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Impact of university brand awareness on students' admission decisions: Cross-cultural analysis

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Abstract: University brand awareness significantly influences students' admission decisions. Existing studies often lack a cross-cultural perspective due to sample geographic limitations and insufficient analytical methods. This study adopts a mixed-method design and constructs a cross-cultural analytical framework. It integrates global university brand data (e.g., QS rankings, social media index, academic influence) and applies natural language processing to extract brand image characteristics. Key decision variables are identified through a transnational education survey, and then factor analysis and structural equation modeling (SEM) are conducted to quantify the impact of brand awareness. Multi-group analysis reveals cross-cultural path differences. Cluster analysis reveals different brand sensitivities. The results show that East Asian students scored 80 points in long-term orientation, which is significantly different from students in other regions (p=0.0348), highlighting the impact of culture on brand influence. This study promotes brand management in higher education and provides strategies for international brand building, social media engagement, and academic collaboration to attract diverse students. It provides practical insights for precise and culturally customized admissions efforts.

Keywords: *Cluster analysis, Cross-cultural analysis, Structural equation model, Students' admission decision, University brand awareness.*

1. Introduction

In the context of globalization, the internationalization of higher education is accelerating, and universities in various countries are competing to attract international students to enhance their global competitiveness. Statistical data show that there are significant differences in the brand influence of universities in global enrollment. Some world-renowned universities attract a large number of international students by virtue of their brand advantages [1, 2], while other universities are relatively weak in the cross-cultural enrollment market [3, 4]. This cultural asymmetry not only affects the enrollment strategy of universities [5, 6] but also determines their position in the global education system. University brand awareness [7, 8] as an important factor affecting students' admission decisions [9, 10] has become a core issue of concern for researchers in transnational education [11, 12]. Existing studies have shown that the brand building of internationalized higher education in European and American countries [13, 14] is relatively mature, while universities in Asia, Africa, Latin America, and other areas face greater challenges in international enrollment. In the cross-cultural [15, 16] context, students' school selection preferences also vary significantly. Asian students pay more attention to rankings [17, 18] and employment prospects, while African and Latin American students pay more attention to financial support and adaptability to studying abroad. However, existing research mainly focuses on the overall impact of the brand effect brought by university brand awareness [19, 20] and pays less attention to the moderating role of cultural differences [21], which leads to limitations in the understanding of brand effects in different market environments.

Further analysis of the literature shows that current research has three main limitations at the methodological level. The sample bias problem is significant. Kethüda [22] explored the impact of

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university ranking reports on brand credibility and differentiation through covariance analysis and found that signals related to academic success could enhance the credibility and differentiation perception of university brands. Similar existing studies are mostly based on data from European and American universities, lacking attention to universities in developing countries, which limits the universality of the research conclusions. The cultural adaptability of measurement tools has not been fully explored, and most studies use a unified brand identification scale. Jois and Chakrabarti [23] constructed and validated a scale to measure global education service brand building through mixed methods and systematic literature review, combined with expert interviews, questionnaires, and structural equation model analysis, providing a more comprehensive theoretical framework and practical guidance for higher education brand research. This failed to adjust to different cultural backgrounds, leading to measurement bias. The application of cross-cultural theoretical frameworks is relatively limited. Most of these brand awareness studies usually fail to systematically incorporate Hofstede's cultural dimensions or other cross-cultural analysis tools, which affects the depth and explanatory power of the research. Abro et al. [24] explored the role of English in internal and external corporate communications and emphasized the importance of English in creating competitive advantages and encouraging entrepreneurial success in an increasingly interconnected world. Similarly, Gammarano et al. [25] constructed a comprehensive framework to explain how influence works in the digital world, focusing on the cultural factors that shape these relationships in today's globalized and digitalized markets. These findings are consistent with the framework of this study, emphasizing the interaction between cultural values and brand communication effects.

To fill the above research gap, this paper proposes a research framework with a cultural moderation effect as the core and systematically explores the mechanism of the impact of university brand awareness on students' admission decisions under different cultural backgrounds. This framework not only expands the brand management theory [25] but also provides theoretical support for universities to formulate precise global enrollment strategies. At the practical level, the research results of this paper are helpful in optimizing the brand communication strategy of universities in the international market and enhancing their enrollment competitiveness. Specifically, universities can adjust their brand positioning [26] according to the needs of different cultural groups, optimize marketing content, and combine cultural adaptation strategies to enhance brand influence, thereby occupying a favorable position in the global enrollment competition.

The role of university brand awareness in international enrollment is becoming increasingly prominent, but due to significant differences in brand sensitivity among students from different cultural backgrounds, enrollment strategies need to be adapted to local conditions and adjusted flexibly. The study finds that groups with high brand sensitivity pay more attention to infrastructure, school location, and teaching staff. Based on this, universities can optimize their strategies in the above three aspects in global enrollment. In terms of school location, Wijaya et al. [27] used SEM to analyze questionnaire data, studied how geographical location indirectly affects student decision-making to choose private universities through brand image, and found that location had a positive impact on students' school choice. Markets with high brand sensitivity should strengthen the promotion of universities located in international cities and economic centers, highlighting career development opportunities and global networks. Markets with low brand sensitivity should emphasize the cost of living, safety, and livability. In terms of teaching staff, the demands of different cultural groups for teaching quality and trust can be met by highlighting the international teaching background, star professors, or teacher resources related to the students' home countries. In terms of infrastructure, universities should showcase technological advantages such as advanced teaching and research equipment and digital learning environments [28] while taking into account the concerns of students with low brand sensitivity about campus life convenience and learning support systems, universities can more effectively exert the influence of brand awareness through differentiated strategic adjustments. This approach can enhance the attractiveness and conversion efficiency of international enrollment [29, 30].

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This paper adopts a cross-national mixed research method, combined with Hofstede's cultural dimension modeling, and constructs a cross-cultural analysis framework for brand awareness to influence student decision-making through SEM, multi-group analysis, and cluster analysis. Based on global university brand awareness indicators and international students' school selection behavior data, this paper explores the differences in brand sensitivity among different cultural groups and their impact on university brand communication.

2. Realization Process of University Brand Awareness Influencing Student Decision-making

2.1. Methods and Data Collection

To deeply explore the communication effect and formation mechanism of university brand cognition in a cross-cultural context, this study adopts a mixed-method approach and systematically conducts data collection and analysis. Regarding research design, the study involves respondents from multiple countries and combines structured and unstructured data sources to model and evaluate the university brand image from the perspectives of cultural psychology and media performance. The research process is divided into three stages: the collection of cross-cultural data, the acquisition and integration of multi-source brand data, and the application of analysis techniques based on structured models. The entire process incorporates questionnaire surveys, in-depth interviews, social media data mining, keyword extraction, and sentiment analysis, utilizing clustering, latent class analysis, and inductive framework construction to develop a comprehensive research system that integrates quantitative and qualitative methods. Figure 1 illustrates the mixed-method approach employed in this study and the main operational procedures of each stage.

