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Projection of University Image and Social Media Engagement: Inference of Optimal Solutions based on Bayesian Model and Influence Graph

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Projection of University Image and Social Media Engagement: Inference of Optimal Solutions based on Bayesian Model and Influence Graph

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Abstract: Social media platforms provide a space for interaction and communication with the public, playing a crucial role in shaping and disseminating the image of destinations. Social media also plays a significant role in shaping and disseminating the online image of universities. Metrics such as likes and shares on Weibo likes and views on DouYin (TikTok), and website traffic serve as indicators of public engagement with university social media. Revealing the triggering patterns of destination image projection and related factors on social media engagement can provide a theoretical basis for destination image marketing strategies. Using data from posts on the official Sina Weibo account and videos on TikTok, as well as website traffic of a Chinese university from 2018 to 2023, this paper constructs Bayesian models and influence graph models to simulate and infer the optimal decisions that lead to social media engagement at universities.

Keywords: Destination image projection, University social media engagement, Bayesian model.

1. Introduction

With the advent of the social media era, the marketing focus of destination management organizations has gradually shifted from traditional offline channels to the online space. The dissemination of information containing marketing strategies and media materials on social media platforms has become an essential means for destination management organizations to establish, maintain, and enhance the attractiveness of tourism destinations [1, 2]. In recent years, universities have garnered attention from both academia and industry in terms of online marketing and media image building. Universities have transitioned from traditional "ivory tower" images to more accessible and "cute" images in the public eye, gaining a large number of followers on social media platforms and sparking several viral trends. However, the appearance of highly popular topics with high attention and high dissemination on social media platforms also contains an element of randomness and uncertainty. Faced with the massive amount of information and complex communication structures on social media platforms, there is still a need to summarize the regularities in triggering public high-interaction participation through destination image projection. Additionally, universities possess rich and multidimensional destination images and play important roles in cultural heritage and public services. Effectively projecting destination images and establishing good interactive communication with the public to continually expand the scope and influence of information dissemination remain crucial challenges for university destination management organizations.

Participation and interaction are crucial stages in which the public constructs and perceives destination images on social media platforms. They can stimulate changes in the willingness to apply for university admission among university or high school students [3, 4]. Previous studies have identified factors influencing public participation on social media platforms, including content publication, timing of publication, language characteristics, and interaction features [5], using statistical methods such as structural equation modeling, multiple regression, and difference testing. These studies have preliminarily explored many factors affecting social media participation and their interactions. However, few studies can simulate and predict the degree of social media participation. Furthermore, existing research has not revealed which factors or combinations of factors can achieve optimal social media participation effects, making it difficult to answer the question of "how " destination management organizations should act on social media platforms.

This study, using the official Weibo account of a Chinese university as an example, aims to answer how educational institutions should project destination images on social media platforms to maximize the effect of social media engagement. Firstly, we review the basic characteristics of the number of Weibo posts and social media engagement in the official university Weibo account and identify the influencing factors of social media engagement. Secondly, we construct a social media engagement Bayesian Network Model and an influence graph, simulating the basic patterns of destination image projection that trigger social media engagement. Finally, we explore the optimal scenarios for maximizing social media engagement through model adjustments and predict the social media engagement effects under different decision scenarios.

2. Literature Review

2.1 Destination Image Projection

Destination image projection, also known as marketing image, is the image that destination management organizations convey to potential tourists through various forms of information dissemination and marketing media. The destination image projected by destination management organizations is the primary source of information for potential tourists [6]. Early research on destination image projection primarily focused on the content of the projected image, exploring the influence of the projected image on tourists' perceptions and behavioral intentions [7-9]. In recent years, with the rise of social media platforms, tourists have not only become recipients of the projected image but also influenced the content structure and dissemination structure of the projected image through actions such as comments and shares [10].

Cultivating a close relationship between tourists and destinations has become a key to the success of destination image projection and marketing on social media platforms [11, 12]. Studies in the field of brand marketing have shown that information published by marketing organizations can stimulate consumers' willingness to interact on social media platforms [13], thus establishing a close connection between consumers and brands [14]. This connection leads to emotional attachment [15], loyalty [16], recommendations and word-of-mouth behavior toward the brand [17]. In other words, the information released by destination marketing organizations on social media platforms not only shapes the image of the tourist destination but also, through online technology, fosters interaction with tourists or potential tourists, developing and maintaining relationships between tourists or potential tourists and the tourist destination.

