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Minimization of algorithmic bias in recommender systems as a factor in enhancing inclusivity and effectiveness of marketing communications

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Abstract. The relevance of the study is determined by the rapid expansion of recommender systems within the digital marketing environment, where algorithmic personalization increasingly shapes consumer interaction with brands, information visibility, and the overall effectiveness of marketing communications. While machine learning–based recommendation algorithms enhance content relevance and marketing performance, they also pose risks of algorithmic bias, manifested in reduced content diversity, the concentration of digital attention, and unequal market access for different actors. The **purpose of the article** is to substantiate approaches to minimizing algorithmic bias in recommender systems in order to strengthen the inclusiveness of the digital environment and improve the effectiveness of marketing communications. The study applies **methods** of system analysis, comparative analysis, generalization of scientific approaches to marketing personalization, structural and functional analysis of recommender algorithms, and logical synthesis to identify key factors in the formation of algorithmic bias and mechanisms for its mitigation. **Results**. The role of recommender systems in transforming digital marketing has been examined, and their decisive influence on shaping consumer behavioral patterns has been established. It has been revealed that optimizing algorithms solely on short-term engagement metrics leads to popularity bias, filter bubbles, and decreased inclusiveness in the digital information space. The necessity of transitioning from narrow personalization models to balanced recommendation approaches combining relevance, diversity, and fair exposure has been substantiated. **Conclusions**. It has been determined that algorithmic bias represents a systemic characteristic of modern recommender technologies affecting both marketing performance and the competitive structure of digital markets. Prospects for further research include the development of quantitative indicators to measure inclusiveness in recommender systems, the investigation of the long-term behavioral effects of personalization, and the analysis of regulatory and ethical frameworks for artificial intelligence that influence the evolution of digital marketing ecosystems.

Keywords: digital marketing, content personalization, consumer behavior analytics, algorithmic fairness, user experience, digital platforms, consumer attention management, electronic commerce, interaction analytics, digital communications.

Мінімізація алгоритмічної упередженості систем рекомендацій як фактор підвищення інклюзивності та ефективності маркетингових комунікацій

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Анотація. Актуальність дослідження зумовлено стрімким поширенням систем рекомендацій у цифровому маркетинговому середовищі, де алгоритмічні механізми персоналізації дедалі більше визначають характер взаємодії споживачів із брендами, структуру інформаційної видимості та результати маркетингових комунікацій. Використання алгоритмів машинного навчання забезпечує підвищення релевантності контенту та ефективності просування, однак одночасно породжує ризики алгоритмічної упередженості, що проявляється у звуженні інформаційного різноманіття, концентрації цифрової уваги та нерівномірному доступі суб'єктів ринку до аудиторії. **Мета статті** полягає в науковому обґрунтуванні напрямів зниження алгоритмічної упередженості рекомендаційних систем задля посилення інклюзивності цифрового інформаційного простору та підвищення результативності маркетингових комунікацій. У роботі використано **методи** системного та порівняльного аналізу, узагальнення наукових підходів до персоналізації маркетингових комунікацій, структурно-функціонального аналізу рекомендаційних алгоритмів, а також метод логічного узагальнення для визначення чинників формування алгоритмічної упередженості та підходів до її мінімізації. **Результати**. Досліджено роль систем рекомендацій у трансформації цифрового маркетингу та встановлено їх визначальний вплив на формування поведінкових моделей споживачів. Виявлено, що оптимізація алгоритмів за короткостроковими метриками взаємодії спричиняє ефект популярності, інформаційні «бульбашки» та зниження інклюзивності цифрового середовища. Доведено необхідність переходу від вузької персоналізації до збалансованих моделей рекомендацій, які поєднують релевантність контенту з різноманіттям пропозицій і рівномірністю алгоритмічної експозиції брендів. **Висновки**. Встановлено, що алгоритмічна упередженість має системний характер і впливає як на ефективність маркетингових стратегій, так і на конкурентну структуру цифрових ринків. Перспективи подальших досліджень пов'язані з розробленням кількісних індикаторів інклюзивності рекомендаційних систем, дослідженням довгострокових поведінкових ефектів персоналізації та аналізом впливу

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регуляторних підходів до штучного інтелекту на розвиток цифрових маркетингових екосистем.

