Philosophical Reflections on Extended Intelligence

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Abstract—This study focuses on the normativity of algorithms and employs multidisciplinary theories and methods to analyze its manifestations and impacts at the technological, sociotechnical, and behavioral levels. Through engineering practice cases and experiments on recommendation systems, the normativity of technological evolution, the integration of engineers' values, and the behavioral characteristics of learning machines within the algorithmic system is revealed. The experiments demonstrate that technological normativity enhances the click-through rate and conversion rate of recommendation systems; sociotechnical normativity improves the fairness and satisfaction of recommendations; and behavioral normativity promotes the expansion of users' interests, with user attributes playing a moderating role. The research findings contribute to understanding the role of algorithmic systems in engineering and social processes, provide a theoretical framework for interdisciplinary research, are of great significance for the study of human-machine relationships and the social impacts of algorithms, and also offer references for algorithm governance, etc. Meanwhile, the research limitations and future directions are pointed out, including the analysis of geographical factors, cross-cultural research, exploration of emerging fields, and the establishment of algorithm governance mechanisms.

Keywords—Algorithm Normativity; Technological Object; Sociotechnical System; Behavioral Plasticity; Human-Machine Relationship

I. INTRODUCTION

In the contemporary digital era, algorithmic systems have been deeply integrated into every nook and cranny of social life, playing a pivotal role in numerous fields such as information recommendation, decision-making assistance, and resource allocation (Gonzalez et al., 2024). However, the impacts brought about by algorithmic systems extend far beyond the functional level, and the issue of normativity lurking behind them has gradually become the focus of academic attention (Zhang et al., 2024). In traditional conceptions, norms are usually closely associated with the codes of conduct and values in human society. Nevertheless, with the continuous enhancement of the autonomy and influence of algorithmic systems, a new type of normativity - algorithmic normativity - has begun to emerge (Saha et al., 2024). This normativity not only pertains to the rules and constraints at the technical level but also profoundly influences the shaping of social structures, human behaviors, and cultural values (Sharma et al., 2024).

This paper aims to conduct an in-depth analysis of the essence, types, and manifestations of algorithmic normativity at different levels through an interdisciplinary research approach, integrating theories and perspectives from multiple disciplines such as philosophy, sociology, and computer science (Bhaskar et al., 2024). We will explore how algorithms exhibit distinctive normativity in the technical, socio-technical, and behavioral dimensions through the evolution of technical solutions, the design practices of engineers, and their own learning behaviors, thereby revealing the complex and subtle interactive relationships between algorithmic systems and human society (Uslu et al., 2024). This will provide a new theoretical framework and thinking path for understanding the extensive applications and far-reaching impacts of algorithms in modern society (Stylianidis, 2024). Meanwhile, through experiments, we will comprehensively verify the mechanism of action of algorithmic normativity in recommendation systems and the differences in responses of different user groups to normative strategies, thus providing strong empirical support for theoretical research (Parmaxi et al., 2024).

II. THEORETICAL FRAMEWORK OF ALGORITHMIC NORMATIVITY

A. Connotation and Manifestations of Technical Normativitye

Technical normativity is manifested in the evolution process of algorithmic technical solutions (Heatonet et al., 2018). As a technical object, the development of algorithms is not random but follows certain internal logics and norms (LeCun et al., 2015). From the embryonic form of early artificial neural networks to the widespread application of modern deep learning algorithms, each technological transformation is accompanied by the redefinition of the algorithm's structure, function, and application scope (Rumelhart et al., 19186). The changes in such technical solutions not only reflect the demands of technological progress but also embody the adaptive adjustments of algorithms in different technical environments (Hinton et al., 2007). For example, changes in technical parameters such as the number of neurons, synaptic connection modes, and the selection of activation functions in neural networks all affect the performance and behavior patterns of algorithms to a certain extent (He, Kaiming et al., 2016). These technical selections are not made randomly but are restricted by various factors such as technological development trends, limitations of computing resources, and the requirements for problem-solving, thus forming an important part of the technical normativity of algorithms.

