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Article

A Study on the Impact of Algorithmic Bias on the Fairness of Film and Television Communication and Regulation

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Abstract: Algorithmic bias is the bias of the algorithm in the operation process, resulting in unfair and unreasonable repeatable results, this paper starts from the perspective of algorithmic recommendation to explore the impact of algorithmic bias on the fairness of film and television dissemination. Using video feature data and user behavior data of short video film and television area as research objects, identifying the fairness of film and television dissemination, selecting feature variables of algorithmic bias, constructing a multiple linear regression model of the influence of algorithmic bias on the fairness of film and television dissemination, and introducing SHAP interpretation framework to quantify and attribute the importance of each feature variable. The results found that recommendation diversity, equalization of opportunities, and population parity have significant positive impacts on the fairness of film and television communication, and the exposure inequality index and discovery path bias both have significant negative impacts on the fairness of film and television communication, which are all significant at the 5% level, and their impacts on the fairness of film and television communication are different in terms of the way, direction, and strength of their impacts. Combined with the advanced regulation experience of today's society and various social media platforms, suggestions and countermeasures are proposed for the regulation direction of algorithmic recommendation.

Keywords: algorithmic bias; multiple linear regression model; SHAP; movie and television communication fairness

1. Introduction

Accompanied by artificial intelligence technology widely embedded in all kinds of social scenes, algorithm has become the technical origin to open the era of intelligent communication, which brings subversive changes to the whole field of information communication [1-2]. As a new media form in the era of intelligent communication, film and television, supported by algorithms, can more accurately insight user needs, realize cross-screen tracking, and provide personalized film and television recommendation services [3-5]. However, at the same time, the movie and television communication based on the logic of algorithmic operation also faces the problem of algorithmic bias and thus affects the fairness of movie and television communication.

Algorithmic bias refers to the algorithmic program in the process of information production and distribution to lose the objective and neutral position, resulting in one-sided or inconsistent with the objective reality of the production and dissemination of information, ideas, affecting the public's objective and comprehensive knowledge of information [6-9]. Based on the performance of algorithmic bias against public rights, it can generally be divided into three types: algorithmic bias that harms the interests of individual consumers, algorithmic bias that harms the basic rights of the public, and algorithmic bias that harms fair competition in the market.

Film and television communication is a form of commercial value, which shares the industry's large audience, relying on the personalized push algorithms of the film and television platform, the film and television will be accurately placed to the target audience, thus achieving a high rate of dissemination of film and television and a high acceptance rate [10-12]. However, the all-round information surveillance of users relying on big data, artificial intelligence, mobile Internet and other technologies inevitably leads to the film and television dissemination triggering algorithmic bias and ethical dilemmas, and causing substantial harm, such as price squeeze, user privacy leakage, and damage to the market mechanism [13-16]. And in the era of intelligent communication, as the use of algorithmic technology continues to expand, the harm of algorithmic bias and risk brought about by it will be further amplified, and it is necessary to explore the path of risk regulation from multiple levels, and to pursue the safety, reliability and fairness of film and television communication on the basis of guaranteeing the effectiveness of algorithms [17-20], such as the establishment of a dual review mechanism of algorithms and artificial, and the improvement of government-led multi-regulation model.