Scholars have found that understanding and predicting the participation behavior of social media users plays an important role in destination image projection and marketing [18, 19]. With the rise of Chinese universities on social media platforms, including accounts such as Tsinghua University, Peking University, Fudan University, and Wuhan University, destination management organizations have registered official accounts on social media platforms and engaged in communication and interaction with social media users to establish and maintain close connections between destinations and university students, alumni, or high school students [20]. However, limited research has focused on the relationship between university destination image projection and social media participation. Existing research has been confined to identifying differences in the number of shares, comments, and likes caused by destination image projection [21], without addressing how to enhance social media participation through university destination image projection.

2.2 Social Media Participation and Its Influencing Factors

Participation is a complex and multidimensional concept that includes various forms of cognition, emotion, and behavior [22]. On social media platforms, participation is usually measured at the behavioral level, manifested as sharing, commenting, or liking [23, 24]. However, users' behaviors such as sharing, commenting, and liking have different behavioral logics, and simply adding up these numerical values does not reflect their underlying behavioral differences. Among them, liking represents the most basic and simplest form of social media participation [25, 26]. Commenting involves users providing feedback in semi-public online communities created by posts, expressed through text, images, and other forms [27]. Sharing involves users sharing post content with friends and other social media users, driving the dissemination and diffusion of original post content, and showcasing self-image and identity [28]. In other words, the content published by destination management organizations and the resulting likes, comments, and shares form a semi-public online community that identifies and cultivates potential tourists, affecting the spread and dissemination of the university destination image.

It has been found that factors such as account attributes, posting content, affective representations, and posting time collectively influence users' social media engagement behaviors [29]. Although the specific content of posting varies in different research scenarios, it basically shows that highly interactive information can trigger more attention and participation behavior [30]. Therefore, university microblogs can enhance the interactivity of messages and guide social media users to participate in online activities by providing links to websites, designing sweepstakes contests, and setting up questions [31]. Some scholars classify online brand-related activities of social media users into three types: consumption, contribution, and creation [32]. Based on this, this study classifies the marketing activities used by message publishers into consumption guidance, contribution guidance, and creation guidance, in order to portray the types of interactive guidance used in messages. Consumption guidance refers to guiding social media users to view and download relevant content; contribution guidance refers to guiding social media users to comment and retweet relevant content; and creation guidance refers to guiding social media users to design and publish relevant content.

In addition to the content of the message, the emotional characteristics presented in the message also affect social media engagement [33]. Research on the dissemination of university admissions information found that messages containing emotions increased social media users' liking and retweeting behavior, but did not affect the number of comments [34]. Recent research has shown that messages containing emotional content on social media platforms are more likely to go viral, have a greater reach [35], and contribute to a stronger connection between social media users and the brand [31, 36]. At the same time, the destination image projected by universities is not only a display and introduction of destination attributes but also a way to evoke an emotional experience and create a positive destination image [37]. In addition, the level of social media engagement is also related to the time of posting [38], the date of posting [39], and seasonality [40]. Research on Facebook has found that social media users post more comments on weekdays, but do not generate more likes or retweets [41]. Some scholars have also found that the date of posting does not affect the number of likes and comments [38]. Travel information posted on weekends can achieve higher social media engagement. It can be seen that there is still no unanimous conclusion on when to post information to form the best social media interaction and marketing effect.

In summary, the projected image of university destinations in social media platforms not only affects the perceived image of tourists but also plays a role in the social media engagement behavior of the public, which is important for destination image marketing. Scholars have explored the relationship between information dissemination and social media engagement behavior, but what kind of information dissemination can guide the public's social media engagement behavior, and how to simulate and predict the social media engagement effect of destination image projection have not been answered by scholars. Based on existing research, this paper focuses on the influencing factors of social media engagement on four factors, namely, destination image projection, interaction strategy, emotional representation, and time frame, distinguishes the different meanings of retweets, comments, and likes in public social media engagement, and simulates the effects of different factors and combinations of factors on the three social media engagement behaviors, so as to explore the optimal path of destination image projection in universities and universities that can be guided and predicted. The optimal path of destination image projection.

