

# On the legal regulation of algorithmic discrimination in digital consumer credit: an empirical study based on the protection of financial consumers' rights and interests

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**Abstract.** Algorithm-driven automated decision-making has become the core operational paradigm of digital consumer credit. While significantly reducing transaction costs, it has also given rise to systemic risks of algorithmic discrimination. Taking the protection of the rights and interests of digitally disadvantaged groups as the analytical starting point, this paper integrates data from the *57th Statistical Report on China's Internet Development*, the financial consumer complaint statistics of the People's Bank of China for 2024, and 120 effective court judgments, and conducts an empirical examination of the legal attributes, typological characteristics, and rights-infringement mechanisms of algorithmic discrimination in the field of digital consumer credit. The study shows that algorithmic discrimination has emerged with three interrelated features—concealment, precision, and amplification—and has reconstructed the stratification structure of the financial market through technological means, causing institutional infringement upon the equal credit rights, fair trading rights, and property rights of the elderly, rural residents, and low-income groups. At present, China's regulatory system for algorithmic discrimination suffers from structural deficiencies, including the absence of special legislation, outdated regulatory technology, imbalance in judicial proof, and malfunctioning mechanisms for consumer rights protection. Accordingly, this paper constructs a coordinated multi-dimensional regulatory framework integrating "legislative regulation—supervisory innovation—judicial relief—rights protection—technical governance", and introduces institutional tools such as algorithmic auditing, penetrating supervision, and reversal of the burden of proof, so as to promote the dynamic balance between algorithmic ethics and financial fairness, and to provide legal support for inclusive financial development in the digital economy era.

**Keywords:** digital consumer credit, algorithmic discrimination, financial consumers, digitally disadvantaged groups, algorithmic auditing

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## 1. Introduction

The rapid growth of China's digital economy has driven profound transformations in the consumer finance market. As of December 2025, China's internet user base reached 1.125 billion, with the internet penetration rate rising to 80.1% and the online payment user penetration rate reaching 90.3% [1]. The widespread

adoption of algorithmic technologies has shifted credit decision-making from traditional manual review processes to fully automated models, significantly expanding the reach of financial services. However, algorithms are not value-neutral technical tools; the structural biases embedded in their training data, feature selection, and objective functions can give rise to systemic discriminatory practices, leading to unfair treatment of certain groups.

Algorithmic discrimination in digital consumer credit is essentially an extension and amplification of the digital divide within the financial sector. Digital disadvantaged groups-such as older adults, rural residents, and low-income populations-face inherent disadvantages in algorithmic decision-making due to limitations stemming from factors like age, economic circumstances, and digital literacy [2]. These groups not only struggle to secure equal access to credit but may also encounter higher interest rates, more stringent repayment conditions, and more frequent debt collection practices [3]. According to 2024 complaint data released by the China Consumers Association, complaints concerning algorithmic discrimination and unfair pricing in the digital financial services sector accounted for 32.7% of all such complaints; among these, complaints from rural residents and individuals aged 60 and above collectively accounted for over 60% of the total.

Existing research has largely concentrated on technological ethics and administrative regulation, leaving the private law remedy mechanisms for financial consumers underexplored and lacking in typological analysis supported by large-scale empirical data. Adopting a civil law perspective and drawing on the theory of protecting digitally disadvantaged groups, this paper employs empirical data to examine the real-world manifestations of algorithmic discrimination and the pathways through which it infringes upon rights and interests. It further identifies the core challenges confronting current legal regulation and introduces forward-looking mechanisms-such as algorithmic auditing and penetrating supervision-to construct a regulatory framework that is both prospective and practicable. This framework aims to provide theoretical foundations and practical guidance for improving the rule of law in digital finance in China.

## **2. Legal theoretical framework and empirical examination of algorithmic discrimination in digital consumer credit**

### **2.1. Definition of core concepts and legal attributes**

Digital consumer credit refers to unsecured small-amount consumer credit services provided to natural persons by licensed financial institutions or internet platforms using digital technologies; its core characteristic is the full-process algorithmicization of credit decision-making [4]. Algorithmic discrimination has not yet been explicitly defined at the legal level in China. The academic community has developed three representative schools of thought based on different theoretical assumptions; the divergences among these schools directly influence the criteria for identifying such practices and the regulatory approaches adopted.

The outcome-oriented approach centers on the effectiveness of decision-making, asserting that any systematic disparity in resource allocation resulting from algorithmic automated decision-making constitutes discrimination-without the need to consider subjective fault. Ding argues that the essence of algorithmic discrimination lies in the unfairness of automated decision-making outcomes, which often stem from historical biases present in the training data [5]; Wang and Ding further contend that proving subjective intent is impracticable within the context of algorithmic black boxes [6]. This approach lowers the threshold for determining discrimination and aligns with consumer protection objectives; however, it may blur the boundary between reasonable risk pricing and actual discrimination. The process-oriented approach focuses on the technical implementation phase, positing that the root of discrimination lies in the technical encoding of

human biases, with subjective fault serving as an essential element. Song argues that discrimination is only constituted when developers incorporate sensitive attributes unrelated to creditworthiness [7]; Gao emphasizes algorithmic neutrality, asserting that no liability should be imposed in the absence of subjective fault [2]. This perspective clarifies the basis for liability but struggles to address unintentional systemic discrimination. The comprehensive approach represents the predominant stance within academia, advocating for a balanced consideration of both procedural flaws and outcome-based unfairness. Zhou and Fang view algorithmic discrimination as an integration of technical defects and social outcome injustice [8]; Zhao and Yang argue that its essence is a composite product of technical bias and institutional exclusion [9]. This approach addresses the limitations of the previous two approaches; however, the distinction between "unreasonable disparity" and "liability" remains contentious. The core disputes surrounding these three theoretical frameworks can be summarized across three dimensions: first, the elements of liability—should subjective fault or objective outcomes be the central focus; second, the regulatory emphasis—should the focus lie on process scrutiny or outcome correction; and third, the criteria for determination—how to distinguish between reasonable risk pricing and unfair discrimination, and who bears the burden of proof.