Regarding the research on algorithmic bias and regulation in the distribution of entertainment categories such as film and television on media platforms, Shruthi and Srihari examined the role of streaming platform algorithms in guiding the recommendation of movies, and found through user interviews that algorithmic bias tends to push commercially popular films while weakening multicultural expressions, thus limiting users' access to independent films, and emphasized the construction of inclusive mechanisms to safeguard the content of film emphasizing the necessity of constructing an inclusive mechanism to safeguard movie content diversity [21]. Lukoff focuses on the problem of reinforcing users' "current bias" in recommender systems, and designs a user research program in the movie domain as an example. By analyzing the correlation between past movie viewing data and long-term value, we explore how to use the existing indicators to predict and avoid algorithmic bias, in order to promote more long-term movie and TV content recommendation [22]. Hauck and Rothlauf examined the impact of editorial versus algorithmic recommendations on the distribution of content categories in German public service media platforms, and through their analysis, they pointed out that algorithmic recommendations are significantly biased towards entertainment content, leading to under-exposure of informational programs with a higher degree of bias than editorial recommendations, thus emphasizing the necessity of constructing autonomous algorithms to safeguard the impartiality of content in public service media [23]. Voinea conducted a systematic literature review to examine how AI has reshaped the audio-visual media ecosystem. He pointed out that while AI enhances efficiency, it also brings about challenges such as creative homogeneity and algorithmic bias. He analyzed the interactive influence of technical architecture, training data, and human collaboration using the "algorithmic author" framework. Additionally, he examined the differences in regulatory models between Europe and the United States and emphasized the importance of constructing an AI integration path that is centered on humans and ensures cultural diversity [24]. Zhang focused on how the algorithms of streaming media platforms reshape the power structure in the film and television industry. Taking Netflix and iQIYI as examples, he analyzed how algorithm recommendations and data analysis strengthen the dominance of the platforms, lead to content homogeneity and squeeze creative freedom. Then, he examined the "algorithm encirclement" effect and emphasized the importance of establishing algorithm transparency and rights protection mechanisms to balance technological empowerment and artistic expression [25]. Kumar examines the systemic inequalities embedded in content production and algorithmic recommendations by streaming platforms through cases and critical race theory, pointing to a tendency to perpetuate dominant cultural norms while marginalizing minorities, thus highlighting the need for equitable content strategies and regulatory frameworks [26]. Abul-Fottouh et al. examined YouTube's recommendation mechanism for vaccine-related videos through social network analysis, noting that it tends to push neutral and pro-vaccine content, and that algorithmic adjustments effectively reduce exposure to anti-vaccine videos, but also emphasizing that homogenization effects in the recommender network may limit users' exposure to opposing viewpoints, highlighting the importance of improving algorithmic transparency [27]. Okoronkwo overviews the impact of algorithmic bias on media content distribution, pointing out that it limits the visibility of disadvantaged groups and exacerbates social injustice, as well as analyzing the risks and opportunities of AI in addressing algorithmic inequality, and emphasizing the need for multi-party collaboration in building inclusive algorithms to promote equity and diversity [28]. Focusing on the field of audiovisual communication such as film and television, Gutierrez emphasizes the importance of constructing a targeted research agenda to regulate gender bias in audiovisual algorithms by analyzing the association between algorithmic bias and sexism, pointing out that audiovisual data has exacerbated the victimization of women in the growth of the internet, and examining the challenges of opaque data and insufficient algorithmic understanding [29]. Singh, from the perspective of critical media theory, examined the profound impact of Instagram's algorithm shift on photography creators. He pointed out that its profit-oriented promotion of Reels led to homogenized content, triggering the "exposure game" of creators and community resistance. Thus, he emphasized the suppression of artistic expression and creative autonomy by the algorithm's utilitarian nature, and explored the possible alternatives to algorithmic platforms [30].

In this paper, we take algorithmic bias as the independent variable, five dimensions of exposure inequality index, recommendation diversity, equalization opportunity, population parity, and search and discovery path bias as the feature variables, and take film and television communication fairness as the dependent variable to construct a multiple linear regression model to study the influence of algorithmic bias on film and television communication fairness. On this basis, a machine learning method is introduced to construct a film and television communication fairness model, and then the SHAP explanatory framework is used to quantify and attribute the importance of each feature variable, to explain the important factors affecting the achievement of film and television communication fairness and their modes of action, so as to provide decision-making reference for regulating algorithmic bias under the fairness of film and television communication.

2. Research methodology

2.1. Description of variables

2.1.1. Determination of independent variables

Algorithmic bias refers to the deviation of algorithmic programs from the objective and neutral value stance in the process of information production, integration and pushing, which leads to the dissemination of relevant information contrary to the facts or unfairly, and thus has an impact on the public's cognitive experience and decision-making. In this paper, algorithmic bias is selected as the independent variable, which consists of exposure inequality index (SOI), recommendation diversity (RD), equalization of opportunity (EO), population parity (EP), and search and discovery path deviation (SDPD).

Exposure Inequality Index (EI): measures whether different groups of film and television works receive equal exposure opportunities in the recommender system, which is calculated as the average exposure of a certain group of works/average exposure of all works; if this ratio is much less than 1, it means that the group is at a disadvantage in the algorithm.

Recommendation diversity: to measure whether the recommendation results are too homogeneous, you can use Simpson's diversity index. To wit:

$$D = 1 - \sum_{i=1}^{n} p_i^{\,2} \tag{1}$$

p_i is a certain type of content in the recommendation list, if the recommendation list is full of movies of the same type, the value of D will tend to 0.

Equalization of opportunity: test whether the algorithm's ability to identify movie and TV targets is consistent across different groups, and calculate the precision and recall rates of content from different groups. True rate = number of good content recommended by the algorithm / number of all good content.

Population parity: check whether the actual share of a certain type of content in the recommended results roughly matches its share in the real world or in the total library. For example, if female directors' works account for 40% of the movie and TV library, but only 15% on the recommended homepage, there may be a systematic bias.

Search and Discovery Path Bias: Analyze the diversity of results returned when users search for different groups of keywords.