Ключові слова: цифровий маркетинг, персоналізація змісту, поведінковий аналіз споживачів, справедливість алгоритмів, користувацький досвід, цифрові платформи, управління споживчою увагою, електронна комерція, аналітика взаємодії, цифрові комунікації.

Problem statement. The active digitalization of marketing activities and the spread of artificial intelligence (AI) technologies have led to a transition from mass communications to personalized models of consumer interaction, in which recommendation systems serve as a key mechanism for shaping the user's information environment. It is the recommendation algorithms that determine which products, services, media content or advertising messages become visible to the audience, actually influencing not only the marketing results of enterprises, but also the structure of digital consumption in general. The growing dependence of marketing communications on automated algorithmic solutions raises questions about their objectivity, since machine learning (ML) models are trained on historical data that may contain hidden social, behavioral, or commercial biases. In modern recommendation systems, optimization is mostly carried out according to indicators of forecast accuracy, user engagement or economic return, while the issue of fairness in representing different audience groups has long remained outside the focus of research. This leads to the reproduction of algorithmic bias, which manifests in the concentration of attention on the most active or commercially attractive segments, narrowing information diversity and limiting individual users' access to relevant offers. As a result, personalization, declared as a tool to increase marketing efficiency, can paradoxically reduce the quality of communications, create an asymmetry in information access, and reduce the inclusiveness of the digital environment.

The scientific problem of the study concerns the need to rethink the criteria for the effectiveness of recommendation algorithms, where, alongside prediction accuracy, indicators of algorithmic fairness, diversity of recommendations, and equality of opportunities across user categories should be considered. There is a need to integrate AI approaches, marketing analytics, behavioral economics, and data ethics to develop models that can simultaneously ensure commercial effectiveness and social balance in digital communications.

The practical dimension of the problem is that algorithmic bias directly affects the effectiveness of marketing strategies, consumer trust, and the long-term competitiveness of digital platforms. Uneven audience coverage results in a loss of potential demand, a decrease in the accuracy of market segmentation, and an increase in business reputational risks, amid growing requirements for the ethical use of data and transparency of algorithms. At the same time, for society, the problem poses a risk of deepening digital inequality, which contradicts modern principles of inclusive development of the information economy.

Analysis of recent research and publications. A review of modern research indicates the gradual formation of an interdisciplinary scientific approach that combines the study of behavioral aspects of human interaction with digital environments, the development of artificial intelligence tools, and the transformation of marketing communications toward human-centeredness. In scientific discourse, considerable attention is paid to the role of users' individual psychological and cognitive characteristics in the decision-making processes for managerial and marketing decisions. In particular, the study by I. Kutova demonstrated that emotional intelligence influences the quality of managerial interaction and managers' productivity, suggesting that recommender systems should consider not only behavioral data but also users' emotional and cognitive features [1]. At the same time, scientists emphasize the importance of the socio-cultural context of digital communication: in particular, Y. Hrushko argues for the cultural adaptation of brand communications in an international environment, noting that algorithmic personalization without accounting for cultural differences can create information inequality between consumer groups [2]. Within the framework of digital marketing research, Y. Yarova demonstrates that the use of AI significantly expands the possibilities of audience segmentation; however, the dependence of algorithms on historical data creates the risk of reproducing systemic biases [3]. At the same time, the work of P. S. Moskalenko shows that AI-based personalization simultaneously increases the relevance of communications and can limit users' information diversity due to excessive optimization of recommendations [4].