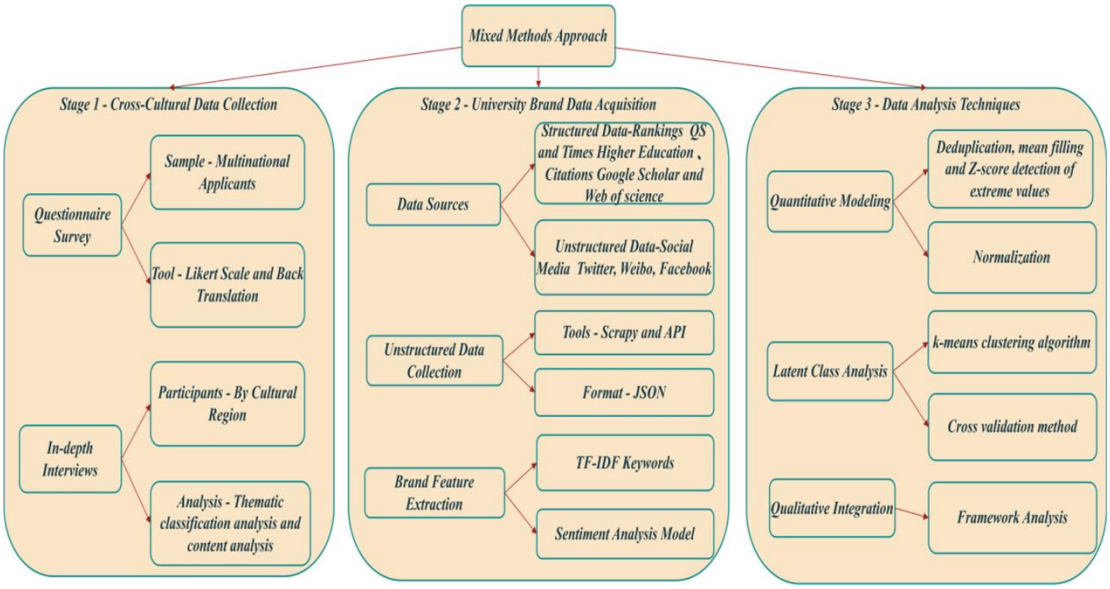

Figure 1.
Flow chart of university brand communication research under the mixed method path.

The study in Figure 1 collects cross-cultural data by combining questionnaire surveys with in-depth interviews. The structured questionnaire covers academic reputation, employment prospects, campus culture, social image, and other dimensions, focusing on the brand awareness variable, and uses the Likert five-point scale to evaluate perceived intensity. The sample design includes applicants from universities in multiple cultural areas such as Asia, Europe, and North America, covering undergraduate, master's, and doctoral levels. The questionnaire employs the backward translation

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method to ensure language consistency. In terms of data acquisition, structured and unstructured information sources are integrated. The former includes QS and THE (Times Higher Education) rankings and Google Scholar and Web of Science citation data. The latter uses the Scrapy framework and API (Application Programming Interface) technology to automatically capture discussion data related to university brands from social platforms such as Weibo, Twitter, and Facebook, combining regular expressions and throttling mechanisms to achieve legal and complete data collection, with data stored in a standardized JSON format. Text data processing utilizes TF-IDF (Term Frequency-Inverse Document Frequency) to extract university brand keywords and combines sentiment analysis to build a cross-platform and cross-language brand awareness index. Regarding analysis methods, the data is cleaned and standardized, and the relationship between university brands and students' enrollment intentions is predicted through machine learning algorithms. K-means clustering is further used to segment student groups, identify potential categories in brand sensitivity, and improve model stability through cross-validation. The thematic variables identified by in-depth interviews are integrated with the results of quantitative analysis, and a theoretical model is constructed using framework analysis to explain how university brands influence cross-cultural students' school selection decisions.

2.2. Definition and Measurement of University Brand Awareness

The core concept of university brand awareness involves students' awareness of universities worldwide, which is usually measured by multi-dimensional indicators. To ensure that this concept is accurately captured in a cross-cultural context, this paper adopts a comprehensive multi-level measurement method to divide university brand awareness into three main dimensions: world university rankings, social media mentions, and academic paper citations. These dimensions reflect the reputation, public awareness, and academic influence of universities worldwide. The specific measurement methods are as follows.

The world university rankings reflect the reputation and influence of universities in the global education community. Data collection uses API interfaces and crawler technology to crawl data from QS Rankings and THE World University Rankings. For each university, its ranking position R_i is set, and the ranking data is standardized to obtain the relative ranking value R_i^*.

$$R_i^* = \frac{R_i - \min(R)}{\max(R) - \min(R)} \quad (1)$$

R is the ranking data; $\min(R)$ is the minimum value in the ranking data R; $\max(R)$ is the maximum value in the ranking data R. This ensures that the ranking values of all universities are within the $[0,1]$ interval, ensuring data comparability and cross-cultural applicability.

The social media mention rate measures the discussion heat and public awareness of universities on social platforms. This paper uses web crawler technology to collect relevant data from social platforms such as Weibo and Twitter, and calculates the number of times each university is mentioned in a specific time period. This method ensures the standardized processing of social media data and facilitates cross-cultural comparison. Data from different social platforms is also processed in the same standardized way to avoid data bias between platforms.

The citation rate of academic papers reflects the influence of universities in the academic field. The API interface is used to extract the number of academic papers and the number of citations of universities from Google Scholar and Web of Science. The number of citations of academic papers is set as , and the Academic Impact Index (AII) of each university is calculated. The calculation formula is:

$$AII_i = \frac{C_i}{P_i} \quad (2)$$

Among them, Pi is the total number of papers published by the university, and Ci is the total number of citations of these papers. For unified comparison, AII_i is standardized and converted into the standardized impact index ALL_i^* to satisfy the same numerical range: $[0, 1]$. These measurement methods combine the global ranking, public awareness, and academic influence of universities to provide a multi-dimensional measurement standard for university brand awareness. In cross-cultural analysis,

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these standardized indicators ensure that brand awareness data in different cultural backgrounds are comparable and prevent cultural differences from interfering with data results.

To further improve data accuracy, this paper combines natural language processing technology to analyze the characteristics of brand image. By using the term frequency-inverse document frequency algorithm to process brand-related content in social media texts and news reports, the brand keywords of each university are extracted, and its brand image is quantitatively described through sentiment analysis. The brand sentiment score of each university is set to Ei, and its calculation method is as follows:

$$E_i = \frac{\sum_{t=1}^{T} w_t \cdot f_{i,t}}{\sum_{t=1}^{T} w_t} \quad (3)$$

w_t is the weight of the keyword t; $f_{i,t}$ is the frequency of the university i on keyword t; T is the total number of all keywords. Through sentiment analysis, the positivity or negativity of the brand image can be quantified, thereby further enriching the measurement of university brand awareness.

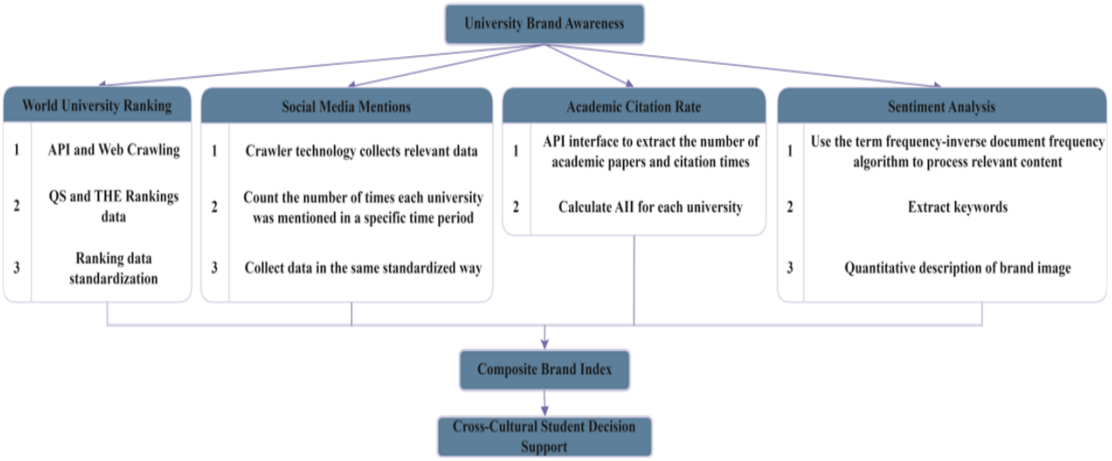

Figure 2.
Structure diagram of a multi-dimensional quantitative system of university brand awareness.