2.1.2. Dependent variable construction

The dependent variable of this paper is the fairness of film and television communication, which can be quantified from three core dimensions: contact fairness, content presentation fairness and effect feedback fairness. Among them, the exposure index measures whether different social groups have equal access to film and television content in terms of ease and opportunity, exposure index = MIN (Group A exposure rate, Group B exposure rate, ..., Group N exposure rate); exposure rate = (number of people in the group who have watched the content/used the platform)/number of samples of the total population of the whole group. Presentation Index measures whether the portrayal of different social groups in film and TV content is fair, diverse and unbiased, avoiding stereotyping and stigmatization;

Presentation Index = MIN (Group A Presentation Score, Group B Presentation Score, ..., Group N Presentation Score). The Effectiveness Index (EI) measures whether the cognitive, emotional and attitudinal impacts of film and television content are balanced among different groups after dissemination, and whether there are misunderstandings due to group differences, Effectiveness Index = MIN (Group A Effectiveness Score, Group B Effectiveness Score, ..., Group N Effectiveness Score).

Integrated Equity Index (IE) = W_1×Exposure Index + W_2×Presentation Index + W_3×Effectiveness Index, where W_1, W_2 and W_3 are the weights of the dimensions.

2.2. Construction of multiple regression model

2.2.1. Multiple linear regression

Regression coefficients are unknown parameters that are closely related to the linear regression model and are obtained from the training data of the linear model. There are multiple regression coefficients in a multiple linear regression model, which indicate the magnitude of the influence of the independent variables on the dependent variable, and all of the independent variables work together through the regression coefficients to produce the dependent variable.

When a dependent variable contains two or more independent variables, multiple linear regression is modeled as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \cdots + \beta_m x_m + \delta \tag{2}$$

where $x_1, \cdots, x_m$ is a non-random variable, β_0 is a constant term, $\beta_1, \beta_2 \cdots \beta_m$ are regression coefficients, and δ is a random error term with a mathematical expectation equal to zero.

If y and x are collected n times, n sets of observations $y_i, x_{1i}, \cdots, x_{mi} (i = 1, 2, \cdots, n)$ are obtained:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} \cdots + \beta_m x_{mi} + \delta_i \tag{3}$$

Represented by a matrix:

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, X = \begin{bmatrix} 1 & x_{11} & \cdots & x_{m1} \\ 1 & x_{12} & \cdots & x_{m2} \\ \vdots & \vdots & & \vdots \\ 1 & x_{1n} & \cdots & x_{mn} \end{bmatrix}, \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_m \end{bmatrix}, \delta = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix} \tag{4}$$

At this point the model can be represented as:

$$y = X\beta + \delta \tag{5}$$

The δ is the error revealed between the data fitted to the model and the actual data.

For multiple linear regression equations, the regression coefficients are unknown and we need to use an algorithm to find out the regression coefficients. In multiple linear regression models, the regression coefficients are a number of ideal optima, which are not available, so they need to be approximated by simulated values. In multiple linear regression, the simulated values can be calculated using the values of the samples to get the simulated values and the simulated values of the dependent variable can be predicted from the simulated values and the independent variables.

After obtaining the general theory of the multiple linear regression model, certain methods are used to obtain the regression coefficients from the samples, a typical method is the least squares method to obtain the regression cost $Q = \sum (y_i - \hat{y}_i)^2 = \sum (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_1 - \cdots - \hat{\beta}_k x_k)^2$ is minimized. This results in a system of standard equations for solving $\hat{\beta}_0$, $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3 \cdots \hat{\beta}_k$, and solving them.

This is a relatively simple method in a univariate linear regression model, which can be obtained by hand, but for a multiple linear regression model, the amount of computation increases steeply, so it needs to be implemented using specialized computational software or programming.

2.2.2. Tests of model parameters and accuracy

The mean square error MSE is generally used to test the accuracy of the optimal solution of the model. The mean square error is the expected value of the square of the difference between the estimated value of the parameter and the true value of the parameter, which is used to evaluate the degree of variation of the data, when the value of the MSE is smaller, it means that the accuracy of the optimal solution of the prediction model is higher. The calculation formula is:

$$MSE = \frac{SSE}{n} = \frac{1}{n}\sum_{i=1}^{m} w_i (y_i - \hat{y}_i)^2 \tag{6}$$

2.2.3. Construction of the regression model

Multiple regression analysis was used to explore the effects of algorithmic bias exposure inequality index, recommendation diversity (measuring information cocooning), equalization opportunity (measuring model fairness), population parity, and search and discovery path bias composition on the fairness of film and television distribution.