A separate area of research is devoted to the functioning of digital marketing ecosystems, in which recommendation algorithms act as a key mechanism for interaction between the brand and the consumer. Thus, the studies by P. I. Koreniuk and M. V. Dmytrochenkov demonstrate that the effectiveness of digital marketing communications depends directly on the quality of customer data analytics and the accuracy of algorithmic models for interpreting user behavior [5]. At the same time, N. Buga and A. Ogrenchuk consider new-generation marketing communications as a digital system of controlled interaction, within which algorithms determine the trajectory of consumer contact with the brand [6]. The study by N. A. Krakhmalova substantiates that integrated marketing communications are effective only when different audience segments have equal access to information channels, which is directly related to the principles of balanced algorithmic ranking [7]. At the same time, the works of Y. Hou and co-authors propose an approach to integrating linguistic and subject representations in recommender systems, which reduces semantic distortions and increases the accessibility of information for users with different information needs [8].

Another aspect of the scientific discourse concerns the development of technical tools to reduce algorithmic bias and ensure the diversity of recommendations. In particular, the studies by S. Lankester and co-authors demonstrate the potential of federated learning for generating recommendations with greater diversity while preserving the confidentiality of user data [9]. At the same

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time, H. Abdollahpouri and co-authors prove the existence of the popularity bias effect - a systemic tendency of algorithms to increase the visibility of popular objects, which reduces the representation of alternative products and limits the balance of the information environment [10]. In behavioral research, N. Hazrati and F. Ricci found that recommender systems can alter the structure of consumer decision-making over the long term, leading to stable patterns of user behavior [11]. At the same time, Q. M. Areeb and co-authors, in a systematic review, confirm the existence of «filter bubbles» that arise from a combination of personalization and algorithmic feedback mechanisms and limit the diversity of available content [12]. A significant area of modern research focuses on assessing the social consequences of recommender system operation and their impact on the effectiveness of marketing communications. In particular, the study by D. Holtz and co-authors experimentally demonstrated a relationship between user involvement and recommendation diversity, indicating the risks of optimizing systems solely on the basis of user interaction indicators, which can narrow the information environment [13].

Summarizing the results of the analyzed studies indicates that minimizing the algorithmic bias of recommendation systems is a key condition for the formation of balanced digital ecosystems, in which the effectiveness of marketing communications is determined by the optimal combination of personalization, content diversity, algorithm transparency, and long-term user trust in digital platforms.

Highlighting previously unresolved parts of the general problem. Despite a significant number of studies on recommendation systems, the impact of these systems on the inclusiveness of marketing communications and the balance of personalization remains unexamined. Most research focuses on improving recommendation accuracy and short-term performance metrics, while the factors that generate algorithmic bias, methods for assessing it in a marketing context, and the implications of algorithmic ranking for competitive brand visibility remain understudied. The limited integration of marketing and algorithmic approaches

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results in gaps in the theoretical underpinnings and practical management of personalized digital communications.

Formulation of the objectives of the article (task statement). The purpose of the article is to substantiate the directions for minimizing the algorithmic bias of recommendation systems in order to increase the inclusiveness of the digital environment and the effectiveness of marketing communications.

To achieve the goal, the following tasks have been defined:

1) to analyze the use of recommendation systems in marketing communications and determine the impact of algorithmic bias on the personalization and results of digital marketing strategies;

2) to substantiate approaches to assessing the inclusiveness and effectiveness of recommendation algorithms and identify the main problems of minimizing algorithmic bias;

3) to develop recommendations for improving the use of recommendation systems to increase the effectiveness and balance of marketing communications.

Presentation of the main material of the study. The digitalization of marketing communications has led to a transformation in approaches to consumer interaction, shifting from mass communication to algorithmically controlled, personalized communication. Under these conditions, recommendation systems serve as intelligent mechanisms for selecting and ranking relevant content, creating a personalized information environment for the user. It is through the use of recommendation algorithms that companies can adapt marketing messages to consumers' behavioral characteristics to optimize communication costs and increase the effectiveness of digital promotion channels. Such personalization is based on the analysis of large datasets on the user's previous interactions with digital services, which enables a transition to a dynamic model of marketing communications, in which the content and sequence of brand contacts are adapted in real time (table 1). The integration of recommendation algorithms into customer relationship management systems (CRM), advertising platforms, and e-commerce enables the

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prediction of consumer interests and the real-time optimization of interaction indicators.