This article endorses the Comprehensive Theory and provides a refined definition of algorithmic discrimination: First, it establishes "irrelevance to credit" as the core criterion for determining discrimination—discrimination occurs only when an algorithm employs feature variables that are not substantively related to a user's credit status (e.g., age, geographic location, digital behavior patterns, etc.) and results in systematic differential treatment; Second, it extends regulatory oversight to encompass the entire algorithmic lifecycle—including all stages from data collection and feature selection to model training and decision output, ensuring that biases at every stage are accounted for; Third, it highlights the systemic and institutional nature of algorithmic discrimination as a form of infringement—this is not merely an isolated individual-level bias but rather a large-scale, institutional exclusion facilitated by technological architectures. From a legal perspective, algorithmic discrimination violates the equal rights of financial consumers and contravenes *Article 4 of the Civil Code*, which enshrines the principle of equality; it also constitutes a violation of the right to be informed and the right to fair trading, thereby undermining consumers' property rights. Such discrimination exerts a cumulative impact on digitally disadvantaged groups, creating a vicious cycle of "digital poverty—financial exclusion—deep poverty"; therefore, regulatory approaches must adhere to the principle of prioritizing the protection of vulnerable stakeholders [10].

## 2.2. Typification and characterization of algorithmic discrimination

Based on the classification criteria for digitally disadvantaged groups and drawing on typical cases from judicial practice, algorithmic discrimination in digital consumer credit can be categorized into four main types.

First, age discrimination. Algorithmic systems, using users' age data, impose systematic credit restrictions on individuals aged 60 or above. According to the *2024 Financial Consumer Rights Protection Report* issued by the People's Bank of China, 62.3% of mainstream consumer credit platforms automatically classify users aged 60 or older as high-risk borrowers; even when their credit histories are flawless, their credit approval rate falls below 15%.

Second, geographic discrimination. Algorithms rely on users' IP addresses, registered domicile, and base station location data to apply differentiated treatment to users in rural or economically underdeveloped areas. Empirical data reveal that the average credit line for rural residents is 41.2% lower than that for urban residents, while their average annualized interest rate is 2.8 percentage points higher [11].

Third, digital literacy discrimination. Algorithms analyze behavioral data—including app usage duration, browsing history, operation frequency, and typing speed—to label users with limited digital skills as "high-risk

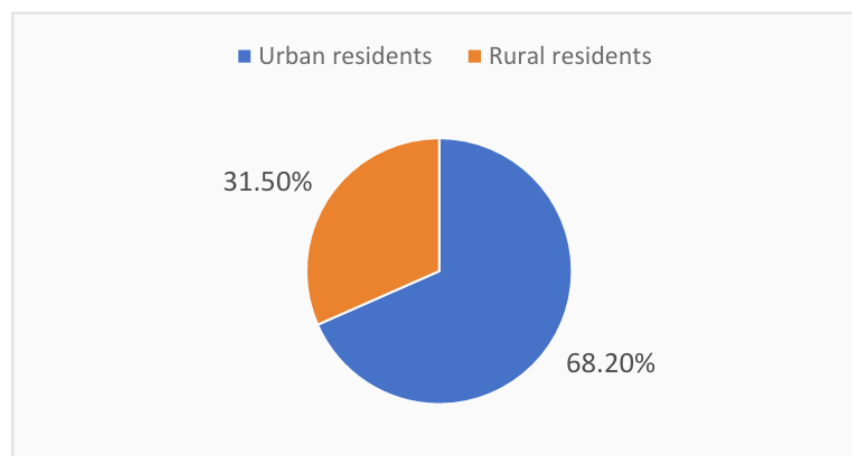
users", thereby increasing their borrowing costs. As of December 2025, only 50.9% of Chinese internet users were proficient in at least one of the surveyed digital literacy and skills. Among rural internet users, this proportion was merely 33.2%, reflecting a digital literacy gap of 24.6 percentage points between urban and rural populations [1].

Fourth, income discrimination. Algorithms draw on users' consumption records, transaction histories, and occupational information to impose more stringent credit approval requirements on low-income individuals. As a result, these users face not only lower credit limits, but also shorter repayment terms and higher default penalty rates.

Algorithmic discrimination in digital consumer credit exhibits the following distinctive characteristics: First, it is concealed. The algorithmic decision-making process is opaque; discriminatory practices are embedded within complex code and models, making it difficult for consumers to detect or substantiate such discrimination. Unlike traditional, overt forms of discrimination, algorithmic discrimination often operates under the guise of "risk assessment", which is highly deceptive. Second, it is systemic. Once deployed, algorithms automatically generate discriminatory decisions across large user bases, giving rise to systemic financial exclusion. This form of discrimination is no longer the isolated action of individual institutions but has become a widespread phenomenon across the entire industry. Third, it is amplifying. Algorithms possess the capacity for self-learning and reinforcement; initial, minor biases are continuously amplified as more data accumulates, leading to increasingly severe levels of discrimination. For example, initial credit restrictions imposed on rural areas may result in a lack of credit data for users in those regions, which in turn causes algorithms to further downgrade their credit ratings. Fourth, it is technical in nature. The emergence of algorithmic discrimination is closely linked to technical design; technical issues-such as biased training data, improper feature selection, or overly simplistic objective functions-can all contribute to the generation of discriminatory outcomes.

