Content-Influencer-Fit: Improving Reach and Impact of Content for Influencers in eWOM

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Abstract. Marketers who integrate influencers into their advertising strategy seek to improve information reach and information impact of their content. At the same time, influencers are overloaded with information. This design research study proposes a content-influencer-fit model to improve the effectiveness of influencer identification and management. Based on a systematic literature review, interview and usage data from an influencer-marketing platform, this study proposes an attribute framework for marketer-generated content at first. By integrating this framework into a predictive content-influencer-fit model it integrates the discussion on influencer and content characteristics. Finally, the model is able to select influencers on their likelihood to perceive marketer-generated content relevant, which is the basis for content-based recommendation.

Keywords: Influencer marketing, Electronic word-of-mouth, Content-based recommendation systems, Design science research

1 Introduction

Web technologies changed the way consumers attain information about new products and services. They use web pages, video portals, or social networks for information and evaluation purposes [1]. Subsequently, literature on word-of-mouth marketing [2–4] extended its view to inquire the effect of such technologies upon more than face-to-face personal contacts and personal social networks. Even more, the significance of electronic word-of-mouth (eWOM) for consumer behavior rises as traditional marketer-generated content loses ground [5, 6]. Consumers tend to give more trust to information if it is not directly associated to the originator of a product or service [5]. Subsequently, such companies integrate influencers into their advertising strategies.

Influencers regularly have a high reach in specific target groups and promise to leverage on consumer's behavior [7–9]. They may fill the gap of perceived trust in product or service information. Particular examples are web journalists or bloggers [10], twitter users with large follower bases [11], or YouTube channel owners [12]. Marketers provide influencers with targeted information and offers to propagate their products or services to their final target group [13]. For this purpose, they prepare special messages for the intermediate with product information, possible modes of

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applications, and information on the marketer itself [14]. However, influencers are mostly overloaded with marketer-generated content [15]. Concerning the importance of influencer marketing strategies, we therefore inquire the question: *How can marketers systematically improve the final reach and impact of their content in influencer marketing?*

In this design research study [16, 17], we follow the methodology as proposed by Peffers et al. [18] to create a prescriptive model. We propose a content-influencer-fit model to support marketers in choosing suitable influencers for marketer-generated content. Finally, we shed light on the individual attributes of such content.

2 Targeting Marketer-Generated Content for Influencers

2.1 The role of Influencers in Electronic Word-of-Mouth

Word-of-mouth describes the positive and negative informal communication between consumers about characteristics of a business and/or its goods and services [19]. Electronic word-of-mouth, in comparison, entails the utilization of electronic means of communication for this purpose [20]. Due to the nature of the regular web technologies involved, eWOM is not limited to synchronous one-to-one, but also entails asynchronous one-to-many, or even many-to-many types of communication [20, 21]. The latter type of communication is especially highlighted in current marketing literature. It goes hand in hand with the term “viral marketing” [14, 22], which “departs from traditional advertising in its reliance on consumer word of mouth instead of mass media as the message conveyance vehicle”[12]. Such viral advertising of products and services may be originated by a marketer, but is carried further as “unpaid peer-to-peer communication of provocative content”[23].

Of particular importance are “individuals who were [more] likely to influence other persons in their immediate environment”[24] and who take an intermediating role on the indirect lines of communication between marketers and consumers. They play a key role in initiating or accelerating eWOM communication [7–9, 25–27]. Such influencers – also referred to as opinion leaders or market mavens – not only know how web technologies are applied to information search and propagation for products and services, other web users also have trust in their opinion on both activities [28]. They engage heavily with their environment as they gain many messages and tend to reply or forward these more often [29].

For influencer marketing it is important to understand the motivation of such individuals and their behavior in eWOM [8, 30]. For this purpose, it is also relevant to understand their position on the communication paths in a (social) network [31], as well as the characteristics of message and content [12, 22] sent to them and by them. Typically, influencer marketing consists of two phases: influencer identification and influencer targeting [5]. In the following, we will concentrate on the latter [32].

2.2 Design Parameters for Content Relevance in Influencer Targeting

In most cases, marketers get in touch with influencers via direct messages, such as e-mails or personal contact, to inform them about a product and its specifications. After a further publication, i.e. in forms of an article, a blog post, video or podcast, the message disseminates and gains *information reach*. As consumers receive it, it may trigger an intended effect, such as a buying, lending, renting or informing behavior, which leads to an *information impact* [32–34].