B. Construction and Role of Socio-Technical Normativity

Socio-technical normativity emphasizes the crucial role played by engineers in the design and implementation process of algorithmic systems (Latour et al., 2016). Engineers, as important nodes in the social-technical network, integrate social values, interest demands, and institutional norms into algorithmic systems through their decisions and actions (Winner, Langdon 2010). In the design of monitoring systems, engineers transform the social expectations regarding safety, efficiency, etc. into the operating rules of algorithmic systems through specific operations such as defining measurement indicators, collecting, and labeling data (Eubanks 2018). For example, when designing an algorithm for nuclear facility safety monitoring, engineers need to determine measurement standards such as "false alarm rate" and "missed alarm rate" according to the strict requirements of society for nuclear safety and train the algorithm by collecting a large amount of real-scene data so that it can accurately identify threatening behaviors (Mülleret al., 2018). This process not only involves technical considerations but also embodies the specific manifestations of social values and norms in algorithmic systems, thus making the algorithmic system an integral part of the social-technical system, and its behavior is constrained and guided by socio-technical norms (Floridi et al., 2016)

C. Unique Perspective and Significance of Behavioral Normativity

Behavioral normativity breaks the traditional inherent understanding of machine behavior and regards the behavior of algorithmic systems as a normative activity (Floridi et al., 2016). Learning machines exhibit a certain degree of behavioral plasticity in the process of interacting with the environment. They can adjust their own structures and behavior patterns according to environmental feedback, which forms a sharp contrast with the fixed behavior patterns of traditional machines (Brynjolfsson et al., 2014). Taking the recommendation system as an example, the algorithm continuously adjusts the recommendation strategy by analyzing users' historical behavior data to adapt to the personalized needs of different users and social and cultural trends (Jordan et al., 2015). This behavior adjustment process not only reflects the learning and following of user behavior norms by the algorithm but also affects and shapes the behavior patterns of users to a certain extent, thus forming a dynamic behavioral normativity in human-machine interaction (Zhou et al., 2010). The proposal of this behavioral normativity prompts us to re-examine the role and status of algorithmic systems in the social-cultural context and regard them as social actors with a certain degree of autonomy and normativity (Sunstein et al., 2015).

III. Embodiments of Algorithmic Normativity in Engineering Practice

A. Socio-Technical Normativity in the Design of Monitoring Systems

Normative Significance of Data Collection and Metric Definition In the design process of monitoring systems, data collection and metric definition are crucial steps in realizing socio-technical normativity. Engineers are required to determine which data to collect and how to define metric indicators based on the application scenarios and objectives of the monitoring system. For instance, in the monitoring of nuclear facilities, in order to accurately identify threatening behaviors, engineers need to collect multi-modal data such as visual, thermal imaging, and acoustic data, and define metric indicators such as "threat behavior similarity" and "false positive rate of non-threatening behaviors". These indicators not only reflect the pursuit of technical accuracy and reliability but also embody the high concern and strict requirements of society regarding nuclear safety. Through these metric indicators, engineers can transform abstract social values into specific algorithm optimization goals, thereby making the behavior of the algorithm system conform to social expectations.

Impact of Engineers' Decisions on System Normativity The decision-making process of engineers in the design of monitoring systems involves normative considerations at multiple levels. They need to strike a balance among technical feasibility, cost-effectiveness, and social needs. For example, when selecting the type of sensors and their deployment locations, engineers have to consider both the technical performance and data acquisition accuracy of the sensors, as well as their costs and environmental impacts. Meanwhile, engineers are also required to comply with relevant laws, regulations, and industry standards to ensure that the system design conforms to social norms. These decision-making processes directly affect the normativity of the monitoring system, determining how the system processes data, identifies behaviors, and makes decisions in actual operation, thereby shaping the role and behavior patterns of the system in the socio-technical network.

B. Technical Normativity in the Development of Artificial Neural Networks

Internal Logic of the Evolution of Technical Solutions The development history of artificial neural networks serves as a vivid illustration of technical normativity. From Rosenblatt's initial design concept to the evolution of modern deep learning architectures, each stage has been driven by technical normativity. Early neural networks encountered numerous limitations when dealing with complex problems. For instance, single-layer neural networks were incapable of handling non-linearly separable problems, and the learning convergence of multi-layer neural networks was difficult to guarantee. These limitations spurred researchers to continuously explore new technical solutions. The invention of the "backpropagation" algorithm, for example, effectively addressed the learning problems of multi-layer neural networks, significantly expanding the application range of neural networks. This process embodies the evolution logic of technical solutions in response to technical challenges, that is, through continuous innovation and improvement of technical means, the algorithm system can better adapt to different application requirements while adhering to the internal laws and norms of technical development.