Table 1

Features of using recommendation systems in modern marketing communications

Recommendation system component	Functional characteristics	Marketing effect of personalization
Behavioral data collection	Analysis of views, purchases, and search queries	Formation of an individual consumer profile
Algorithmic segmentation	Automatic user grouping	Precise audience targeting
Interest prediction	ML models of behavior prediction	Increased relevance of offers
Content ranking	Determining the order of information display	Increased user engagement
Adaptive learning	Self-learning based on new data	Continuous improvement of communications
Feedback	Analysis of reactions to recommendations	Optimization of marketing strategy

Source: formed by the author based on [3, p. 122; 4, p. 53; 5, p. 66; 7, p. 95; 8; 11]

So, as can be seen, the personalization of marketing communications is formed as a multi-level process of sequential processing of users' behavioral data - from their collection and algorithmic segmentation to interest prediction, content ranking and adaptive learning of models based on feedback. As a result, recommendation algorithms create a continuous cycle of optimizing interaction with consumers, in which each user action affects the subsequent structure of marketing messages and the digital experience.

The practice of operating modern digital platforms confirms the high efficiency of this approach. In particular, the Amazon recommendation system provides a personalized digital showcase of the consumer, using analysis of viewing history, purchases, and behavioral signals to adapt product offers and marketing messages in real time [14]. As a result, recommendation algorithms perform not only the function of searching for relevant content but also serve as a key tool for managing consumer attention, thereby increasing the conversion of personalized offers and the effectiveness of digital marketing strategies.

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A similar model is integrated by Netflix, where personalization algorithms determine the majority of user interaction with content. Modern research on the platform's recommendation infrastructure [15, p. 83] shows that personalized ranking significantly reduces search time for relevant content and increases audience retention, directly affecting the effectiveness of digital marketing strategies. The use of federated learning and adaptive ranking models allows for the simultaneous maintenance of high recommendation relevance and expands the diversity of proposed content. In modern digital marketing ecosystems, algorithmic bias in recommendation systems arises from the optimization of ML algorithms based on behavioral performance indicators. Recommendation models are trained on historical user interaction data that reflects the already-formed demand structure, resulting in an uneven distribution of information visibility across digital market objects. Studies of popularity bias [16] show that recommendation algorithms tend to systematically increase exposure for the most popular products or content, while a significant portion of the catalog receives minimal representation in the recommendations. Thus, personalization is gradually shifting from a tool for individual selection of information to a mechanism for concentrating digital attention, leading to the emergence of a complex of interconnected factors of algorithmic bias (table 2).

Table 2

Algorithmic bias formation factors in recommender systems and their impact on digital marketing results

A factor in the formation of bias	Mechanism of occurrence	Impact on marketing strategies
Historical educational data	Training models on previous behavior	Consolidation of existing demand
The popularity effect	More frequent ranking of popular objects	Concentration of market visibility
CTR optimization	Maximizing clicks	Reducing the diversity of content
Cold start problem	Insufficient initial data	Barriers to entry for new brands

A factor in the formation of bias	Mechanism of occurrence	Impact on marketing strategies
Algorithmic self-reinforcement	Learning on own recommendations	Information «bubbles»
Opacity of models	Lack of explainability of decisions	Risks of hidden discrimination

Source: created by the author based on [3, p. 123; 4, p. 55; 8; 10; 11; 12; 13, p. 76]

In particular, after the launch of a recommendation system, even a small difference in the initial interaction indicators can quickly scale. Empirical research has shown [17, p. 95–97] that recommendation algorithms increase inequality in content exposure over several iterations of training, resulting in popular objects receiving a disproportionately larger share of user attention, while most alternative positions gradually disappear from the information field.

