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Visual Narratives and Audience Engagement: Edutainment Interactive Strategies with Computer Vision and Natural Language Processing

Abstract

Purpose

This study explores how the integration of visual storytelling and textual elements within edutainment content drives recursive, emotionally grounded consumer engagement in interactive marketing environments. It challenges linear models of the consumer journey by emphasizing cyclical, meaning-making processes shaped by visual-symbolic and narrative cues.

Design/methodology/approach

Using a multimodal AI-assisted analytical approach, this study draws on natural language processing and computer vision to analyze over 10,000 social media posts from leading educational media brands. It identifies underlying engagement mechanisms by examining how visual themes and textual expressions interact to influence consumer behavior across different stages of the educationment experience.

Findings

Visual themes, especially those featuring human or natural elements, trigger early-stage attention, while emotionally resonant language anchors deeper involvement. This co-activation supports a recursive engagement model, where consumers continuously reinterpret and contribute to brand narratives through micro-actions and user-generated content. Engagement becomes a dynamic, participatory loop rather than a discrete outcome.

Research implications

Future research could explore how different visual and narrative elements influence emotional and cognitive engagement across diverse consumer groups. Additionally, investigating the long-term impact of recursive engagement on brand loyalty and consumer behavior will be valuable for further advancing interactive marketing theory.

Practice implications

For practitioners in interactive marketing, this research underscores the importance of using visually compelling narratives to craft personalized content that resonates emotionally with consumers. By integrating both emotional and cognitive dimensions into content strategies, brands can enhance consumer engagement. Furthermore, incorporating interactive features, such as user-generated content and real-time feedback loops, is crucial for fostering deeper consumer involvement and strengthening long-term brand loyalty.

Social implications

The growing influence of interactive marketing via edutainment and visual storytelling presents opportunities for brands to create more meaningful content that fosters engagement and learning. By aligning with consumers' values, brands can contribute to societal change, advocating for social and environmental causes while enhancing public awareness and participation.

Originality/value

This research reframes interactive marketing as a psychologically layered and dialogic process, offering new theoretical insight into the symbolic and affective mechanics of edutainment. It provides a data-driven foundation for designing content strategies that foster long-term emotional resonance and participatory brand relationships. By demonstrating how AI tools can decode and optimize multimodal engagement, the study contributes both conceptual advancement and methodological innovation to the field.

Keywords

1. Introduction

Interactive marketing has undergone a profound transformation, evolving from a traditional, oneway flow of information into a dynamic, interactive dialogue between brands and consumers (Wang, 2025). Historically, marketing was largely a passive process, where brands communicated messages to audiences with minimal feedback or participation. The advent of social media has reshaped this model, giving rise to a more engaging, reciprocal form of communication (Wang, 2023), empowering consumers to interact with brands and to share their opinions, influence content, and co-create marketing narratives (Valenzuela-Gálvez et al., 2022). As a result, consumers have transitioned from passive recipients to active participants, fundamentally altering the way brands engage with their audiences (Tong and Chan, 2023). In an era of fragmented attention spans and selective consumption, it is no longer sufficient for brands to simply deliver information. Instead, they must create experiences that emotionally resonate with their audience (Kim and Kim, 2023). In this newly established paradigm, symbolic visual narratives have emerged as crucial instruments for capturing consumer attention and fostering deeper engagement (Coker et al., 2021). It transforms traditional marketing from mere communication into immersive, shared experiences that drive deeper connections (Wang, 2024). Visual imagery captures attention instantly and evokes emotion, engaging the brain more rapidly and deeply than linear text (Kanuri et al., 2024). This cognitive immediacy forms the foundation for edutainment, which harnesses the persuasive power of visuals to deliver educational content in entertaining, emotionally resonant ways (Khalil et al., 2024). By transforming passive learning into immersive, participatory experiences, edutainment meets the modern consumer's desire for both engagement and insight, turning marketing into a space where storytelling, learning, and emotional connection converge (Krishen et al., 2024).

Despite the widespread recognition of visual storytelling's significance in interactive marketing, existing research has predominantly treated visual and textual elements in isolation. Studies have often focused on the impact of either visual or textual strategies independently, without addressing the potent synergy that arises when these elements are used together (Kunz and Wirtz, 2024, Chen et al., 2025). In response, our study proposes an integrated AI-driven methodology combining NLP and computer vision to explore how visual and textual components interact to enhance consumer engagement in marketing content (Hao and Demir, 2024). The central objective of this research is to explore how the combination of visual symbolism and narrative structure influences consumer engagement within edutainment contexts. Specifically, the study seeks to address three key questions: (1) How do visual themes, identified through topic modeling, affect user engagement in an edutainment context? (2) Which textual elements, as analyzed through NLP, most effectively enhance engagement? (3) What are the comparative effects of using visual and textual elements independently versus synergistically, and how do these differences inform interactive marketing strategies?

2. Literature review

2.1 Symbolic Visual Meaning in Consumer Engagement

In the evolving landscape of interactive marketing, symbolic visual meaning is pivotal in shaping consumer engagement, as visual elements have been shown to communicate complex information more efficiently than textual or linguistic representations (Aljukhadar et al., 2020). Narrative paradigm positions storytelling as a central mode of human communication, wherein meaning emerges through narrative logic rather than formal argumentation (Fisher, 1989). When brands are

framed as "actors" seeking to achieve the "goals" of consumer needs, visual narratives take on a transactive structure. This configuration invites viewers to decode the intended message while embedding their own interpretations into the narrative arc. The result is a participatory interpretive process that shifts the consumer role from passive viewer to co-narrator, establishing a communicative exchange where meaning is jointly constructed (Shao, 2024). In digital environments, visuals serve as powerful emotional triggers, generating instant responses that are both intense and memorable. Their non-verbal nature allows them to bypass cognitive filters, evoking empathy, identification, and even prompting action. This emotional immediacy captures attention and strengthens recall, making audiences more likely to engage with and respond to the content (Sharakhina et al., 2024). When integrated into interactive narratives, visuals do more than illustrate, they create immersive moments that deepen emotional connection and drive meaningful consumer engagement. Moreover, the Optimal Distinctiveness Theory explains why consumers gravitate toward content that maintains a balance between personal identity expression and social group belonging (Liao et al., 2023). Visuals that satisfy this dual need are more likely to be shared, thereby serving as markers of both individuality and collective affiliation. The compositional arrangement of visual content further shapes how consumers interact with and contribute to brand narratives. Social media platforms facilitate a fluid boundary between content creation and consumption, enabling users to remix, reinterpret, and redistribute branded visuals (Herrada-Lores et al., 2025). This co-creative process reconfigures the locus of authorship. Visuals become vessels for communal storytelling, where meaning is derived from both their aesthetic composition and the contextual interplay with user-generated responses. By leveraging the emotional power of narrative-driven visuals, coupled with interactive participation and co-creation, brands can cultivate deeper, more sustained connections with their audiences (Cuevas et al., 2021).