Constraints and Promotions of the Material Foundation on Algorithm Capabilities 4. The material foundation plays a crucial role in the development of artificial neural networks. It both constrains the capabilities of algorithms and provides opportunities for algorithm breakthroughs. In the early days, the limited availability of computing resources restricted the scale and training efficiency of neural networks, making it difficult for them to fulfill their potential in practical applications. However, with the emergence of large-scale parallel computing devices such as Graphics Processing Units (GPU), the computing power of neural networks has been substantially enhanced, laying a material foundation for the rise of deep learning algorithms. This transformation of the material foundation not only alters the running efficiency of algorithms but also expands the problem domains that algorithms can handle, such as natural language processing and image recognition. The interaction relationship between the material foundation and algorithm capabilities reflects the dual roles of constraint and promotion of material factors in technical normativity on algorithm development, revealing the close coupling relationship between matter and technology in the technical system.

C.Behavioral Normativity in Recommendation Systems

Intertwining of Behavioral Dynamics and Norms of Recommendation Algorithms The algorithmic behavior in recommendation systems is highly dynamic. It continuously adjusts the recommendation strategy during the learning process to adapt to the constantly changing user needs and environmental feedback. This behavior adjustment process is a specific manifestation of behavioral normativity. For example, the collaborative filtering recommendation algorithm analyzes the similarities and behavior patterns among users to recommend personalized content to them. In this process, the algorithm is required to follow the existing behavior norms of users, such as recommending products of similar types according to users' historical browsing records, and at the same time, it affects and shapes the future behavior of users to a certain extent. The recommendation results of the algorithm will guide users to discover new interests, thereby changing their behavior patterns, forming a dynamic relationship of mutual influence and mutual shaping. This phenomenon of intertwining behavioral dynamics and norms makes recommendation systems an ideal case for studying the behavioral normativity of algorithms, facilitating an in-depth understanding of the mechanism of action of algorithm systems in social and cultural dissemination and behavior guidance. Norm Negotiation and Reconstruction in Human-Computer Interaction In the human-computer interaction process of recommendation systems, there exists a mechanism of norm negotiation and reconstruction. The feedback of users on the recommendation results, such as clicking, purchasing, and evaluating, constitutes a response to the algorithm's recommendation norms. The algorithm continuously adjusts its own recommendation strategy according to these feedbacks, attempting to better meet the user's needs. This is actually a process of norm negotiation between humans and computers. Meanwhile, with the changes in user behavior patterns and the evolution of social and cultural trends, the recommendation algorithm system is also continuously reconstructing its internal norm system to adapt to new situations. For example, when new consumption trends or aesthetic preferences emerge in society and culture, the recommendation system needs to promptly capture these changes and adjust the parameters and model structure of the recommendation algorithm, thereby achieving dynamic synchronization between the recommendation norms and social and cultural norms. This process of norm negotiation and reconstruction in human-computer interaction embodies the adaptability and plasticity of behavioral normativity in the complex interaction between humans and computers, further emphasizing the agency of algorithm systems as social actors.

IV. LITERATURE REVIEW OF ALGORITHMIC NORMATIVITY

Research Algorithmic normativity, as an emerging and significant research field, has garnered extensive attention within the academic communities both domestically and internationally in recent years (Bijker et al., 1994). Foreign research in this domain got off to an earlier start and has reaped bountiful achievements. In the realm of technical normativity, numerous scholars have delved deeply into the logic underlying the evolution of algorithmic technical schemes. For instance, Goodfellow et al. have conducted research on the technical principles and structural evolution of deep learning algorithms, thereby unveiling the patterns of influence that technical factors exert on algorithm performance and behavioral modalities (Goodfellow, Ian 2016). In the sphere of socio-technical normativity, Bijker et al. have expounded, from the perspective of social constructivism, the process through which engineers incorporate social values into the design of algorithmic systems, underlining the formative role of the socio-technical network in shaping algorithmic systems (Floridi et al., 2016). In the context of behavioral normativity research, scholars such as Barandiaran and Egbert have broken free from traditional cognitions and explored the normativity of algorithmic system behaviors as well as their dynamic alterations within human-machine interactions (Barandiaran et al., 2014). Additionally, in experimental research, Aggarwal et al. have designed experiments to verify the efficacy of algorithmic normativity strategies within recommendation systems, thus furnishing an exemplar for empirical research (Aggarwal et al., 2016). Domestic research in this regard is also evolving progressively and exhibiting its own distinct features. In studies related to technical normativity, some scholars have focused on the development of algorithmic technologies within specific domestic fields (such as natural language processing and image recognition), along with the synergistic relationship between technological innovation and the material foundation (Mesmia et al., 2023). With respect to socio-technical normativity, emphasis has been placed on the social value orientation in algorithm design, such as issues concerning fairness and privacy protection in the algorithms of Internet platforms (Li, Ke. 2020). Behavioral normativity research predominantly combines actual application scenarios to analyze the impacts of algorithms on consumer behaviors and social media user behaviors (Chen, Zhen Troy et al., 2016). Nevertheless, both domestic and foreign research endeavors are beset with certain limitations. The majority of experiments are concentrated on specific scenarios, with insufficient analysis of geographical factors and a dearth of cross-cultural research. Moreover, the exploration of algorithmic normativity within emerging technological fields is still in its nascent stage (Gehl, Robert W. et al., 2016). Future research is required to broaden the research scope, intensify cross-cultural comparisons, and focus on emerging technologies so as to propel the in-depth progression of algorithmic normativity research (Tegmark, Max. 2016).