The four types of data sources presented in Figure 2 bear different weight divisions in the calculation of the comprehensive brand index. From the perspective of global university rankings, the two authoritative rankings of QS and THE provide a structured evaluation basis through standardized scoring; the social media mentions use crawler technology to capture relevant information of universities in the same period and count them uniformly, which enhances the capture of brand popularity in informal scenarios; the academic citation rate obtains the output and citation frequency of each school's papers through the API interface, and the calculated AII value directly reflects the impact of scientific research output; the sentiment analysis part uses the word frequency-inverse document frequency algorithm to extract keywords and emotional tendencies to achieve a quantitative expression of the public image of universities. Although the four types of data are different in nature, they all have an objective and comparable measurement system, and the constructed brand index has strong credibility and explanatory power.

2.3. Key Factors in Students' Admission Decisions

The factors that affect students' choice of universities involve many aspects, including academic reputation, employment prospects, and campus culture. The weights of these factors vary in different cultural backgrounds, and it is necessary to combine education survey datasets from multiple countries and areas for quantitative analysis to ensure the wide applicability of the research results.

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The key variables of students' admission decisions are identified by statistical methods and quantitatively analyzed using a multivariate regression model. The students' admission decision variable is set to Y, and its influencing factors include the academic reputation of the university X_1, employment prospects X_2, campus culture X_3, etc. The linear regression model is assumed to be:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon \quad (4)$$

β_0 is the constant term; β_1, β_2, and β_3 are the parameters to be estimated; ε is the random error term. The least squares method is used to estimate the parameter value so that the residual sum of squares is minimized:

$$\min_{\beta_0,\beta_1,\beta_2,\beta_3} \sum_{i=1}^{n} (Y_i - \beta_0 - \beta_1 X_{1i} - \beta_2 X_{2i} - \beta_3 X_{3i})^2 \quad (5)$$

n is the number of samples; Y_i is the admission decision result of the i-the sample; X_{1i}, X_{2i}, and X_{3i} are the academic reputation, employment prospects, and campus culture index values of the sample, respectively.

The key factor analysis under different cultural backgrounds is estimated by a multilevel model. Assuming that the admission decision of students in the j-th cultural group is affected by the same factors, but there are cultural differences in the influencing coefficients. The multilevel regression model is expressed as:

$$Y_{ij} = \beta_{0j} + \beta_{1j} X_{1ij} + \beta_{2j} X_{2ij} + \beta_{3j} X_{3ij} + \varepsilon_{ij} \quad (6)$$

Y_{ij} is the admission decision result of the i-th student in the j-th cultural group; β_{0j}, β_{1j}, β_{2j}, and β_{3j} are the specific regression coefficients of the cultural group; ε_{ij} is the error term.

To improve the model's predictive ability, the cross-validation method is used to evaluate the model's generalization error. The dataset is divided into a training set and a test set, and the k-fold cross-validation method is employed to verify the model. The training error is defined as:

$$\text{Train Error} = \frac{1}{N_{\text{train}}} \sum_{i=1}^{N_{\text{train}}} (Y_i - \hat{Y}_i)^2 \quad (7)$$

The test error is:

$$\text{Test Error} = \frac{1}{N_{\text{test}}} \sum_{i=1}^{N_{\text{test}}} (Y_i - \hat{Y}_i)^2 \quad (8)$$

N_{train} and N_{test} are the number of samples in the training set and the test set, respectively, and $\hat{Y}_i$ is the model prediction value. The model with the smallest test error is selected as the final model to ensure the model's generalization ability.

The differences in cultural background are encoded by categorical variables. The cultural variable C is set as a dummy variable:

$$C_j = \begin{cases} 1, If\ students\ belong\ to\ cultural\ group\ j \\ 0, or \end{cases} \quad (9)$$

The cultural variable is applied to the regression model, and the interaction term is tested:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 C + \beta_5 (X_1 \cdot C) + \beta_6 (X_2 \cdot C) + \beta_7 (X_3 \cdot C) + \varepsilon \quad (10)$$

Among them, β_4, β_5, β_6, and β_7 are used to measure the moderating effect of cultural factors on each influencing factor. If the interaction term is significant, it indicates that there are differences in the impact of cultural factors on admission decisions. According to the model estimation results, the importance of academic reputation, employment prospects, and campus culture is ranked, and the standardized regression coefficient is calculated.

$$\beta_k^* = \frac{\beta_k \cdot \sigma_{X_k}}{\sigma_Y}, k \in \{1,2,3\} \quad (11)$$

σ_{X_k} and σ_Y are the standard deviations of X_k and Y, respectively, and k represents the number of the variable coefficient involved in the operation in the formula, with a value range of 1,2,3. The larger the standardized coefficient, the stronger the influence of the variable on student decision-making. The

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above analysis method can fully reveal the core factors of students' school selection decisions and quantify the moderating role of cultural factors in the decision process.

2.4. Influence Mechanism of University Brand Awareness on Student Decision-Making

The influence of university brand awareness on students' admission decisions involves multiple paths, including direct and indirect effects. The factor analysis method is used to identify the core variables that affect the student decision-making process, and the SEM [29, 30] is constructed to quantify the influence of brand awareness on student decision-making. It is assumed that the student decision-making variable is Y, which is directly affected by brand awareness and indirectly affected by the latent factor F. The direct path influence of brand awareness is modeled as follows:

$$Y = \gamma_0 + \gamma_1 B + \gamma_2 F + \zeta \quad (12)$$

γ_0 is the intercept term, which represents the basic level of the students' admission decision variable Y when brand awareness B and latent factor F are both 0. γ_1 is the direct path coefficient of brand awareness on admission decision, reflecting the explicit effect of university brand identification on student behavior. γ_2 represents the influence coefficient of the latent variable F on decision variable Y, reflecting the role of brand influence through indirect channels. ζ is the residual term, which represents the individual differences or error part that cannot be explained by the model.

To analyze the structural relationship of latent factors, the factor analysis model is applied:

$$X = LF + U \quad (13)$$

X is the observed indicator variable matrix, which is directly measurable data. L is the factor loading matrix, which indicates the degree to which each observed variable is affected by the latent factor. F is the latent factor matrix, which indicates the degree to which each observed variable is affected by the latent factor. U is the error term matrix, which reflects the noise part of the observed data that is not explained by the latent variable.

The minimum variance estimation method is used to solve the factor model to improve the stability and explanatory power of the estimation results. The factor score estimation adopts the following regression method:

$$\hat{F} = (L^T \Sigma^{-1} L)^{-1} L^T \Sigma^{-1} X \quad (14)$$

$\hat{F}$ is the estimated latent factor score, and Σ is the covariance matrix of the observed variable X. This method regresses the standardized data of the observed variables to determine the optimal linear combination between the observed variables and the latent factors, thereby obtaining the score estimate of the latent factor.

This factor score estimation method constructs a factor score coefficient matrix. It adjusts the correlation between observed variables and eliminates interference caused by measurement error, enabling the latent variable to more accurately explain student behavior in subsequent models. Next, the measurement model of the latent variable is constructed within the structural equation model as follows:

$$F_t = \lambda_t X + \delta_t \quad (15)$$

F_t is the estimated value of the t-th latent variable. λ_t is the measurement factor loading coefficient, which measures the strength of the linear relationship between the factor and the observed variable. X is the observation indicator. δ_t is the measurement error term, which represents the uncertainty and interference in the measurement process of the latent variable.

To estimate the model, the maximum likelihood estimation method is applied, and its log-likelihood function is defined as:

$$L(\theta) = -\frac{N}{2}(\ln|\Sigma(\theta)| + \mathrm{tr}(\Sigma(\theta)^{-1} S)) \quad (16)$$

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θ refers to the model parameter set, including path coefficient, loading coefficient, error variance, etc. $\Sigma(\theta)$ is the covariance matrix of the model estimation, which represents the model's prediction of the data covariance structure under given parameters. S is the sample covariance matrix, which is calculated from the actual observed data. N is the sample size. Maximizing the log-likelihood function can obtain the optimal model parameter estimate, so that the difference between the model covariance and the sample covariance is minimized.