For successful influencer marketing, information reach and information impact need to be considered. However, just raising the amount of messages to influencers does not seem to be effective. Influencers are limited in their resources and time and need to decide quickly on messages for referral [15]. They evaluate the relevance of a message and its content [35], and decide either on its referral or against it. Such messages need to carry useful information for the individual influencer and its target group. Hence, its content has to be close to their needs and interests while be current at the same time [36, 37]. For this reason, we propose our first design parameter, which seeks to incorporate historical data on influencer behavior on marketer-generated content.

Design parameter 1 (DP1): The model predicts the relevance of marketer-generated content for individual influencers (content-influencer-fit)

If a sender of a message is trustworthy in the eye of a recipient, its messages are considered more relevant [38]. At the same time, a lack of trustworthiness reduces the likelihood of message referral [39]. Hence, if influencers get messages by a marketer they as not relevant, this may trigger negative effects on subsequent messages [29, 40]. To raise information reach and impact while at the same time limit negative effects of low reactions from influencers on marketer-generated content, we formulate our second design parameter as follows:

Design parameter 2 (DP1): The model recommends sending content to a selection of influencers with a sufficient content-influencer-fit.

In alignment with both design parameters, we will create a predictive model to assess content-influencer-fit prior to sending marketer-generated content.

3 Content-Influencer-Fit Model

3.1 Method

In the following, we describe our development of a content-influencer-fit model, which fulfills both design parameters and finally seeks to raise information reach and impact in influencer marketing. As we focus on marketer-generated messages, we concentrate on a content-based predictive model [41]. Our design research study follows an iterative and prototypical development, testing, and learning process [42] to create a prescriptive and abstract model [43]. For this purpose, we apply the procedural model proposed by Peffers et al. [18]. The prior sections already outlined (1) problem and context as well the (2) design parameters of the model. To test our assumptions, we inquired six influencer-marketing platforms on their capacity to fulfill DP1 and DP2 and interviewed two platform owners.

In the following, we outline the (3) development of the artifact, which followed two steps. At first, we iteratively created an (3a) attribute framework for describing marketer-generated content. For this purpose, we systematically reviewed literature on influencer marketing [44]. Afterwards, we applied the attribute framework to real marketer-generated content to (3b) predict influencer behavior and assess the importance of particular attributes of content on influencer behavior. While several predictive models for classification are potentially useful in this scenario, we focused on probabilistic techniques to assess the likelihood of content relevance for influencers. We chose to test two classification models, a Naive Bayes Classifier and a logistic regression model [45, 46], and after first iterations on the data, finally decided for the latter. Following an iterative design research procedure, our (4) evaluation entails artificial and naturalistic methods of artifact evaluation [47] as we abductively design a prescriptive model and test it on real-world data. Figure 1 summarizes our approach.

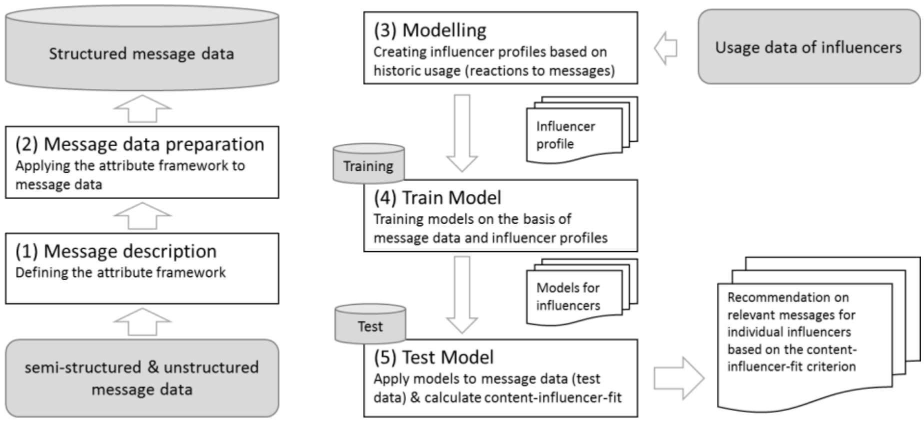

Figure 1 Procedure for designing a content-based recommendation system [45] we followed as part of the design phase in design science research methodology [18]

3.2 Attribute Framework for Marketer-Generated Content

A systematic literature review [44] on attributes, conceptualizations, or categorizations of content for influencers or consumers in eWOM revealed 56 publications. We queried focal libraries (Science Direct, EBSCO Business Source Premier, Web of Science and Scopus) concerning eWOM, message, and attributes (including synonyms). A backward- and forward search led to additional 14 articles. Most publications (>87%) have been published since 2011.