The regression model is shown in equation (7):

$$IE = \alpha + \beta_0 SOI + \beta_1 RD + \beta_2 EO + \beta_3 EP + \beta_4 SDPD \tag{7}$$

2.3. Interpretability techniques for models

2.3.1. Characteristic importance assessment methodology

In multiple regression models, the standardized regression coefficient $|\beta|$ is one of the measures of feature importance, however, the comparison results of $|\beta|$ are only applicable to specific environments, such as when the variable coefficients are not significant the authenticity of the feature importance rankings corresponding to $|\beta|$ will be significantly reduced, as well as the multiple regression model must pass the F-test and so on. With the rise of machine learning, scholars have begun to try to use feature importance analysis methods based on machine learning models to rank and analyze the input features of each model.

Traditional machine learning often uses the default Feature Importance method of the tree model to rank the importance of features, which is based on the principle of using the number of feature splits or the gain of the feature splits to measure the features and rank their importance by the magnitude of their values. The Permutation Importance method is used to analyze the feature importance, the Permutation Importance method evaluates the feature importance depending on the degree of degradation of the model performance after a feature is reordered randomly, specifically:

$$i_j = s - \frac{1}{K}\sum_{k=1}^{K} s_{k,j} \tag{8}$$

Assuming a trained model $\hat{f}$, a training set or a test set D, and the performance score of the model $\hat{f}$ on D is s, the following repetitive steps are performed for each feature j on the dataset D: firstly, for each iteration k in K repetitions of the experiments, randomly re-arrange the features j to construct a randomized processed dataset $D_{c_{k,j}}$; second, compute the performance score $s_{k,j}$ of the model $\hat{f}$ on the dataset $D_{c_{k,j}}$; and lastly, compute the importance scores i_j of the features j based on (Eq. 8).

2.3.2. Partial Dependency Diagram (PDP)

Partial Dependency Plots (abbreviated as PDP or PD plots), PDPs show the marginal effect of one or two features on the predicted outcome of a machine learning model and can show linear, monotonic, or other more complex relationships between objectives and features. The partial dependence function used for regression is defined as:

$$\hat{f}_{x_s}(x_s) = E_{x_C}[\hat{f}(x_s, x_C)] = \int \hat{f}(x_s, x_C)\, d\mathbb{P}(x_C) \tag{9}$$

The x_s are the features whose partial dependency functions should be plotted, and x_C are the other features used in the machine learning model $\hat{f}$. Usually, there are only one or two features in the set S. The features in S are the ones that we want to understand their impact on the prediction. The feature vectors x_s and x_C are combined to form the total feature space x. Partial dependencies work by marginalizing the machine learning model output over the distribution of features in the set

C , so the function shows the relationship between the features in the set S that we are interested in and the predictions. By marginalizing other features, we obtain functions that depend only on the features in S and the interactions with other features.

The partial dependence function $\hat{f}_{x_s}$ is estimated by computing the mean in the training data, also known as the Monte Carlo method:

$$\hat{f}_{x_s}(x_s) = \frac{1}{n}\sum_{i=1}^{1}\hat{f}(x_s, x_C^{(i)}) \tag{10}$$

The partial dependence function tells us exactly what the average marginal effect of a given value of the feature S is on the prediction, x_C is the actual feature value of the feature in the dataset that we are not interested in, and n is the number of instances in the dataset.An assumption of the PDP is that the features in C are uncorrelated with the features in S . If this assumption is violated, the average computed for the partial dependency plot will contain highly unlikely or even impossible data points.

For categorizing the output probability of a machine learning model, the partial dependency function shows the probability of a particular category given different values of the features in S . A simple way to handle multiple categories is to draw a line or graph for each category.

Partial dependency plots are a global approach: the approach considers all instances and gives an indication of the global relationship between the feature in question and the predicted outcome.

2.3.3. SHAP

The SHAP model can be used for both global and local interpretation, i.e., the possible relationship between the predicted values given by the model and certain features in a single sample, which can be used for SHAP.

SHAP belongs to the method of model ex post explanation, its core idea is to calculate the marginal contribution of features to the model output, and then from the global and local level to explain the “black box model”.SHAP constructs an additive explanatory model, and all the features are regarded as “contributors”. ". For each prediction sample, the model generates a prediction value, and the SHAP value is the value assigned to each feature in that sample.

The basic idea: calculate the marginal contribution of a feature when it is added to the model, and then take the mean value of the different marginal contributions of the feature in the case of all feature sequences into account, i.e., the SHAP value of a feature assumes that the i th sample is x_i , the j th feature of the i th sample is x_{ij} , the marginal contribution of the feature is mc_{ij} , and the weight of the edge is w_i ; where $f(x_{ij})$ is the SHAP value of x_{ij} , e.g. the SHAP value of the 1st feature of the i th sample is calculated as follows:

$$f(x_{i1}) = mc_{i1}w_1 + \cdots + mc_{i1}w_n \tag{11}$$

The model's predicted value for this sample is y_i , and the baseline for the entire model (usually the mean of the target variable for all samples) is y_{base} , then the SHAP value obeys the following equation:

