



Research on the Application of Enterprise Digital Profiling in Social Governance Scenarios

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Abstract. As a crucial application of big data and artificial intelligence technologies, enterprise digital profiling exhibits significant potential in enterprise management and social governance. This paper delves into the practices and challenges of digital profiling technology in social governance scenarios. Through multidimensional data collection, mining, and modeling, digital profiling technology constructs precise enterprise characteristic models, unveiling multidimensional insights such as behavioral preferences, risk features, and policy needs. In the realm of enterprise management, digital profiling has been successfully applied in customer relationship management, supply chain optimization, market analysis, and risk control, providing dynamic decision-making support and significantly enhancing management efficiency. In social governance, digital profiling supports intelligent analysis for financial regulation, tax audits, credit risk assessment, and the development of targeted government assistance policies, substantially improving the efficiency and accuracy of governance. Looking ahead, digital profiling technology is expected to achieve deeper innovation and application in areas such as algorithm optimization, blockchain integration, and IoT integration. However, challenges persist, including data privacy protection, algorithmic fairness, and cross-departmental collaboration.

Keywords: digital profiling, social governance, big data, application scenarios

1 Introduction

With the rapid development of big data and artificial intelligence technologies, digital profiling has emerged as a critical analytical tool, increasingly integrated into various domains of enterprise management and social governance. Digital profiling technology constructs precise user or enterprise characteristic models through the collection, mining, and modeling of multidimensional data. These models not only reveal the basic attributes of their subjects but also uncover their behavioral preferences, operational characteristics, policy demands, and behavioral patterns. Consequently, digital profiling technology demonstrates significant value in fields such as customer service, market analysis, and strategic optimization in enterprise management, as well as risk monitoring, resource allocation, and policy implementation in social governance [1].

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In enterprise management, digital profiling technology has been widely applied in scenarios such as customer relationship management and risk assessment. For example, by analyzing multidimensional behavioral data of customers, precise customer profiles can be constructed, enabling enterprises to segment customer groups, optimize marketing resource allocation, and develop personalized service strategies [2]. Additionally, enterprise profiling serves as a comprehensive tool that integrates internal data (e.g., financial status, production capacity) with external data (e.g., market environment, industry policies) to provide dynamic decision-making support, thereby enhancing market competitiveness. Particularly in risk management, intelligent analysis systems based on profiling technology enable real-time monitoring of operational risks, helping managers identify potential issues early and implement timely countermeasures.

Despite the promising prospects of digital profiling technology in enterprise management and social governance, its practical implementation and application face numerous challenges. On one hand, constructing enterprise profiles must overcome issues such as data silos, data privacy concerns, and technical compatibility. On the other hand, in social governance, digital profiling technology must address complex challenges related to data fairness, ethical risks, and cross-departmental collaboration. Therefore, systematically studying the application scenarios and optimization strategies of digital profiling technology is of great significance for advancing the intelligent and digital transformation of enterprise management and social governance.

This paper explores key application scenarios of digital profiling technology in enterprise management and social governance. First, it summarizes the fundamental theories of digital profiling technology and its application logic in these domains through a review of the literature. Second, it examines practical experiences in enhancing management efficiency, optimizing resource allocation, and strengthening risk control through case studies. Finally, it proposes feasible optimization strategies to address practical challenges in technology application, aiming to provide theoretical support and practical guidance for the intelligent and digital transformation of enterprises and social governance [2].

2 Overview of Literature and Methods

2.1 Digital Profiling: Definition and Framework

Digital profiling, based on techniques such as big data analytics, statistics, and machine learning, constructs digital models of objects by integrating and analyzing multidimensional data. These models dynamically reflect the attributes and behavioral patterns of objects, providing scientific support for applications such as personalized services, precision marketing, and risk assessment [3]. For example, in enterprise management, analyzing operational data can generate a corporate profile encompassing financial health, market position, and potential risks, thus supporting strategic decision-making and risk management [4].

Although closely related, digital profiling and big data are distinct. Big data serves as the foundation, while digital profiling is its application. Digital profiling constructs

multidimensional, precise digital models of specific entities (e.g., users, enterprises, or products) based on big data analytics. Its core lies in "application," aiming to reveal the characteristics and behavioral patterns of the target entity. Big data, on the other hand, refers to the collection, storage, processing, and analysis of massive, diverse datasets, emphasizing breakthroughs in data scale, processing capability, and insight generation. Digital profiling relies on big data technology and platforms for data collection, storage, and processing. Big data provides the technical and data foundation, while digital profiling represents actionable outcomes derived through analytics.

