Towards Fuzzy Analytics for Digital Video Advertising Campaign Effectiveness and Customer Experience

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Abstract

The recent growth of digital marketing channels has continued to drive the increase in brands' budgetary allocation for these marketing channels. However, questions are beginning to arise from marketing practitioners and brands on the justification of these budgets along these digital channels concerning their effectiveness and customer experience. This paper focuses on the aspect of mobile digital video advertisement with a view of examining its effectiveness and how viewers experience can be measured. This article proposes a fuzzy measurement approach to mobile video ad campaign experience using triangular fuzzy number evaluation approach. The experiment includes a comprehensive study on three different groups of mobile video ad viewers on a mobile network. A broad characteristic cross-section of mobile users with different types of mobile devices was randomly selected ($N = 150$) for empirical analysis. Videos and ads were tracked for these segmented users for 14 days. Also, a real-time online survey was enabled for these users and captured. This study models and clarifies fuzzy linguistic approach for measuring customer experience of mobile video ad campaign viewers. The result gives a better overall understanding of customer experience to advertisers and brands rather than relying only on score or scale of measurement.

Keywords:

1. Introduction

Using data analytics to improve customer experience and to target the right set of customers is very important for the optimization of digital advertisement campaigns. More than ever before, the need for customer experience tracking capabilities for effective generation of user experience-related data for analytics and measurement purposes is also growing [1].

Metrics that are related to the moment of experience for users are now more relevant compared to metric like click-through rate (CTR). Time, session and duration related metrics that give visibility into the user engagement are beginning to gain relevance than the tracking of clicks in the advert. Brands are more interested in engagement-related measurements as these give visibilities into the brand acceptance and connection between their audience and their brands [2].

As companies continue to increase their digital marketing budget yearly, demand for more customer experience trackable events is also on the increase [3]. Hence, a need for more innovative ways to measure campaign effectiveness along the customer experience journey in

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in order to justify the growing budget of digital marketing. Metrics such as the number of times a video advertisement is shared, downloads, scroll tracking, conversions leading to purchase, and count of interactions with ad are more trackable events. However, brands and advertisers require more granular measurement metrics that can stand the justification of the growing budget of digital marketing. While metrics on view ability are available and tracked by the digital ad industry, firms are more critical about segmentation metrics such as device, consumer lifestyle data, and metrics which can easily be layered on their internal data to make a sound marketing decision.

Digital era presents us with two unique opportunities that make measurement in the digital setting more authenticated than traditional advertising. Firstly, at a low cost, granular ad delivery data at the individual level of purchases are tracked and made available to advertisers. Secondly, at the individual level, ad delivery can be randomized to generate exogenous variation which is critical to identifying the drivers of the customers' actions [4]. Digital advertising has grown rapidly in such that its size has been doubled in the past 5 years and has demanded for more sophisticated audience measurement [5, 6]. One of the significant challenges for firms is on how to match the online ad spend with returns on digital advertising investment and customer experience.

In this study, we consider the video advertisement effectiveness along with the customer experience of the video ad viewers. By leveraging fuzzy analytics, we measure the customer experience at the moment truth when the digital ad is fresh in the memory of the viewers. This information is layered on other digital metrics at the individual viewer's level for robust measurement and justification of the customer experience and effectiveness of the video advertisement. In order to study this problem of customer experience and effectiveness of digital video advertisement, we consider a fuzzy evaluation approach and model the customer experience of digital video advertisement viewers. The viewers consist of three different segments of mobile users. Using fuzzy set theory, we define the linguistic terms and express it as a triangular fuzzy numbers (TFNs). The real digital video advertisement effectiveness and experience are captured along with the evaluation of the viewers' experience within the moment of the experience.

2. Method and Theoretical Approach

In this section, we briefly describe the method and the theoretical approach for fuzzy theory along with video and ad

effectiveness and customer experience and introduce TFNs.