To assess the suitability of content for influencers, marketers need to consider both, its attributes as well as preferences of individual influencers [48–50]. However, only two publications explicitly focus on the relationship between particular content attributes and their effects on influencer's publication and referral behavior [29, 36]. In sum, we found 37 attributes from the literature review and sorted them into four categories. We discern between the **(a) formal quality**, **(b) informativity**, **(c) emotionality**, and **(d) other attributes** of a message. We coded the messages according to the attribute framework. After applying the result of our systematic literature review to five percent of the data, we added three additional attributes inductively (see table 1) from the interviews and from the additional meta-information provided by our case data. The following section presents the data set we used to train and test the model.

3.3 Data

We applied data from a local influencer-marketing platform "MoreImpact" (anonymized). Marketers use the platform to send messages to registered influencers from YouTube, Instagram, and Facebook. MoreImpact presents marketer-generated content as an offer for referral on its platform. Influencers react to these by explicitly signaling their interest. We applied data from messages to YouTube-influencers to limit a potential bias from diverging behavior between influencers on different networks. All influencers on MoreImpact have at least 1000 subscribers. We attained data on 415 messages from January 2015 to June 2016. The dataset also includes text, image, and metadata. We applied usage data from reactions of 674 active influencers on 4019 events in that timespan to the model. Each event represents an influencer who either reacted or not reacted to a message provided by MoreImpact. However, besides from 28 individuals most influencers lack a minimal activity needed for proper classification [46] per influencer. Minimal activity has been set to 15 positive reactions, which account for five percent of the overall positively coded messages.

Most of the attributes were human coded. However, we also automated coding of some attributes. Readibility was coded by applying the Flesch-Reading-Ease-Metric [52], supported by the web service Fleschindex.de. The length of a message was calculated by the number of characters in each string. "Language negativity and positivity" as well as "Degree of positivity of language" were coded by performing a sentiment analysis on the messages [22, 71]. After considering cross-correlations (correlations between attributes > 0.5) and after applying a variance-filter on binary attributes (variance < 0.1), the model contained 27 attributes.

The target variable for the predictive classification model reflects the reaction of an influencer to an offer provided by marketer-generated content on a binary scale. For this purpose, we controlled for the registration date of the influencer on MoreImpact in comparison to when messages were provided.

Table 1 Attribute framework for marketer-generated content (attributes applied to the models are marked with *)

Attributes on Formal Quality	Informativity Attributes
Error-free text [38] * Sufficient media quality [51] * _Media comprehensibility [inductive]_ * Readability [52] * Product comprehensibility [53] * _Comprehensibility of marketer aim [inductive]_ * Time of content placement [54] Image placement [39] * Video placement [39] * Link placement [55] Length [48] *	Experiential product characteristics [56] Application domain [57, 58] Branch [59] * Market stage [60] * Luxury product [61] Niche product [62] * Stage of development [63] Product availability [4] Distribution channels [64] * Price information [65, 66] * Specific advertising campaign [49] * Product utility explanation [65, 66] * List of (product) specifications [63, 64] * Comparison with other products [67] * Information on market performance [68] Application for target group exemplified [67]* Independent studies and tests [65, 66]
Emotionality Attributes	**Other Attributes**
Language negativity / positivity [22] * Degree of positivity of language [22] Exemplification through (personal) storytelling [37] * Interactivity with recipient [6] * Explicit call to action for influencer [49, 69] * Humor [59, 69] Message originality [22] Product originality [22, 70]*	Incentives [27, 49]* Amount of product specific information [65] * _Pre-specified video content type (“Review”,“Haul”, “Mention”, “Favorite”, “Tutorial” , “Lookbook”) [inductive]_ *

3.4 Iterative Design of the Content-Influencer-Fit Model

We designed the models in five steps. For each iteration, we sampled the data into 20 percent training data and 80 percent test data using a stratified sampling method in relation to the target variable [41]. In a first step, we performed a pre-test on a subsample of five highly active influencers (830 positive and negative reactions). We applied two predictive modelling techniques, a naive Bayes classifier and logistic regression. On our data set, both techniques are fundamentally able to predict the reaction probability of an influencer to marketer-generated content with the coded attributes (see table 1). This probability represents the *content-influencer-fit*.

Subsequently, these techniques assess the individual relevance of a message for an influencer as demanded by DP1. However, DP2 calls for a minimal quality of recommendation. For this reason, we evaluated both techniques on their prediction quality measuring accuracy and the F-measure for individual models of influencers [72]. Accuracy describes the ratio of correct classifications to all classifications. The F-measure, in comparison is a weighted harmonic mean between recall and precision of the model. While the accuracy of naive Bayes is about ten percent higher than logistic regression (0.77 to 0.84), the F-Measure is overall 33 percent higher (0.17 to 0.23). It can largely be explained by a relatively higher recall of logistic regression (0.25 to 0.12) in comparison to an only mildly lower precision (0.21 to 0.29) on average. As accuracy remains relatively high, we considered reducing false negatives in this case as more important than false positives. Subsequently, we moved on with a logistic regression technique and predicted the outcome for the 28 influencers who showed a minimum reaction to 15 marketer-generated messages.