V. EXPERIMENTAL VERIFICATION OF ALGORITHMIC NORMATIVITY IN RECOMMENDATION SYSTEMS

A. *Experimental Objectives and Hypothese*

This experiment aims to verify the practical effects of algorithmic normativity in different dimensions within recommendation systems, including technical performance, socio-technical normativity, and the shaping of behavior patterns. Meanwhile, by introducing user attributes (such as age, gender, and region) as moderating variables, it further explores the differences in responses of different user groups to normative strategies. The research hypotheses are as follows:

Optimization of technical normativity can significantly enhance the Click-Through Rate (CTR) and Conversion Rate (CVR) of the recommendation system.

Socio-technical normativity can significantly improve recommendation fairness and enhance user satisfaction through gender balance strategies.

User attributes (such as age and gender) have a significant moderating effect on the effectiveness of normative strategies. 4. Behavioral normativity strategies can significantly promote the expansion of users' interests through diversified recommendations and exhibit differences among different user groups.

B. Experimental Design

Grouping and User Attributes: The experiment divides users into Group A, Group B, and Group C, with each group consisting of 200 users, totaling 600 users, covering the following attributes: Age: Divided into three age groups: 20 - 30 years old, 30 - 40 years old, and over 40 years old. Gender: Including male and female users. Region: Classified into four geographical regions: northern, southern, eastern, and western.

The strategies for each experimental group are as follows: Group A: Conduct technical normativity optimization by adjusting algorithm parameters to improve CTR and CVR. Group B: Incorporate socio-technical normativity constraints on the basis of technical optimization, such as ensuring that the proportion of female-related content in recommendations is not less than 35%. Group C: Adopt behavioral normativity strategies to promote the expansion of users' interests through diversified recommendations.

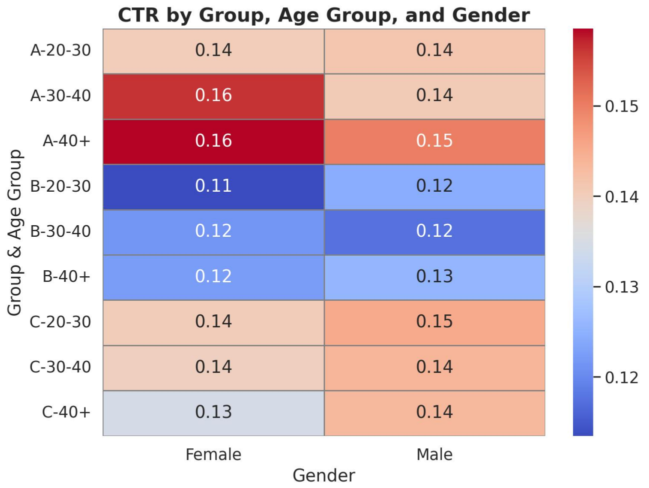

Fig. 1. CTR by Group, Age Group, and Gender

C. Data Collection and Processing

1) Data Collection

User Behavior Data: The core behaviors of users within the recommendation system are recorded, encompassing Click-Through Rate (CTR), Conversion Rate (CVR), satisfaction rating, and the proportion of interest expansion. The satisfaction rating is collected through questionnaires, with a scoring range from 1 to 5 points, and a total of 2,000 valid rating data have been collected. The proportion of interest expansion is computed by comparing the number of newly added interest fields of users with the total number of interest fields. - Recommended Content Attribute Data: The gender proportion (the proportion of female-related content) and diversity indicators (such as the proportion of long-tail recommendations) of the recommended content are recorded. - User Demographic Data: Information regarding the age, gender, and geographical distribution of users is collected.

