the visual mode is not confined solely to static forms (photos, slideshows) but extends to dynamic forms associated with videos of varying lengths. Therefore, it is proposed to diversify the multimodal approach into static multimodality (SMM), encompassing photos and/or slideshows, and dynamic multimodality (DMM), involving film content in the form of shared videos or short reels. Stepaniuk and Jarosz (2021), discussing the process of imitating the language mode in response to shared MGC, revealed a positive relationship between the presence of emotionally neutral text phrases in posts and their imitation in the comments left by recipients. Thus, it becomes essential to examine the impact of not only a single mode but also their synthesis on the level of interaction among recipients of messages based on MGC.

Building upon the presented literature review, the following research questions were formulated:

RQ1: How does the number of modes used in MGC posts exhibit a linear relationship with the overall level of interaction among message recipients, considering the number of likes, comments, and shares?

RQ2. How does the diversity of multimodality in messages affect the level of audience interaction from the perspective of different social media platforms?

RQ3: Can the dynamic multimodality (DMM) of MGC be considered a key factor influencing the level of interaction among message recipients?

In light of the literature review, studies related to machine learning or the use of AI in analysing the impact of message modality on predictions of post popularity dominate. The proposed considerations simplify the research approach somewhat, focusing on finding a statistical relationship between unimodality, static multimodality, and dynamic multimodality, and their potential relationship with the frequency of interactions on the part of message recipients.

The specific objectives of the study include building and testing a methodology for analysing the impact of the level of modality of content (posts) on various social channels on the level of interaction among message recipients (users), following the Social Semiotic Multimodality (SSMM) framework proposed by Mehmet et al. (2014). This approach is based on resources of semiotic meanings, expressed in the form of various modes. Based on the synthesis of these modes, holistic meanings are generated in the form of specific content that is used to communicate and build relationships with users of social networking sites.

Methods

To demonstrate potential differences in the impact of modally differentiated content on the level of audience interaction, a study was conducted on the two dominant social media platforms: Facebook and Instagram. The subjects for both the pilot and main studies were purposively selected.

For the pilot study, designed primarily to test the developed methodology and research tool, posts from three leading clothing brands in Poland, namely Sinsay (3.4 million FB followers), Cropp (2.2 million FB followers), and Reserved (4.1 million FB followers), were chosen (Rejer, 2021). The official profiles of these brands were analysed for posts published between October and November 2023.

The main research focused on profiles of leading recreational facilities in one of the provincial capitals in north-eastern Poland, including Champion Gym (3.1 thousand FB followers), Fitness Club Magic Gym & Magic Medical (10 thousand FB followers), and STARS Gym & Fitness (10 thousand FB followers). Posts from 2021-2023 were studied.

Data collection and initial processing were carried out using an MS Excel spreadsheet, with values entered and derived variables calculated. For each post on both platforms, the number of likes (variable: likes), comments (variable: comments), and shares (variable: shares) were examined, and mean values were calculated. Normality tests were conducted using the Shapiro-Wilk test. Due to the lack of normal distribution, non-parametric statistics, specifically the Kruskal-Wallis test, were used to compare mean values.

The Interactivity Index (IAI, Sotrender, 2023) was calculated based on the number of interactions for posts on both platforms. One "like" was weighted as 1, a comment as 4, and a share as 16, using the formula: IAI= (no. of likes*1) + (no. of comments*4) + (no. of shares*16).

Similarly, the Post Modality Value (PMV) index was created and defined, based on differentiated weights assigned to each mode. Weights were assigned considering the single modal (SM) as the basic mode with the lowest weight, multimodal dynamic (DMM) visual mode with the highest weight, and multimodal static (SMM) mode with an intermediate weight. Weights used in PMV were: text (spoken or written) – 1, static images with spatial mode and/or gestural mode – 4, and dynamic video with spatial mode and/or gestural mode and/or sound mode – 16. Similarly to IAI calculation procedure, by analysing individual shared content element (post), the presence of a given mode was determined and its occurrence was marked in the spreadsheet. Using the similar formula as indicated above in the case of IAI, the appropriate PMV value for a specific post was calculated in the spreadsheet.