2.2 Literature Review

2.2.1 International Studies.

Globally, digital profiling technology emerged alongside the rapid development of big data and artificial intelligence, finding widespread applications in enterprise management, marketing, and risk assessment. For instance, machine learning algorithms have been employed to model corporate financial data, enabling predictions of profitability and market performance. Additionally, risk profiling techniques allow researchers to effectively predict financial crises and market risks for enterprises. In marketing, consumer profiling research leverages historical purchasing and behavioral data to help businesses design precision marketing strategies, enhancing campaign effectiveness and customer satisfaction.

2.2.2 Domestic Studies.

In China, research and application of digital profiling began relatively late. However, with the rapid development of relevant technologies in recent years, this field has garnered increasing attention. Domestic scholars have not only adopted international research findings but also introduced innovations tailored to local contexts. For example, Wang Yibo et al. (2024) used LDA topic modeling and random forest algorithms to construct corporate profiles, enabling precise characterization of enterprise features [5]. Similarly, Chi Renyong et al. (2022) developed credit profiles to evaluate corporate credit risks, supporting loan approval decisions for financial institutions [6].

In the field of social governance, domestic researchers are exploring the application of digital profiling. Liang Chen et al. (2024) constructed urban digital profiles to monitor environmental quality and traffic conditions, providing scientific guidance for environmental governance and traffic management. Furthermore, digital profiling has been applied in areas such as targeted poverty alleviation, public safety, and community governance, significantly enhancing the efficiency of social governance.

2.3 Technical Applications

2.3.1 Enterprise Management.

Digital profiling is widely applied in customer management, risk assessment, and resource allocation. For example, precision customer profiling enables businesses to segment target customer groups and develop personalized marketing strategies,

thereby improving conversion rates and customer satisfaction. Moreover, corporate profiling, by analyzing financial data and market dynamics, provides scientific support for strategic planning and plays a key role in risk management. For instance, securities regulators construct profiles of delisted companies to identify high-risk enterprises and implement targeted supervision, enhancing regulatory efficiency and reducing administrative costs [7].

2.3.2 Social Governance.

In social governance, digital profiling enables real-time monitoring and early warning of social dynamics by constructing profiles of cities, communities, or regions. For instance, Nasraoui et al. used urban profiling technology to predict traffic congestion and crime rates, offering decision-making support for government departments to optimize traffic and public security management [8]. Additionally, tax authorities use corporate profiling to identify tax evasion behaviors, thereby conducting targeted enforcement, improving administrative efficiency, and reducing operational costs [8].

2.4 Major Methods

Corporate digital profiling relies on in-depth analysis of multi-source data to construct dynamic feature models of enterprises, with broad applications in customer management, market analysis, and risk control. Five major techniques and models are summarized below along with their application scenarios:

2.4.1 LDA Topic Model.

The Latent Dirichlet Allocation (LDA) is an unsupervised text topic analysis algorithm used to extract hidden topics in textual data. In corporate profiling, LDA analyzes social media, news reports, and user reviews to identify public attention topics and sentiment trends, helping businesses understand brand image and market feedback.

Application Scenarios: User interest analysis, brand reputation management, content recommendation.

2.4.2 RFM Model.

The RFM model analyzes customer behavior from three dimensions: Recency (time since last purchase), Frequency (purchase frequency), and Monetary (purchase value). Businesses use this model to identify high-value customers and potential churners, enabling the formulation of precision marketing strategies.

Application Scenarios: Customer segmentation, personalized marketing, customer relationship management [10].

2.4.3 Random Forest Model.

The random forest algorithm is an ensemble learning method that enhances classification and regression accuracy through multiple decision trees. In corporate profiling, it processes high-dimensional, multi-source data (e.g., transaction and social media data), evaluates feature importance, and builds refined user profiles, supporting precision marketing and risk management.

Application Scenarios: Credit risk assessment, user profile identification, market trend prediction [11].

2.4.4 PAM Clustering Algorithm.

Partitioning Around Medoids (PAM) is a clustering method based on representative points that divides datasets into clusters by selecting specific data points as medoids. In corporate profiling, PAM identifies distinct customer group characteristics, providing insights for market segmentation and product development.

Application Scenarios: Market segmentation, customer group identification, competitor analysis [12].