Through this structural modeling analysis, not only can the role path of university brands in student decision-making be quantified, but significance tests can also be performed based on the path coefficients to verify the actual influence of brand variables, providing data support for universities to optimize brand communication strategies.

2.5. Influence Path of Brand Awareness from a Cross-cultural Perspective

The influence path of brand awareness in different cultural backgrounds is analyzed using multi-group SEM, combined with latent variable cluster analysis to explore the decision patterns of groups with different brand sensitivities. The brand awareness variable is set as B_i, and the student decision-making variable is set as D_i. The relationship between the two is modeled through multiple mediating variables. Assuming that brand awareness affects perceived value V_i through social media communication and further acts on the decision variable D_i, the SEM is set as follows:

$$V_i = \alpha_1 B_i + \epsilon_i \quad (17)$$

$$D_i = \beta_1 V_i + \beta_2 B_i + \eta_i \quad (18)$$

ϵ_i and η_i both represent residual terms and obey a normal distribution. The former represents the random disturbance not explained by the model, and the latter represents the fluctuation part of the second-stage path that cannot be explained by the model. α_1 is the path coefficient of the influence of brand awareness on brand cognition. β_1 is the self-feedback path coefficient, which represents the influence of students' own brand cognition in the previous stage on the current stage cognition. β_2 is the path coefficient that measures the independent influence of brand awareness on brand cognition after controlling for cognitive self-feedback.

To further characterize the differences in sensitivity among student groups to brand awareness, latent variable cluster analysis is used to identify individuals with varying sensitivities. The latent variable Z_i is set to represent brand sensitivity. The distribution of the latent variable is estimated based on the maximum expectation algorithm. The calculation formula is as follows:

$$P(Z_i = j|X_i) = \frac{\pi_j f(X_i|\theta_j)}{\sum_{j'} \pi_{j'} f(X_i|\theta_{j'})} \quad (19)$$

X_i is the set of observed variables of the i-th student. π_j is the prior probability of the category j. θ_j is the model parameter vector of the j-th category. $f(X_i|\theta_j)$ is the conditional probability density function of the j-th category for the sample X_i under parameter condition θ_j. The model optimization is addressed using the variational Bayesian method. The optimal number of categories is determined based on the Bayesian Information Criterion (BIC). The number of clusters is adjusted to halt the classification optimization when $\Delta BIC < 2$.

For different brand sensitivity groups, their SEM path parameters are estimated independently; the path diagram is constructed; and the standardized regression weights are calculated. To test the impact mechanism of brand awareness on students' admission decisions under different groups, the interaction effect analysis is further combined with the group's cultural background C_i to establish a regression model containing interaction terms:

$$D_i = \gamma_1 B_i + \gamma_2 Z_i + \gamma_3 C_i + \gamma_4 B_i Z_i + \gamma_5 B_i C_i + \gamma_6 Z_i C_i + \zeta_i \quad (20)$$

D_i represents the brand selection behavior or attitude decision of the i-th student. B_i represents the degree of awareness of the i-th respondent about a certain brand. γ_1 represents the direct impact of

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brand awareness on the decision. γ_2 refers to the independent effect of brand sensitivity on decision making. γ_3 refers to the direct effect of cultural background on students' brand decision making. γ_4 is the moderating effect of the interaction between brand awareness and sensitivity on decisions. γ_5 is the interactive moderating effect of brand awareness and cultural background. γ_6 refers to the interactive moderating effect of brand sensitivity and culture. ζ_i is the error term, which represents the part of the decision variation that is not explained by the model. The model estimation adopts the generalized linear regression method. To improve the robustness of the path coefficient estimation under small sample conditions, the bootstrap resampling technique is applied for repeated estimation to evaluate the significant differences in path coefficients and interaction terms in different sensitive groups.

3. Impact of University Brand Awareness from a Cross-cultural Perspective

3.1. Overall Impact of University Brand Awareness

Against the background of increasingly fierce global higher education competition, the impact mechanism of brand awareness on students' admission decisions has become a research hotspot. To explore how brand awareness affects student decision-making through different media paths, this study collects data from various areas and constructs a multi-path regression analysis model. By quantifying the path coefficient β of brand awareness under direct and indirect effects, its performance in different areas is compared and analyzed. Table 1 shows the statistical results of the impact of brand awareness on student decision-making through different communication paths.

Table 1.
Path analysis of brand awareness on admission decisions.

Impact Path	Global overall β	Asia β	North America β	Europe β	Other areas β
Brand awareness → Student decision-making	0.42	0.38	0.45	0.41	0.39
Brand awareness → word-of-mouth → student decision-making	0.47	0.53	0.41	0.45	0.44
Brand awareness → Social media communication → Student decision-making	0.35	0.4	0.32	0.34	0.36
Brand awareness → Academic reputation → Student decision-making	0.5	0.55	0.48	0.51	0.49

Table 1 shows that there are obvious regional differences in the impact path of brand awareness on student decision-making. Globally, the coefficient of brand awareness directly affecting student decision-making is 0.42, while in North America, this value rises to 0.45, indicating that the brand effect is more significant in this area. The path coefficient of brand awareness influencing student decision-making through word-of-mouth communication reaches 0.53 in the Asian market, which is higher than in other areas. This is related to the high dependence of the Asian market on social evaluation. The coefficient of the influence of social media communication path in Asia is 0.4, higher than 0.32 in North America, indicating that Asian students rely more on social media information in their admission decisions, while the influence of social media in the North American market is relatively weak. Academic reputation, as a key component of brand awareness, has a greater impact on student decision-making in all areas, among which the path coefficient in the Asian market is the highest, at 0.55, indicating that students in this area attach more importance to the academic influence of institutions. The mechanism by which brand awareness affects student decision-making through different communication paths shows regional characteristics, and brand strategies should be optimized in combination with the communication characteristics of each regional market.

In the context of the current global development of higher education, more and more countries are paying attention to the comprehensive competitiveness of colleges and universities in order to gain advantages in talent training, scientific research cooperation, and international influence. The evaluation is conducted around the multi-dimensional performance of universities in China, America, and Germany,

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taking into account key indicators such as global ranking, academic reputation, and employment reputation, so as to explore the characteristics and development focus of higher education systems in different countries. To more intuitively present the comparison of universities in the three countries in various dimensions, Figure 3 is drawn.

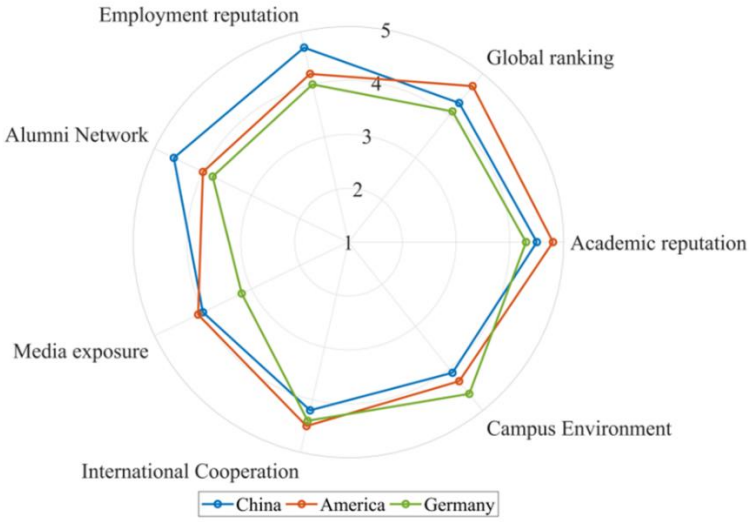

Figure 3.
Importance evaluation of university brand elements by students from different countries.