3. Data Source and Research Methodology

3.1 Data Source

For this study, data was collected using PyCharm Community Edition (version 2023.1.2) from 2018 to 2023 regarding all Weibo posts published by a certain Chinese university's official Weibo account. The collected data included the full text of Weibo posts, posting time, number of retweets, number of comments, and number of likes, resulting in a total of 6,532 Weibo posts and associated data (Table 1). The dimensions of the destination image and interactive guidance type represented in the Weibo text were manually coded. The manual coding process involved three stages: firstly, the two authors jointly discussed and initially determined the coding rules based on existing research. Secondly, the two authors independently coded 300 randomly selected Weibo posts according to their coding standards, and discrepancies in coding were discussed, leading to further modifications and refinements of the coding rules. Finally, one author completed the coding of all Weibo posts based on the finalized coding rules to ensure consistency and stability in the coding process.

Table 1 A university has published Weibo and received retweets over the years (2018-2023)

Index	2018	2019	2020	2021	2022	2023
Number of Weibo	945	1019	1335	1175	1317	669
Average Retweets	14	8	16	13	11	9
Average number of comments	54	62	51	63	75	45
Average number of likes	137	128	127	102	114	96

3.2 Variable Selection

Based on existing research, this study focuses on four factors that influence social media participation: destination image projection, interactive strategies, emotional representation, and time frame. Destination image projection is divided into six dimensions: university buildings, natural landscapes, historical and cultural aspects, creative products, facilities and services, and student activities. Interactive strategies are categorized into two indicators: interactive guidance and mentions of others. Interactive guidance refers to how Weibo text guides social media users' participation behavior and can be divided into four categories: no guidance, application guidance, contribution guidance, and collaboration guidance. Mentioning others refers to whether the Weibo text uses the "@" function to mention other social media users and is categorized as either present or absent.

Emotional representation is divided into positive emotions, negative emotions, and no emotions, and these categories are obtained as continuous data using Wenxin software. The time frame includes three indicators: season, date, and posting time. Seasons are categorized according to meteorological divisions, with March to May as spring, June to August as summer, September to November as autumn, and December to February of the following year as winter. Posting dates are divided into weekdays and weekends, considering a one-week cycle. Posting times are categorized into five time periods: 8:00–11:59, 12:00–13:59, 14:00–17:59, 18:00–22:59, and 23:00–7:59.

Social media engagement in this study comprises three indicators: retweets, comments, and likes. The retweets, comments, and likes data collected through web scraping are all continuous variables and are statistically significant for variance analysis and influence graph modeling. However, Bayesian models require nominal variables, so it was necessary to convert continuous variables into nominal ones. To achieve this, the Weibo posts were sorted based on the number of retweets, comments, and likes in descending order, and the top 20% of Weibo posts were categorized as high retweet, high comment, and high like Weibo posts, while the remaining Weibo posts were categorized as low retweet, low comment, and low like Weibo posts. These categories were used for constructing Bayesian models and statistical inferences.

3.3 Research Methodology

3.3.1 Research Steps

The inference process for the optimal scenario in this study can be roughly divided into 5 steps. The first step involves collecting data from Weibo posts published by the university's official Weibo account and encoding it. Six nominal variables are formed, representing the dimensions of destination image projection, interactive guidance, mentioning others, seasonality, date, and posting time. Emotional representation scores (positive emotions, negative emotions) are calculated, and both emotional representation and social media engagement data (retweets, comments, likes) are converted into nominal variables. Continuous variables are used for Bayesian model parameter determination and expected utility inference, while nominal variables are used for Bayesian model parameter determination and probability inference. The second step utilizes SPSS 23.0 software to conduct chi-squared tests and analysis of variance to identify factors influencing social media engagement. In the third step, based on existing research and the conclusions from step two, a Bayesian model is constructed using Netica V5.18 software. This involves parameter mathematical learning using the encoded Weibo data to determine Bayesian model parameters. Sensitivity analysis and probability inference are then carried out, targeting social media engagement as the goal node, to identify key factors and factor combinations influencing social media engagement with destination image projection. The fourth step extends the Bayesian model by incorporating decision nodes and value nodes to construct an influence diagram model based on the Weibo posting decision process. In the fifth step, considering the findings from the previous steps, the values of the influence diagram model nodes are adjusted. This allows for the simulation and calculation of the expected utility of social media engagement, resulting in the inference of the optimal path for inducing social media interaction through destination image projection.