$$y_i = y_{base} + f(x_{i1}) + f(x_{i2}) + \cdots + f(x_{is}) \tag{12}$$

$f(x_{i1})$ is the value of the contribution of the 1st feature in the i th sample to the final predicted value y_i , and the SHAP value for each feature indicates the change in the model prediction when conditioned on that feature. For each feature, the SHAP value states its contribution to account for the difference between the average model prediction of the instance and the actual prediction. When $f(x_{i1}) > 0$, it means that the feature improves the prediction, and vice versa, it means that the feature makes the contribution lower.The great advantage of the SHAP value calculation lies in its ability to reflect the influence of each feature in the sample on the prediction results, and also to point out the positivity or negativity of the degree of its influence.

3. Experiments and analysis of results

3.1. Research data

For videos with different contents, the characteristics that users pay more attention to will be different, thus this paper only selects the videos of movie and TV uploaders in Shake video area as the research object. Five upmasters with 50 to 1.5 million, 1.5 to 3 million, and 3 to 6 million fans were selected to disseminate the same 20 film and television works, and a crawler program was written in Python language to crawl and calculate the data related to the dissemination of the film and television videos of these upmasters, and a total of 1,200 samples were obtained. The time span of the acquired video samples is November 5, 2019 - January 11, 2023 the descriptive statistics of each data variable are shown in Table 1. The fairness index of video communication is 0.69, and its communication fairness is fair, but there are still large differences in its features, with a large difference between the maximum value and the minimum value, and each feature shows a positive skewed distribution. It is hypothesized that the difference between the video features comes from the different types of videos, and different types of videos have different audience groups, and some types, such as “Heavenly Officials” and “Naoki Hanzawa”, have less video audience, so the video playback is lower than other types.

Table 1. Descriptive statistical analysis

Variable	Mean	SD	Minimum	Maximum	Skewness
SOI	0.66	0.75	0.02	0.95	4.75
RD	0.52	0.81	0.09	0.88	4.21
EO	0.58	0.62	0.05	0.75	5.36
EP	0.61	0.77	0.12	0.91	4.69
SDPD	0.56	0.96	0.11	0.98	3.35
IE	0.69	0.78	0.25	0.92	3.78

3.2. Analysis of regression analysis results

3.2.1. Correlation coefficient analysis

Considering that the variables affecting the fairness of film and television communication may have too high correlation with each other, in order to ensure the reasonableness and scientificity of the selection of indicators, this study conducted a preliminary analysis of the correlation coefficients between the selected indicators by using Pearson correlation coefficient method, and Fig. 1 shows the Pearson correlation coefficients between the variables, with darker colors indicating stronger negative correlation, and lighter colors indicating stronger positive correlation. The darker the color means the stronger the negative correlation, the lighter the color means the stronger the positive correlation, and the bigger the square box means the stronger the correlation, and vice versa the weaker the correlation. Among them, there is a significant negative correlation between the exposure inequality index and the bias of search and discovery paths and the fairness of film and television communication, with correlation coefficients of -0.43 and -0.08 respectively. There is a significant positive correlation between Recommendation Diversity (RD), Equalization of Opportunities (EO), Equalization of Population (EP), and the fairness of film and television communication, with correlation coefficients of 0.32, 0.15, and 0.29, respectively, which can preliminarily confirm that the algorithmic bias has an effect on the fairness of film and television communication.