From the data analysis in Figure 3, it can be seen that Chinese universities perform most prominently in the employment reputation dimension, with a score of 4.7, significantly higher than that of America and Germany. This is closely related to China's emphasis on the employment quality of college graduates in recent years, and also reflects the continuous improvement of Chinese companies' recognition of local higher education. America is slightly higher than the other two countries in the two indicators of global ranking and academic reputation, with scores of 4.7 and 4.8, respectively, thanks to its long-term and stable investment in scientific research and the concentrated distribution of high-quality educational resources. Germany, on the other hand, performs relatively well in international cooperation, with a score of 4.4, which is closely related to its strong support from the EU (European Union) education network and the extensive development of international exchange projects. Considering various indicators comprehensively, the overall performance of American universities is relatively balanced, demonstrating strong comprehensive strength.

To gain a deeper understanding of the impact of different factors on student decision-making, this study analyzes relevant data from multiple regions worldwide. The study focuses on the weight differences of four factors in the student decision-making process: brand awareness, word-of-mouth communication, social media communication, and academic reputation. Data collection covers five categories: global, Asia, North America, Europe, and other areas. The proportion of each factor in different regions is displayed through visualization to reveal possible trend differences between areas. Figure 4 shows the proportion of factors affecting student decision-making in different regions.

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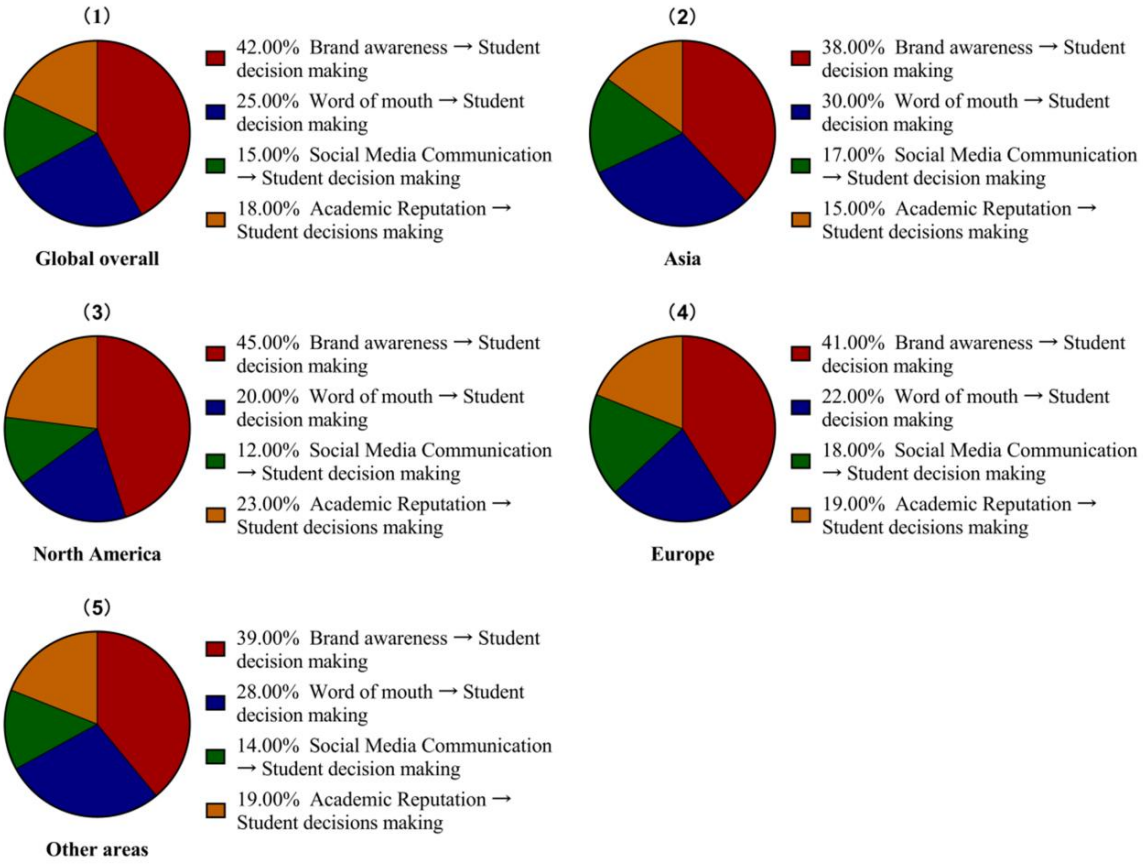

Figure 4.
Direct and indirect contribution of brand awareness in different cultural backgrounds.
Note:
Figure 4 (1). Direct and indirect contribution of brand awareness globally.
Figure 4 (2). Direct and indirect contribution of brand awareness in Asia.
Figure 4 (3). Direct and indirect contribution of brand awareness in North America.
Figure 4 (4). Direct and indirect contribution of brand awareness in Europe.
Figure 4 (5). Direct and indirect contribution of brand awareness in other areas.

In Figure 4, brand awareness has the highest impact on student decision-making in North America, at 45%. It reaches 42% and 41% globally and in Europe, respectively, while it is relatively low in Asia and other areas, at 38% and 39%, respectively. This shows that in developed areas, brand effects have a stronger influence on student choices, while in Asia and other regions, students may be more inclined to consider other factors in their decisions. Word-of-mouth communication has the highest proportion in Asia, at 30%, while in North America it is only 20%, indicating that word-of-mouth communication is more significant among Asian students, which is related to their social network usage habits. The influence of social media communication in Europe is higher than the global average, at 18%, while North America is the lowest, at only 12%, reflecting that European students may rely more on social media to obtain information about institutions. The influence of academic reputation on student decision-making is similar in North America, Europe, and other regions, at 23%, 19%, and 19%, respectively, while Asia is the lowest, at 15%, which is related to the diversity of education systems and student information acquisition channels in different areas. Overall, there are obvious differences in the main influencing factors in the decision-making process of students in different regions, indicating that regional culture, information dissemination methods, and socio-economic development levels significantly impact student choices.

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3.2. Role of Word-of-mouth Effect and Social Media Communication

The core variables identified by factor analysis are used to analyze the impact of word-of-mouth effects and social media communication on student decision-making. To further explore students' trust in various word-of-mouth information sources under different cultural backgrounds, this study collects and analyzes trust score data from Asia, Europe, North America, South America, and Africa, covering five aspects: alumni recommendations, high school teacher recommendations, social media, official websites, and university rankings. The data is obtained through questionnaires, and the results are standardized to ensure the comparability of each score. The trustworthiness of various information sources may be affected by factors such as the education system, social network influence, and information transparency. The core of the study is to identify the differences in trust patterns under different cultural backgrounds. Table 2 shows the scores of respondents in different areas on different information sources.

Table 2.
Credibility scores of word-of-mouth information sources.

Cultural Background	Alumni Recommendation	High School Teacher	Social Media	Official Website	University Rankings
Asia	8.2	7.5	6	7.8	8.5
Europe	7	6.8	7.2	7.5	8
North America	8.5	7.8	7.5	8	8.8
South America	7.5	6.5	6.8	7.2	8.2
Africa	6.5	6	5.5	6.8	7.5

In Table 2, alumni recommendations are given a high credibility rating in all cultural contexts. Respondents in North America give the highest rating, reaching 8.5. The ratings in Asia and South America are relatively high, at 8.2 and 7.5, respectively, and the rating in Africa is the lowest, at only 6.5. This is related to the close alumni networks in North America and Asia and the strong influence of alumni recommendations in the admissions process. The rating of high school teachers in North America is 7.8, higher than 7.5 in Asia and 6.8 in Europe, indicating that high school teachers in North America play a strong guiding role in the college selection process. The rating of social media is relatively low in all categories, with North America having the highest rating of 7.5 and Africa having the lowest rating of only 5.5, reflecting that the degree of trust in social media information in different areas is greatly affected by the quality of information and the level of supervision. The rating of official websites fluctuates between 6.8 and 8, and the trust in official information is high in various areas. North America has the highest credibility score of university rankings, reaching 8.8, while Africa has the lowest score, only 7.5, indicating that respondents in North America have a high degree of identification of ranking institutions, while some areas may have low trust in them due to data transparency or applicability issues of the ranking system.