In comparison to classical statistical methods, Bayesian methods, including Bayesian models and influence diagrams, have the ability to integrate multiple data sources, perform simulation inference, and provide graphical representations. They are effective at handling relationships between prior knowledge and new observational data, allowing for simulations under different scenarios, and offering an intuitive display of the probability changes for decision-making. Bayesian methods have been widely applied in fields such as organizational management, environmental management, risk management, and consumer behavior to predict engineering issues, risks, and consumer behavior probabilities. In recent years, scholars have increasingly applied Bayesian models to analyze student behavior and have made significant progress. Influence diagrams extend Bayesian models for probabilistic inference of discrete variables into predicting expected utility for decision alternatives. They capture not only decision alternatives and decision preferences but also compute the expected outcomes of different decision alternatives. Influence diagrams have been widely applied in fields such as risk decision-making and organizational decision-making. The application of this method in school management research has promoted innovative methods in the study of university network image projection and social media marketing.

3.3.2 Bayesian Modeling

Bayesian networks are graphical models based on probabilistic descriptions of dependencies between data variables, capable of probabilistic inference in the presence of multiple factors and uncertain information. A Bayesian model consists of a directed acyclic graph and a conditional probability table. The directed acyclic graph consists of nodes and directed arcs, where the nodes represent the variables and the directed arcs represent the influence of the parent nodes to the child nodes; the conditional probability table is used to represent the strength of the relationship between the nodes. The Bayesian formula is considered to be the basis of Bayesian modeling and can be expressed as:

$$\mathrm{P(X|Y)} = \frac{\mathrm{P(Y|X)P(X)}}{\mathrm{P(Y)}} \tag{1}$$

In equation (1), the $\mathrm{P(X|Y)}$ is the known event Y occurring at the time of X the probability of occurrence, and $\mathrm{P(X|Y)}$ is the probability of X the conditional probability of the occurrence of Y of the conditional probability. Two random variables X and Y The joint distribution of can be expressed as:

$$\mathrm{P(X,Y)} = \mathrm{P(X)P(Y|X)} \tag{2}$$

In equation (2), the $\mathrm{P(X)}$ is called the a priori probability and $\mathrm{P(Y|X)}$ is the posteriori probability. The a priori probability is the probability that the factor occurs independently and separately from the other factors. The posteriori probability is the probability of the factor occurring given the probability of the antecedent factor. The complexity of the probabilistic model can be reduced by combining the chain rule, then The joint distribution of the individual variables is:

$$\mathrm{P}(X_1, X_2, \dots, X_n) = \prod_{i=1}^{n} P(\,X_1|X_{pa(i)}) \tag{3}$$

Set S to be a network structure containing X the structure of a network of variables, where $\mathrm{X} = \{X_1, X_2, \dots, X_n\}$, P is the set of local probability distributions associated with each variable, and X_1 denotes a variable node, and $X_{pa(i)}$ denotes the parent node of the variable node in the network structure S. According to the above formulas, the conditional probability table for each node can be calculated and the probability inference for each node of the Bayesian network model can be performed according to the Bayesian formula.

4. Data Analysis and Research Results

4.1 Number of Weibo Posts Published by a Certain University's Official Weibo Account and Its Influencing Factors

We conducted a statistical analysis of the number of Weibo posts published by a certain university's official Weibo account from 2018 to 2023, considering different dimensions of destination image. We also examined their combinations with interactive strategies, emotional representation, and temporal frameworks, followed by conducting chi-square tests (Table 2). The results reveal that the university's official Weibo account employs distinct interactive strategies, emotional representations, and differentiated posting schedules when projecting different dimensions of destination image.

From the perspective of destination image dimensions, it is noteworthy that the university's Weibo account predominantly posts content related to the historical and cultural dimension, which accounts for over 47% of all Weibo posts. Following closely are the dimensions of school buildings and student activities, both exceeding 14% of the total Weibo posts. Conversely, the dimensions related to school facilities and services, among others, have fewer posts.