The described processes can be traced in streaming services and social platforms, where personalization increases short-term engagement indicators but reduces the diversity of recommendations. Research on user behavior has shown [18, p. 2] that algorithmic systems can reduce the diversity of consumed content by approximately 20–25% while increasing the time spent interacting with the platform. This means that marketing strategies become more effective in terms of user engagement indicators, but less inclusive of new brands and niche products.

In modern digital markets, algorithmic bias actually transforms competition: businesses compete not only for consumers, but also for algorithmic visibility. The recommendation system begins to act as a market access intermediary, determining which products or information messages get a chance to be seen by the audience. That is why minimizing algorithmic bias is considered a necessary condition for the balanced development of digital marketing strategies and ensuring the inclusiveness of the communication environment.

Assessing the inclusivity and effectiveness of recommendation algorithms in digital marketing communications involves moving from assessing only users' behavioral responses to a comprehensive analysis of the quality of personalization. Modern recommendation systems affect not only conversion rates, but also the structure of brand information visibility, the formation of consumer choice and the long-term stability of interaction with the audience, which necessitates the use of integrated criteria for evaluating the effectiveness of algorithms (table 3).

Table 3

Criteria for evaluating inclusiveness and effectiveness of recommendation algorithms in marketing communications

Evaluation criterion	Content characteristic	Marketing value
Relevance of recommendations	Correspondence to the interests of the user	Increase in conversion
Audience engagement	Frequency and depth of interaction	Increasing loyalty
Variety of offers	Availability of alternative content	Expansion of demand
Inclusiveness of exposure	Uniform visibility of brands	The fairness of digital competition
Long-term customer value	Stability of interaction	LTV growth
Balance of personalization	A combination of precision and novelty	Sustainability of marketing strategies

Source: created by the author based on [1, p. 1199; 5, p. 68; 7, p. 97; 9; 11; 13, p. 75]

The recommendation systems performance in digital marketing is increasingly assessed by their long-term impact on user behavior. Analysis of the criteria presented in table 3 allows concluding that the effectiveness of personalization is determined by the balance between the relevance of recommendations, the level of user involvement, and the diversity of information offers, and that optimization of algorithms based solely on interaction indicators does not ensure the strategic effectiveness of marketing communications. Empirical data on promotion on digital platforms confirm the existence of a compromise between personalization and content diversity. In particular, the Spotify recommendation system uses behavioral data, collaborative filtering models, and audio feature analysis to increase the relevance of recommendations, thereby contributing to the growth of user activity, but at the same time focusing attention on a limited part of the catalog [19]. Similar patterns of algorithmic ranking influence can be observed on video platforms: YouTube's recommendation

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mechanisms form a personalized viewing feed based on the user's interaction history, which can gradually narrow the spectrum of consumed content [20].

From a practical point of view, this means that marketing campaigns compete not only for audience attention but also for algorithmic visibility in recommendation delivery. That is why leading digital platforms are implementing balanced personalization approaches, combining the accuracy of recommendations with the discovery of new content and alternative brands, which helps maintain the effectiveness of marketing communications without excessive concentration of digital attention.

Therefore, the modern evaluation of recommendation algorithms in marketing is based not on maximizing a single metric, but on achieving a balance between commercial efficiency, information diversity, and the long-term value of the interaction with the consumer.

Minimizing algorithmic bias in recommendation systems involves a set of interconnected scientific and practical problems that arise in the use of personalized marketing communications. First of all, the source of distortions is the dependence of ML algorithms on historical behavioral data that reflects the already formed structure of demand. As a result, recommendation systems amplify the popularity effect, focusing users' attention on a limited range of products or brands and reducing the visibility of new market entrants [11]. This transforms digital competition, since access to the audience is increasingly determined by algorithmic ranking rather than by the marketing quality of the offer.

A significant problem is the contradiction between short-term effectiveness and long-term inclusiveness of personalization. Optimizing recommendations based on clickthrough and conversion indicators demonstrates the most predictable content, which increases immediate business results, but narrows information diversity and limits the discovery of new products [5, p. 68]. Algorithmic self-learning amplifies this effect: user responses become new training data, forming a closed loop that reinforces the same behavioral scenarios and leads to the emergence of information "bubbles".