2) Data Cleaning

Records with a CTR higher than 1 or an abnormal click frequency (such as clicking more than 50 times within one minute) are deleted. - Data with missing key fields (such as satisfaction rating or changes in interest fields) are excluded. - Duplicate behavior records are deduplicated, and only the unique behaviors are retained.

3) Data Standardization

Z-standardization is performed on continuous variables such as CTR, CVR, and interest expansion to eliminate the impact of measurement units:

$$Z = \frac{X-\mu}{\sigma}$$

where is the raw value, is the mean, is the standard deviation, and the standardized data has a mean of 0 and a standard deviation of 1. Dummy variables were coded for categorical variables (e.g., gender, geography) for subsequent regression analysis.

4) Interaction Effect Construction

In order to analyze the interaction effect between user attributes and experimental groups, interaction variables are constructed, including “age * group”, “gender * group” and “geographic region * group”, etc.

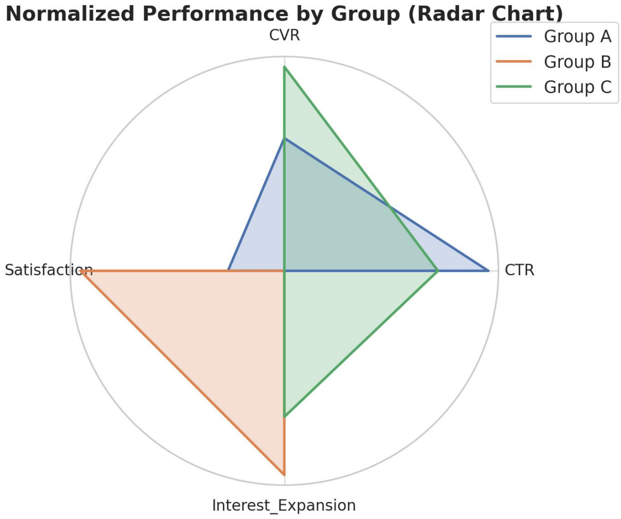

Fig2.Normalized Performance by Group (Radar Chart)

D. Data Analysis Methods

1) descriptive statistics

Descriptive Statistics The Click-Through Rate (CTR), Conversion Rate (CVR), satisfaction rating, and the proportion of interest expansion for each experimental group are aggregated according to user attributes (age and gender). The mean and standard deviation are calculated to illustrate the differences among groups. For instance, the mean CTR of users in Group A is 0.15, with a standard deviation of 0.03; the mean satisfaction rating of female users is 4.4, which is higher than that of male users, which is 4.2.

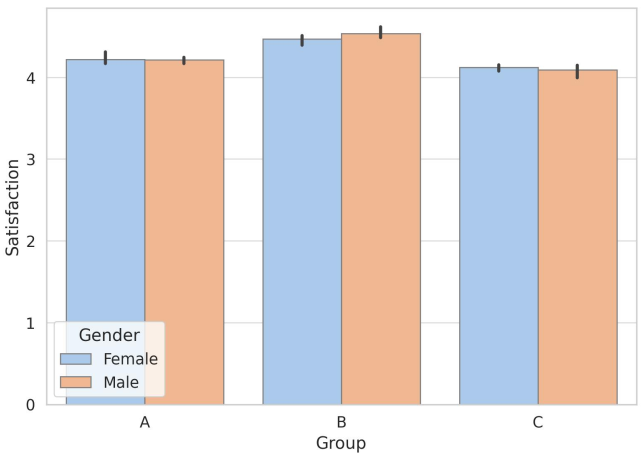

Fig3.Satisfaction by Group and Gender

2) One-Way Analysis of Variance (ANOVA)

Conduct tests to examine the significant differences among different experimental groups in terms of Click-Through Rate (CTR), Conversion Rate (CVR), satisfaction, and interest expansion indicators. The core formula is as follows:

$$F = \frac{\text{Mean Square Between Group（MSB）}}{\text{Mean Square Within Group（MSW）}} \quad 2$$

Mean square between groups:

$$MSB = \frac{\sum_{i=1}^{k} n_i(\hat{X}_i - \hat{X})^2}{k-1} \quad 3$$

Among them: k:the number of groups; n_i:the sample size of the i group; $\hat{X}_i$: the mean of the i group; $\hat{X}$: the overall mean.