2.1 Fuzzy Theory and Analytics

Measuring customer experience and satisfaction metrics cannot be purely statistical because the experience of the customer cannot be easily defined since it is inherently intangible [7]. Consumers' judgment on a service is a function of their expectations regarding various factors associated with the service [8]. Expectations and perceptions are part of the factors that form customers' beliefs regarding a service. The attributes of this would come from their experience with the service. Hence, perception, customer conclusion and expression of customer experience depend significantly on the linguistic judgment which depends on subjective knowledge and linguistic information. It is challenging to measure linguistic values using a classical mathematical function. The mathematical theory has been developed to deal with linguistics judgment in fuzzy set theory. For the vagueness of human thought, the fuzzy set theory was initially used. This is because it can easily represent the vague expression such as 'fair', 'satisfied', 'better', and 'good', which are usually the natural description of customers' preference and judgment [9]. With fuzzy set theory, we have seen alternative mean to accommodate boundaries that are unclear and subjective such as customer judgment about an experience from viewing a video advertisement on a mobile phone [10].

Many real-life scenarios have leveraged linguistic applications in different domains of decision making along with several mathematical formulations. For example, two alternatives were compared by [11] through a fuzzy linguistic scale which is characterized by trapezoidal fuzzy numbers. Also, in assessing the maintenance strategies and practices in a firm, in [12], the fuzzy linguistic approach was applied. In this study, all perceived statements such as 'very low', 'low', 'middle', 'high', and 'very high' are expressed into linguistic value.

In this study, we use the fuzzy set theory that has been applied in the field of management science to examine customer experience. Since customer experience is subjective, this study applies a fuzzy approach in analyzing the perceived quality of experience [13]. Our objective in this research is to determine the level of customer experience from the perceived quality of experience of a mobile video ad viewer using fuzzy linguistic evaluation.

2.2 Measuring Effectiveness in Digital Advertising

Comparing the measurement in early media with the digital era, the early days of radio, print, and television firstly focused on reach and frequency and then the effectiveness of advertising. In the case of this digital era, the availability of data from the beginning makes the scenario different. However, the availability of data has given room for the development of many metrics which today's advertiser are struggling with in terms of addressing their customer engagement and proving justification for their digital marketing budget. Digital advertising as an industry has evolved and measuring the exposure of ad alone is no longer satisfactory to advertisers and brands that are committing a massive portion of their marketing budget on these channels. Debate on the effectiveness of digital ad will continue as long as new media channels evolve and more data are available [14]. Also, surveys, home panels, sampling and extrapolation which characterized the traditional media measure could have been overcome by digital advertising, but this claim can only be on the area of reach and frequency of contact. Unfortunately, these metrics are not satisfying the needs of the advertisers.

The expectation of a typical firm buying and running a digital ad is simple. A brand wants to campaign and reach a certain amount of audience out of which a fraction should notice the brand, some to have an enhanced opinion about the brand with a considerable portion to end likely to buy the product. While a strong correlation is yet to be proven with sales, clicks were often viewed as a metric that is valid in measuring digital advertising impact. Big names in marketing research such as GfK, Kantar Millward Brown and Nielsen are unable to show a strong correlation between clicks and brand metrics [15]. Control and target group measurement methodology is acceptable for determining the effectiveness of the campaign. It has been widely argued that measuring exposure in a panel along with a comparison group of the non-exposed panel in the digital channel by adding a tracking pixel to a campaign is suitable for digital ad effectiveness and measurement. Brand metrics that have been impacted by the campaign can be tracked by the difference and by how much. While this approach still comes with challenges, it affords advertisers with more meaningful metrics than clicks [6] (Table 1).

Table 1. Trackable events and analytic usage

Event name	Description	Analytic usage
Start	-Time the player initializes	-Buffer time
Play	-The time the video starts to play -Reports a video ID and channel ID -Video offset	-The number of video playback -Video play by content hierarchy
Resume	-Time the video resumes following the video history -Reports progress marker, video ID, channel ID, and video offset	-The number of video playbacks -Which video is played
Progress	-Progress event indicates play progress of a video -Always report progress maker, video ID, and channel ID with the event -Triggered every 10 seconds after the video is played (or resumed) -Even when the user skips or rewinds, keep sending this event every 10 seconds of actual video played. This is also referred to as ?heartbeat?	-Minutes of video played
Pause	-When the user pauses the ad	-Number of pause events
Rewind	-When the user clicks the rewind button on the video player, reports rewind action with asset ID, channel ID, and playlist ID	-The number of rewind events
End	-When playback ends, user closeout or move to another video -Also, reports video ID, channel ID, and progress marker	-Minute of video played
AdStart	-When the ad starts	-Ad impression
AdEnd	-When the ad ends	-Ad impression
Click	-When a user clicks an ad	-CTR