2.2 Leveraging Edutainment in Interactive Marketing: Cognitive, Emotional, and Co-Creative Dynamics in Consumer Engagement

Collective intelligence, as defined by Lévy (1997) is a dynamic, evolving process that thrives on the differentiation and integration of individual contributions. Within the context of interactive marketing, this collective process fosters a shared identity while enhancing the distinct input of each participant. It is shaped by key elements such as continuous interaction (Aljukhadar et al., 2020), interactive learning (Bertsimas and Mersereau, 2007), distributed collaboration (Achrol and Kotler, 2022), and the expansion of shared knowledge (Varadarajan et al., 2022). Interactive marketing environments serve as platforms where consumers and brands co-create meaning through digital dialogues and engagements, allowing individuals to learn from one another via mediated technologies. Drawing from sociocultural theory, individuals internalize knowledge in these spaces through tools and artifacts that scaffold social learning, echoing Vygotsky's zone of proximal development (Vygotsky and Cole, 1978). This underscores how marketing content, particularly in gamified or edutainment-based formats, can act as a "learning scaffold" that bridges personal and collective understanding. These mediated exchanges promote a shift from intrapsychological processes (internal cognition) to interpsychological interactions (shared cognition), where marketing becomes a cognitive and social act (Valor and Carrero, 2014). Such dynamics are vividly demonstrated in interactive environments, where users alternate between roles of competitors, collaborators, or co-creators. These experiences rely heavily on dialogue, immersion, and engagement, which are foundational to both collective intelligence and the effectiveness of edutainment in marketing (Wang, 2021). By merging education and entertainment, edutainment campaigns stimulate deeper cognitive and emotional involvement, encouraging

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consumers to actively participate in brand narratives and knowledge exchange (Qin, 2020). At the cognitive level, edutainment enhances consumer attention and comprehension by strategically combining verbal and visual cues. This multimodal presentation strengthens information encoding and retrieval, allowing individuals to absorb and retain content more effectively (Yoo et al., 2023). Visual content plays a critical role in simplifying abstract concepts and enhancing retention, facilitating sustained attention and deeper cognitive processing (Lyu and Huang, 2024). As consumers become mentally engaged, emotional resonance follows through immersive narratives featuring relatable characters and meaningful goals. This affective involvement strengthens perceived relevance, fostering empathic alignment and shaping how brand messages are interpreted and evaluated (Peltier et al., 2024). Within edutainment, emotional and cognitive engagement converge to drive behavioral responses, manifested through participation, customization, and co-creation across interactive platforms, transforming passive viewers into active brand collaborators (Khalil et al., 2024).

2.3 AI in Social Media Engagement Analysis

AI transforms interactive marketing by offering data-driven approach to understanding and engaging consumers. By analyzing key engagement metrics such as likes, shares, comments, and click-through rates, AI can predict future interactions and tailor content to suit individual user preferences (Peltier et al., 2024). Supervised learning algorithms use historical data to refine content delivery, while unsupervised methods, like clustering and association rule mining, uncover hidden user patterns, improving content targeting and audience segmentation (Hao and Demir, 2024). NLP enhances this by processing large volumes of text data from social media, performing sentiment analysis to gauge the emotional tone of discussions, and topic modeling to identify trending themes (Graham and Stough, 2025). This enables brands to craft educational content that resonates emotionally and aligns with cognitive needs, strengthening engagement. Moreover, computer vision enables the analysis of visual elements, such as color, shapes, facial expressions, and image content, linking these features to engagement metrics like time spent on content, interactions per post, and conversion rates (Kang and Lou, 2022). By integrating visual and textual data, brands gain a holistic view of consumer interaction across platforms. This comprehensive , th , pation , can craft motional con. understanding allows marketers to create immersive edutainment experiences that foster both intellectual and emotional involvement, driving sustained attention and participation (Johnson et al., 2023). Through AI-powered insights and creative storytelling, brands can craft dynamic content strategies that encourage active consumer participation and deepen emotional connections with the audience.

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Figure 1. Conceptual map.

Figure 1 illustrates a cyclical and integrative framework for understanding consumer engagement within the context of social media-based interactive marketing. It delineates how various layers of meaning, representational, interactive, and compositional, interact to produce cognitive and emotional resonance, ultimately shaping brand identity and consumer relationships. The process begins with representational meaning, where consumers engage cognitively by interpreting visual narratives that align a brand (as the actor) with consumer goals or desires. This symbolic alignment initiates intellectual resonance, serving as a cognitive entry point for deeper engagement.

As consumers progress through the engagement process, interactive meaning emerges through emotional responses elicited by experiences, behaviors, and symbolic storytelling. Emotional resonance deepens involvement by establishing affective bonds between the consumer and brand, setting the stage for more sustained interaction. This transition from cognitive to emotional processing reflects the dual-channel pathways through which meaning is constructed and internalized in interactive marketing environments. Compositional meaning operationalizes these responses by capturing observable actions, such as likes, shares, and comments, that indicate how users interact with and respond to content. These behavioral cues are not merely passive reactions; they signal active participation in content circulation and community co-creation. At this stage, content personalization becomes crucial, particularly in edutainment contexts, where educational material is adapted to be both cognitively manageable and emotionally engaging. This is where cognitive load management intersects with symbolic communication, optimizing content so it is easier to process, remember, and act upon. The framework is supported by AI-enabled engagement analytics, which act as feedback mechanisms to assess emotional and cognitive impact. Ultimately, the integration of representational, emotional, and behavioral dynamics converges in the development of brand identity and consumer relationships, reinforced through community building and iterative personalization. This conceptual map captures the recursive nature of

engagement: cognitive attention leads to emotional involvement, which is expressed through behavioral interaction, fed back through AI analysis, and translated into adaptive content strategies.