2.4.5 Monte Carlo Simulation.

Monte Carlo simulation uses random sampling to estimate probability distributions in complex systems. In corporate profiling, it simulates financial risk scenarios, predicts market fluctuations and credit risks, and supports decision-making in complex environments. Application Scenarios: Financial risk assessment, market risk analysis, project cost estimation [13].

Each technique and model for corporate digital profiling has its unique strengths. Enterprises should select methodologies based on specific needs. For instance, the LDA topic model is suitable for text sentiment analysis, the random forest model excels at handling high-dimensional data, and Monte Carlo simulation focuses on risk evaluation through probability distributions. By integrating these techniques, enterprises can gain deeper customer insights, optimize marketing strategies, and improve risk management capabilities, thereby providing robust support for precision marketing and strategic planning.

3 Technical Pathways of Corporate Digital Profiling

With the rapid advancement of big data and artificial intelligence, corporate digital profiling has become an essential analytical and decision-support tool. By collecting, integrating, and analyzing multidimensional data, digital profiling provides comprehensive insights into a company's characteristics, behavioral patterns, growth potential, and potential risks. Its applications demonstrate substantial potential in corporate management, risk prevention, and social governance [7]. The definition of objectives and application scenarios forms the foundation of the technical pathways for corporate digital profiling, determining data selection, processing, model development, and application directions.

3.1 Objectives and Scenarios of Corporate Digital Profiling

3.1.1 Defining Profiling Objectives.

The objectives of corporate digital profiling serve as the starting point for its technical pathway, as different objectives dictate the choice of profiling methods and analytical priorities. Common profiling objectives include:

(1) Risk Management: Identifying potential risks by analyzing financial health, credit history, and operational behavior of a company (Feng et al., 2020). This is especially significant for banks and financial institutions, supporting loan decisions and credit ratings.

(2) Strategic Decision-Making: Providing top executives with comprehensive operational data to optimize resource allocation and adjust market strategies.

(3) Investment Analysis: Offering investors a quantitative evaluation of a company's overall characteristics and growth potential to support precise investment decisions.

(4) Mergers and Acquisitions: Assisting critical decision-making during M&A processes by comprehensively analyzing the value, risks, and strategic alignment of target companies.

3.1.2 Diversity of Application Scenarios.

The application scenarios of digital profiling determine the data requirements and model designs. For instance, in industry analysis, profiling technology helps companies understand market trends, competitive landscapes, and industry benchmarks. In customer analysis, it explores customer behavioral patterns to support precision marketing and service optimization. In supply chain management, profiling evaluates supplier capabilities, reliability, and risk profiles, enabling the optimization of supply chain stability and cost-efficiency.

3.2 Data Collection and Preprocessing

3.2.1 Comprehensive and Multidimensional Data Collection.

Data is the core of corporate digital profiling. Effective data collection must be both comprehensive and multidimensional, encompassing internal and external data sources:

(1) Internal Data: Includes financial statements, sales records, customer relationship management (CRM) systems, and enterprise resource planning (ERP) systems, which directly reflect a company's operational status [3].

(2) External Data: Covers business registration information, company announcements, market reports, industry trends, policies, regulations, news media, and social media sentiment. These sources provide insights into the external environment and market dynamics [7].

By combining publicly available and private data, digital profiling offers a more holistic representation of the company. For example, public data can be acquired using web crawling tools to gather information from official websites, news outlets, and

industry reports, while private data can be sourced through enterprise systems or interviews with industry experts [6].

3.2.2 Ensuring Data Quality Through Preprocessing.

Data preprocessing is crucial for improving data quality, eliminating biases, and ensuring analytical reliability. Key steps include:

(1) Handling Missing Values: Using mean imputation, interpolation, or regression methods to fill in missing data, ensuring data completeness.

(2) Identifying and Removing Outliers: Detecting outliers with boxplots or statistical measures and addressing them to avoid misleading model outcomes [4].

(3) Standardizing Data: Employing methods such as Z-score or Min-Max scaling to normalize data and eliminate dimensionality disparities.

(4) Data Anonymization and Privacy Protection: Encrypting or masking sensitive information to comply with data privacy regulations.

High-quality data serves as the foundation for precise profiling, while a comprehensive preprocessing workflow ensures reliable modeling.

3.3 Tag Construction for Profiling

Corporate profiling tags digitally describe company characteristics and form the core of the profiling model.