### 2.3. Discrimination representation analysis based on empirical data

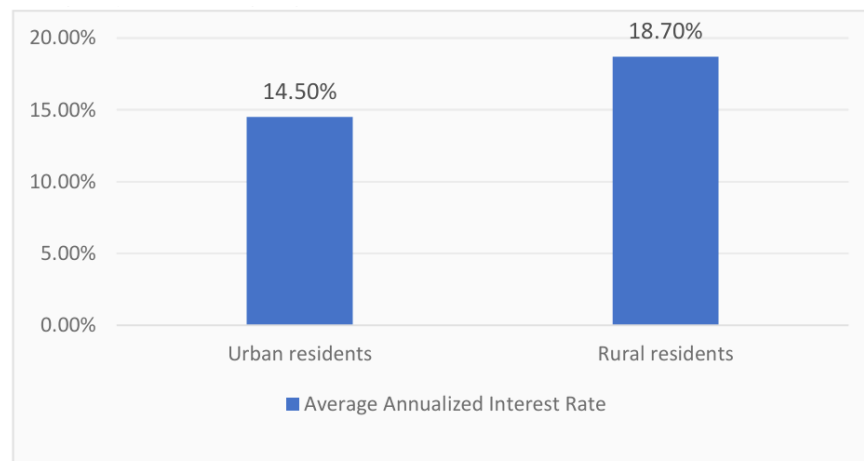
This paper integrates the *57th Statistical Report on the Development of China's Internet Network*, the 2024 complaint data from the Financial Consumer Rights Protection Bureau of the People's Bank of China, and 120 relevant judicial judgments to conduct an empirical analysis of the practical manifestations of algorithmic discrimination in digital consumer credit.



**Figure 1.** Comparison of digital consumer credit penetration rates

From the perspective of user demographic distribution, digitally disadvantaged groups are the primary victims of algorithmic discrimination. As of December 2025, the number of rural internet users in China reached 314 million, accounting for 27.9% of the total internet user population [1]; however, the digital consumer credit penetration rate among rural residents stood at only 31.5%, significantly lower than the 68.2% observed among urban residents [12] (Figure 1). Among elderly internet users aged 60 and above, merely 17.3% had ever utilized digital consumer credit services, while the proportion of those whose credit applications were rejected reached as high as 52.8%. This data indicates that the digital divide is directly translating into a financial divide, placing the elderly and rural residents in a severely marginalized position within the digital consumer credit market.

From the perspective of varying credit conditions, algorithmic discrimination has led to significant disparities in credit cost across different demographic groups. Empirical data show that the average annualized interest rate for digital consumer credit among rural residents is 18.7%, which is 4.2 percentage points higher than that among urban residents (Figure 2); for low-income groups (with a monthly income below RMB 3,000), the average annualized interest rate is 21.3%, which is 7.5 percentage points higher than that for high-income groups (with a monthly income above RMB 10,000). Furthermore, the average credit amount available to digitally disadvantaged groups is merely 35% of that available to other groups, while the proportion of overdue penalty interest charges is more than twice as high. These credit conditions-characterized by "high interest rates, low credit limits, and high penalty interest charges"-significantly exacerbate the economic burden on digitally disadvantaged groups.



**Figure 2.** Comparison of average annualized interest rates for digital consumer credit

From a judicial practice perspective, algorithmic discrimination disputes are characterized by "difficult evidence collection, low likelihood of winning litigation, and low compensation amounts". Among 120 relevant court judgments, only 12 rulings found that the platforms had engaged in algorithmic discrimination. In these cases, more than 90% of the lost lawsuits occurred because the consumers were unable to provide sufficient evidence to prove that the algorithms were discriminatory. Among the five typical cases listed in Table 1, only the "Liang Ying v. Quying Company – Standard Contractual Clauses Dispute Case" and the "Wu Shengwei v. iQIYI Company – Service Contract Dispute Case" resulted in compensation being awarded; in contrast, the "Han v. Beijing Duwang Technology Co., Ltd. – Infringement Dispute Case" and the "Li Mofang v. A Certain Live Streaming Platform – Sales Contract Dispute Case", which involved the substantive determination of algorithmic discrimination, both saw the plaintiffs' claims dismissed or resulted in no compensation being awarded. Even in the "Zhang v. A Certain Bank – Algorithmic Credit Discrimination

Case", which was ultimately resolved through mediation, no compensation for emotional distress was awarded. This reflects the severe inadequacy of consumers' ability to provide evidence in the face of opaque algorithmic systems, and indicates that current judicial practice is ill-equipped to effectively curb platform-based algorithmic discrimination; therefore, there is an urgent need to enhance this framework through adjustments to the burden of proof and the establishment of rules governing algorithmic explainability.