Table 2. Critical factors for robust digital experience

Experience-related factors	Description
The ad load and repetition	Making sure that the amount of ads and length of (video) ads impact positively the viewer engagement.
Relevance	Ensuring that the ad aligns with the viewer's interest or needs. The more relevant – the greater the impact and ROI.
Customization	The degree to which a viewer is able to customize its ad experience.
Delivery	Technical aspects that can affect the viewing experience, including the content delivery/buffering and discoverability.

Effective measurement of customer experience is key to mobile network providers and brands that leveraged mobile platforms for digital advertisement. Most of the time, when an experience is bad, mobile users find it challenging to identify where the problems are coming from. They attribute most factors to mobile operators. Factors such as device capability, device settings, and data exhaustion can be easily attributed to bad quality of network when users are trying to view a video. Sometimes, the issues may be coming from the user as a result of the opening of many browsers. We measure the video experience of mobile users at the moment of truth. When the video has just been viewed, pause or terminated. We want to capture the experience of the video viewer when the customer can still remember exactly what happens during the video. In trying to measure specific service level management metrics, [16] demonstrates the effective use of the fuzzy evaluation method. Also, the fuzzy similarity approach was used for clustering the QoS opinions for web services by [17]. We saw an introduction of a fuzzy oriented approach for clustering service attributes along with the definition of the most significant of these attributes in personalized related services by [18]. Also, in [19], fuzzy evaluation of service level agreement (SLA), oriented quality metrics were applied in the next-generation network (NGN). For determining the application of fuzzy logic in such complex evaluation problems highlighted above, hypothetical values and not real values were used for this determination. However, our research combines both the actual data of the customer from the time the video is viewed till the end of the video with the customer responses of the experience at the end of the view which we refer to as the moment of truth.

2.2.1 Ad experience and effectiveness

Publishers and advertisers have critical role to play when it comes to monitoring the quality of ad viewing experience by the target audience (Table 2). Giving to customers an acceptable

viewing experience is not an easy task. Advertisers or firms have certain objectives which the ad needs to clearly deliver, and publishers need to be able to deliver on these through adequate content acquisition and distribution. There must be trade-offs in trying to balance these two factors which only experimentation can address [4].

Also, there are some common behavioral traits across digital channel for digital advertising that are also tracked. For social media we have behavioral traits such as shares, mentions, retweets, and web traffic followers. In content marketing, behavioral traits like downloads, shares, leads and conversion are also tracked. In the case of email, open rates, CTR, and conversion are tracked. In digital advertising, firms need to decide on marketing strategy which will inform the desired marketing mix to achieve their objectives. For an organization that has attained a convergence channel in customer engagement, each channel of strength needs to be considered in the marketing strategy. Complexity that characterized digital video needs to be understood as we seek to leverage its associated benefits. So many factors are in the play for a quality experience to be delivered to consumer in video advertising.

These include and not limited to branding, planning, pricing and creative decisions [6]. Opportunities to reach and engage consumers are open across many video platforms in different forms and shapes [2].

2.2.2 Mobile video advertising

Mobile devices have presented a robust platform for brands to tell their brands' story to customers through rich content on devices that are always with them. According to [20], consumer in the United States check their mobile phones 46 times per day on average across all age groups. With the penetration of smartphones across all ages and enhanced data speed technology, brands are left with no choice than to adopt mobile phones as a means of engaging and staying relevant with the consumers

at all times. However, despite growth in video consumption and content creation on mobile, there is still a gap between the time consumers spend with these devices and how much brands are willing to commit to this medium [4].

While desktop advertising through cookies has passed the primary identification issue to support measurement and ad delivery, there is still a difficulty in effective measurement of video on mobile [12]. There is a limitation to cookies on mobile due to the browser limitations and fragmented app/web environments. In identifying a user with a mobile device, cookies cannot be totally relied upon. While technology work around exists that can take off this challenge, frequent introduction of new video format still makes it a challenge [6, 20].