Regarding interactive strategies, only 29% of the Weibo posts employ interactive guidance, and merely 5% of the posts mention others. Notably, the dimensions of university activities and cultural events utilize more application and cooperation guidance strategies, often mentioning other social media users. In contrast, other dimensions tend to use contribution guidance more frequently, while employing fewer interactive strategies overall.

In terms of emotional representation, approximately 53.6% of the Weibo posts incorporate positive emotional vocabulary, albeit with relatively lower positive emotional scores. Remarkably, no negative emotional vocabulary is present in these posts.

When examining the temporal framework, the university's official Weibo account tends to post more Weibo content during the autumn enrollment season compared to the spring enrollment season, especially within the dimensions of school buildings and natural landscapes. Furthermore, during weekdays, there is a slightly higher volume of Weibo posts compared to weekends, particularly within the dimensions of school facilities and student activities. The time slot between 8:00 AM to 11:59 AM sees the highest number of Weibo posts, with an emphasis on the historical and cultural dimension. Meanwhile, the time slots of 14:00 PM to 17:59 PM witness an increase in Weibo posts related to school facilities and services, student activities, and other dimensions. However, during the time slots of 12:00 PM to 13:59 PM, 18:00 PM to 22:59 PM, and 23:00 PM to 7:59 AM (non-working hours), the university's official Weibo account posts relatively fewer Weibo entries.

Table 2 Cross-tabulation of the difference in the number of microblogs between projected images and interaction strategies, affective representations, and time frames at a university in China

Variables	Level	Projeceted destination image						
		School buildings(bu)	School natural landscape(nl)	School history and culture(hc)	School creative products (cc)	Student activities (sa)	School facilities services(sf)	Cardina x^2 (sig.)

Interactive strategies	Interactive guidance	No guidance	1024	552	2416	58	509	96	12.000[a](0.213)
		Application guidance	118	89	239	17	236	96	
		Contribution guidance	89	147	254	5	86	77	
		Collaboration guidance	59	21	134	13	113	84	
	@others	Yes	257	215	863	18	362	98	2.000[a] (0.157)
		No	1033	594	2180	75	582	255	
Emotional representation	Emotion	Positive emotion	628	386	1796	33	475	186	6.000[a] (0.199)
		Negative emotion	0	0	0	0	0	0	
		Not have	662	423	1247	60	469	167	
Time frame	Seasons	Spring (march-may)	417	209	715	26	293	109	12.000[a](0.213)
		Summer (june-august)	193	179	771	20	172	63	
		Fall(september-october)	462	230	798	28	315	122	
		Winter (december-	218	191	759	19	164	59	

	february)							
Post date	Workdays	1020	601	2360	79	812	287	2.000[a] (0.157)
	Weekends	270	208	683	14	132	66	
Post time	8:00—11:59	512	321	690	0	459	128	20.000[a](0.220)
	12:00—13:59	214	69	271	17	122	43	
	14:00—17:59	350	271	1165	63	248	116	
	18:00—22:59	199	145	858	10	112	63	
	23:00—7:59	15	3	59	3	3	3	
Total		1290	809	3043	93	944	353	

4.2 Social Media Engagement Triggered by Official University Weibo and Its Influencing Factors

The number of reposts, comments, and likes on official university Weibo posts from 2018 to 2023 follows a power-law distribution, characterized by a small number of highly popular posts with a substantial amount of interactions and a large number of posts with very few interactions, failing to achieve high levels of social media engagement. According to the Pareto principle, the top 20% of posts by reposts account for 98.27% of the total reposts, the top 20% of posts by comments account for 90.20% of the total comments, and the top 20% of posts by likes account for 85.41% of the total likes. This indicates that social media engagement on official university Weibo is concentrated within a small number of popular posts, generating a significant amount of reposts, comments, and likes, thus exerting a considerable societal influence. However, a large number of posts, particularly those related to campus activities and cultural dimensions, have failed to generate significant social media engagement.