In the analysis of the global influence of social media platforms, regional factors have an important impact on user preferences. The study uses a scoring mechanism to collect data statistics on major social media platforms in different continents, covering five platforms: Twitter, Facebook, Weibo, TikTok, and Instagram, to quantify their performance in different areas. The data comes from user interactions in a specific time period, and the scores are calculated according to a unified standard to ensure the fairness of the comparison. The differences in scores across various continents can reflect the popularity of different social platforms worldwide and their regional distribution characteristics. The specific results are shown in Figure 5.

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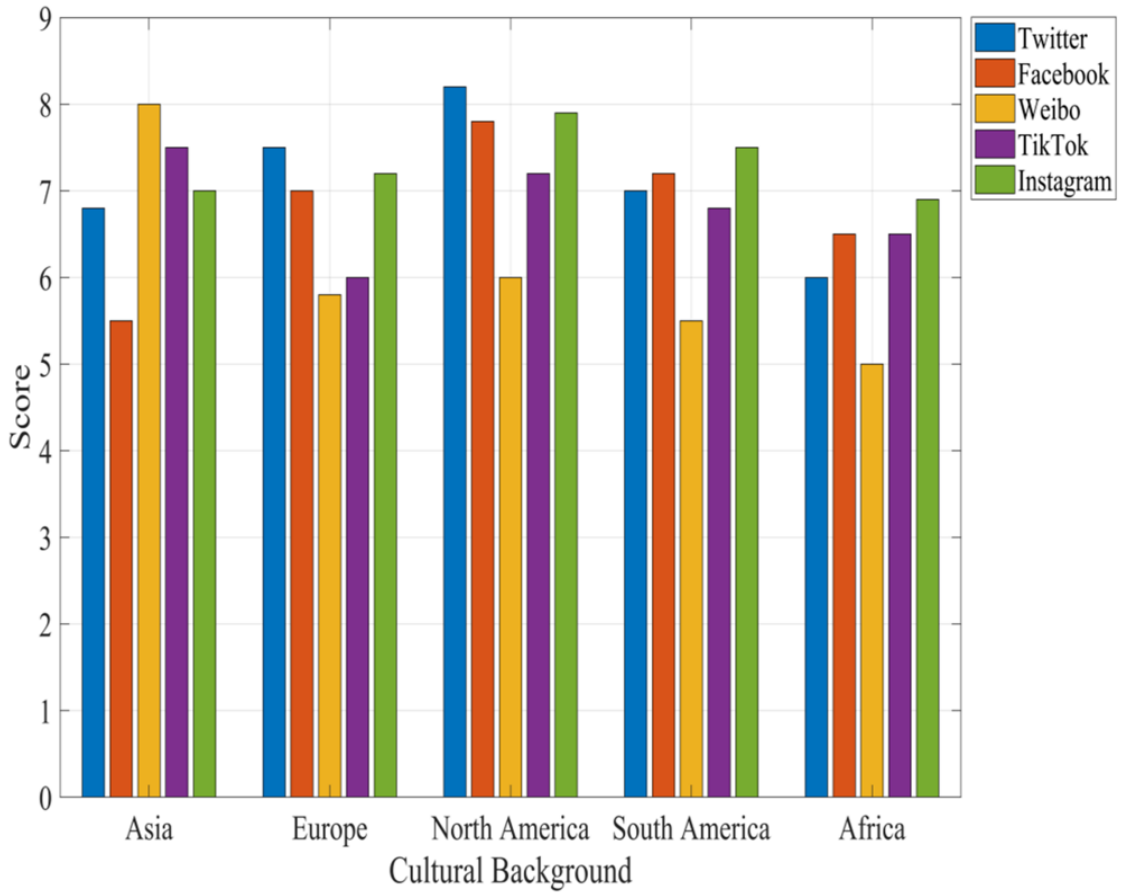

Figure 5.
Social media platform influence scoring.

In Figure 5, Facebook has the highest scores in North America and South America, reaching 7.8 and 7.2 points, respectively, which is related to the long-term high dependence of these two areas on the platform. Twitter performs relatively well in Europe and North America, while its scores in other areas are slightly lower, reflecting that its influence is still mainly concentrated in Western countries. Weibo scores 8 in Asia, but its scores in other areas are all below 7, indicating that its main user groups are concentrated in Asia. TikTok's scores are evenly distributed across continents, with an overall score stable between 6 and 7.5, indicating that the platform's globalization strategy is relatively successful and receives high attention in multiple areas. Instagram's scores are relatively close in all areas, indicating that its user base is relatively broad, and there is no obvious regional bias. Overall, Twitter and Instagram are more popular worldwide, while Weibo's influence is more regionally limited.

3.3. Correlation between Cultural Differences and Brand Awareness Sensitivity

This study explores the performance of different areas in five key cultural dimensions, covering individualism, power distance, uncertainty avoidance, long-term orientation, and brand awareness sensitivity. By comparing the scores of these cultural dimensions in different areas, the study aims to reveal the differences in marketing strategies and management methods that may be adopted by various regions in the global market. To this end, the study collects cultural data from Europe and the Americas, East Asia, South Asia, Latin America, and Africa, and constructs a comprehensive cultural

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difference model. Figure 6 shows the distribution of scores of these areas in each cultural dimension, which helps to deepen the understanding of the cultural characteristics of each region.