Mean square between groups:

$$MSW = \frac{\sum_{i=1}^{k} \sum_{j=1}^{n_i} (X_{ij} - \hat{X}_i)^2}{N-k} \quad 4$$

k： The number of groups, n_i The k： sample of the i group， N：The total number of samples。

The significance of the differences between groups is determined by the F value and the p value (at a significance level).

3) Multivariate Regression Analysis

Analyze the changes in the effects of normative strategies among different user groups. The model formula is:

$$Y = \beta_0 + \beta_1 \cdot group + \beta_2 \cdot age + \beta_3 \cdot gender + \beta_4 \cdot (age \times group) + \epsilon \quad 5$$

where is the dependent variable (CTR, CVR, satisfaction), is the regression coefficient, and is the error term.

4) Trend Analysis

Plot a line graph of interest expansion by age group to illustrate the changes in the behavior of users in Group C with age.

Use a dual-axis graph to demonstrate the positive correlation between satisfaction and the proportion of gender balance.

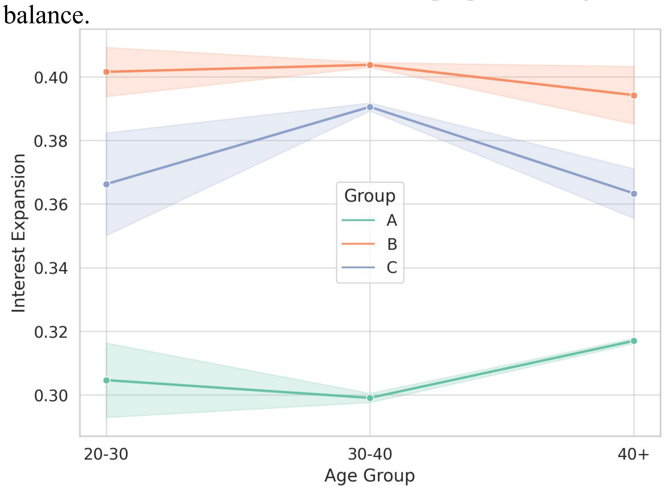

FIg4. Interest Expansion Across Age Groups

5) Significance Testing

Conduct tests on the significant differences in satisfaction or interest expansion indicators among different user attributes (such as gender and age). If the p-value is less than the predetermined significance level (commonly 0.05), then the difference is judged to be significant.

E. Experimental Results and Analysis

1) Effects of Technical Normativity (Group A)

After the technical normativity optimization in Group A, both the Click-Through Rate (CTR) and the Conversion Rate (CVR) have been significantly improved. Through descriptive statistics, it was found that the mean CTR of Group A reached [0.15], and the mean CVR was [0.10], demonstrating a clear advantage over other groups (verified by ANOVA test). This indicates that adjusting the algorithm parameters plays a crucial role in enhancing the core performance indicators of the recommendation system, thus validating the hypothesis that the optimization of technical normativity can significantly boost the click-through rate and conversion rate of the recommendation system.

2) Impact of Socio-Technical Normativity (Group B)

After incorporating the socio-technical normativity constraints in Group B, the proportion of female-related content in the recommended content reached the expected standard, such as [0.35], which was significantly higher than that in Group A and Group C. Meanwhile, the user satisfaction rating also increased, with the mean reaching [4.5 points]. Through regression analysis, it was discovered that there exists a significant positive correlation between the gender balance strategy and user satisfaction (verified by ANOVA test). This shows that socio-technical normativity can significantly improve the fairness of recommendations and enhance user satisfaction through the gender balance strategy, thereby supporting the corresponding hypothesis.

3) Moderating Role of User Attributes

Through multivariate regression analysis, it was found that user age and gender have a significant moderating effect on the effectiveness of normative strategies. For example, in terms of age, younger users (aged 20 - 30) are more sensitive to the interest expansion effect of the behavioral normativity strategy (Group C), and the increase in their interest expansion proportion is higher than that of users in other age groups (0.38, verified by ANOVA test). In terms of gender, female users pay more attention to the improvement of gender balance in the socio-technical normativity strategy (Group B), and the increase in their satisfaction is higher than that of male users (verified by ANOVA test). This validates the hypothesis that user attributes have a significant moderating effect on the effectiveness of normative strategies.