An analysis of the mean differences in reposts, comments, and likes on official university Weibo posts was conducted across different factors, including social media image projection dimensions, interactive strategies, emotional representation, and time frames (Table 3). The results indicate that different dimensions of social media image projection, types of interactive guidance, seasonality, and posting time significantly influence the number of reposts, comments, and likes on official university Weibo posts. Posts related to school creative products achieved the highest number of reposts, significantly surpassing posts from other dimensions. Posts related to student activities and school natural landscapes triggered higher levels of comments and likes. Posting time had an impact on comments and likes, while mentioning others only affected reposts. Positive emotions only affected comments and likes, whereas negative emotions did not significantly influence reposts, comments, or likes on official university Weibo posts.

Table 3 Differential analysis of the number of retweets and likes of the official blog of a university in China under the influence of different

Variables	Levels	Average number of forwards	Average number of comments	Average number of likes
Projecting an image of a destination	BU	5.04	8.00	112.00
	NL	6.00	13.00	133.00
	HC	5.00	12.00	142.00
	CC	12.00	15.00	213.00
	SA	58.00	52.00	313.00
	SF	7.00	27.59	184.85
Interaction guide	No guidance	3.00	5.00	143.00
	Application guidance	12.00	26.00	156.00
	Contribution guidance	43.00	55.00	212.00
	Collaboration guidance	78.11	88.30	319.66
@Others	Yes	36.43	38.00	211.00
	No	4.00	10.32	144.56
Emotion	Positive emotion	21.64	25.00	223.00
	Negative emotion	0.00	0.00	0.00
	No emotion	3.00	9.90	93.57
Seasons	Spring	15.00	20.00	169.00
	Summe	9.00	14.00	152.00
	Fall	16.00	21.00	173.00
	Winter	10.30	15.30	152.51
Post date	Workdays	14.30	20.00	175.00
	Weekends	8.12	10.49	117.91
Post time	8:00—11:59	8.00	12.00	63.00
	12:00—13:59	18.00	23.00	291.00
	14:00—17:59	12.00	18.00	130.00
	18:00—22:59	20.04	25.00	306.00
	23:00—7:59	5.00	9.52	63.93

4.3 Bayesian Model of Social Media Engagement in Official University Weibo

4.3.1 Construction of the Bayesian Model and Sensitivity Analysis

Based on existing research and the results of the statistical tests mentioned above, we constructed a Bayesian model of social media engagement triggered by the projection of destination images on official university Weibo. The direction of the connections follows the decision sequence during Weibo posting and has been confirmed for consistency by the three authors of this paper (Figure 1). A total of 2,095 data points containing eight variables, including social media image projection, interactive guidance, mentioning others, positive emotion, negative emotion, season, date, and posting time, were imported into Netica V5.18. We calculated the parameters of the Bayesian model using a parameter learning method. The target nodes were set as reposts, comments, and likes. Sensitivity analysis was conducted to assess how changes in the target nodes' probabilities were influenced by changes in various factors or combinations of factors, as indicated by the color depth of nodes in the model

Sensitivity analysis revealed the impact of changes in node probabilities on the probabilities of target nodes, helping to identify critical nodes affecting Bayesian inference results. The results showed that, except for negative emotions, adjusting the levels of various factors would affect social media engagement on official university Weibo. Among them, the posting time, image projection dimension, and interactive guidance type were factors with relatively high sensitivity. Small changes in the probabilities of these three nodes would lead to significant changes in the probability of social media engagement.