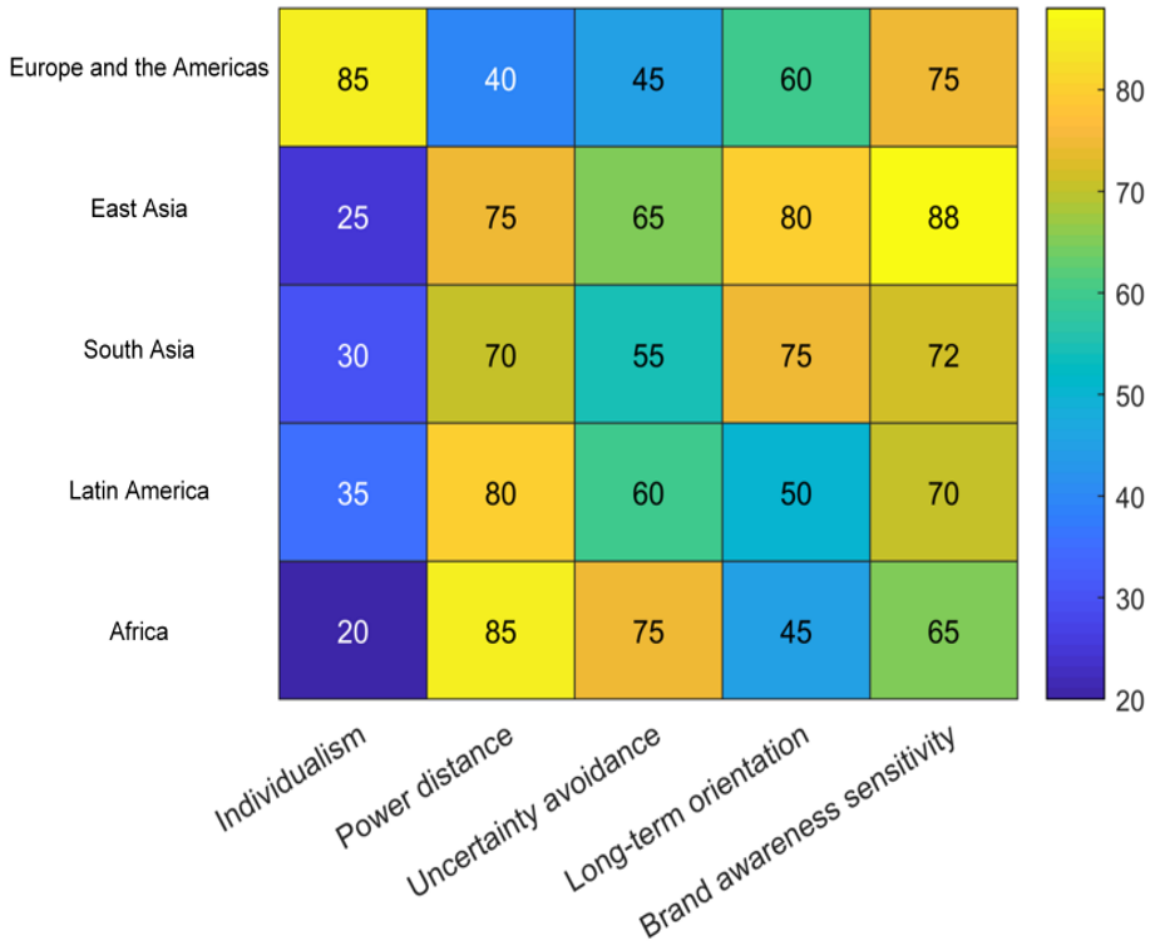

Figure 6.
Brand awareness sensitivity under different cultural values.

Based on the data in Figure 6, a one-way ANOVA (analysis of variance) was conducted on the scores of the five cultural dimensions across different areas. The results show a p-value of 0.0348, indicating statistically significant differences in the scores of various cultural dimensions. This suggests that the variation in scores among different areas is statistically meaningful, supporting the assertion that there are distinct cultural characteristics across regions. Europe and the Americas scored the highest in individualism, reaching 85, which indicates a tendency toward individualistic values emphasizing independence and autonomy. Conversely, Africa scored the lowest in this dimension, with a score of 20. Regarding power distance, Africa scored the highest at 85, reflecting a high acceptance of hierarchical structures. Europe and the Americas scored lower, with a score of 40, indicating a lesser acceptance of power inequality and social stratification. In the dimension of uncertainty avoidance, East Asia scored 65, suggesting a preference for environments with clear rules and expectations to reduce uncertainty. In terms of long-term orientation, East Asia ranked first with a score of 80, emphasizing a focus on long-term planning and future development. The scores for brand awareness sensitivity in Africa and Latin America were relatively low, at 65 and 70, respectively, indicating weaker brand awareness in these regions. In summary, the significant differences in cultural dimensions among areas

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provide valuable insights for developing global market strategies and managing cross-cultural interactions effectively.

3.4. Interaction of Other Influencing Factors in Student Decision-Making

To explore the impact of brand awareness on academic reputation, career prospects, and campus culture in different countries, this experiment collects data from five countries, including China, America, Germany, India, and Japan, through questionnaire surveys and data analysis, as shown in Figure 7.

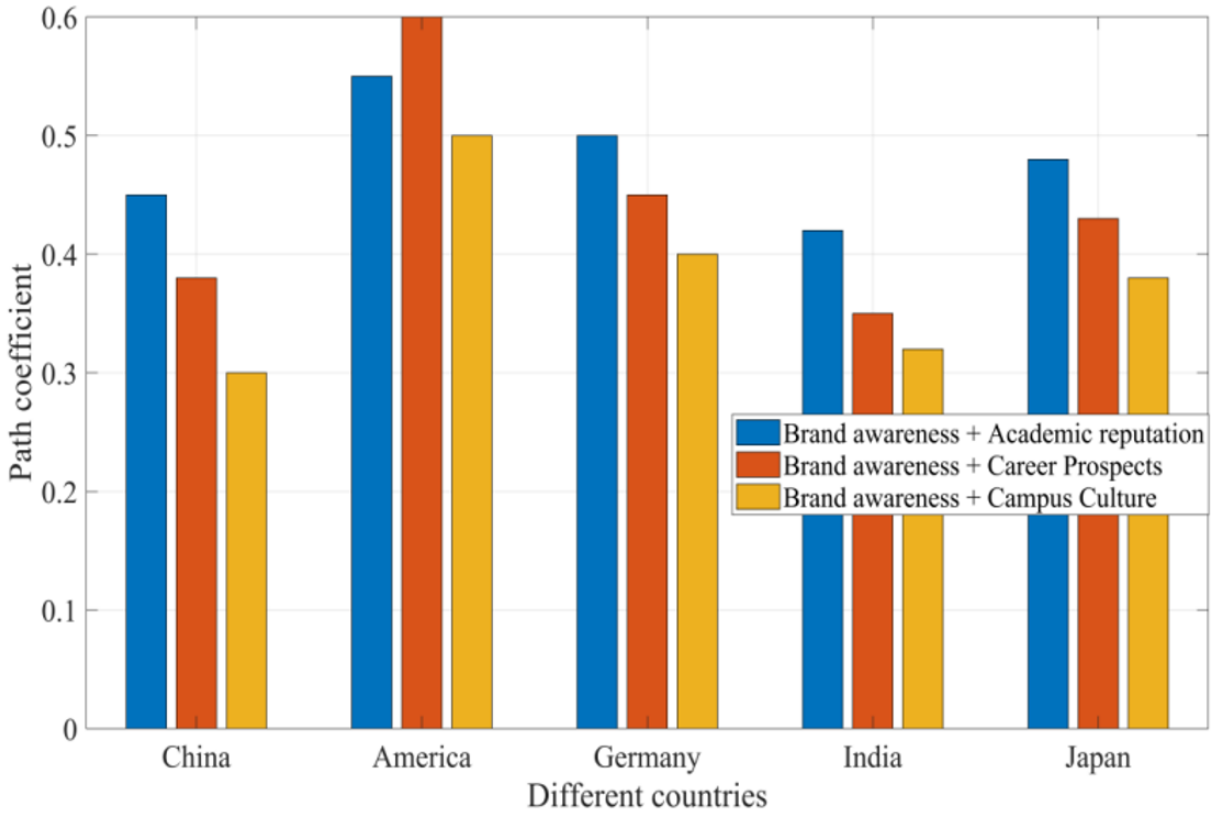

Figure 7.
Comparison of path coefficients in different countries after brand awareness interacts with other influencing factors.

As can be seen from Figure 7, the path coefficient between brand awareness and academic reputation is the highest in America (0.55), indicating that brand awareness has the most significant impact on academic reputation in America. In contrast, the path coefficients between brand awareness and academic reputation in China, Germany, India, and Japan are relatively low, approximately 0.45, 0.50, 0.42, and 0.48, respectively. This variation is related to the high degree of marketization of the higher education system in America, where brand awareness plays a crucial role in attracting international students and enhancing the reputation of institutions. Additionally, the path coefficient between brand awareness and employment prospects is also the highest in America (0.60), further emphasizing the importance of brand awareness in career development. However, regarding campus culture, the path coefficient of brand awareness is generally low, especially in China and India, at about 0.30 and 0.32, respectively. This reflects that campus culture is more influenced by local factors rather than directly driven by brand awareness. There are significant differences in the mechanisms of brand awareness

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across countries, with its influence mainly concentrated in the fields of academic reputation and career prospects. Its impact on campus culture remains relatively weak.