**Table 1.** Comparison of judicial cases involving algorithmic discrimination in digital consumer credit

| Case                                                                                | Court                                                | Year | Plaintiff                       | Focus of Dispute                                                                  | Outcome                                        | Compensation              |
|-------------------------------------------------------------------------------------|------------------------------------------------------|------|---------------------------------|-----------------------------------------------------------------------------------|------------------------------------------------|---------------------------|
| Li Mifang v. A Certain Live-Streaming Platform - Sales Contract Dispute             | Longhua District People's Court, Shenzhen, Guangdong | 2024 | Elderly consumers               | False advertising in live-streaming e-commerce and consumer loan defaults         | Claim dismissed                                | RMB 0                     |
| Liang Ying v. Quying Company - Standard Form Clauses Dispute                        | Guangzhou Intermediate People's Court, Guangdong     | 2022 | Young and middle-aged consumers | Validity of automatic renewal standard terms                                      | Standard form clauses annulled                 | Full refund of fees       |
| Wu Shengwei v. iQIYI Co., Ltd. - Service Contract Dispute                           | Beijing Internet Court                               | 2020 | Young and middle-aged consumers | Unilateral alteration of service content by platform                              | Platform breach of contract established        | Partial loss compensation |
| Han v. Beijing Duwang Network Technology Co., Ltd. - Copyright Infringement Dispute | Haidian District People's Court, Beijing             | 2012 | General consumer                | Whether search engine algorithm recommendations constitute copyright infringement | Platform deemed to have fulfilled duty of care | RMB 0                     |
| Zhang v. A Certain Bank - Algorithmic Credit Discrimination                         | Pudong New Area People's Court, Shanghai             | 2023 | Rural residents                 | Geographic discrimination leading to lower credit limits                          | Resolved through mediation                     | Credit limit adjusted     |

To uncover the underlying mechanisms behind the challenges of "difficult evidence production, difficulty in securing a favorable judgment, and low compensation amounts", this study systematically codes 120 court judgments, covering five variables-plaintiff type, type of discrimination, judgment outcome, compensation amount, and evidence production status-and uses descriptive statistics and cross-tabulation to reveal the inherent relationships among these variables.

Descriptive statistics reveal the following distribution of plaintiffs: elderly individuals (37 cases, 30.8%), rural residents (41 cases, 34.2%), low-income groups (28 cases, 23.3%), and other general consumers (14 cases, 11.7%); the digital disadvantaged group collectively accounted for 88.3%. Regarding the types of discrimination: geographic discrimination (43 cases, 35.8%), age discrimination (31 cases, 25.8%), income discrimination (27 cases, 22.5%), and digital literacy discrimination (19 cases, 15.8%). As for the judicial outcomes: 8 cases resulted in a full victory (6.7%), 17 cases resulted in a partial victory (14.2%), 15 cases were resolved through mediation or withdrawal of the lawsuit (12.5%), and 80 cases resulted in a full defeat (66.7%). The compensation amounts were as follows: RMB 0 (including cases with full defeat) in 88 cases (73.3%); RMB 1–1,000 in 13 cases (10.8%); RMB 1,001–10,000 in 11 cases (9.2%); and RMB 10,000 or

more in 8 cases (6.7%). As for the evidence provided: in 97 cases (80.8%), only individual instances of differential treatment could be presented; in 18 cases (15.0%), indirect evidence-such as comparative data analysis among similar users-could be provided; and in 5 cases (4.2%), direct evidence-such as access to partial algorithmic decision-making logic-could be obtained. For details, see Table 2.

**Table 2.** Descriptive statistics of coding dimensions for 120 judicial decisions

| Variable            | Category                                                  | Frequency ( <i>n</i> ) | Percentage (%) |
|---------------------|-----------------------------------------------------------|------------------------|----------------|
| Plaintiff Type      | Elderly (aged 60 or above)                                | 37                     | 30.8           |
|                     | Rural residents                                           | 41                     | 34.2           |
|                     | Low-income groups                                         | 28                     | 23.3           |
|                     | Other consumers                                           | 14                     | 11.7           |
| Discrimination Type | Geographic discrimination                                 | 43                     | 35.8           |
|                     | Age discrimination                                        | 31                     | 25.8           |
|                     | Income discrimination                                     | 27                     | 22.5           |
|                     | Digital literacy discrimination                           | 19                     | 15.8           |
| Judgment Outcome    | Full victory                                              | 8                      | 6.7            |
|                     | Partial victory                                           | 17                     | 14.2           |
|                     | Mediation or withdrawal                                   | 15                     | 12.5           |
|                     | Complete loss                                             | 80                     | 66.7           |
| Compensation Amount | RMB 0 (incl. complete losses and no compensation)         | 88                     | 73.3           |
|                     | RMB 1-1,000                                               | 13                     | 10.8           |
|                     | RMB 1,001-10,000                                          | 11                     | 9.2            |
|                     | RMB 10,000 or above                                       | 8                      | 6.7            |
| Evidence Status     | Only individual evidence of differential treatment        | 97                     | 80.8           |
|                     | Indirect evidence (e.g., comparative data analysis)       | 18                     | 15.0           |
|                     | Direct evidence (e.g., algorithmic decision-making logic) | 5                      | 4.2            |