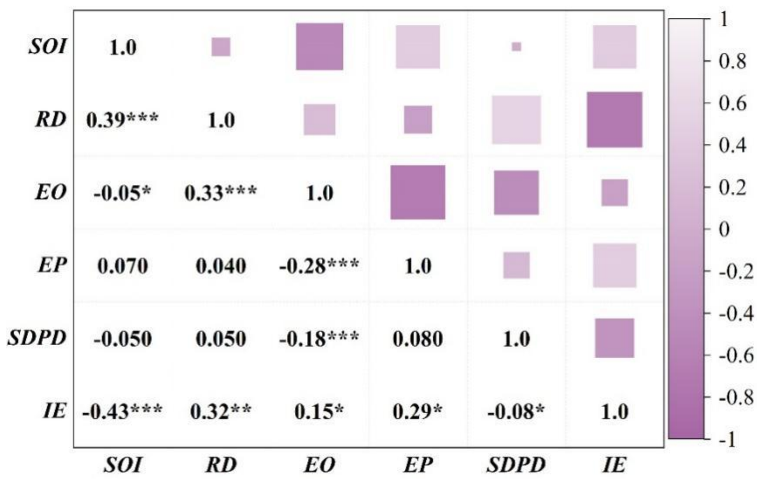


Figure 1. Pearson correlation coefficient between variables

3.2.2. Regression analysis

Test whether the explanatory effect of each characteristic variable on the fairness of film and television communication is significant. The corresponding variables of each characteristic (exposure inequality index, recommendation diversity, equalization of opportunities, population parity, and search and discovery path bias) are used as regression independent variables, depending on the fairness of film and television communication as the dependent variable, and the significance of the coefficients of each characteristic front of the regression model are observed as well as the positivity and negativity. In the regression, in order to reduce the impact of outliers on the model, all continuous variables are shrink-tailed at the 1% level. The results of the model regression are shown in Table 2. The F-value of the regression model is 288.56, and the model passes the overall coefficient test, and R2 = 0.65 indicates that the model fits well. In addition, the VIF value of each feature is not higher than 3, indicating that there is no strong multicollinearity among the model variables and the model results are more reliable. According to the regression results, Exposure Inequality Index, Recommendation Diversity, Equalization Opportunity, Population Parity, and Search and Discovery Path Bias are all significant at the 5% significance level, which means that all dimensions of algorithmic bias have an impact on film and television communication fairness.

Table 2. Regression model results

Variable	Nonnormalized coefficient	Standard error	t	p	VIF
Constants	28.68	2.55	2.11	0.00	2.55
SOI	-2.52	0.33	-1.01	0.00	2.41
RD	1.72	0.58	1.12	0.03	2.33
EO	1.05	0.45	1.08	0.00	1.58
EP	1.22	0.39	0.98	0.01	1.09
SDPD	-1.68	0.41	-0.89	0.02	1.74
$F=288.56$, $R^2=0.65$					

Combining the results of regression analysis, recommendation diversity, equalization of opportunities, and population parity have a significant positive effect on the fairness of film and television communication, and the exposure inequality index and discovery path bias both have a significant negative effect on the fairness of film and television communication. To analyze the reasons, on the one hand, videos related to film and television communication are more about processing, interpreting and sharing of content, with less emotional resonance and catharsis; on the other hand, it may be because users are more concerned about obtaining and analyzing the information of video content when they watch the videos in the knowledge zone, and then thinking, exploring and exchanging after watching the videos. In order to further verify the effect of algorithmic bias in each dimension on the fairness of movie and TV communication, an interpretable machine learning method based on SHAP will be used to verify the effect of each feature on the fairness of movie and TV communication.

3.3. SHAP-based model interpretive analysis

3.3.1. Importance analysis of characteristic variables

SHAP feature importance refers to the degree to which each feature contributes to improving the predictive power of the overall model, characterized by the absolute value of the degree to which each feature influences the target variable. It can visualize the degree of influence of features on the model. The higher the importance of a feature variable, the greater the influence of that feature variable on the fairness of film and television communication.

The analysis of the importance of the characteristic variables is shown in Figure 2, and the importance of the characteristic variables in descending order is: exposure inequality index, recommendation diversity, discovery path bias, population parity, and equalization opportunity. The fairness of film and television communication is greatly influenced by the discovery path bias characteristic variable and recommendation diversity characteristic variable, and less influenced by the equalization opportunity characteristic variable. Among them, the exposure inequality index is an important characteristic that affects the fairness of film and television communication.

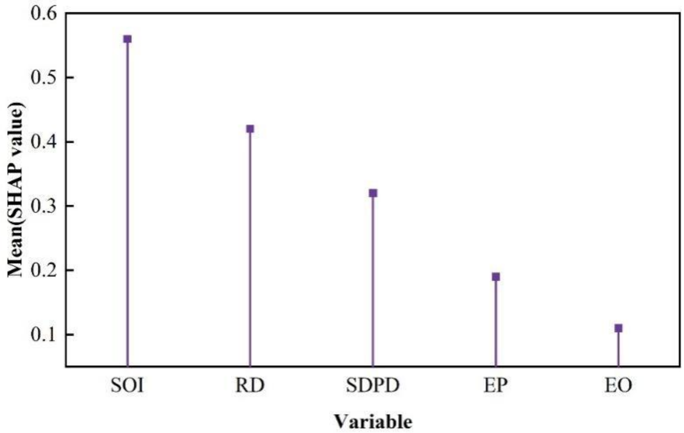


Figure 2. Analysis of the importance of characteristic variables

3.3.2. Analysis of the direction of influence of characteristic variables

The SHAP feature summary chart combines feature importance and feature effect to reflect the overall positive or negative relationship between feature value and public value consensus, and the SHAP feature summary chart is shown in Figure 3. The horizontal coordinate in Figure 3 is SHAP value, each line represents a feature variable, and each dot represents a sample, the redder the color of the dot indicates that the value of the feature itself is larger, and the bluer the color indicates that the value of the feature itself is smaller.