However, despite all these challenges, consumers are shifting to mobile media consumption which reflects mobile ad-revenue growth. Several factors are responsible for this growth such as broadband deployment, speed and bandwidth capacity which are enablers to quality video delivery. Another factor is a general shift towards mobile and growth in content, tablet, smartphone and connected application penetration.

2.3 Triangular Fuzzy Numbers

One of the fundamentals of marketing science is that customer behavior cannot be claimed to be well understood until it can be detailed into quantitative terms [21]. Fuzzy logic set effectively handles vague, inexact, stochastic input variables, and treats the dynamic nature of such variables. Classical or two-valued logic has to do with propositions that are either true or false. Fuzzy logic is an extension of many classical logic with proposition more than two truth values [22]. It incorporates fuzzy sets and relations, deals with linguistic variables and defines modifiers such as very, mostly, fairly, and so on.

Marketers determine the linguistic terms and the appropriate membership functions along the data mining process [22]. These linguistic terms can be quantified and expressed as TFNs using fuzzy set theory [23]. A special type of fuzzy number with three parameters is referred to as TFN. Each of the parameter represents the linguistic variable associated with a degree of membership of 0 and 1. TFN is commonly used in practice because of its convenience and ease of implementation in arithmetic operations [24].

In this work, we attempt to leverage fuzzy evaluation approach to the customer experience measurement of video advertisements that are viewed by mobile users. The experiment includes a wide study on three different groups of video adver-

tisement viewers on a mobile network. This study proposes an approach for the customer experience, where the main metrics for the evaluation are the perception and the individual satisfaction with the services used. However, in this article, we consider the real video views and capture the evaluation of their experience within the moment of the experience. Our experiment captures the real video advertisement viewers along their experience in real-time and draws heavily on materials in [23, 25].

2.4 Linguistic Variables and Integral fuzzy Numbers

The membership function of a fuzzy number $\tilde{A}$ is represented as:

$$f_A(x) = \begin{cases} \frac{x-b}{b-a}, & a \leq x \leq b, a \neq b, \\ \frac{x-c}{b-c}, & b \leq x \leq c, b \neq c, \\ 0, & \text{otherwise,} \end{cases} \quad (1)$$

Then, $\tilde{A}$ is referred to as TFN and denoted as $\tilde{A} = (a, b, c)$. A comparison between TFNs is very critical in decision making because of its flexibility nature and openness. In order to compare and later rank more than two fuzzy numbers simultaneous, Integral values for TFNs are proposed [25].

Eq. (2) defines the integral values for TFN $\tilde{A}$ as follows:

$$I(A) = (1 - \alpha) \int_0^1 g_A^L(\mu) d\mu + \alpha \int_0^1 g_A^R(\mu) d\mu,$$

where

$$0 \leq \alpha \leq 1,$$

and

$$\alpha = \frac{1-\alpha}{2}a + \frac{1}{2}b + \frac{\alpha}{2}c. \quad (2)$$

The α , which is the index of optimism is representing the degree of optimism for a person. The higher the α , the higher the degree of optimism. This index represents the level of optimism of a decision maker. In this case, a mobile viewer of the advertisement. Suppose the mobile user experience is neutral or moderate, the value of α equals 0.5. When $\alpha = 0.5$, the total integral value of the TFA $\tilde{A}$ equals:

$$I(A) = \left(1 - \frac{1}{2}\right) \int_0^1 g_A^L(\mu) d\mu + \frac{1}{2} \int_0^1 g_A^R(\mu) d\mu$$

$$= \frac{a + 2b + c}{4}. \quad (3)$$

Eq. (1)-(3) are directly used in the customer experience measurement computation [9].

3. Results

In this section, we present the result of the experiment along with the computational procedures step by step and suggested the outcome of the fuzzy triangular number (FTN) approach for the customer experiment measurement.

3.1 Analysis and Experiment

A large characteristic cross-section of mobile users with different types of mobile devices were randomly selected. They were categorized by their mobile devices into 3G (third generation technology) and 4G LTE (long-term evolution) enabled devices. Since mobile telecommunication operator where this study is carried out has a mixed of 4G and 3G networks, it is important we segment at the level of device to examine and neutralize the impact of the network on the experiment. Videos and ads were tracked for these segmented users over a period of 14 days. Also, a real-time online survey was enabled for these users. The survey popped up after the end of the video ad or after it was terminated by the user to evaluate the video experience—the experience was measured in real-time. It is expected that customers will remember fully their video experience at this time and their judgement can be leveraged for immediate improvement by the mobile telecommunication service provider or the advertising brand on the network. The real-time questionnaire was designed following questionnaire development of fuzzy ANP [26]. Table 3 shows the 10 perceived criteria for the evaluation of the customer experience that is used in this experiment.