3.3.1 Behavior-Based Tags.

Behavior-based tags reveal dynamic characteristics by analyzing corporate operational and transactional activities. Examples include:

(1) RFM Model: Describes corporate behavior using Recency (time since last transaction), Frequency (transaction frequency), and Monetary (transaction amount).

(2) RFCLS Model: Extends the RFM model by adding Lifecycle and Service Cycle dimensions to further enrich the analysis of corporate behavioral data.

3.3.2 Attribute-Based Tags.

Attribute-based tags describe the fundamental characteristics and operational models of companies. Examples include:

Basic attributes such as company size, years since establishment, and registered capital.

Operational models (e.g., online/offline, B2B/B2C) and developmental stages (e.g., startup, growth, maturity, transformation).

3.3.3 Text-Based Tags.

Text data provides a rich source for constructing profiling tags. Common methods include:

(1) Topic Modeling: Using LDA to analyze text for identifying business priorities (Wang Yibo et al., 2024).

(2) **Keyword Extraction:** Leveraging TF-IDF to identify key terms in text data, reflecting market concerns and public sentiment.

By integrating behavioral, attribute, and text-based tags, corporate profiling achieves multidimensional and dynamic feature representation.

3.4 Model Construction and Optimization

Constructing digital profiling models is a critical step in the technical pathway, as it directly determines the accuracy and applicability of the profiles.

3.4.1 Model Selection and Design.

Machine learning models are chosen and designed based on profiling objectives and data characteristics:

(1) **Classification Tasks:** Models such as Random Forest and Support Vector Machines (SVM) are suitable for tasks like risk assessment and credit scoring [4].

(2) **Clustering Tasks:** K-means and hierarchical clustering are used to identify latent groups, such as categorizing companies into innovative, stable, or risky types [9].

Prediction Tasks: Regression models or deep learning techniques (e.g., neural networks) are used to forecast financial performance and market demand.

3.4.2 Model Optimization and Integration.

Model optimization is key to improving profiling performance. Techniques such as grid search and random search are used to fine-tune model parameters, while ensemble learning methods (e.g., Bagging, Boosting) and deep learning further enhance performance [3].

3.5 Application and Evaluation of Profiling Results

The ultimate goal of corporate digital profiling is to support management decisions. Its applications are extensive, including risk assessment, strategic planning, marketing optimization, and supply chain management.

3.5.1 Applications of Profiling Results.

(1) **Risk Control:** Identifying high-risk companies and implementing mitigation measures based on profiling results.

(2) **Market Strategies:** Optimizing marketing campaigns and product positioning using customer profiles.

(3) **M&A Evaluation:** Analyzing the value and synergy of target companies during mergers and acquisitions.

3.5.2 Evaluating Profiling Effectiveness.

Metrics such as accuracy, recall, and F1-score are used to evaluate model performance. Adjustments to data features or model parameters are made based on business needs [8].

3.6 Comprehensive Pathway

The technical pathway of corporate digital profiling encompasses objective and scenario definition, data collection and preprocessing, tag construction, model optimization, and result application. This technical logic spans the entire data analysis process. Future research can focus on the following directions: enhancing the intelligence of tag construction, improving the real-time and dynamic nature of profiling models, expanding applications across more industries, and addressing challenges related to data privacy and fairness. These advancements will provide profound support for the intelligent transformation of enterprise management and social governance.

4 Application Scenarios of Enterprise Digital Profiling Technology

With the widespread application of big data and artificial intelligence technologies, enterprise digital profiling has gradually become an important tool for social governance. By constructing comprehensive enterprise profiles, government agencies and financial institutions can more accurately manage risks, formulate policies, allocate resources, and make regulatory decisions. This paper discusses the application of enterprise digital profiling in several social governance scenarios, including the China Securities Regulatory Commission's (CSRC) identification of financial fraud in companies, tax authorities' profiling of enterprises engaged in tax evasion, enterprise risk assessment by banking institutions, and the use of enterprise profiles in government fiscal and tax policy support. Based on these scenarios, this paper proposes an enterprise profiling index system, aiming to provide a reference for the application of profiling technologies in social governance.

4.1 CSRC Financial Fraud Detection Through Enterprise Digital Profiling

4.1.1 Empirical Case Study.

In the field of financial regulation, Wang and Li (2020) investigated the identification of financial fraud in Chinese listed companies. By applying machine learning techniques to analyze corporate financial data, they discovered that abnormal fluctuations in financial ratios and non-linear patterns serve as effective indicators for fraudulent behavior. Their study indicated that by constructing financial anomaly profiles, regulatory agencies can more efficiently detect potential financial fraud, achieving an accuracy rate of over 85% in identifying fraudulent firms (Wang & Li, 2020) [14].