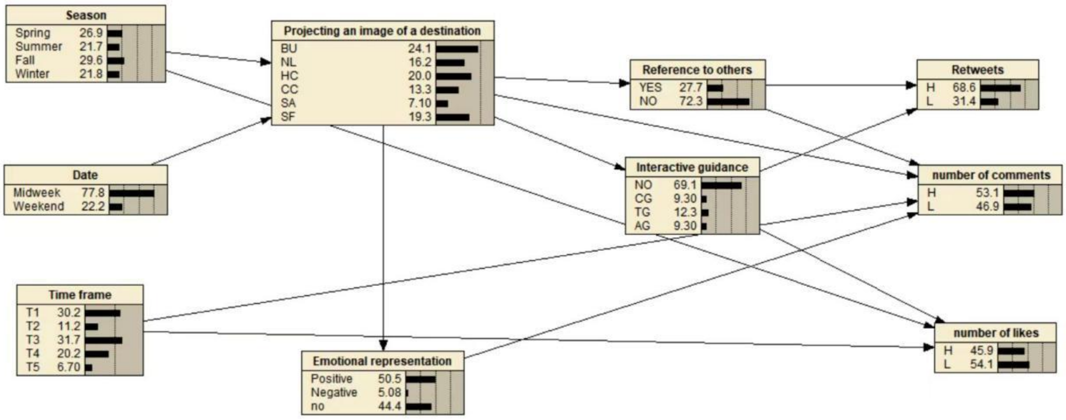

Figure 1: Bayesian model of social media engagement triggered by tourism destination image projection

Note: BU: School Buildings, NL: School Natural Landscape, HC: School History and Culture, CC: School Cultural and Creative Products, SA: Student Activities, SF: School Facilities and Services, NO: No Guidance, CG: Collaborative Guidance, TG: Contribution Guidance, AG: Application Guidance.

4.3.2 Probability Inference of University Social Media Engagement Scenarios

The goal of official university Weibo in projecting social media images is to trigger high levels of social media engagement, thereby increasing dissemination efficiency and social influence. Therefore, in this study, we set the states of the three nodes, reposts, comments, and likes, as high. We calculated the posterior probabilities of other nodes in the Bayesian model and revealed the direction and strength of the impact of various factors on social media engagement by observing changes in posterior probabilities (Table 4).

Table 4: Posterior Probability Changes of Various Influential Factors in Different Scenarios of Social Media Engagement

Variables	Levels	Original probability(%)	Posterior probability (%)		
			Retweets = high	Comments = high	Likes Volume-High
	BU	0.24	56.4	60.2	44.7

	NL	0.16	56.8	45	45.4
Projecting an image of a destination	HC	0.20	56.9	47.8	45.7
	CC	0.13	56.5	43.1	48.1
	SA	0.07	56.7	49.9	45.8
	SF	0.19	56.9	57.1	42.9
Interactive guidance	NO	0.69	59.2	51.7	44.9
	CG	0.09	41.1	51.9	45
	TG	0.12	54.2	51.3	47.2
	AG	0.09	57.2	51.9	52.3
Reference to others	YES	0.28	29.9	48.6	45.9
	NO	0.72	83.4	54.8	45.9
Emotional	Positive	0.51	56.7	50.2	45.9
	Negative	0.05	56.7	49.8	45.9
	No	0.44	56.7	53.6	45.9
Season	Spring	0.27	68.6	54.5	42.8
	Summer	0.22	56.7	49.5	51.4
	Fall	0.30	56.7	51.7	48.4
	Winter	0.22	56.7	50.8	40.8
Date	Midweek	0.78	56.7	52	45.9
	Weekend	0.22	56.7	50.4	45.9
Time frame	T1	0.30	56.7	50.5	34.3
	T2	0.11	56.7	56.3	52.2
	T3	0.32	56.7	53.6	43.7
	T4	0.20	56.7	48.2	59.9
	T5	0.07	56.7	54.7	55.7

The results show that the posterior probability of school creative product dimensions and high positive sentiment increased significantly in both the high retweet, high comment, and high like scenarios. The posteriori probabilities for the spring school season increased more in the high retweet and high like scenarios, and the contribution guidance and creation guidance increased more in the high comment scenarios. From the results of the posterior probability changes, it can be seen that school's natural landscape dimension, using interaction strategies and high positive emotions are the key to triggering high levels of social media engagement, while different interaction strategies can lead to the formation of different types of social media engagement, and tweets posted in the spring enrollment season and non-study time are more likely to trigger high social media engagement.

5. Conclusions and Outlook

5.1 Conclusion and Discussion

This study uses the number of forwards, comments, and likes as indicators to evaluate public social media engagement. It constructs two hierarchical decision reference models: a Bayesian model and an influence diagram. The study simulates and predicts the optimal scenarios and expected effects of information dissemination by destination management organizations, bridging the complex relationship between destination image projection and social media engagement.