If SHAP value>0, it means that the feature variable has an enhancing effect on the fairness of film and television communication, and if SHAP value<0, it means that the feature variable has a reducing effect on the fairness of film and television communication. Among the characteristic variables, the exposure inequality index and recommendation diversity are obtained by numerical statistics, which can directly determine the overall positive and negative relationship between them and the fairness of film and television communication. The exposure inequality index shows a significant negative correlation with the fairness of movie and television communication, and the recommendation diversity shows a significant positive correlation with the fairness of movie and television communication. And the discovery path bias, population parity, and equalization opportunity are all based on the coding conversion, which need to be combined with the corresponding coding method to make further judgments.

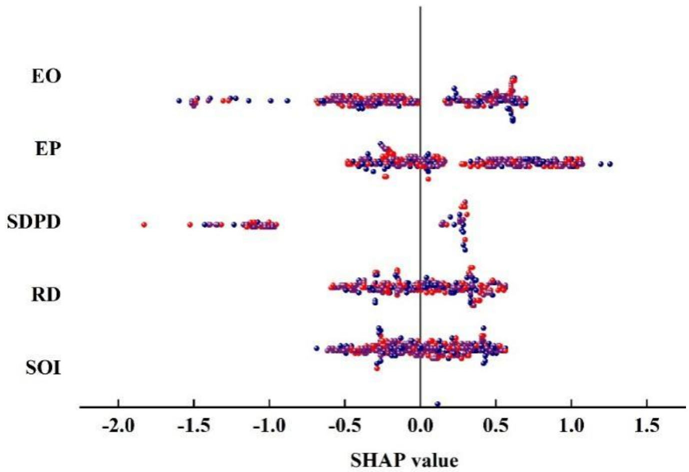
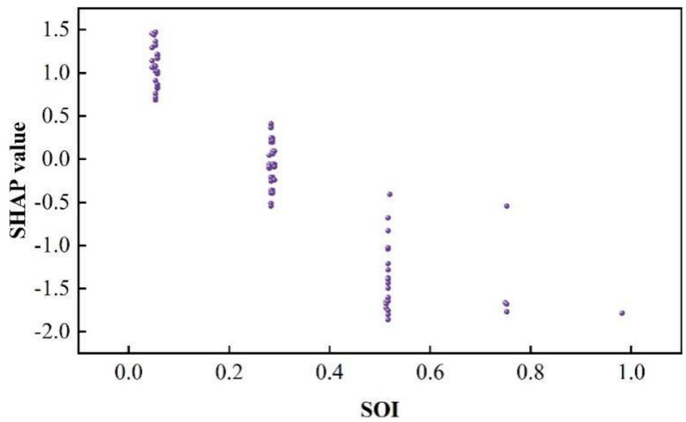


Figure 3. SHAP profile

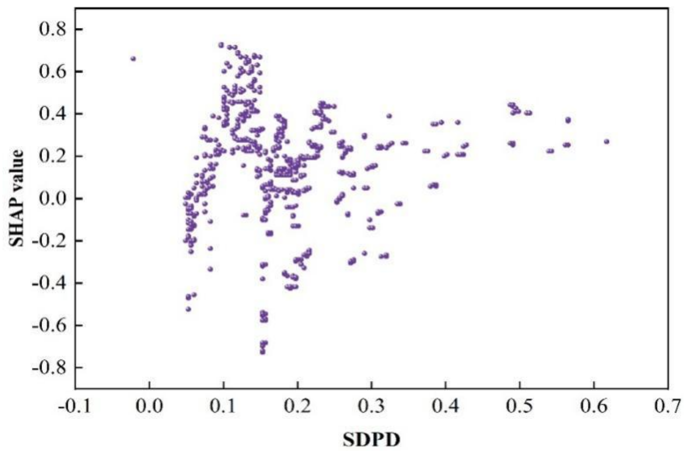
3.3.3. Impact analysis of specific values of characteristic variables

The partial dependency graph of a feature variable describes the marginal effect of that feature variable on the fairness of film and television communication. It reflects the way in which the feature affects the fairness of film and television communication and reveals how the feature variable affects the fairness of film and television communication, and the SHAP feature dependency analysis is shown in Figure 4. Figures (a) and (b) show the exposure inequality index and search and discovery path bias, respectively. Considering SHAP value as a force, the SHAP value corresponding to each feature is a force that increases or decreases the fairness of film and television communication, and the magnitude of the force is indicated by |SHAP Value|. If SHAP Value > 0, it means that the feature enhances the predicted value, and if SHAP Value < 0, it means that the feature reduces the predicted value. |SHAP Value| indicates the magnitude of the force that lifts or lowers the force when conditioned on the feature. The larger the |SHAPValue| represents the greater the force of the feature on the fairness of film and television communication, and the greater the degree of influence on the fairness of film and television communication.