The variables IAI and PMV were studied for both platforms: IAI_FB and PMV_FB for Facebook, and IAI_INST and PMV_INST for Instagram.

To establish a statistically significant relationship between user interactions and the modality of posts (in terms of MMS and MMD), Spearman correlation analyses were performed between the variables PMV_FB and IAI_FB, as well as PMV_INST and IAI_INST. Spearman's nonparametric correlation coefficient is widely used in social networking exploratory data analysis (Xiao et al., 2016). The following scale was used for interpreting Spearman coefficients: $0.0 \le |\rho| \le 0.2$ - lack of correlation; $0.2 < |\rho| \le 0.4$ – weak correlation; $0.4 < |\rho| \le 0.7$ - average correlation; $0.7 < |\rho| \le 0.9$ – strong correlation; $0.9 < |\rho| \le 1.0$ – very strong correlation. Statistical analyses were conducted separately for each platform using Statistica 13.3 software. The collected data and analyses were deposited in the Mendeley Data repository. ChatGPT 3.5 was used for final language corrections.

Results

From the perspective of the pilot study (N=120), the 40 shared posts were examined for each of the three brands. For Sinsay and Reserved brands, all posts published on Facebook were of a multimodal static (SMM) nature. Regarding the Cropp brand, static multimodal (SMM) posts constituted 85 % of the total, i.e., 34 posts, while the remaining 15 % were multimodal dynamic (DMM). Due to the lack or minimal diversity of the analysed posts in terms of multimodality, it was not feasible to calculate the correlation coefficient for Sinsay and Reserved, or, in the case of Cropp, due to ρ values ≥ |0.2|, no statistically reliable inference could be drawn.

The main study encompassed a total of 1172 posts published by selected recreational facilities on Facebook (N=579) and Instagram (N=593). No single modal (SM) posts were identified. There were 108 Facebook posts of multimodal dynamic (DMM) nature (81.35 %), with multimodal static (SMM) constituting 471 posts (18.65 %). For Instagram, these statistics were: DMM – 185 posts (31.25 %); SMM – 407 posts (68.75 %). Descriptive statistics for the fanpages of individual entities are presented in Table 1.

Table 1

Descriptive Statistics Concerning user Interactions, where: I - Champion Gym; II - Fitness Club Magic Gym & Magic Medical; III - Stars Gym & Fitness

	Facebook					Instagram			
	Likes	Comments	Shares	IAI_FB		Likes	Comments	Shares	IAI_INST
	$[\bar{x};\ SD]$					$[\bar{x};\ SD]$			
I (N=177)	39.4; 109.6	4; 9.6	5.5; 8.2	107.8 187.7	I (N=199)	124.2; 385	8.7; 23.2	1.9; 3	171.7; 417.3
II (N=201)	15; 17.2	1.23; 4.2	1.4; 2.9	42.7 65.4	II (N=194)	50.3; 36	2.25; 7.3	0.5; 1.7	66.7; 66.5
III (N=201)	19.4; 29.1	1.27; 5	0.65; 2	34,9; 70,4	III (N=200)	51; 28	1.5; 1.9	0.01; 0.1	57.26; 32.2

The results of the Kruskal-Wallis tests reveal statistically significant differences among the variables: likes, comments, and shares from the viewpoint of the scrutinized fanpages on the Facebook platform. Notably, there is a substantial discrepancy in the means for the shares variable concerning each entity (H (2, N=513)=98.5; p=0.00). Conversely, concerning likes (H (2, N=578)=46.46; p=0.00) and comments (H (2, N=530)=57.3; p=0.00), no disparities in means were observed between the Facebook profiles of objects II and III. In the context of Instagram, statistically significant differences were noted for the variables likes (H (2, N=593)=43.4; p=0.00), comments (H (2, N=549)=97.5; p=0.00), and shares (H (2, N=520)=114.2; p=0.00) from the perspectives of fanpages I, II, and III. However, for all variables, no statistically significant differences exist between the fanpages of entities II and III.