Table 2 A 5x5 excerpt from the content-influencer-fit matrix

Influencer ID	**Message ID 517**	**Message ID 509**	**Message ID 506**	**Message ID 494**	**Message ID 427**
3870	0	0.000001	0	0	**0.998379**
292	0.013985	0.231794	0.01477	0.956613	0.734248
2918	0	0	0	0	**1**
3166	**1**	0	**0.992319**	**0.981688**	0
1188	0	0.000504	**0.999985**	0	0

DP2 demands a minimal content-influencer-fit as a threshold to contact influencers. To find an optimal threshold value, we chose to optimize the receiver operating characteristic (ROC) curve of the model to raise its precision, and contribute to a higher F-measure. In an iterative optimization process, we tested various threshold values and finally derived a minimal content-influencer-fit of 0.97. In comparison to the initial threshold of 0.5, we were able to raise precision by 0.11. Table 2 gives an overview on the results of the predictive analysis as presented in an excerpt of the content-influencer-fit matrix.

3.5 Evaluation

Design science research asks for a rigorous design process and a relevant artifact [17]. With regards to the latter, studies need to give proof to the artifact's usefulness [16]. For this purpose, the artifact needs to solve a relevant problem and fulfill the derived design parameters [18]. A systematic literature based problem definition and iterative design already represents first steps of a formative, ex-ante evaluation [47, 73, 74]. An inquiry into current influencer marketing platforms on the market together with two interviews with platform owners support our problem definition and design principles as part of the ex ante evaluation. One platform owner subsumed, that “such a function would be a real gain for our platform to create more value and provide additional service to our linked companies and influencers”. The other complemented this by saying: “no other providers has such a function at the moment, even though the importance of such a solution is by all means decisive.” Throughout the iterative design process of the attribute framework and the predictive model, we performed ex post summative and naturalistic evaluations, as we evaluated the model performance on real world data [47, 75]. The chosen metrics are sufficient for classification-based artifacts [17].

The results of this study are nonetheless also limited. The data focused on YouTube as one advertising platform for influencers. Regarding an inductive addition of attributes which refer to pre-defined video content types (i.e., haul, tutorial, lookbook etc.), we assume, other mediums will add further attributes or characteristics. While we created clear definitions for human coding of the attributes, the framework needs further testing, especially with regards to subjective codes, such as “originality” or “availability of a product”. Classifying 335 marketer-generated messages for 28 influencers on average leads to 9,380 classification decisions overall. Even while this is sufficient to test a predictive model with 27 attributes, additional influencers would add a larger variety of individual preferences into the training and test data set.

4 Summary and Contribution

Improving information reach and information impact of marketer-generated content is of decisive relevance for influencer marketing platforms and marketers, alike. However, current solutions for marketers to contact influencers mirror this only partially. Based on two design perimeters, this study proposes three important contributions. First, we present an attribute framework for marketer-generated content. Publications in the field of eWOM tend to reflect only particular attributes and rarely focus on specific target groups such as influencers [29, 36].

Second, we adopt the framework to design a predictive content-influencer-fit model. We integrate the separated discussions on influencer characteristics and attitude [3, 76] on one side, and content characteristics on the other [48].

Third, we find that influencers largely differ in their relevance criteria of marketer-generated content, which may be caused by the variety of underlying motivations to share the content [30]. However, a few patterns emerge, as some attributes tend to raise the content-influencer-fit for many influencers. Concerning the formal quality of marketer-generated content, readability of a message and a comprehensive use of additional media raises the likelihood that an influencer reacts positively mostly in all cases. From an informativity perspective, explaining the utility of a product or service as well as exemplifying the application for a specific target group shows mostly positive effects. Finally, we find that if marketers require a certain type of publication from the influencer, such as a “Mention” or “Tutorial”, it may raise the likelihood of a positive reaction. At the same time, other types, such as a lookbook, unanimously reduces it. Further behavioral research might inquire these patterns more deeply to propose recommendations for fitting the content to particular influencers.

The content-influencer-fit model, however, considers individual relevance criteria; a subsequent recommendation of influencers for given marketer-generated content is able to reduce the amount of irrelevant content and lowers the information overload.

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