3.2 Computational Procedure

In this computation, four procedural steps are followed (Figure 1).

Step 1: Definition of TFNs linguistic variables

Customer experience measurement criteria and corresponding linguistic values are first defined (Table 4).

Mobile users need to select on their screen for a given value from ‘bad experience’, ‘fair experience’, ‘good experience’, ‘very good experience’, and ‘excellent experience’. See the scale and its linguistics values in Table 5.

Table 3. Measurement criteria for customer experience evaluation

Segment	Perceived criteria
Ad	Content
	Ad length
	Ad positioning
Network	Video quality
	Video clarity
	Smoothness of view
	Network provider
Viewer	Connection type
	Device
	Geography

Table 4. TFN and linguistic variables

Linguistic variable	Symbol	TFN
Bad experience	BE	(0, 0, 1.5)
Fair experience	FE	(0, 1.5, 2.5)
Good experience	GE	(1, 2.5, 4)
Very good experience	VE	(2.5, 3.5, 5)
Excellent experience	EE	(3.5, 5, 5)

Table 5. Linguistic variable scale

Number	Linguistic variable
1	Bad experience
2	Fair experience
3	Good experience
4	Very good experience
5	Excellent experience

Step 2: Defining weight of linguistics variables

Suppose C_i denote the evaluation criteria of user experience, and let W_i denote corresponding C_i , $i = 1, 2, \dots, n$. The weights of C_i are defined as the peak, $(a_p, 1)$ of central triangular fuzzy number (a_i, a_p, a_2) for each linguistic value. Each linguistic variable comes with different weight (Table 6).

Step 3: Weights and TFNs Grouping

Criteria that are measured in TFNs are combined with corresponding weights to obtain the overall customer experience. Let the set of linguistic terms be $A_c = \{BE, FE, GE, VE, EE\}$. In assessing the customer experience, c_i denotes the measurement result of each experience criterion c_i , and $c_i \in A_c$. The corresponding TFN of c_i is represented by $\hat{c}_i$. In order to simplify

Figure 1. TFN evaluation procedure of mobile video ad experience.

Table 6. Weight of linguistic variables

Linguistic variable	Weight, W_i
Bad experience	(1.5, 1.5, 4)
Fair experience	(1.5, 4, 6.5)
Good experience	(4, 6.5, 9)
Very good experience	(6.5, 9, 11.5)
Excellent experience	(9, 11.5, 11.5)

the customer experience approximation, the linguistic terms in assessing the customer experience level of the video ad viewer are presented by TFNs $\tilde{A}$.

Following the measured criteria and their associated weights in Step 1 and Step 2, respectively, the overall customer experience $\tilde{A}$ can be derived from the following equation:

$$A = \left(\frac{1}{\sum_{i=1}^n W_i} \right) \otimes (W_1 \otimes \tilde{c}_1 \oplus W_2 \otimes \tilde{c}_2 \oplus \dots \oplus W_n \otimes \tilde{c}_n). \quad (4)$$

Step 4: $\tilde{A}$ Transformation into Linguistic Terms

For the advertisers to better understand the overall customer experience level and not relying on the score or scale, there is a need for the transformation of TFN of customer experience $\tilde{A}$ into linguistic terms, which is the original form. Few methods

such as shortest distance have been proposed for the conversion of the fuzzy numbers to corresponding linguistic terms [27, 28].

In this study, [29] methodology is leveraged to incorporate ranking fuzzy numbers with integral value in order to convert fuzzy numbers to their associated linguistic term.

Suppose

$$\tilde{u}_1 = BE, \tilde{u}_2 = FE, \tilde{u}_3 = GE, \tilde{u}_4 = VE, \tilde{u}_5 = EE.$$

Following Eq. (3) with $\alpha = 0.5$, the integral value of $\hat{u}_1 = 1, 2, \dots, 5$, can be obtained and later used as a preference comparison standard.