Cross-analyses reveal a strong positive correlation between the burden of proof and the likelihood of winning a case. Among the 80 cases in which plaintiffs suffered a complete defeat, 76 cases (95.0%) involved plaintiffs who could only present isolated pieces of evidence; among the 18 cases in which the evidence reached the "indirect evidence" threshold, 61.1% (11 cases) resulted in a full or partial victory for the plaintiffs; in the 5 cases where the evidence reached the "direct evidence" threshold, all plaintiffs won their cases. The significant disparity in the burden of proof arising from the "algorithmic black box" is the primary reason for consumers losing their legal claims. When analyzed by type of plaintiff, the defeat rate among digitally disadvantaged groups is significantly higher than that among ordinary consumers: 78.4% (29/37) among elderly individuals, 73.2% (30/41) among rural residents, and 71.4% (20/28) among low-income groups, compared to just 7.1% (1/14) among ordinary consumers. When analyzed by type of discrimination, cases involving geographic discrimination or age discrimination incurred the lowest average compensation amounts (RMB 320 and RMB 450, respectively), and in most such cases, the outcome was either a loss of the

case or no compensation awarded; cases involving higher compensation amounts were often related to procedural violations (e.g., breaches of standard contractual terms) rather than the substantive determination of algorithmic discrimination. The above analysis demonstrates that the evidentiary difficulties stemming from the algorithmic black box reduce consumers' chances of winning their cases; moreover, the courts' cautious approach toward substantively determining algorithmic discrimination further depresses the compensation amounts, creating a progressive dilemma characterized by "inability to meet the burden of proof – high defeat rate – low compensation amount".

The systematic coding and cross-analytical examination of 120 judicial judgments identified "the difficulty in producing evidence, the difficulty in securing a favorable judgment, and low compensation amounts" as structural challenges with statistical significance. In 80.8% of the cases, the evidentiary burden fell under the category of "experiencing only differential treatment", which represents a direct technical reason for losing the case; the complete loss rate exceeding 70% among digitally disadvantaged groups highlights the severe inadequacy of judicial remedies in protecting these groups; and in 73.3% of the cases, no compensation was awarded, thereby undermining the protective function and deterrent effect of litigation.

## 2.4. The dimension of algorithmic discrimination against financial consumer rights and interests

Algorithmic discrimination constitutes a multi-dimensional and systemic infringement of financial consumers' rights and interests; it encompasses not only property rights but also personal rights and developmental rights [13].

### 2.4.1. *Institutional deprivation of equal credit rights*

Equal credit access is a fundamental right of financial consumers; however, algorithmic discrimination uses technological means to deprive digitally disadvantaged groups of the opportunity to obtain credit services on an equal basis, effectively excluding them from the digital financial system [14]. This exclusion not only limits their purchasing power but also hinders their ability to improve their living conditions through financial means.

### 2.4.2. *The technical erosion of the right to fair trade*

Algorithmic discrimination subjects digitally disadvantaged groups to unfair pricing terms and contractual conditions in credit transactions. These groups not only pay higher interest rates and service fees but may also be compelled to accept more stringent repayment terms and exclusion clauses. For example, the standard terms and conditions set by certain platforms for rural users unilaterally exempt the platforms from liability for breach of contract, thereby imposing heavier repayment obligations on the consumers [15].

### 2.4.3. *Weakening of the right to informed consent and the right to autonomous choice*

The existence of the algorithmic black box prevents consumers from understanding the specific rationale and computational process behind credit decisions, making it difficult for them to accurately assess their own credit standing [16]. Furthermore, through targeted push notifications and persuasive marketing tactics, algorithms compel consumers to accept unnecessary credit products, thereby depriving them of their right to make autonomous choices.

### 2.4.4. *Dual infringement of property rights and personal rights*

Unreasonable high interest rates and penalty interest have exacerbated the debt burdens of vulnerable digital consumers, sometimes pushing them into a predicament of "using loans to service existing loans". Additionally, during debt collection processes, some platforms exploit algorithms to obtain consumers' personal information and engage in violent debt collection and harassment practices, thereby seriously infringing upon consumers' privacy and reputation rights.

#### 2.4.5. Long-term limitations on the right to development

Financial exclusion further exacerbates social inequality and hinders the upward mobility of digitally disadvantaged groups. Rural residents and low-income populations, unable to access the necessary credit support, find it difficult to engage in business activities or invest in education, thereby falling into a state of chronic poverty [17].

### 3. Practical dilemmas in the legal regulation of algorithmic discrimination in digital consumer credit services

#### 3.1. Insufficient specialized legislative framework and regulatory conflicts

Currently, China does not yet have specialized legislation specifically governing algorithmic discrimination; relevant provisions are instead scattered across various laws and regulations, such as the *Civil Code*, the *Personal Information Protection Law*, and the *Law on the Protection of Consumer Rights and Interests*, which suffer from issues such as fragmented rules, limited specificity, and poor practical enforceability. While the *Civil Code* establishes fundamental principles-including equality, fairness, and good faith-it does not provide clear definitions, constitutive elements, or legal liabilities regarding algorithmic discrimination [18]. The *Personal Information Protection Law* primarily focuses on the collection and processing of personal information and addresses the fairness of algorithmic decision-making only sparingly. Although the *Law on the Protection of Consumer Rights and Interests* stipulates consumers' right to fair transactions, it lacks specific remedial measures tailored to algorithmic discrimination. Furthermore, there are conflicts between the rules established by different laws and regulations. For example, *Article 24* of the *Personal Information Protection Law* grants individuals the right to refuse automated decision-making, but it does not explicitly define the scope of this right in the context of credit applications; meanwhile, *Article 5* of the *Commercial Bank Law* requires commercial banks to adhere to the principle of fairness, yet it does not impose mandatory requirements for assessing the fairness of algorithmic credit practices, creating ambiguous zones in the application of these rules. Such rule conflicts lead to inconsistent application of law in judicial practice, often leaving judges uncertain when adjudicating cases involving algorithmic discrimination. It is particularly noteworthy that Chinese law lacks a clear definition or unified criterion for identifying "digital disadvantaged groups". In judicial practice, courts employ varying interpretations and standards when determining which groups fall under the special protection scope of algorithmic discrimination or how such discriminatory practices should be identified, resulting in instances of inconsistent rulings even for cases with identical facts.