4.1.2 Technological Application.

The study developed an anomaly detection model based on multi-dimensional financial indicators, which includes the following aspects:

(1) Model Construction: The random forest algorithm was employed to classify and predict financial data from listed companies, such as balance sheets, income statements, and cash flow statements. Anomaly Feature Extraction: By combining horizontal industry comparisons and vertical time series analysis, the model identifies abnormal data points in the financial records.

(2) Model Validation: The effectiveness of the model was validated using historical financial fraud cases, and the results showed that the model significantly outperforms traditional methods in terms of accuracy and recall rates in identifying anomalous enterprises.

4.1.3 Profiling Model Indicators.

The study proposed several key indicators for constructing financial anomaly profiles:

(1) Financial Ratio Anomaly Index: The deviation of the debt-to-equity ratio, net profit margin, and other financial ratios from industry averages.

(2) Profit Volatility: The variation in net profit across multiple fiscal years, indicating the stability of a company's earnings.

(3) Cash Flow Anomalies: Whether there is a significant mismatch between cash flow and profits, potentially indicating fraudulent activities.

(4) Audit Risk Rating: The number of non-standard opinions found in audit reports, which serves as an indicator of the potential audit risk associated with a company.

4.2 Tax Authorities' Enterprise Digital Profiling for Tax Evasion

4.2.1 Empirical Case Study.

Zhang et al. (2019) investigated tax inspection methods based on machine learning technology. By analyzing tax declaration and invoice data from Chinese enterprises, they successfully identified a group of high-risk enterprises involved in tax evasion. The study demonstrated that digital profiling technology could transform complex behaviors such as abnormal invoicing patterns and related-party transactions into quantifiable indicators, significantly improving the efficiency of tax audits (Zhang et al., 2019) [15].

4.2.2 Technological Application.

The study employed a Support Vector Machine (SVM) model to model enterprise tax data:

(1) Data Sources: The research integrated enterprises' tax declaration information, value-added tax (VAT) invoice data, and related-party transaction data.

(2) Model Analysis: By using classification algorithms, the study modeled invoicing patterns to identify abnormal transaction frequencies and amounts.

(3) **Audit Strategy Optimization:** The profiling technology helped select high-risk enterprises and precisely targeted those involved in tax evasion.

4.2.3 Profiling Model Indicators.

The study proposed the following key indicators for constructing a tax evasion profiling model:

(1) **Tax Burden Anomaly Index:** The deviation between an enterprise's actual tax burden rate and the industry average.

(2) **Invoice Issuance Frequency:** Frequency analysis of invoice issuance during unusually concentrated time periods.

(3) **Transaction Amount Distribution:** The degree of dispersion and concentration of individual transaction amounts.

(4) **Related-Party Transaction Detection:** The flow paths and frequencies of fund transfers between enterprises.

4.3 Bank Enterprise Risk Assessment Profiling

4.3.1 Empirical Case Study.

Li and Chen (2018) proposed a multi-indicator credit scoring model for the risk assessment of small and medium-sized enterprises (SMEs). By integrating financial data, credit records, and market performance, the study developed a credit risk assessment system driven by digital profiling technology. The results showed that the model could accurately predict the default risk of enterprises, helping banks improve the accuracy of credit approvals, with a default prediction accuracy rate of 88% (Li & Chen, 2018) [16].

4.3.2 Technological Application.

The study used a Logistic Regression model combined with multi-source data to construct credit scoring profiles for enterprises:

(1) **Data Integration:** The financial statements (e.g., debt-to-equity ratio, current ratio), operational data (e.g., sales growth rate, order volume), and credit records were integrated.

(2) **Credit Scoring:** A weighted algorithm based on multiple indicators was used to calculate the enterprise's comprehensive credit score.

(3) **Model Optimization:** Feature selection and cross-validation were applied to ensure the model's robustness and generalizability.

4.3.3 Profiling Model Indicators.

The study proposed several key indicators for constructing a credit risk profiling model:

(1) **Financial Health Index:** Liquidity ratio, debt-to-equity ratio, and profit margin.

(2) **Credit Risk Rating:** Historical overdue records and non-performing loan records.