In finding j , we can have, $I(u_j) \leq I(A) \leq I(u_{j+1})$.

Let

$$P = \min \left\{ I(A) - I(\tilde{u}_j), \left| I(A) - \frac{I(\tilde{u}_j) + I(\tilde{u}_{j+1})}{2} \right|, I(\tilde{u}_{j+1}) - I(A) \right\}. \quad (5)$$

For the conversion, one of the following rules holds:

If

$$P = I(A) - I(\tilde{u}_j),$$

then, we represent the customer experience by $\hat{u}_j$.

Table 7. Integral values for $\hat{u}_i$

Linguistic term	BE	FE	GE	VE	EE
Corresp. TFN	$\hat{u}_1$	$\hat{u}_2$	$\hat{u}_3$	$\hat{u}_4$	$\hat{u}_5$
$I(\hat{u}_i)$	0.375	1.375	2.5	3.625	4.625

If

$$P = I(\tilde{u}_{j+1}) - I(A),$$

then the customer experience level is given by $\hat{u}_{j+1}$.

In case,

$$P = I(A) - \frac{I(\tilde{u}_j) + I(\tilde{u}_{j+1})}{2},$$

then the customer experience level is between $\hat{u}_j$ and $\hat{u}_{j+1}$. Before the decision, the integral value of $\hat{u}_i = 1, 2, \dots, 5$, are derived by Eq. (3) with $\alpha = 0.5$.

Table 7 represents the integral values of each linguistic terms.

In making linguistic decision, the integral values have been used as a guidance. The result for this experiment follows these computational procedures.

3.3 Computational outcome

From the online questionnaires that popped up after the termination of the video ad, which was viewed by the mobile users, responses for each criterion from the questionnaire were analyzed by taking the arithmetic mean from the scale. In order to have a smooth conversion to define TFN from linguistic variable, the scale is rounded off to nearest whole number. Following Step 2, the weight of each criterion is determined. We present an example of computation from a video advertisement viewer. Summation of weight is calculated as:

$$\sum_{i=1}^n W_i = 65.$$

We combined the TFNs of criteria and associated weights to arrive at the customer experience in Eq. (4).

Hence,

$$A = \left(\frac{235}{65}, \frac{412}{65}, \frac{535}{65} \right).$$

We used Eq. (3) for obtaining integral value $\tilde{A}$ which is 3.10204. This shows that linguistic terms that represents customer experience falls between ‘Good Experience’ ($\hat{u}_3$) and

‘Very Good Experience’ ($\hat{u}_4$). In a similar manner, all other viewers were calculated along their associated variables. The average integral value for all viewers with 3G capable device is 2.5177141. This shows that customer experience is between ($\hat{u}_3$) and ($\hat{u}_4$) which is between ‘Good Experience’ and ‘Very Good Experience’ in linguistic terms.

4. Conclusion

A comprehensive overview of digital video advertisement effectiveness and customer experience is provided in this paper, both from theoretical and empirical point of view. The recent growth in digital marketing budget allocation of brands is generating questions from marketing practitioners and brands on the need for the budget justification along effectiveness and customer experience. Several methods, metrics and approach for measuring video ad effectiveness and experience have been provided by literature. However, this study shows that due to the subjective nature of customer experience, which is fuzzy in nature, a linguistic approach can be leveraged for the measurement of customer experience of video ad campaign customers.

A straightforward and easy to follow approach are highlighted in this study for customer experience measurement of digital video viewers. Using selected criteria that are associated with a typical video ad, this paper has shown the importance of linguistic model in enhancing customer experience measurement. The captured perception of mobile video ad viewer is transformed into pre-defined fuzzy numbers. Weight are assigned, upon which fuzzy number of the criteria and corresponding weight are combined. Fuzzy experience score is later converted into linguistic term that reflects the customer experience of the video ad viewers.

This research and its associated results are significant for academics in the area of customer experience measurement as a theoretical concept. As marketing practitioners continue to find appropriate balance for the allocated digital budget and the effectiveness of these channels, this research will narrow the effectiveness and customer experience measurement gap that exist in mobile video ad campaign space.

Conflict of Interest

No potential conflict of interest relevant to this article was reported.

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