3. Methodology

The research process (Figure 2) begins with Data Extraction, where raw data is collected via Instagram Application Programming Interfaces (APIs), following the protocols outlined by Grewal et al. (2021), the process begins with assembling a Source Dataset to structure the extracted data. This is followed by Data Preprocessing and Feature Engineering, where the data is cleaned and relevant features are prepared for model input. The Microsoft Azure AI Vision Service is then used to extract visual features, followed by model training and evaluation. Concurrently, Topic Modeling is applied to uncover hidden themes in the text, with the number of topics optimized using Coherence Scores. After identifying the optimal number of topics, the Topic Model is refined, and its significance is analyzed. Finally, the Optimized Engagement Prediction Model is evaluated to predict user engagement, with the insights applied to assess engagement for the identified topics.



Figure 2. Process Flow.

3.1 Data extraction and dataset preparation

In December 2023, a comprehensive dataset was assembled using the Instaloader (instaloader.github.io), a Python-based tool designed for data extraction on Instagram. The dataset incorporated various metrics indicative of user engagement, including URLs of individual posts, counts of comments and likes, captions, image URLs, and the presence of video content. According to Table 1, National Geographic stands out with an impressive follower count of 283 million, dwarfing PBS Nature's modest 150,000 followers. Notably, both BBC Earth and National Geographic exhibit considerable online activity, each with a post count exceeding 3,000, which markedly surpasses the post frequency of the other entities in the dataset, all of which have posted in excess of 1,000 times.

Table 1. Social Media Engagement Data (Acquired on 15th December 2023).

Brand	User Name	Total Posts	Number of followers
National Geographic	natgeo	3,161	283M

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BBC Earth	bbearth	3,662	10.5M	
Animal Planet	animalplanet	1,127	5.5M	
PBS Nature	pbsnature	1,000	150K	
The Discovery	discovery	1,548	19.5M	

3.2 Data preprocessing and feature engineering

The data preprocessing methodology in this research follows a sequential approach (Onikoyi et al., 2023). Text is first converted to lowercase to unify word variations, then non-ASCII characters are removed. Lemmatization is applied to reduce words to their dictionary form, and punctuation is stripped to minimize noise. Finally, Term-Frequency - Inverse Document Frequency (TF-IDF) vectorization is used for English words, reflecting the importance of a word in a document relative to its frequency across all documents (Berger et al., 2020).

The engagement metric is the target variable for feature engineering (Kamal and Bablu, 2022). Features like 'number_of_likes' and 'number_of_comments' are standardized by dividing them by their maximum values (Rajendran and Karthi, 2022). The post with the highest values for each feature will have them scaled to one. The engagement score is calculated as a weighted average of the standardized likes and comments. The median number of comments (237) and likes (51,000) are used to classify posts as high or low engagement, with posts exceeding the median categorized as high engagement (Narayanan, 2023).

Model evaluation is crucial for assessing predictive models (Shmueli et al., 2019), providing a quantitative measure of performance and identifying areas for improvement. Without thorough evaluation, the model's predictions lack reliability in real-world applications (Sharma and Shafiq, 2022). We used Accuracy, ROC-AUC, and F1-Score to evaluate our models. Accuracy provides a direct measure of effectiveness (Dhaoui et al., 2017), while ROC-AUC assesses the model's ability to distinguish between classes, with a score close to 1 indicating strong performance (Berger, 2013). The F1-Score balances precision and recall, crucial when false positives and false negatives have different costs, such as misidentifying high or low engagement posts (Chicco and Jurman, 2020).

3.3 Computer vision

Prior to incorporating all images, it is necessary to extract visual features from the images obtained via their respective URLs (Philp et al., 2022). For each image, descriptive labels were generated by employing the Object Identification module within Microsoft Azure's Computer Vision Services (Lee et al., 2022). This service enables the application of Microsoft's advanced pre-trained models to discern and classify visual information within the images. Typically, an array of tags or labels is associated with each image, providing a multi-faceted representation of its content. The classification models were trained to predict whether a post will receive high engagement or not. The median of each brand was used to calculate the binary target to account for the differences in the number of followers. It is framed as a binary classification problem (Zhu et al., 2021). Since the target variable was split using the median, the classes are well-balanced for the classification models were

used to train the classification models. All the models we validated using 20% of the data that was held out during the training for evaluation of unseen data. The data was split randomly into train and test using the train_test_split function from the sklearn package.

- Global model: Contains all posts of all the different brands.
- ii) Five different individual models with each dataset containing only the data of a single brand.

For both sets of datasets, models were trained using features generated by the corresponding captions and labels split into three feature groups.

- iii) Only Text Model Captions only features
- ii) Only Image Model Labels only feature
- iv) Both Text and Image Captions + Label Features

3.4 Natural language processing

i)

Topic modeling, particularly LDA, is a key tool in text mining and NLP, widely used in marketing (Das et al., 2023). LDA was chosen for its ability to handle large datasets and uncover latent structures, which is crucial in marketing research (Pavlinek and Podgorelec, 2017). The process began with data review and pre-processing, including tokenization, stop-word removal, and lemmatization, to optimize the corpus for topic modeling (Albalawi et al., 2020). Coherence measures helped determine the optimal number of topics by evaluating semantic similarity, with higher scores indicating more meaningful topics (Abdelrazek et al., 2023).

3.5 Optimized engagement prediction model

Logistic regression estimates the probability of an event, such as a social media post receiving high engagement, based on independent factors (Li and Xie, 2020). Unlike linear regression, it is suited for binary outcomes like 'high' or 'low' engagement (Table 2). To handle the complexity of numerous text features, L1 regularization (Lasso) was applied to eliminate irrelevant coefficients, simplifying the model without losing predictive power (Yang et al., 2023). Table 2. Engagement Classification Based on Median Scores for Different Brands.

Brand	High Engagement	Low Engagement	Total Posts
National Geographic	1,580	1,581	3,161
BBC Earth	1,831	1,831	3,662
Animal Planet	564	563	1,127
PBS Nature	500	500	1,000
The Discovery	774	774	1,548
All Brands Together	5,249	5,249	10,498

4. Results

4.1 Model Performance

The area under the ROC-AUC curve is 0.63, which suggests that the model has a moderate ability to distinguish between the two classes (Figure 3). The red dot at a threshold of 0.50 indicates a specific point on the ROC curve where the true positive rate and false positive rate are both just

above 0.5, implying that this threshold provides a balance between sensitivity and specificity for the classifier in question.



Figure 3. Receiver Operating Characteristic Curve.