Based on the number of interactions and following the formulas outlined in the Methods section, the Interactivity Index (IAI) was computed. The Shapiro-Wilk test results indicated that the distribution of both variables - derivatives of the IAI variable - in a holistic approach (without division into studied fanpages for Instagram and Facebook, as well as with the division into individual entities) is not normal. From an all-encompassing perspective, the results of the Shapiro-Wilk test were as follows: IAI_INST, W=0.2; p<0.00; and IAI_FB, W=0.43; p<0.0.

In addition, based on the analysis of post modality, PMV coefficient values were calculated for content published on both platforms. Details are presented in Table 2.

Table 2

Descriptive Statistics for the PMV Coefficient from the Perspective of Analysed Fanpages on Both Platforms; where: I - Champion Gym; II - Fitness Club Magic Gym & Magic Medical; III - Stars Gym & Fitness

	PMV_FB [$\bar{x}$; SD]		PMV_INST [$\bar{x}$; SD]
I (N=177)	10.8; 7,25	I (N=199)	13,3; 7.8
II (N=201)	6.6; 4.6	II (N=194)	9.7; 7.14
III (N=201)	5.9; 3.8	III (N=200)	6.1; 4.1

The results of the Shapiro-Wilk (S-W) test underscore that the distribution of both variables derived from post modality (PMV) for Instagram and Facebook is non-normal, both in an overarching sense and from the viewpoint of individual entities. The W parameter values in a comprehensive context were as follows: PMV_FB, W=0.53; p < 0.000, and PMV_INST, W=0.62; p < 0.000. Considering the perspective of the examined entities, both the IAI and PMV variables did not exhibit a normal distribution. The sample sizes and relevant statistics are detailed in Table 3.

Table 3

Sample Size and Results of the Shapiro-Wilk Test (p < 0.00); where: I - Champion Gym; II - Fitness Club Magic Gym & Magic Medical; III - Stars Gym & Fitness

	Facebook			Instagram	
	IAI_FB	PMV_FB		IAI_INST	PMV_INST
	[W]			[W]	
I (N=177)	0.51	0.75	I (N=199)	0.26	0.72
II (N=201)	0.57	0.38	II (N=194)	0.7	0.61
III (N=201)	0.4	0.28	III (N=200)	0.89	0.28

Dynamic Multimodality (DMM) and Static Multimodality (SMM) vs. the Number of user Interactions (IAI)

The results concerning the impact of post modality on the level of user interaction, taking a comprehensive approach without distinguishing between DMM and SMM posts, and without categorization into individual entities, reveal a minimally statistically significant relationship of a very weakly positive nature between recipient interactions (IAI_FB) and the level of post modality (PMV_FB) on Facebook: $\rho = 0.19$; $p < 0.05$. Conversely, for Instagram, this relationship is stronger, showing a moderately positive correlation. The Spearman's correlation coefficient values for variables IAI_INST and PMV_INST are $\rho = 0.43$; $p < 0.05$. This implies a plausible linear relationship between an important level of post modality and the number of user interactions from the perspective of their cognitive, affective, and behavioral activities. In the subsequent analysis, this relationship is examined concerning individual fanpages. From the perspective of Facebook, ρ values were below 0.2, suggesting a probable lack of dependence between the multimodality of posts and the number of user interactions. When analyzing individual entities in the context of posts on both platforms, no statistically significant relationship was identified between SMM and DMM posts and the number of interactions by content recipients. This implies that DMM and SMM are equivalent in generating an important level of audience interaction. Regarding individual fanpages (Table 4), the results obtained for the PMV_FB and IAI_FB variables also suggest a lack of correlation between the two variables. The relationship between PMV_INST and IAI_INST variables ranges from average to poor.