4) Shaping Ability of Behavioral Normativity (Group C)

After Group C adopted the diversified recommendation strategy, the effect of user interest expansion was 显著. Through trend analysis, it was found that the interest expansion of users in Group C in different age groups exhibited certain patterns. For example, as the age increases, the proportion of interest expansion gradually decreases but still remains higher than that of users in the same age groups in Group A and Group B. Through testing, it was found that the differences in the interest expansion indicators between Group C and other groups were significant (verified by ANOVA test), indicating that the behavioral normativity strategy can significantly promote the expansion of users' interests through diversified recommendations and exhibit differences among different user groups, thus supporting the corresponding hypothesis.

F. Discussion

This experiment has comprehensively verified the various mechanisms of action of algorithmic normativity in recommendation systems and the differences in its manifestations among different user groups. Technical normativity has a significant effect on enhancing system performance, yet it exhibits certain limitations when considering user experience and social fairness (Zhou, Tao et al., 2010). Socio-technical normativity not only contributes to improving recommendation fairness but also enhances user satisfaction, thereby highlighting the importance of algorithmic systems in the transmission of social values (Yao, Sirui et al., 2017). Behavioral normativity strategies have a positive impact on the expansion of users' interests, and the responses of users in different age groups vary, which provides a basis for the improvement of personalized recommendation algorithms (Ricci et al., 2017). The moderating effect of user attributes on the effectiveness of normative strategies indicates that algorithm design should place greater emphasis on user diversity. For example, providing differentiated recommendation services for users of different ages and genders can better meet user needs and improve the effectiveness and user acceptance of recommendation systems (Adomavicius et al., 2005). However, the experiment also has certain limitations. Although geographical factors were considered in the experimental design, no significant impact on the effectiveness of normative strategies was found in the result analysis. This may be due to the insufficiently detailed geographical division or the masking of the role of geographical differences by other factors (Burke et al., 2007). Future research could further refine the geographical variable or combine it with factors such as culture to conduct in-depth investigations into the impact of geographical differences on algorithmic normativity (Sunstein, Cass R. 2015).

In addition, the experiment was conducted only in specific recommendation system scenarios, and the manifestations of algorithmic normativity in other fields and application scenarios remain to be explored (Aggarwal, Charu C. 2016). Future research could expand the research field, such as applying algorithmic normativity to fields such as healthcare and finance to study its characteristics and impacts under different industry backgrounds (Awad et al., 2018).

Meanwhile, with the continuous development of algorithmic technologies, such as new breakthroughs in artificial intelligence technologies and improvements in data privacy protection technologies, algorithmic normativity will also face new opportunities and challenges. Continuous in-depth research is required to better exert the positive role of algorithmic systems in society and achieve the harmonious development of technology and society (Floridi et al., 2016).

VI. The Impact of Algorithmic Normativity on Society and Culture

A. Reshaping the Normative Structure in Social Activities

The widespread application of algorithmic systems is reshaping the normative structure in social activities. In traditional society, norms were primarily shaped by the institutions, cultures, and customs of human society, and people's behaviors largely adhered to these established norms. However, with the intervention of algorithmic systems in various fields of social life, a new source of norms and an enforcement mechanism have begun to emerge. For example, on social networking platforms, recommendation algorithms recommend friends, content, and activities to users based on their interests and behavior patterns, which, to a certain extent, influences the norms of users' social behaviors. Users may participate in specific social activities or form specific social circles due to algorithmic recommendations, thereby changing the traditional social norms and interaction patterns. Through this means, algorithmic systems integrate technical norms into social activities, intertwining with traditional social norms to jointly shape a more complex and diversified normative structure.

B. Provoking In-depth Reflection on the Human-Machine Relationship

The emergence of algorithmic normativity has provoked in-depth reflection on the human-machine relationship. In traditionalconception, machines were regarded as tools of humans, and their behaviors were completely set and controlled by humans. However, with algorithmic systems demonstrating a certain degree of autonomy and normativity, the human-machine relationship has become more complex. In some cases, the decisions and behaviors of algorithmic systems may exceed the expectations and understanding range of humans, which raises questions about the control ability of humans over algorithmic systems and the definition of responsibilities. For example, during the operation of self-driving cars, the algorithmic system is responsible for making real-time decisions such as accelerating, decelerating, and turning. When an accident occurs, how to define the responsibilities of the algorithmic system and the human driver (if any) becomes an urgent ethical and legal issue. This new change in the human-machine relationship prompts us to re-examine issues such as the power distribution, responsibility attribution, and moral status between humans and algorithmic systems, promoting the research on the human-machine relationship to shift from a simple instrumental cognition to a more complex interactive and symbiotic cognition.