The confusion matrix (Figure 4) shows that the model is quite adept at identifying class 0, with a commendable number of 713 instances accurately classified as true negatives. It also demonstrates a substantial ability to recognize class 1, with a total of 613 true positives. The model does encounter some challenges, such as misclassifying 371 instances of class 0 as class 1 (false positives) and 403 instances of class 1 as class 0 (false negatives).



Figure 4. Confusion Matrix.

4.2 Feature Importance

Figure 5 presents a bar chart detailing the influence of various textual features on the predictive performance of a social media engagement model. The chart reveals 'amazinganimal', 'video', and 'landmammal' as the most positively influential features, with 'amazinganimal' exhibiting the highest importance score, suggesting a substantial positive correlation with increased user engagement. On the opposite spectrum, features such as 'community', 'watch', and 'bbcearth' demonstrate the most significant negative impact, with 'bbcearth' showing the largest negative score, indicating a strong inverse correlation with engagement.



Figure 5. Feature Importance Plot.

4.3 Comparison of Predictive Models

Table 3 evaluates three predictive models for social media engagement using captions, labels, or a combination of both. The "Captions Only" model outperformed others (66% accuracy, 0.71 ROC-AUC), with high-engagement terms such as *earthlover*, *potd*, and *landmammal*, while community and bbcearth were negatively associated. The "Labels Only" model showed lower predictive power (59% accuracy, 0.62 AUC), though visually salient terms like *leopard* and *wing* contributed positively. The combined model achieved balanced performance (63% accuracy, 0.68 AUC), reinforcing the impact of caption-driven features. Among the 18 evaluated models, the global model was the most robust, offering broad applicability across brands by using median engagement scores to adjust for follower differences. The captions-only model achieved 65% accuracy, 0.71 ROC-AUC, and 0.64 F1-score, with terms like 'earthlover' and 'potd' boosting engagement, while terms like 'bbcearth' and 'community' correlated with lower interaction. The model combining captions and labels showed slightly lower performance (63% accuracy, 0.68 ROC-AUC, 0.61 F1-score), with 'amazinganimal' and 'video' increasing engagement, while 'link' and 'watch' decreased it. Appendix 1 shows that 'amazinganimal' was linked to higher engagement in 71% of top posts, with a coefficient of 4.06. Appendix 2 highlights that terms like 'link' and 'watch' are associated with reduced engagement, suggesting a need for revised content strategies.

Table 3. Accuracy, ROC AUC Score, F1 Scores, and words contribute to positive and negative engagement of predictive models with different feature sets.

Accurac	ROC_	F1	Confusion	Top 10 Positive	Top 10
У	AUC		Matrix	Words	Negative Words
0.66	0.71	0.64	[[748, 336],	earthlover, potd,	story,
			[384, 632]]	landmammal, read,	earthcapture,
				ornithology, video,	team, bio,
				vid,	community,
					episode, bbc,
	Accurac y 0.66	AccuracROC_yAUC0.660.71	AccuracROC_F1yAUC0.660.710.64	Accurac ROC_ AUC F1 Confusion Matrix 0.66 0.71 0.64 [[748, 336], [384, 632]]	Accurac yROC_ AUCF1 MatrixConfusion MatrixTop 10 Words0.660.710.64[[748, 336], [384, 632]]earthlover, potd, landmammal, read, ornithology, video, vid,

					amazinganimal,	earthonlocation,
					beautifulbird, baby	pm, bbcearth
Labels	0.59	0.62	0.61	[[582, 454],	leopard, new,	landform,
Only				[405, 659]]	wing, star, rodent,	wearing, man,
					human, animal,	aqua, breed,
					snake, penguin,	transport, body,
					whale	sun, clothing,
						chimpanzee
Captions	0.63	0.68	0.61	[[713, 371],	amazinganimal,	month, change,
and Labels				[403, 613]]	potd, video,	area, meet,
Together					landmammal, read,	clothing, nature,
					naturephotography	watch,
					, birdsofinstagram,	community,
					baby,	link, bbcearth
					earthloveranimal,	
		1			photo	

4.4 Topic Modeling and Thematic Engagement

According to Figure 6, both 5 and 7 topics produce higher coherence scores than 3, 4, and 6 topics, suggesting that these configurations offer the most semantically consistent and coherent interpretation of the corpus. The dip in coherence at 6 topics indicates that the corpus does not naturally separate into six distinct topics, making 5 or 7 topics more suitable for analysis.



Figure 6. Number of topics vs Coherence.

The pyLDAvis tool visualizes these findings, with Figure 7 showing an Intertopic Distance Map and the Top-30 Most Salient Terms for one of the five topics. The map highlights the relative positioning of the topics, where proximity between bubbles indicates similarity. Topics 1 and 3 show some overlap, suggesting a thematic correlation, while Topics 2, 4, and 5 are more distinct, reflecting unique thematic content. The size of the bubbles indicates the relative prevalence of each topic in the corpus, with larger bubbles representing more dominant topics. On the right, the bar chart displays the most relevant terms for Topic 1, such as "bird", "marine", and "wildlife", which reveal the naturalistic focus of this topic.



Figure 7. pyLDAvis tool and the visualization of topics.

In Figure 8, the Intertopic Distance Map further emphasizes the isolation or overlap between topics, complementing the previous figure by focusing on a different topic. Again, bubble size reflects the discourse share of each topic, while the bar chart illustrates the Top-30 Most Relevant Terms for another topic, showing a focus on terms like "animal," "wildlife," and "outdoor," suggesting that or ortoist ithin the this topic is heavily associated with naturalistic themes. Terms like "tortoise" and "field," while less frequent, are also significant, providing additional context within the broader thematic landscape.



Figure 8. Topic Dominance and Keyword Specificity in Content Analysis.

Tables 4 and 5 provide further insight into the topic modeling results, summarizing the terms that define each topic. For example, Topic 1, "Wildlife Kingdom," is characterized by terms like "animal," "wildlife," and "tiger," reflecting its focus on ecological and biological themes. Topic 2, "Natural Wonders," emphasizes outdoor scenery and environmental photography, with terms like "nature," "landscape," and "mountain." "Avian Serenity" (Topic 3) merges avian life with celestial themes, while "Human Portraits" (Topic 4) centers on personal and social aspects of human life, as indicated by terms like "person," "dog," and "clothing." Finally, "Marine Exploration" (Topic 5) is dominated by terms related to marine ecosystems, such as "marine," "reef," and "shark."

Table 4. Topical Word Frequencies Across Five Distinct Topics.