Table 4

Spearman's ρ Values from the Perspective of DMM and SMM Posts on Facebook and Instagram (* - Significant Correlation p < 0.05); where: I - Champion Gym; II - Fitness Club Magic Gym & Magic Medical; III - Stars Gym & Fitness

		Facebook			Instagram
		IAI_FB			IAI_INST
I (N=177)	PMV_FB	0.12	I (N=199)	PMV_INST	0.58*
II (N=201)		0.02	II (N=194)		0.2*
III (N=201)		0.13	III (N=200)		0.26*

Discussion

The presented research findings reveal significant differentiation between Marketer Generated Content and content shared across various social media platforms from several perspectives. Firstly, a crucial differentiating factor is the modality of the content. In both cases, multimodal, static, and dynamic content dominate, with no strictly textual content identified in the studied material. This suggests that in the process of creating content for marketing communication, high content modality plays a vital role, serving as a necessary condition for achieving appropriate communication effects, such as building a significant content range.

Secondly, multimodal content is categorized into two types: multimodal static (SMM) and multimodal dynamic (DMM). Examining the quantitative relations between them, it can be concluded that SMM is the dominant content, with a ratio of approximately 5 to 1 from the perspective of Facebook and approximately 2 to 1 for Instagram. Concerning the impact of multimodality on the frequency of audience interactions, the obtained results likely indicate the existence of a statistically significant relationship between high modality content and the number of audience interactions. This is particularly evident from the perspective of Instagram, where both in terms of the entire research material and the three individually examined profiles, a positive relationship was found between the multimodality of messages and the number of recipients' interactions. Multimodal content fosters audience interaction (RQ1), albeit with some caveats dependent on the social media platform. Because, on the other hand, from Facebook's perspective, this relationship was weakly positive only in the holistic sense. For individual entities, the values of the Spearman correlation coefficient did not indicate the existence of any relationship. This, in turn, addresses the second research question (RQ2), as the results show that the type of platform and, consequently, the specific audiences associated with it, are likely to have a potential impact on the level of user interaction, even in the context of multimodal content. This impact is determined by the socio-demographic characteristics of the average user of a given platform. As indicated by the cited results of statistical analyses (Statista, 2023a; Statista 2023b), Instagram is a platform more popular among young people, specifically Generation Z. This group, often referred to as "digital natives" (Smith, 2017), perceives Instagram as a digital ecosystem for establishing relationships, building an image, and following current events related to the broadly understood reality (Chen, 2018).

Regarding the third research question (RQ3), it should be stated that the dynamic multimodality of content would likely be challenging to consider as a factor significantly influencing the level of interaction of content recipients. The obtained results suggest that there is no relationship between static or dynamic multimodality and the level of interaction among recipients. Hence, from the content management perspective, the issue of content generation and profiling target audiences becomes important. These findings have direct practical and theoretical implications for content management, primarily concerning the need to create content with high modality, targeting a specific and strictly profiled group of recipients. Theoretical contributions mainly include the PMV coefficient with its theoretical foundations. This coefficient, based on different ranks, allows for a simplified but effective analysis of the impact of content modality on the level of behavioral and emotional reactions of various audience groups. On this basis, it will be possible to construct analytical tools to generate data enabling effective content management. This is the basic practical implication enabling the use of research results. It is essential to track trends in the popularity of content and capture content that generates a high level of interaction, which may result, among other things, from the phenomenon of herd behaviors (Sun, 2013) and broadly understood imitation of activities generated by other users (Salganik *et al.*, 2006).

In this context, it can be assumed that the high popularity of a post as well as specific reactions connected, may be more due to the observed high number of interactions. Thus, their increase may be determined not so much by the substance of the post but by its popularity (Chang *et al.*, 2020). In this case, the interactions associated with the post can refer to imitating the behavior of others without delving into the content of the post itself. This type of dependency can be highly probable, especially from the perspective of a fanpage with many followers. The functioning of the recipient in conditions of information overload and attention deficit (Menczer & Hills, 2020) enables them to perform certain mechanical activities related to the consumption of content and the reaction to it.