In terms of innovation, this study treats social media engagement as a crucial indicator for evaluating the effectiveness of destination image projection, revealing the impact of destination image projection on social media engagement patterns. Regarding methodological innovation, by using Bayesian network models and influence diagrams, this study intuitively illustrates the relationships and strengths of influence among various factors. It predicts the effects of different destination image projection strategies through scenario simulations.

First, official microblogs of universities trigger social media engagement following a power-law distribution. In other words, only a small number of microblogs lead to extensive social media engagement behaviors. Among the six dimensions of the Forbidden City's destination image projection, scenarios with the highest likelihood of generating high social media engagement occur in microblogs related to the dimension of school natural landscapes. Previous research has found that popular topics such as the cherry blossoms of Wuhan University, Weiming Lake of Peking University, and Shui Mu Qing Hua of Tsinghua University are key to the transformation of destination images [42]. Similarly, this study also found that, compared to the dimension of school natural landscapes and school cultural and creative products, microblogs related to the dimension of school history and culture are less likely to generate extensive social media engagement. The stimulating effect of university destination image projection seems to be limited to attracting visual landscape attention and has not yet delved into the core charm of university history and culture.

Second, social media engagement is not only related to the dimensions of destination image projection but also to the interactive strategies, emotional representations, and publishing time frames in the content. Previous research mainly focused on comparing the differences between information published by social media users and destination marketing organizations, treating closing the gap between projected images and perceived images as the marketing goal [43]. In contrast, this study concentrates on the social media engagement triggered by destination image projection, emphasizing the role of university destination image dimensions and marketing strategies in shaping the interaction between social media users and destinations. This study finds that using interactive strategies in microblog texts can enhance social media engagement. Mentioning others and consumption guidance can attract more likes and forwards, while contribution guidance and creation guidance are more conducive to generating high comments. The use of positive emotional vocabulary not only helps shape a positive destination emotional image but also attracts more users to comment and like.

Third, the time frame for publishing microblogs is an essential decision factor for destination image projection. In different scenarios of university destination image projection, the optimal publishing time for triggering social media engagement varies. In the summer enrollment season, social media users are more likely to engage frequently with official university microblogs. Therefore, the summer vacation is a critical period for shaping the destination image and promoting enrollment intentions. The time frame of 12:00–22:59 is generally more likely to achieve higher social media engagement and is more likely to create microblogs with high comments and likes. Official university microblogs posted during active hours align with the active times of social media users, which is consistent with previous research [44]. Furthermore, this study demonstrates that different combinations of microblog content, interactive strategies, and publishing times can guide different types of social media engagement. Using an influence diagram, this study can simulate and infer the scale of social media engagement that can be achieved under different scenarios.

Finally, for historical and cultural dimension microblogs, which have the largest number but have not triggered extensive social media engagement, the combination of interactive strategies and time frames plays a crucial role in enhancing social media engagement. In the summer, guiding the public to engage in student enrollment behavior in the virtual space and organizing public-school cooperation activities in the spring is the optimal strategy for generating high social media engagement. Moreover, the time frames of 12:00–13:59 and 18:00–22:59 are the optimal publishing times for microblogs related to the school history and culture dimension. During these times, combining interactive guidance strategies can achieve more extensive social media engagement. Unlike other dimensions, mentioning others in microblogs related to the school history and culture dimension has a weaker impact on social media engagement. Only mentioning others in the context of enrollment promotion can promote social media engagement. This may be related to the special characteristics of the school's history and cultural dimension. Compared to the popularity of celebrities, the matching degree between celebrities and the destination may be an essential factor affecting tourists' attitudes toward the destination. However, how to stimulate the public's cultural participation and cultural learning through interactive marketing is still an issue that needs further exploration.

5.2 Limitations and Outlook

This study uses microblog data from official university accounts for the years 2018–2023 to construct Bayesian models and influence diagrams for social media engagement triggered by university destination image projection. Considering the diversity of tourism destinations, future research can further verify the models in other types of tourism destinations. In addition, this study employs quantitative analysis and model simulations to establish a model for the rules of university destination image projection that triggers social media engagement. However, it has not yet revealed the psychological and behavioral logic behind the model from the perspective of individual public users. Subsequent research still needs to use methods such as interviews and experiments to further investigate the mechanisms of university destination image network marketing.

Data Availability Statement

All relevant data are within the manuscript and its Supporting Information files.

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