Topics	Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Word 9	Word 10
Topic 1	animal	wildlife	cat	tiger	grass	outdoor	snout	field	mammal	monkey
Topic 2	nature	landscape	mountain	sky	water	cloud	plant	sunrise	outdoor	photography
Topic 3	bird	beak	wildlife	night	space	star	branch	penguin	moon	seal
Topic 4	person	dog	ice	face	clothing	art	indoor	cap	man	woman
Topic 5	marine	biology	water	reef	sea	fin	organism	shark	aquarium	underwater
					4					
Т	able 5. Top	ic Identifica	ation.							

Table 5. Topic Identification.

Торіс	Theme	
Topic 1	Wildlife Kingdom	To
Topic 2	Natural Wonders	
Topic 3	Avian Serenity	

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Topic 4	Human Portraits
Topic 5	Marine Exploration

Table 6 links these topics to user engagement, revealing that "Human Portraits" commands the highest proportion of high engagement posts at 54.40%, followed closely by "Wildlife Kingdom" at 53.77%. "Marine Exploration" shows moderate engagement at 47.94%, while "Avian Serenity" and "Natural Wonders" exhibit lower engagement at 45.29% and 45.03%, respectively. Table 6. Proportion of High Engagement Posts.

Торіс	Proportion of High Engagement Posts
Human_Portraits	54.40%
Wildlife_Kingdom	53.77%
Marine_Exploration	47.94%
Avian_Serenity	45.29%
Natural_Wonders	45.03%

5. Discussion

Today's audiences, especially within social media environments, are no longer passive recipients of content, they demand experiences that are emotionally resonant, cognitively enriching, and personally relevant. Edutainment, content designed to educate through entertainment, meets this demand by blending informational value with affective appeal, transforming learning into an accessible and desirable experience (Khalil et al., 2024). Visual storytelling intensifies this impact, using the immediacy of imagery to convey complex ideas with clarity and emotional depth, allowing consumers to connect with content both intuitively and reflectively (Ryu, 2024). As digital ecosystems grow increasingly visual and interactive, understanding how narratives are constructed through the interplay of image and language becomes essential for brands seeking to foster sustained, reciprocal relationships (Swaminathan et al., 2022). Against this backdrop, traditional conceptions of the consumer journey, often framed as linear progressions from awareness to purchase, prove inadequate. In edutainment-driven interactive marketing, the consumer journey is better understood as a recursive, psychologically layered cycle in which each encounter with content is shaped by prior experiences and anticipates future engagements (Ahmed et al., 2024). Emotional and cognitive responses do not simply follow sequential stages; they accumulate, interact, and feed back into the journey, forming a dynamic loop of participation and meaning making (Kim, 2024). Studying this evolving form of engagement offers timely insights into how consumers make sense of content, construct identities, and forge connections in the saturated, visually driven environments that now define digital life.

In the initial stages of consumer engagement, visual narratives function as the primary entry point into meaningful interaction (Malodia et al., 2024). The data from this study indicate that imagery featuring human faces, natural landscapes, or wildlife, particularly those that evoke emotional familiarity, serves as a powerful stimulus for attention. These visual cues draw on inherent psychological mechanisms such as pareidolia and narrative inference, creating an immediate affective response that extends the duration of attention and invites reflective processing (Shen et al., 2024). When complemented by semantically resonant textual cues, the visual content signals

a level of personal alignment, suggesting that the consumer's values, interests, or aspirations are being acknowledged (Al-Tameemi et al., 2024). This perception of mutual recognition often initiates micro-engagement behaviors such as liking, commenting, or sharing. Rather than incidental reactions, these behaviors represent meaningful gestures that reflect the user's emotional and cognitive involvement. In this way, consumers begin to integrate the brand's message into their personal interpretive frameworks, allowing the content to take root within their everyday digital experiences.

As the consumer progresses into a more evaluative mindset, the narrative function of content begins to shift. At this stage, the experience must support discernment while maintaining affective connection. Content that feels too generic or excessively promotional tends to be bypassed in favor of material that feels sincere and contextually relevant. A well-calibrated balance of emotional texture and informational clarity provides consumers with both the motivation to stay engaged and the tools to make thoughtful decisions (Drossos et al., 2024). In edutainment-driven contexts, this balance is achieved through visuals that are emotionally compelling and language that is conceptually transparent. Effective content at this phase presents complex ideas with clarity, inviting consumers to engage intellectually without overwhelming them. When consumers encounter media that validates their sense of self while supporting decision-making, trust is reinforced (Kim et al., 2025).

Following the point of purchase, visual narratives continue to shape the consumer's experience, though the objective now moves toward affirmation and continuity. Post-purchase content functions as a mirror, reflecting back the values associated with the consumer's decision. Imagery and language that emphasize shared ideals, community, purpose, environmental awareness, personal growth, anchor the consumer's actions within a broader narrative arc. Through this reflective process, consumers are encouraged to revisit and reinterpret their relationship with the brand, not as a static memory, but as an evolving part of their self-concept (He and Zhang, 2022). Importantly, this stage also introduces opportunities for consumer expression. Storytelling becomes dialogic, consumers begin contributing their perspectives through reviews, comments, and personal stories (Crespo et al., 2023). These participatory actions grant consumers a degree of narrative authorship, reinforcing their emotional ties and embedding the brand further into their cultural and personal lives.

What emerges from this cycle is a model of engagement that is fluid, recursive, and dialogically constructed. Consumer involvement unfolds not through isolated reactions but through a sequence of recognitions, reflections, and reinforcements that evolve across time. Emotional and cognitive dimensions of engagement operate in parallel and in tandem, responding to the shape and texture of content at each touchpoint (Ahmed et al., 2024). Visual storytelling that evokes emotional identification while guiding conceptual understanding activates both processes simultaneously, generating a deeper and more durable connection. Within the context of edutainment, this dual engagement becomes particularly salient, as audiences navigate content that seeks to inform without compromising on enjoyment (Chong et al., 2024). The findings suggest that the success of interactive marketing in this space relies less on the novelty of technological delivery and more on the psychological precision of narrative construction, how effectively content anticipates emotional cues, speaks to internal motivations, and accommodates critical thought (Hao et al., 2024). In this mechanism, engagement ceases to be a momentary metric of attention and becomes

a measure of relational resonance, accumulated, sustained, and continually shaped through collaborative meaning-making.