#### 3.2. The lagging nature of the regulatory enforcement mechanism

The rapid advancement of algorithmic technologies poses significant challenges to traditional regulatory frameworks; currently, China's regulatory approach to algorithmic discrimination exhibits notable lagging characteristics. Firstly, the regulatory paradigm trails behind technological innovation, remaining predominantly reliant on ex-post supervision while lacking proactive prevention and real-time control mechanisms. Regulatory authorities often only intervene to investigate algorithmic discrimination issues after large-scale complaints or public incidents have arisen, making it difficult to effectively prevent such risks from materializing. Secondly, regulatory technical capacity is inadequate to address the challenges posed by the "black box" nature of algorithmic systems. The complexity and specialized nature of these systems make it challenging for regulators to conduct comprehensive and in-depth reviews. Most regulatory personnel lack the necessary technical background to understand the operational mechanisms and decision-making logic of

algorithms, hindering their ability to identify discriminatory practices concealed within the code. Finally, the regulatory coordination mechanism is inadequate. Digital consumer credit activities involve multiple authorities-including financial regulators, cyberspace administration agencies, and market supervision departments-yet there is a lack of effective information sharing and law enforcement collaboration among these entities, resulting in both regulatory gaps and overlapping oversight. For example, in the case of consumer credit services provided by internet platforms, the delineation of regulatory responsibilities between financial regulators and market supervision authorities is not sufficiently clear, which undermines the effectiveness of regulatory oversight.

### 3.3. The challenge of allocating judicial remedies and the burden of proof

Judicial remedies serve as the last line of defense in protecting the rights and interests of financial consumers; however, in cases involving algorithmic discrimination, consumers face a severe burden of proof dilemma. Under the general principle of *ei incumbit probatio qui dicit* ("he who asserts must prove"), consumers are required to demonstrate that the platform engaged in algorithmic discrimination, that they suffered cognizable harm, and that a causal nexus exists between the two. Yet, because algorithmic systems are controlled and operated exclusively by the platforms, consumers are denied access to the source code, training data, and internal decision-making logic, rendering effective evidence gathering extremely difficult. Moreover, the inherent opacity and systemic nature of algorithmic discrimination further compound the evidentiary challenge. Discrimination often operates indirectly-producing disparate outcomes through the interplay of multiple variables-which makes it exceedingly difficult for consumers to establish the platform's subjective intent to discriminate. In addition, the harm sustained by an individual consumer is typically modest, while the litigation costs far outweigh any potential compensation, leading most consumers to forgo judicial recourse. In practice, courts have adopted overly stringent standards for determining algorithmic discrimination, typically requiring direct proof of algorithmic bias while refusing to recognize the probative value of indirect or statistical evidence. Such a strict evidentiary threshold renders consumer victory virtually unattainable, effectively nullifying the judicial remedy mechanism.

### 3.4. Failure of the financial consumer rights protection mechanism

China's current financial consumer rights protection mechanisms exhibit significant shortcomings when addressing the issue of algorithmic discrimination. First, the suitability obligation imposed on financial institutions has not been adequately fulfilled. The suitability principle requires financial institutions to provide consumers with financial products that align with their risk tolerance; however, under algorithm-driven credit models, financial institutions often prioritize profit maximization over assessing consumers' risk tolerance, and may even promote high-risk credit products to digitally disadvantaged groups who lack the capacity to repay such loans. Second, the complaint-handling mechanisms are inadequate. For the majority of platforms, the complaint channels are inefficient and the processing procedures are cumbersome, meaning that consumer complaints often do not receive timely or effective responses. Even when complaints are addressed, platforms typically adopt ad-hoc solutions rather than modifying their algorithmic systems, which fails to address the root cause of algorithmic discrimination. Third, financial education remains insufficient. Digitally disadvantaged groups generally lack the necessary financial knowledge and digital skills, and their understanding of the risks associated with algorithmic credit is limited, making them vulnerable to consumer traps. Currently, China's financial education initiatives primarily target urban residents and younger populations; there is a severe lack of financial education tailored to elderly individuals, rural residents, and low-income groups.

### 3.5. The dilemma of the disconnect between algorithmic black boxes and compliance governance

The "algorithmic black box" phenomenon represents a core technical challenge in regulating algorithmic discrimination. The complexity and opacity of algorithmic systems make it difficult for external parties to understand their decision-making processes and underlying rationale, thereby hindering effective supervision and scrutiny. Furthermore, platform companies often refuse to disclose relevant algorithmic information on the grounds of trade secret protection, which exacerbates the algorithmic black box issue. Additionally, there exists a significant disconnect between corporate algorithmic compliance governance practices and legal requirements. While most companies have established formal algorithmic compliance frameworks, they often lack substantive mechanisms for fairness assessment and review. During the algorithm design and training phases, companies tend to focus solely on the model's predictive accuracy and profitability, while neglecting algorithmic fairness and ethical considerations. Even when discriminatory issues are identified, companies frequently hesitate to modify or optimize their algorithms due to cost considerations.