(3) Market Performance Score: Order growth rate and customer retention rate.

(4) Industry Comparison Indicators: Comparison of the enterprise's revenue and profitability with industry benchmarks.

4.4 Government Fiscal and Tax Policy Support Enterprise Profiling

4.4.1 Empirical Case Study.

Sun and Zhao (2017) proposed a data-driven enterprise identification method in their research on high-tech enterprise support policies. By constructing digital profiles of enterprises, the government can accurately identify small and medium-sized technology enterprises in need of support and provide them with targeted policy assistance. The study demonstrated that profiling technology significantly enhanced the specificity and effectiveness of government policies (Sun & Zhao, 2017) [17].

4.4.2 Technological Application.

The study combined clustering analysis and Principal Component Analysis (PCA) to identify enterprises' compatibility with fiscal and tax policies:

(1) Data Collection: Data on enterprise size, research and development (R&D) investment, number of patents, and social contributions were integrated.

(2) Clustering Analysis: Enterprises were categorized into different types (e.g., high-growth, stable, resource-constrained).

(3) Policy Matching: Based on profiling results, differentiated tax reduction and financial support policies were formulated.

4.4.3 Profiling Model Indicators.

The study proposed several key indicators for constructing a policy support profiling model:

(1) Innovation Capacity Index: Proportion of R&D expenditure, number of patents, and patent grant rate.

Social Contribution Score: Employment numbers, total tax payments, and industry influence.

(2) Growth Potential Index: Business revenue growth rate and changes in market share.

Policy Compatibility Score: The degree of alignment between enterprises and policy directions (e.g., green economy, high-tech industries).

In summary, enterprise digital profiling technology has become an essential tool in social governance. Through the integration and modeling of multi-dimensional data, it significantly enhances the efficiency of regulation and policy implementation. In the fields of financial supervision, tax inspection, risk assessment, and policy support, decision-making systems driven by digital profiling provide scientific support for organizations. Future research can further optimize the dynamics and real-time capabilities of profiling models and expand their application in emerging fields, such as environmental policies and fintech regulation.

5 Conclusion

Enterprise digital profiling technology, a driving force behind intelligent management and social governance, has vast potential. With advancements in algorithms, technology integration, and policy support, it is poised to enhance resource optimization, risk prevention, and governance. However, challenges like data privacy and fairness require balancing innovation with social responsibility. In the future, digital profiling will play a key role in smart governance, offering technological support for sustainable development. Key findings from research include:

(1) **Digital Profiling Models:** By analyzing multi-dimensional data, digital profiling constructs accurate, detailed models that uncover enterprises' or users' attributes, behavioral patterns, operational characteristics, policy needs, and risk factors, aiding decision-making.

(2) **Enterprise Management:** Digital profiling optimizes customer relationships, supply chains, market forecasting, risk assessment, and HR management. It helps businesses target potential customers, allocate resources efficiently, and enhance competitiveness through data-driven decisions.

(3) **Social Governance:** Digital profiling supports smart city initiatives, public safety, social welfare, disease prevention, and education. Integrating multi-source data allows governments to achieve precise governance and effective resource allocation, improving governance efficiency.

The development of enterprise digital profiling technology will face both new opportunities and challenges, focusing on the following key areas:

Algorithm Optimization and Model Innovation: Current profiling models have limitations in accuracy and adaptability. Future research should optimize algorithms, integrating deep learning and reinforcement learning for better handling of unstructured data, real-time updates, and complex scenarios. Transparency and interpretability will be crucial to address the "black box" problem.

(1) **Integration of Blockchain Technology:** With growing concerns over data security and privacy, blockchain can enhance the security, transparency, and traceability of data. It enables secure multi-party profiles and cross-departmental collaboration, ensuring compliance and privacy protection.

(2) **Data Privacy and Compliance:** The rise of digital profiling heightens concerns about data misuse and leakage. Future efforts should focus on advanced encryption and differential privacy mechanisms to safeguard sensitive data, while promoting international legal and ethical standards for responsible data use.

(3) **Policy Regulations and Social Equity:** Digital profiling may lead to technological discrimination and algorithmic bias, affecting resource distribution. Governments must create policies ensuring fairness and establish mechanisms to minimize bias and negative social impacts.

As digital profiling technology evolves, it will expand into areas like the green economy, poverty alleviation, and healthcare. It will provide insights for sustainable development, dynamic resource allocation, and personalized health management, contributing to societal progress across multiple sectors.

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