6. Conclusion

This study provides a novel perspective on how visual storytelling and textual cues jointly shape user engagement within the interactive marketing landscape of edutainment. Rather than treating consumer engagement as a one-directional progression from awareness to purchase, our findings suggest that engagement unfolds as a recursive and emotionally layered process, where each content encounter is shaped by prior experiences and in turn redefines future interactions. In this dynamic process, visual and textual content elements act not merely as tools for message delivery but as interwoven narrative mechanisms that influence how consumers feel, think, and participate in brand experiences.

Visual storytelling plays a foundational role in capturing attention and initiating affective responses at the early stages of the consumer journey. In interactive marketing contexts, especially those driven by edutainment, this visual component acts as a powerful stimulus for engagement by tapping into consumers' social cognition and emotional memory. Familiar patterns, such as human faces, natural scenes, or symbolic imagery, evoke recognition and emotional proximity, encouraging users to move beyond passive viewing and toward immersive interaction. When these visual cues are strategically paired with emotionally aligned textual expressions, language that reinforces the narrative tone, intention, or cultural relevance, the synergy between modalities amplifies cognitive and emotional processing. This co-activation leads to more meaningful engagement behaviors, such as liking, commenting, or sharing, which function as micro-signals of the consumer's interpretive alignment and affective investment. These micro-interactions, though often subtle, represent an important layer of participatory meaning-making. Rather than viewing them as isolated actions, they can be understood as early indicators of narrative transportation and personal identification with brand stories. As the consumer journey progresses into more evaluative stages, visual and textual cues continue to operate as dual channels guiding decisionmaking. At this point, consumers are not simply seeking entertainment or information, they are searching for content that aligns with their self-concept, social values, and aspirational goals. Effective edutainment content sustains this engagement by providing emotional resonance and conceptual clarity simultaneously. It supports consumers as they negotiate the symbolic value of what they consume, linking brand messaging to broader identity narratives and lived experiences. Crucially, this emotional-cognitive integration transforms content from a persuasive device into a vehicle for self-exploration and psychological meaning. Content that resonates across both channels becomes transformative, it empowers the consumer to feel seen, understood, and connected. In this way, the brand becomes less of a message sender and more of a narrative partner in the consumer's unfolding sense of self. Post-engagement, the interaction does not end but enters a new phase of narrative re-entry. Consumers revisit the brand from a different vantage point, one shaped by prior emotional experience and social recognition. Content in this stage shifts from driving action to affirming identity, reinforcing shared values and deepening relational ties. Visual storytelling operates as a mirror, reflecting community, ideals, and symbolic alignment, while textual content invites user contribution, whether through comments, reinterpretations, or content co-creation.

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This study contributes to the understanding of consumer engagement within interactive marketing, particularly in the context of edutainment. By integrating visual storytelling and participatory engagement, it opens new avenues for research on how emotional and cognitive engagement interact to shape consumer behavior. Future studies can explore the psychological mechanisms behind visual storytelling in more detail, investigating how different types of visuals and narrative structures impact emotional and cognitive responses across various demographic groups. Additionally, this research encourages further exploration into the long-term effects of recursive engagement, examining how repeated brand interactions influence consumer loyalty and brand affinity over time. For practitioners, this study offers valuable insights into how visual narratives can be used to craft personalized and emotionally resonant content that fosters deeper consumer engagement. Brands should focus on creating content that aligns with consumers' values and aspirations, enhancing the emotional connection and trust. The study also highlights the importance of integrating both emotional and cognitive dimensions in content design, ensuring that edutainment content is entertaining informative and intellectually stimulating. Furthermore, interactive features such as user-generated content and real-time feedback loops should be incorporated into marketing strategies to encourage consumers to become co-creators of the brand narrative, ultimately strengthening brand loyalty and long-term engagement. From a societal perspective, the rise of edutainment and visual storytelling presents an opportunity for more meaningful and impactful content consumption. By merging education with entertainment, brands can contribute to a more informed and engaged public, fostering a culture of learning through enjoyable experiences. As consumers increasingly seek content that aligns with their personal values, there is an opportunity for brands to use their platform to advocate for social causes, environmental awareness, and positive societal change.

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- Abdelrazek, A., Eid, Y., Gawish, E., Medhat, W. and Hassan, A. (2023), "Topic modeling algorithms and applications: A survey", *Information Systems*, Vol. 112, p. 102131.
- Achrol, R. S. and Kotler, P. (2022), "Distributed marketing networks: The fourth industrial revolution", *Journal of Business Research*, Vol. 150, pp. 515-527.
- Ahmed, S., Sharif, T., Ting, D. H. and Sharif, S. J. (2024), "Crafting emotional engagement and immersive experiences: Comprehensive scale development for and validation of hospitality marketing storytelling involvement", *Psychology & Marketing*, Vol. 41 No. 7, pp. 1514-1529.
- Al-Tameemi, I. K. S., Feizi-Derakhshi, M.-R., Pashazadeh, S. and Asadpour, M. (2024), "A comprehensive review of visual-textual sentiment analysis from social media networks", *Journal of Computational Social Science*, Vol. 7 No. 3, pp. 2767-2838.
- Albalawi, R., Yeap, T. H. and Benyoucef, M. (2020), "Using topic modeling methods for short-text data: A comparative analysis", *Frontiers in artificial intelligence*, Vol. 3, p. 42.
- Aljukhadar, M., Bériault Poirier, A. and Senecal, S. (2020), "Imagery makes social media captivating! Aesthetic value in a consumer-as-value-maximizer framework", *Journal of Research in Interactive Marketing*, Vol. 14 No. 3, pp. 285-303.
- Berger, J., Humphreys, A., Ludwig, S., Moe, W. W., Netzer, O. and Schweidel, D. A. (2020), "Uniting the tribes: Using text for marketing insight", *Journal of marketing*, Vol. 84 No. 1, pp. 1-25.
- Berger, J. O. (2013), *Statistical decision theory and Bayesian analysis*, Springer Science & Business Media.
- Bertsimas, D. and Mersereau, A. J. (2007), "A learning approach for interactive marketing to a customer segment", *Operations Research*, Vol. 55 No. 6, pp. 1120-1135.
- Chen, X., Yang, Y., Bilgihan, A. and Liu, W. (2025), "Eyeing the pun: an eye-tracking study on the synergistic effects of visual and textual elements in tourism advertising", *Journal of Hospitality and Tourism Technology*.
- Chicco, D. and Jurman, G. (2020), "The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation", *BMC genomics*, Vol. 21 No. 1, pp. 1-13.
- Chong, S.-E., Ng, S.-I., Basha, N. K. and Lim, X.-J. (2024), "Social commerce in the social media age: understanding how interactive commerce enhancements navigate app continuance intention", *Journal of Research in Interactive Marketing*, Vol. 18 No. 5, pp. 865-899.
- Coker, K. K., Flight, R. L. and Baima, D. M. (2021), "Video storytelling ads vs argumentative ads: how hooking viewers enhances consumer engagement", *Journal of Research in Interactive Marketing*, Vol. 15 No. 4, pp. 607-622.
- Crespo, C. F., Ferreira, A. G. and Cardoso, R. M. (2023), "The influence of storytelling on the consumer-brand relationship experience", *Journal of Marketing Analytics*, Vol. 11 No. 1, pp. 41-56.
- Cuevas, L., Lyu, J. and Lim, H. (2021), "Flow matters: antecedents and outcomes of flow experience in social search on Instagram", *Journal of Research in Interactive Marketing*, Vol. 15 No. 1, pp. 49-67.
- Das, K., Patel, J. D., Sharma, A. and Shukla, Y. (2023), "Creativity in marketing: Examining the intellectual structure using scientometric analysis and topic modeling", *Journal of Business Research*, Vol. 154, p. 113384.