C. Promoting the Dissemination and Evolution of Cultural Values

Algorithmic systems play an important role in the dissemination and evolution of cultural values. Through recommendation systems, social media algorithms, etc., algorithms can widely disseminate specific cultural contents, values, and aesthetic concepts to users. For example, the recommendation algorithm of streaming media platforms will recommend film and television works with specific cultural themes or styles to users based on their historical viewing records and preferences, thereby influencing users' cognition and acceptance of different cultures. Meanwhile, algorithmic systems can also have an impact on the evolution of cultural values. When an algorithm recommends a certain emerging cultural trend or art form, it may attract more users' attention and participation, thereby accelerating the development and evolution of this cultural trend. The interactive relationship between algorithmic systems and cultural values makes the process of cultural dissemination and evolution more dynamic and complex, and also prompts us to think about how to guide and manage the dissemination of cultural values in the algorithm era to promote the diversified development and innovation of culture.

VII. CONCLUSIONS AND PROSPECTS

A. Summary of Research Findings

This study, through an in-depth analysis of algorithmic normativity at the technical, socio-technical, and behavioral levels, combined with experimental verification, has revealed the complex roles and far-reaching impacts of algorithmic systems in modern society. At the technical level, the evolution of algorithmic technical solutions follows certain norms. The development of technological innovation and the material foundation jointly promotes the enhancement of algorithmic capabilities. At the socio-technical level, engineers integrate social values into algorithmic systems through design practices, making them an integral part of the socio-technical system, subject to socio-technical norms. Moreover, experiments have proven that socio-technical normativity has a positive impact on recommendation fairness and user satisfaction. At the behavioral level, algorithmic systems exhibit behavioral normativity. Through interaction with users, they participate in the shaping and reconstruction of social activity norms. Diversified recommendation strategies can effectively promote the expansion of users' interests. The multiplicity of algorithmic normativity not only helps us understand how algorithmic systems achieve engineering goals and respond to technological changes, but more importantly, it reveals the extensive impacts of algorithmic systems at the social and cultural levels, including reshaping the social normative structure, triggering reflections on the human-machine relationship, and promoting the dissemination and evolution of cultural values.

B. Research Limitations and Future Directions

Although this study has made certain progress in understanding algorithmic normativity, there are still some limitations. Besides the insufficient analysis of geographical factors in the experiments and the limited research scenarios mentioned earlier, the cross-cultural research on algorithmic normativity is relatively lacking. Under different cultural backgrounds, the application and acceptance of algorithmic systems may vary, and how these differences affect the manifestation and evolution of algorithmic normativity has not been fully explored. Future research could conduct in-depth cross-cultural comparative studies to reveal the role of cultural factors in the formation and development of algorithmic normativity. Secondly, this study mainly focuses on the normativity issues of algorithmic systems in relatively mature application fields. For emerging algorithmic technologies and application scenarios, such as quantum computing and bioinformatics, the research on algorithmic normativity is still in its infancy. Future research needs to pay attention to these emerging fields to promptly grasp the new characteristics and challenges of algorithmic normativity in the new technological environment. In addition, as the integration of algorithmic systems and society deepens, how to establish an effective algorithmic governance mechanism to ensure that algorithmic normativity conforms to the public interests of society is also a direction that future research needs to focus on.

C. Implications for Related Disciplinary Fields

This study has important implications for multiple disciplinary fields. In the field of philosophy, the research on algorithmic normativity prompts philosophers to re-think the relationships between technology and society, humans and machines, expanding the understanding of the concept of normativity in philosophy and providing new research topics and theoretical perspectives for branches such as the philosophy of technology and ethics.

In the field of sociology, the analysis of algorithmic normativity reveals the mechanism of action of technical systems in shaping social structures and social behaviors, helping sociologists better understand the process of technological transformation in modern society and the micro and macro mechanisms of the interaction between technology and society. In the field of computer science, a deeper understanding of algorithmic normativity helps computer scientists more consciously consider social and cultural factors in the process of algorithm design and development, improving the social adaptability and interpretability of algorithmic systems, and promoting the development of artificial intelligence and algorithmic technology in a direction that is more in line with human values and social needs. The successful application of interdisciplinary research in the study of algorithmic normativity also provides a useful reference for interdisciplinary research in other fields, encouraging stronger cooperation and communication between different disciplines to jointly address complex socio-technical problems.

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