## 4. Pathways for improving legal regulation of algorithmic discrimination in digital consumer credit systems

### 4.1. Legislative level: establishing an integrated regulatory framework

Robust legislation serves as the foundation for regulating algorithmic discrimination. It is essential to establish an integrated regulatory framework for addressing algorithmic discrimination—one centered on the *Civil Code*, supported by specialized legislation, and supplemented by judicial interpretations. First, provisions regarding liability for algorithmic discrimination infringement should be added to the *Tort Liability Chapter of the Civil Code*. These provisions should clarify the constitutive elements, the principles of liability attribution, and the methods of assuming liability for algorithmic discrimination; they should stipulate that algorithm providers are responsible for the fairness of their algorithmic decision-making processes, and that they shall bear tort liability when such discrimination causes harm to others. Additionally, the application of fundamental principles of civil law in digital contexts should be expanded; the principles of good faith and fairness should be adopted as guiding tenets for the design and operation of algorithms [19], and the use of algorithms for discriminatory purposes should be prohibited. Second, a dedicated "*Algorithmic Fairness Regulation*" should be enacted. This regulation should define algorithmic discrimination, its various types, and the criteria for identifying such discrimination; it should also establish systems for algorithmic filing, algorithmic impact assessment, and periodic auditing. It should mandate that algorithmic systems used in the digital consumer credit sector undergo fairness assessments; the resulting assessment reports shall be filed with the relevant regulatory authorities and made publicly available. Furthermore, the scope of digitally vulnerable groups and corresponding special protection measures should be clearly defined; algorithm providers should be required to develop dedicated algorithmic models tailored for specific groups—such as elderly individuals and rural residents—to safeguard their right to equal access to credit services. Finally, relevant supporting laws and regulations should be enhanced. The "*Consumer Rights and Protection Law*" should be amended to include specific provisions addressing algorithmic discrimination, thereby granting consumers the right to algorithmic interpretation and the right to refuse algorithmic recommendations. The "*Commercial Bank Law*" and the "*Banking Supervision and Administration Law*" should also be amended to clarify the fairness obligations and regulatory requirements imposed on financial institutions in the context of algorithmic credit services.

Meanwhile, coordinate the relationships among various laws and regulations, resolve conflicts between rules, and foster a cohesive regulatory framework.

#### 4.2. Regulatory level: implementation of penetrating supervision and algorithmic auditing

Given the unique characteristics of algorithmic technologies, regulatory frameworks should be innovated by implementing "penetrating supervision" and algorithmic audit systems to achieve comprehensive, end-to-end oversight of algorithmic discrimination. First, a full lifecycle penetrating supervision mechanism for algorithms should be established. Regulatory authorities should move beyond the misconception of "technological neutrality" and delve into the inner workings of algorithmic systems to exercise full-process supervision over the design, training, deployment, and operation of algorithms. Platform enterprises shall be required to submit to regulatory authorities information such as the algorithm's source code, training data, feature variables, and decision-making logic; regulatory authorities shall have the right to conduct real-time monitoring and dynamic review of these algorithms. Additionally, an algorithmic risk early-warning mechanism should be established to promptly identify and address risks associated with algorithmic discrimination. Second, an independent third-party algorithmic audit system should be introduced. Third-party professional institutions accredited by regulatory authorities shall conduct regular audits of algorithmic systems used in the digital consumer credit sector to assess the fairness, transparency, and compliance of these algorithms. Audit reports shall serve as a key basis for the filing and renewal of algorithms; for algorithms that fail the audit, regulatory authorities shall order the platform enterprises to rectify the issues within a specified timeframe; if the rectification is unsatisfactory, the continued use of such algorithms shall be prohibited. Furthermore, a qualification accreditation and management system for algorithmic audit institutions should be established to ensure the objectivity and fairness of audit outcomes. Third, cross-sectoral regulatory coordination should be strengthened. A mechanism for information sharing and law enforcement collaboration among financial regulatory authorities, cyberspace administration authorities, market supervision authorities, and other relevant departments should be established to clarify the respective regulatory responsibilities of each entity and foster a coordinated regulatory approach. A cross-sectoral algorithmic supervision platform should be created to enable the interconnection, sharing, and collaborative utilization of algorithmic information. Meanwhile, international regulatory cooperation should be enhanced by drawing on advanced global practices to elevate the effectiveness of China's algorithmic regulation framework.

#### 4.3. Judicial level: optimizing remedial rules and burden of proof allocation

Judicial authorities should proactively respond to the demands of the digital age by optimizing relief mechanisms and the allocation of the burden of proof in algorithmic discrimination cases, thereby providing financial consumers with effective judicial remedies. First, implement an inverted burden of proof: in cases of algorithmic discrimination, the burden of proof should be shifted to the platform enterprises, who must demonstrate that their algorithms do not exhibit discriminatory behavior. Consumers need only provide preliminary evidence showing that they belong to a protected vulnerable group and have suffered unfair treatment; under such circumstances, it may be presumed that the algorithmic system is discriminatory. If the platform enterprise fails to provide sufficient evidence to rebut this presumption, it shall bear liability for infringement. Second, lower the standard of proof and recognize the probative value of statistical evidence. For determining algorithmic discrimination, the "preponderance of evidence" standard should be adopted, rather than the "beyond a reasonable doubt" standard. As long as the evidence provided by the consumer demonstrates a substantial likelihood that the platform engages in algorithmic discrimination, the court should find such discrimination to have occurred. Additionally, the probative value of indirect evidence and statistical

evidence should be recognized, allowing consumers to prove the existence of algorithmic discrimination through methods such as comparing group-level data or analyzing similar cases. Third, improve the civil compensation system and establish a class-action litigation mechanism. The scope of compensation in algorithmic discrimination cases should be expanded to include not only direct economic losses but also compensation for emotional distress and punitive damages. For platform enterprises that intentionally engage in algorithmic discrimination under serious circumstances, punitive damages should be imposed to increase the cost of non-compliance [20]. Meanwhile, a class-action litigation system should be established, enabling consumers who have suffered algorithmic discrimination to file collective lawsuits, thereby reducing the cost for individual consumers to seek redress.