Dhaoui, C., Webster, C. M. and Tan, L. P. (2017), "Social media sentiment analysis: lexicon versus machine learning", *Journal of Consumer Marketing*, Vol. 34 No. 6, pp. 480-488.

- Drossos, D., Coursaris, C. and Kagiouli, E. (2024), "Social media marketing content strategy: A comprehensive framework and empirically supported guidelines for brand posts on Facebook pages", *Journal of Consumer Behaviour*, Vol. 23 No. 3, pp. 1175-1192.
- Fisher, W. R. (1989), "Clarifying the narrative paradigm", *Communications Monographs*, Vol. 56 No. 1, pp. 55-58.
- Graham, C. and Stough, R. (2025), "Consumer perceptions of AI chatbots on Twitter (X) and Reddit: an analysis of social media sentiment and interactive marketing strategies", *Journal* of Research in Interactive Marketing.
- Grewal, R., Gupta, S. and Hamilton, R. (2021), "Marketing insights from multimedia data: text, image, audio, and video", SAGE Publications Sage CA: Los Angeles, CA pp. 1025-1033.
- Hao, X. and Demir, E. (2024), "Artificial intelligence in supply chain decision-making: an environmental, social, and governance triggering and technological inhibiting protocol", *Journal of Modelling in Management*, Vol. 19 No. 2, pp. 605-629.
- Hao, X. and Demir, E. (2024), "Artificial intelligence in supply chain management: enablers and constraints in pre-development, deployment, and post-development stages", *Production Planning & Control*, pp. 1-23.
- Hao, X., Demir, E. and Eyers, D. (2024), "Exploring collaborative decision-making: A quasiexperimental study of human and Generative AI interaction", *Technology in Society*, Vol. 78, p. 102662.
- He, J. and Zhang, F. (2022), "Dynamic brand positioning: a firm-customer synergistic strategy of brand meaning cocreation in a hyperconnected world", *European Journal of Marketing*, Vol. 56 No. 10, pp. 2774-2803.
- Herrada-Lores, S., Palazón, M., Iniesta-Bonillo, M. Á. and Estrella-Ramón, A. (2025), "The communication of sustainability on social media: the role of dialogical communication", *Journal of Research in Interactive Marketing*, Vol. 19 No. 2, pp. 307-332.
- Johnson, O., Alyasiri, O., Akhtom, D. and Johnson, O. (2023), "Image Analysis through the lens of ChatGPT-4", *Journal of Applied Artificial Intelligence*, Vol. 4 No. 2.
- Kamal, M. and Bablu, T. A. (2022), "Machine Learning Models for Predicting Click-through Rates on social media: Factors and Performance Analysis", *International Journal of Applied Machine Learning and Computational Intelligence*, Vol. 12 No. 4, pp. 1-14.
- Kang, H. and Lou, C. (2022), "AI agency vs. human agency: understanding human–AI interactions on TikTok and their implications for user engagement", *Journal of Computer-Mediated Communication*, Vol. 27 No. 5, p. zmac014.
- Kanuri, V. K., Hughes, C. and Hodges, B. T. (2024), "Standing out from the crowd: When and why color complexity in social media images increases user engagement", *International Journal of Research in Marketing*, Vol. 41 No. 2, pp. 174-193.
- Khalil, A., Khan, R. and Rashid, S. (2024), "A Study on Digital Marketing Strategies of the Edutainment Sector: A Case Study of Giggle Town", *Journal of Social Sciences and Humanities*, Vol. 63 No. 2, pp. 15-47.
- Kim, J. and Kim, M. (2023), "Using personalization for cause-related marketing beyond compassion fade on social media", *Journal of Research in Interactive Marketing*, Vol. 17 No. 2, pp. 299-316.