The overall direction of the influence of each characteristic variable on the fairness of film and television communication, the direction and strength of the influence of specific values, according to which the role of the characteristics can be analyzed. Taking the exposure inequality index as an example, the labeled exposure inequality index samples are distributed in five situations, respectively, the number of emotion symbols is 0, 1, 2, 3, 4, the part of the dependency graph from left to right in the five columns correspond to these five types of samples. First, the overall influence direction analysis, the SHAP Value of the exposure inequality index is between [-2, 1.5], and its overall negative correlation with the exposure inequality index. The second is the analysis of the influence direction and strength of specific values. With the exposure inequality index SHAP Value = 0 as the dividing line, the sample is divided into two parts, when SHAP Value > 0, the exposure inequality index = 0, the fairness of film and television communication plays a role in lifting up, at this time |SHAP Value | = [0.1,1.5], lifting the strength of [0.1,1.5]. When SHAP Value < 0, the title mood character = {1,2,3,4}, which plays a role in reducing the fairness of film and television dissemination, at this time |SHAPValue| = [0.1,2], the intensity of reduction is [0,2].



(a) Exposure inequality



(b) Search and discovery path deviation

Figure 4. SHAP feature dependence analysis

3.4. Regulatory Paths for Algorithmic Bias in Film and Television Communication

(1) Strengthen regulation and improve algorithm design

First, since algorithmic recommendation is based on data, regulation of algorithmic recommendation can start with data, purifying and managing the data needed for algorithmic recommendation. Secondly, strengthen regulation to avoid algorithm designers substituting personal bias into the algorithm program, and implement algorithm regulation and algorithm self-awareness in the whole process of algorithm design and operation. Finally, pay attention to the remediation after the fact, and compensate those whose rights and interests are damaged through legal procedures for the social injustice caused by algorithmic bias, and penalize the technical party as appropriate. On the one hand, it is necessary to strengthen the awareness of media ethics of the algorithm designers; on the other hand, it is necessary to strengthen the awareness of the responsibility of the government, telecommunication authorities, public security departments, and other regulators, so as to carry out reasonable and effective supervision of the technical parties, and to find a suitable balance between social fairness and technological development.

(2) Strengthening privacy protection through legislation

Whether it is direct privacy protected by users' confidentiality measures or indirect privacy mined by the technical parties in users' public information and behaviors, its protection should be accomplished in accordance with the characteristics of the information and through the collaboration of both users and data users.

(3) Transparent algorithms to prevent algorithmic manipulation

People call algorithms “black boxes”, on the one hand, because of the complexity and intelligence of their programs, on the other hand, because of the opacity of their operation procedures and decision-making mechanisms. The “black box” nature of the algorithm makes users more curious and skeptical about the operation and decision-making mechanism of the algorithm, which inadvertently aggravates the users' uneasiness about artificial intelligence. Accelerating the transparency of algorithms can not only alleviate users' uneasiness, but also prevent the absolute concentration of data and power. Therefore, data owners should be required by law to regularly disclose the operation mechanism of their algorithms, explain the design principle of the algorithms, and make algorithmic procedures transparent, so as to eliminate the misunderstandings and suspicions of users, and to avoid the in-depth manipulation of data by algorithms and technology companies.

4. Conclusion

This study uses film and television communication data from short video platforms to explore the impact of algorithmic bias on the fairness of film and television communication from the perspective of communication and society using multiple linear regression, based on which the model incorporates the SHAP interpretability framework to quantify and attribute the importance of each feature variable in order to accurately identify the ways in which the feature variables work. The main findings are as follows:

(1) Exposure Inequality Index, Recommendation Diversity, Equalization Opportunity, Population Parity, and Search and Discovery Path Bias are all significant at the 5% significance level. Among them, recommendation diversity, equalization opportunity, population parity have significant positive impact on film and television communication fairness, and exposure inequality index and discovery path bias have significant negative impact on film and television communication fairness, i.e., all dimensions of algorithmic bias have impact on film and television communication fairness.

(2) Based on the resolvability analysis of the model, the importance of the algorithmic bias feature variables are, in descending order, exposure inequality index, recommendation diversity, discovery path bias, population parity, and equalization opportunity, and their influence on the fairness of film and television dissemination varies in terms of the way, the direction, and the strength of their influence. Among them, the exposure inequality index is an important feature that affects the fairness of film and television communication.

(3) The algorithmic recommendation mechanism not only alters the way users obtain information, but also inevitably leads to the expansion of the "information bubble" effect due to its "tailoring to users' preferences" feature. The underlying algorithmic biases are even influencing social development through an "invisible hand". Therefore, algorithmic recommendations should combine instrumental rationality and value rationality. Under the supervision of laws, regulations, and the public, they should strengthen content quality control and incorporate social humanistic value orientation into them.

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