This explanation also accounts for the lack of differentiation in reactions to Multimodal Static (SMM) and Multimodal Dynamic (DMM) content. Additionally, it should be remembered that the subject and focus of the research influence the results obtained, particularly concerning the level of studied interactions, such as consuming, liking, commenting, and sharing content, in the context of the phenomenon of homophily, i.e., user activities based on common interests (Bucur, 2019). The key factor, in this case, would be the sheer popularity of modally differentiated content, conditioned by the memetic imitation of behaviors. Such a memetic character would necessitate a clear definition of the concept of the meme.

In the classical view (Dawkins, 1976), memes are immaterial carriers of cultural information - having numerous analogies with genes (genes are a material entity, although invisible), and serving as carriers of biological information - and subject to similar processes of inheritance related to the process of cultural evolution. On the other hand, Schlaile et al. (2018) based on Distin (2014) suggest that memes can be defined as a mental representation of cultural content that can impact those who assimilate it. The authors point out that memes somehow control behavior. The more a meme influences an increase in adaptability level, the more frequently, from the perspective of social learning and imitation, it is assimilated and replicated. This means that the fundamental characteristics of a meme (Dawkins, 1976), such as copy-fidelity, longevity, and fecundity, are high, and the meme itself tends to spread and express rapidly.

This expression may take the form (individually or in combination with others):

- Cognitive, relating to the acquisition of knowledge that can reduce uncertainty regarding the functioning of an individual in a specific reality (Kowalczyk-Purol, 2015). This cognitive activity can also contribute to the creation of new realities, for example, within disinformation campaigns (Glabus, 2008), or other activities aimed at shaping public opinion on various aspects of contemporary social life.
- Affective, referring to the usually subconscious emotional effect triggered by the assimilation of knowledge/ideas arising from a meme, which influences the declared attitudes of the recipient and thus their behaviors (Ruys and Stapel, 2008).
- Behavioral, linked to the emergence and dissemination of behavior patterns based on the assimilated meme, such as imitating the behaviors of others associated with effective knowledge acquisition in the education process (Yoon, 2008), or controlling behaviors (Distin, 2014), or i.e. mimicking business practices in times of economic uncertainty (Xue & Hu, 2023).

The above forms of expression are based on the AIDA model of consumer behavior according to Strong (1925). The model was the core for other models related to web content consumption: AIDAT (Charlesworth, 2012) and COBRA (Muntinga, 2013). Both the basic AIDA model and the two derivative models of content consumption available on social networking sites indicated above are based on three components: cognitive, emotional and behavioral. These are elements that complement each other and imply specific human activities in the real and virtual environment.

The theoretical foundation for the proposed considerations is therefore the concept of the meme, based on the theory of modalities of communication (Kress, 2003), and social learning theory (Bandura, 1977), according to which human activity is conditioned by observation and imitation of the behaviors of others. Observation, in turn, is conditioned by the perception of communication, i.e., decoding and assimilating the combination of modal modes contained in the message. A similar approach, related to imitation of activities observed in digital media, is also present and described (Bandura, 2001). As also mentioned by Chung et al. (2020) in the broadly understood virtual space, which includes the space of social media, individual users learn specific behaviors from each other. According to social reward theory, imitation can be understood as a way to achieve positive consequences, including social ones, by the imitator (Cracco et al., 2018). The specific "positivity" of the consequences arises from the suggestion put forward by Conte (2000), according to which people are not vectors of cultural transmission but actors who drive this process. According to the author, the transmission of a meme is conditioned by the intentionality of the actors' actions, who, based on declared social norms, perceptions, and preferences, make conscious decisions related to memetic selection. Imitated behaviors must bring benefits associated with increasing social status and gaining acceptance from any defined social group.