- Kim, J., Kim, M. and Lee, S.-M. (2025), "Unlocking trust dynamics: An exploration of playfulness, expertise, and consumer behavior in virtual influencer marketing", *International Journal* of Human–Computer Interaction, Vol. 41 No. 1, pp. 378-390.
- Kim, J. J. (2024), "Brand portfolio extension of international hotel chains: a perspective on consumer confusion and consumer decision-making process", *International Journal of Contemporary Hospitality Management*, Vol. 36 No. 9, pp. 3093-3111.
- Krishen, A. S., Barnes, J. L., Petrescu, M. and Janjuha-Jivraj, S. (2024), "Tweeting for change: social media narratives for sustainable service", *Journal of Research in Interactive Marketing*, Vol. 18 No. 6, pp. 1178-1204.
- Kunz, W. H. and Wirtz, J. (2024), "Corporate digital responsibility (CDR) in the age of AI: implications for interactive marketing", *Journal of Research in Interactive Marketing*, Vol. 18 No. 1, pp. 31-37.
- Lee, J., Gadsden, S. A., Biglarbegian, M. and Cline, J. A. (2022), "Smart agriculture: A fruit flower cluster detection strategy in apple orchards using machine vision and learning", *Applied Sciences*, Vol. 12 No. 22, p. 11420.
- Lévy, P. (1997), Collective intelligence: Mankind's emerging world in cyberspace, Perseus books.
- Li, Y. and Xie, Y. (2020), "Is a picture worth a thousand words? An empirical study of image content and social media engagement", *Journal of Marketing Research*, Vol. 57 No. 1, pp. 1-19.
- Liao, J., Chen, K., Qi, J., Li, J. and Yu, I. Y. (2023), "Creating immersive and parasocial live shopping experience for viewers: the role of streamers' interactional communication style", *Journal of research in interactive marketing*, Vol. 17 No. 1, pp. 140-155.
- Lyu, M. and Huang, Q. (2024), "Visual elements in advertising enhance odor perception and purchase intention: The role of mental imagery in multi-sensory marketing", *Journal of Retailing and Consumer Services*, Vol. 78, p. 103752.
- Malodia, S., Filieri, R., Otterbring, T. and Dhir, A. (2024), "Unlocking Social Media Success: How Prosumers Drive Brand Engagement through Authentic Conversations with Consumers", *British Journal of Management*, Vol. 35 No. 4, pp. 2197-2212.
- Narayanan, A. (2023), "Understanding social media recommendation algorithms".
- Onikoyi, B., Nnamoko, N. and Korkontzelos, I. (2023), "Gender prediction with descriptive textual data using a Machine Learning approach", *Natural Language Processing Journal*, Vol. 4, p. 100018.
- Pavlinek, M. and Podgorelec, V. (2017), "Text classification method based on self-training and LDA topic models", *Expert Systems with Applications*, Vol. 80, pp. 83-93.
- Peltier, J. W., Dahl, A. J., Drury, L. and Khan, T. (2024), "Cutting-edge research in social media and interactive marketing: a review and research agenda", *Journal of Research in Interactive Marketing*, Vol. 18 No. 5, pp. 900-944.
- Philp, M., Jacobson, J. and Pancer, E. (2022), "Predicting social media engagement with computer vision: An examination of food marketing on Instagram", *Journal of Business Research*, Vol. 149, pp. 736-747.
- Qin, Y. S. (2020), "Fostering brand–consumer interactions in social media: the role of social media uses and gratifications", *Journal of Research in Interactive Marketing*, Vol. 14 No. 3, pp. 337-354.
- Rajendran, R. and Karthi, A. (2022), "Heart disease prediction using entropy based feature engineering and ensembling of machine learning classifiers", *Expert Systems with Applications*, Vol. 207, p. 117882.

- Ryu, S. (2024), "From pixels to engagement: examining the impact of image resolution in cause-related marketing on Instagram", *Journal of Research in Interactive Marketing*, Vol. 18 No. 4, pp. 709-730.
 Shao, Z. (2024), "Revealing consumers' hedonic buying in social media: the roles of social status recognition, perceived value, immersive engagement and gamified incentives", *Journal of*
 - Research in Interactive Marketing.
 Sharakhina, L., Ilyina, I., Kaplun, D., Teor, T. and Kulibanova, V. (2024), "AI technologies in the analysis of visual advertising messages: survey and application", *Journal of Marketing Analytics*, Vol. 12 No. 4, pp. 1066-1089.
 - Sharma, A. and Shafiq, M. O. (2022), "A comprehensive artificial intelligence based user intention assessment model from online reviews and social media", *Applied Artificial Intelligence*, Vol. 36 No. 1, p. 2014193.
 - Shen, Y.-C., Lee, C. T. and Lin, W.-Y. (2024), "Meme marketing on social media: the role of informational cues of brand memes in shaping consumers' brand relationship", *Journal of Research in Interactive Marketing*, Vol. 18 No. 4, pp. 588-610.
 - Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S. and Ringle, C. M. (2019), "Predictive model assessment in PLS-SEM: guidelines for using PLSpredict", *European journal of marketing*, Vol. 53 No. 11, pp. 2322-2347.
 - Swaminathan, V., Schwartz, H. A., Menezes, R. and Hill, S. (2022), "The language of brands in social media: Using topic modeling on social media conversations to drive brand strategy", *Journal of Interactive Marketing*, Vol. 57 No. 2, pp. 255-277.
 - Tong, S. C. and Chan, F. F. Y. (2023), "Strategies to drive interactivity and digital engagement: a practitioners' perspective", *Journal of Research in Interactive Marketing*, Vol. 17 No. 6, pp. 901-920.
 - Valenzuela-Gálvez, E. S., Garrido-Morgado, A. and González-Benito, Ó. (2022), "Boost your email marketing campaign! Emojis as visual stimuli to influence customer engagement", *Journal of research in interactive marketing*, Vol. 17 No. 3, pp. 337-352.
 - Valor, C. and Carrero, I. (2014), "Viewing responsible consumption as a personal project", *Psychology & Marketing*, Vol. 31 No. 12, pp. 1110-1121.
 - Varadarajan, R., Welden, R. B., Arunachalam, S., Haenlein, M. and Gupta, S. (2022), "Digital product innovations for the greater good and digital marketing innovations in communications and channels: Evolution, emerging issues, and future research directions", *International Journal of Research in Marketing*, Vol. 39 No. 2, pp. 482-501.
 - Vygotsky, L. S. and Cole, M. (1978), *Mind in society: Development of higher psychological processes*, Harvard university press.
 - Wang, C. L. (2021), "New frontiers and future directions in interactive marketing: inaugural Editorial", *Journal of Research in Interactive Marketing*, Vol. 15 No. 1, pp. 1-9.
 - Wang, C. L. (2023), "Interactive marketing is the new normal", *The Palgrave handbook of interactive marketing*, Springer, pp. 1-12.
 - Wang, C. L. (2024), "Editorial-what is an interactive marketing perspective and what are emerging research areas?", *Journal of Research in Interactive Marketing*, Vol. 18 No. 2, pp. 161-165.
 - Wang, C. L. (2025), "Demonstrating contributions through storytelling", Journal of Research in Interactive Marketing, Vol. 19 No. 1, pp. 1-4.

- Yang, M., Lim, M. K., Qu, Y., Li, X. and Ni, D. (2023), "Deep neural networks with L1 and L2 regularization for high dimensional corporate credit risk prediction", Expert Systems with Applications, Vol. 213, p. 118873.
- Yoo, J., Kim, J.-H., Kim, M. and Park, M. (2023), "Imagery evoking visual and verbal information presentations in mobile commerce: the roles of augmented reality and product review", Journal of Research in Interactive Marketing, Vol. 18 No. 2, pp. 182-197.
- Zhu, J. J., Chang, Y.-C., Ku, C.-H., Li, S. Y. and Chen, C.-J. (2021), "Online critical review classification in response strategy and service provider rating: Algorithms from heuristic processing, sentiment analysis to deep learning", Journal of Business Research, Vol. 129, pp. 860-877.

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