Additional difficulties arise from the cold start problem, when new products or users have insufficient data for accurate ranking, which increases barriers to entry into digital markets. At the same time, the complexity of interpreting AI model decisions makes it difficult to control the fairness of recommendations and creates risks of hidden discrimination against audiences or content. An equally important challenge remains the balance between the depth of personalization and privacy protection, since limiting access to personal data reduces the accuracy of algorithms, while excessive use raises ethical and regulatory risks.

Improving the application of recommendation systems in marketing communications requires a transition from exclusively behaviorally oriented personalization to guided models of algorithmic decision-making, combining efficiency with the principles of inclusiveness and balanced information presentation. Reducing algorithmic bias primarily involves reviewing approaches to forming training samples, since it is the data structure that determines the subsequent logic of recommendations. The practice of digital platforms demonstrates the feasibility of using mixed data sets that combine historical behavioral signals with elements of controlled content diversity, thereby avoiding the automatic reproduction of market imbalances.

An important direction for improving algorithmic personalization mechanisms is to shift the focus of algorithm optimization from narrow click-through rates to comprehensive interaction metrics that account for the long-term value to the client, the stability of interest, and the breadth of consumer choice. The practical implementation of such an approach involves including a share of new or less popular products in recommendations, which stimulates the discovery of alternative offers without significantly reducing the relevance of personalization. This allows for simultaneously increasing the effectiveness of marketing campaigns and ensuring more uniform digital visibility of brands.

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Further reducing algorithmic bias requires the development of explainable AI models that enable marketing specialists to analyze the reasons behind recommendation decisions and adjust ranking parameters in line with strategic communication goals. A practical tool is the implementation of regular algorithmic audits, which allow identifying exposure imbalances, assessing the impact of recommendations across different audience segments, and timely adjusting the personalization model.

An equally important direction is the combination of personalization with the principles of protecting user privacy. The use of aggregated or anonymized behavioral data, as well as learning models that do not require centralized storage of personal information, helps increase audience trust and reduce regulatory risks without sacrificing marketing effectiveness. At the same time, marketing strategies should account for the dependence of communication results on platforms' algorithmic logic, which requires adaptive content management and ongoing testing of recommendation scenarios.

In modern conditions, effective recommendation systems should serve as a tool for strategic management of consumer interaction, rather than merely as a mechanism for automatic content ranking. The combination of controlled personalization, algorithmic transparency, and regular assessment of the impact of recommendations on the demand structure reduces algorithmic distortions, expands the audience's access to different brands, and increases the long-term effectiveness of marketing communications in the digital environment.

Conclusions. The study found that recommendation systems have become a key tool for shaping personalized marketing communications and actually determine the structure of digital brand visibility and consumer information choices. It is proven that the use of ML algorithms increases the relevance of communications, the level of audience engagement, and the effectiveness of marketing strategies, but at the same time causes the emergence of algorithmic bias, which manifests itself in the concentration of attention on popular content, reducing the diversity of offers,

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and making it difficult for new market participants to access the audience. The main problems in the functioning of recommendation systems are identified, including dependence on historical data, optimization based on short-term interaction metrics, the self-reinforcing effect of recommendations, the cold start problem, limited transparency of algorithmic solutions, and the contradiction between the depth of personalization and the protection of user privacy. It is shown that algorithmic bias is systemic and affects both consumer behavior and the competitive structure of digital markets. The feasibility of moving to balanced personalization is substantiated, which involves expanding the criteria for evaluating the effectiveness of recommendation algorithms to account for inclusivity, content diversity, and the long-term value of consumer interactions. Directions for improving the application of recommendation systems are proposed, including the use of balanced data, algorithmic audit, increased model transparency, and the integration of ethical principles into digital marketing strategies. Prospects for further research include developing methods to quantitatively measure the inclusivity of recommendations, assessing the long-term behavioral effects of personalization, and studying the impact of regulatory requirements for artificial intelligence on the development of marketing communications in digital ecosystems.

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