Based on the presented theoretical approach and considering the issue of the modality of the message and its impact on the activities of the recipients, a meme could be defined as any message with varied modalities taking into account the linguistic, textual, audio, visual, spatial, gestural modes, or being a synthesis of selected ones - that has been made available and can be received and assimilated. The effect of meme assimilation is the emergence of a specific pattern of cognitive, emotional, and/or behavioral activity or a resultant of the same, which increases the level of adjustment of the individual, group, or organization in their real and/or virtual environment. From the perspective of both individuals and groups or organizations, an increase in adjustment can be defined by specific social rewards (i.a. admiration, prosocial interactions, sociability, passivity) expressed in verbal and/or non-verbal forms and such issues were broadly presented by Matyjek et al. (2020) and Smeijers et al., (2022). However, the presented approach requires further refinement to arrive at the final definition of the meme, as well as an exploration of the potential relationship between the broadly understood multimodality of MGC and the imitation of audience activity, within the framework of the theory of herd behavior. In this context, a meme assimilation effect should be perceived as the imitation of specific behavior related to engaging with interactions with content that is already highly popular with the audience. Analyses related to understanding the psychological principles of consuming shared content from the perspective of eye tracking, i.e., research related to tracking eye movements during contact with content, would also be significant (Mikalef *et al.*, 2023). This is because both visual modes and those involving spoken or written language are the only signals that users access when interacting online, especially from an SNS perspective. Even with the widespread use of social networking sites, researchers still have insufficient knowledge about the cognitive perception of UGC and MGC posted on various platforms (Seidman and Miller, 2013). In this context, it would be necessary to integrate users' behavior towards the shared content, taking into account what content elements and their expression in specific modes they pay attention to.

Although the current modality typology meets current requirements related to the analysis of shared content, the proposed PMV factor also has some limitations. In the future, if appropriate digital technologies for olfactory signaling become common (e.g. Cowan *et al.*, 2023), it will be necessary to extend the factor to include the olfactory mode and rank it appropriately.

The current approach is simplified. An intriguing area of investigation would involve examining the influence of message modality on different generations: X, Y, and Z (Levickaite, 2010; Slepian *et al.*, 2024), in the context of preferred social media platforms, and terms of their reactions to shared messages. This would be especially compelling considering the challenges posed by information overload and feature overload (Sheng *et al.*, 2023), as well as the associated phenomenon of attention economy (Menczer & Hills, 2021).

An interesting research problem would also be the analysis of the above issues in the context of behavioral mimicry (Stel & Vonk, 2010) related to emotional activities in social media (Xu et al., 2022) and behavioral activities (Song *et al.*, 2022). To solve this problem, it would be necessary to use more complex statistical tools, which include: factor analysis or structural equation models (Chen *et al.*, 2021). This would make it possible to define specific groups of users in the context of their preferences for modally differentiated messages and the most common reactions. This would have a significant impact on better profiling of recipient groups, in the context of generating a specific message and influencing the way of reaction. An interesting approach related to the automation of text content generation about profiled content is presented by Fang et al. (2024), where they use AI tools to extract specific trends and styles for building appropriate text content. This type of research would also be important in terms of other modalities.

Conclusions

As the results show, the content provided by the analysed entities is dominated by multimodal static and multimodal dynamic. There is no strictly textual content here, but this may result from the specificity of the analysed entities and the method of their marketing communication on SNS. The level of user interaction is influenced not by the modal nature of the content, but also by the platform used to build relationships with users. The results also suggest that there is probably no difference in the impact of SMM or DMM content on the level of interaction of content recipients.

The presented results address general issues related to the analysis of the impact of SNS content modality made available in social media on two different platforms and with a relatively small and very specific group of entities operating in the service industry. This constitutes one of the main limitations of the study. The research concept should be expanded to include various industries. The size of the communities gathered around the analysed entities was not taken into account. However, it can be assumed that the community size does not significantly impact the level of interaction, as indicated by pilot studies. For instance, in the case of the results of initial study with the Reserved brand (4.1 million FB followers), the level of interaction with individual posts was comparable to the studied content shared by the examined local entities in the leisure industry (10 thousand FB followers). Moreover, due to the absence of single-modal (SM) content representation, its actual role in the dissemination of marketing messages on social networking sites (SNS) cannot be fully determined. This justifies the need for further, more detailed research.

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