#### 4.4. Rights and interests level: strengthening special protection for financial consumers

Given the unique characteristics of digitally disadvantaged groups, it is essential to establish and strengthen special protection mechanisms for financial consumers to enhance their ability to protect themselves and improve the safeguarding of their rights and interests. First, the suitability obligations of financial institutions should be reinforced. A tiered and categorized suitability management system should be implemented; consumers should be classified into different tiers based on factors such as age, income, digital literacy, and risk tolerance, and tailored credit products should be offered accordingly. The marketing of high-risk credit products to elderly individuals aged 60 or older, low-income rural residents, and other vulnerable groups should be prohibited. Additionally, a credit cooling-off period mechanism should be introduced, allowing consumers to unconditionally cancel credit contracts within seven days without incurring any fees. Second, the complaint-handling mechanism for algorithmic discrimination should be improved. Platform enterprises should be required to establish dedicated channels for receiving complaints regarding algorithmic discrimination, simplify the complaint-handling process, and enhance the efficiency of resolving such complaints. For any consumer complaint, platform enterprises must respond within 15 working days and provide a detailed explanation and clarification. If consumers are dissatisfied with the outcome of the complaint-handling process, they may file a complaint with the relevant regulatory authorities or initiate legal proceedings in court. Finally, targeted financial education and digital skills training should be strengthened. For digitally disadvantaged groups-such as the elderly, rural residents, and low-income populations-targeted financial education and digital skills training programs should be conducted to improve their financial literacy and digital proficiency. Platforms such as community centers, village committees, and senior citizen universities can be leveraged to educate these groups on the basics of digital consumer credit and risk prevention skills using straightforward, easy-to-understand language. Furthermore, social organizations and volunteers should be encouraged to participate in financial education activities, fostering a comprehensive, society-wide approach to financial education.

#### 4.5. Technical level: establishing an algorithmic ethics and compliance mechanism

Technical challenges must ultimately be addressed through technical solutions. It is essential to foster the innovative development of algorithmic technologies and establish mechanisms to ensure that algorithms serve the public good and comply with relevant regulations, thereby preventing algorithmic discrimination at its source. First, advance explainable Artificial Intelligence (AI) technologies. Encourage enterprises to research, develop, and deploy explainable algorithms to enhance the transparency of algorithmic decision-making. Platform enterprises should be required to provide consumers with clear justification for their credit decisions, including the primary factors influencing those decisions and their respective weights. Additionally, establish standards and guidelines for algorithmic interpretation to ensure that such interpretations are both accurate and

easy to understand. Second, create a mechanism for assessing and dynamically optimizing algorithmic fairness. Enterprises should be required to conduct comprehensive fairness assessments throughout the entire lifecycle of algorithm design, training, and deployment-identifying and eliminating any discriminatory elements within their algorithms. Use diversified training data to mitigate data bias; carefully select feature variables to exclude sensitive variables unrelated to credit evaluation; and optimize the objective function to balance predictive accuracy with fairness. Furthermore, implement a dynamic monitoring mechanism for algorithmic fairness, enabling regular re-evaluation and optimization of algorithms. Third, encourage enterprises to establish robust algorithmic ethics governance frameworks. Guide companies to embrace the "algorithmic well-being" philosophy by integrating ethical principles-such as fairness, justice, and transparency-into every stage of algorithm design and operation. Establish internal algorithmic ethics committees responsible for reviewing the ethical risks associated with algorithms and overseeing their compliant operation. Encourage enterprises to publish algorithmic ethics white papers, publicly disclosing the principles and standards governing their algorithm design to facilitate public oversight.

## 5. Conclusion

The issue of algorithmic discrimination in digital consumer credit represents, at its core, a conflict between technological rationality and humanistic concern-and it constitutes a new challenge to social fairness and justice in the digital age. Technological innovation must be grounded in the safeguarding of human dignity and rights; the development of digital finance should not come at the expense of infringing upon the rights and interests of digitally disadvantaged groups. Through empirical analysis, this paper finds that algorithmic discrimination has already severely undermined the financial rights and interests of digitally disadvantaged groups, yet China's current legal regulatory framework is still inadequate in addressing this issue effectively. Establishing a legal regulatory framework to address algorithmic discrimination in digital consumer credit requires adhering to the principle of "balancing technological innovation with the protection of rights and interests", and entails coordinated efforts across five dimensions: legislation, regulation, judiciary, rights protection, and technology. This can be achieved by: improving legislation to clarify the legal liabilities arising from algorithmic discrimination; innovating regulatory approaches to ensure comprehensive, end-to-end supervision of algorithms; optimizing judicial mechanisms to provide consumers with effective remedies; strengthening rights protection to enhance the self-protection capabilities of digitally disadvantaged groups; and leveraging technological innovation to prevent algorithmic discrimination at its source. With the continuous emergence of new technologies-such as generative artificial intelligence and the metaverse-the models and forms of digital consumer credit will undergo even more profound transformations, and the issue of algorithmic discrimination will exhibit new characteristics and trends. Future research could further examine the application of generative artificial intelligence in the consumer credit sector and the novel discrimination risks it entails, explore interdisciplinary approaches to algorithmic governance, and provide theoretical support for building a more equitable and inclusive digital finance system.

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