This study explores the differences in perceptions among various cultural groups regarding multiple evaluation indicators of higher education institutions. Through quantitative analysis, the scores of five dimensions, namely brand awareness, internationalization, employment prospects, campus culture, and tuition and scholarship policies are compared to reveal the preference characteristics and focus areas of students from different regions. The data collection covers five major cultural groups: Europe and the Americas, Latin America, Africa, the Middle East, and Southeast Asia. The specific results are shown in Table 3.

Table 3.
Comparison of brand awareness and other influencing factors.

Cultural groups	Brand awareness score	Internationalization score	Employment prospects score	Campus culture score	Tuition and scholarship policy score
Europe and the Americas	7.5	8.2	7.8	7.5	6.9
Latin America	7	7	6.5	6.8	7.5
Africa	6.5	6.8	6.2	6	6.5
Middle East	7.8	8	7.2	7	7.2
Southeast Asia	7.6	7.8	7.3	7.2	7.6

Table 3 compares brand awareness with other influencing factors. The Europe and the Americas group scores the highest in the internationalization index, 8.2, reflecting that students in the area attach great importance to globalized educational resources; the Middle East and Southeast Asia perform well in brand awareness, scoring 7.8 and 7.6, respectively, which is related to the strong identification of international brands in the local higher education market. Latin American students give tuition and scholarship policies a high score of 7.5, indicating that economic factors play an important role in their decision-making. The African group scores low in all dimensions, suggesting that infrastructure or cultural adaptability may become a constraint in their choice of university. The data shows that students from different cultural backgrounds have systematic differences in their emphasis on university evaluation indicators, which is closely related to the regional economic level, educational tradition, and market demand.

3.5. Impact Path of Brand Awareness on Different Groups

This study explores the differences in the weight of influencing factors in the selection of educational institutions by different brand sensitivity groups. Through a questionnaire survey, the evaluation data of four types of brand sensitivity groups (very high, high, medium, and low) on six key dimensions is collected to reveal the relative importance of each factor in the consumer decision-making process. The survey results are shown in Figure 8.

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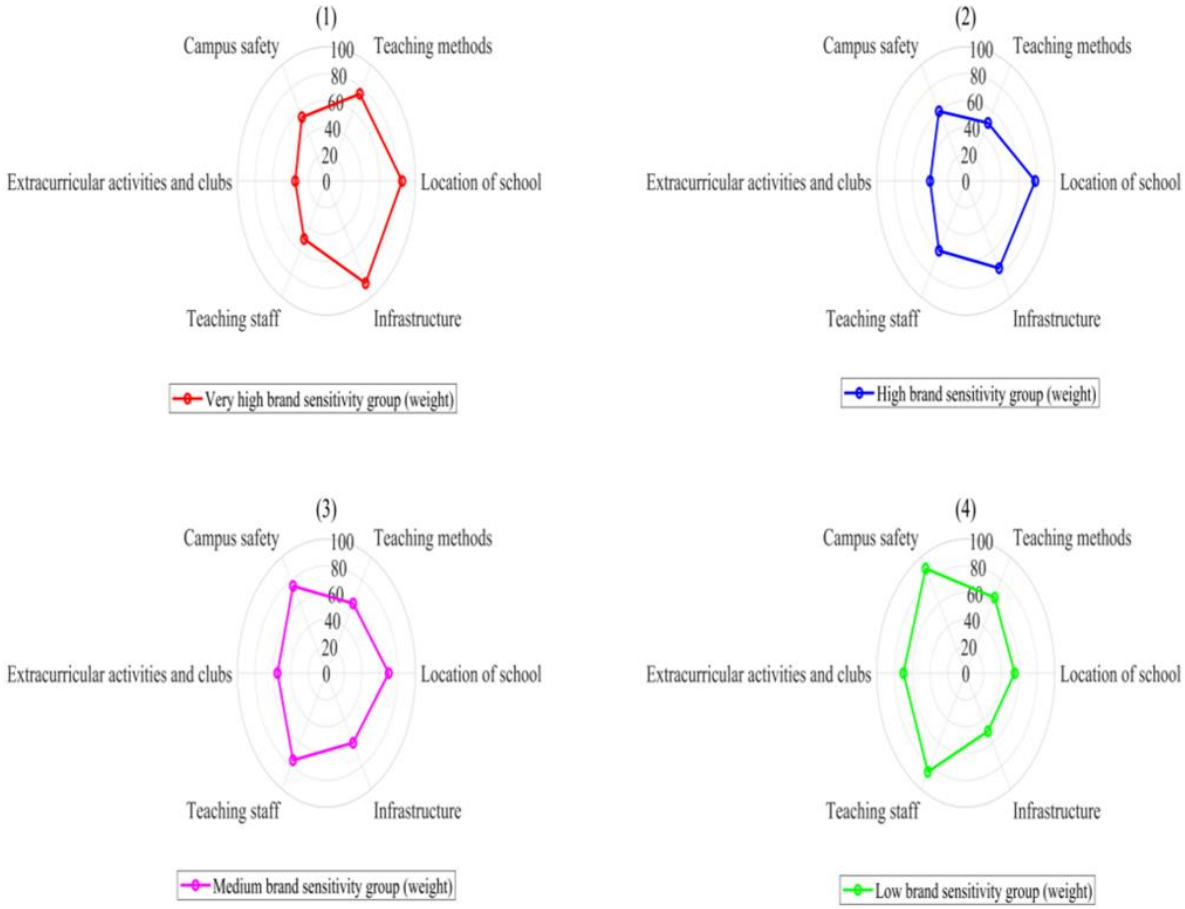

Figure 8.
Other influencing factors of different brand sensitivity groups.

Figure 8 shows that the very high brand sensitivity group attaches the most importance to infrastructure and school location, with weights of 88 and 85, respectively, reflecting the group's strong preference for hardware conditions and geographical advantages. The high sensitivity group's emphasis on location and infrastructure has slightly decreased, with weights of 78 and 75, but it remains significantly higher than other factors. The medium sensitivity group shows a high degree of attention to campus safety and teaching staff, with a weight of 75, indicating that this group prioritizes education quality and a safe environment. The low-sensitivity group assigns the highest importance to campus safety, with a weight of 90, and the lowest attention to infrastructure, only 50, reflecting the decision-making characteristics of this group that prioritize safety above other factors. The differences in weight distribution among each group reveal the systematic relationship between brand sensitivity and the priority of decision-making factors.

4. Conclusions

This study has made positive progress both in theory and practice. Regarding theoretical contribution, it integrates cross-cultural theory and brand management models, reveals the direct path of university brand awareness on students' admission decisions, and identifies the moderating role of cultural values, deepening the understanding of brand cognition and cultural interaction. The use of multinational data and multi-level moderation effect methods enhances the empirical rigor of cross-cultural research, constructs a classification framework for university brand influence based on cultural

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dimensions, and provides a systematic tool for subsequent research. Regarding empirical findings, the study shows that brand awareness has a significant impact on student decision-making in different cultural contexts. In North America, its direct impact is significant (coefficient 0.45), while in Asia, the indirect path through academic reputation is more prominent (coefficient 0.55). Further analysis shows that cultural values such as uncertainty avoidance and individualism indirectly affect school selection behavior by affecting brand trust and information processing depth. For example, individualism scores 85 in Europe and the Americas, while it is only 20 in Africa, highlighting the systematic impact of cultural variables on brand cognition and decision-making tendencies. At the practical level, the study suggests that when formulating international enrollment strategies, colleges and universities should combine the cultural characteristics of the target market, build differentiated brand communication methods, and embed cultural adaptability elements in brand communication to enhance international influence and appeal.

Although this study has made progress in theoretical construction and empirical analysis, there are still limitations. For example, the dynamic nature of cultural variables has not been fully reflected. In the future, the perspective of cultural evolution should be applied. At the same time, emerging media such as artificial intelligence and virtual reality have not yet been included in the analysis framework. Subsequent research can further expand the impact of technological variables on university brand strategies.

Transparency:

The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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