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Generative Models in Creative Work: How LLM and Multimodal AI are Transforming A/B Testing

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Abstract: ***The article examines how, under the influence of generative artificial intelligence, primarily large language models and multimodal models, the methodology of A/B testing of advertising creatives is being reconsidered and reconfigured. The introduction justifies the research relevance of the topic by pointing to the rapid expansion of the market for generative AI technologies and draws attention to the methodological limitations of the classical A/B approach that have created the preconditions for the current technological and conceptual shift. The aim of the study is to analyze the transformations in experimental procedures, optimization principles, and the structure of associated risks within the framework of A/B testing. The research strategy is based on a systematic review of scientific publications and a content analysis of a corpus of academic articles and industry analytical reports. It is demonstrated that the introduction of generative AI can fundamentally increase the scalability of producing diverse creative solutions, and that the use of multimodal models enables their integrated synthesis and multidimensional evaluation. Particular attention is paid to the emerging optimization paradigm based on reinforcement learning (RL) methods, in which business metrics such as CTR become the direct maximization objective. The institutionalization of a hypothesis-driven approach, which increases the interpretability of results and the operational efficiency of experiments, is discussed separately, and the risks of algorithmic bias, creative homogenization, and erosion of consumer trust are analyzed in detail. The conclusions drawn in the final part of the article indicate a qualitative paradigmatic shift from empirical trial-and-error to a systematically structured experimentation methodology grounded in AI and scientifically justified principles. The article is addressed to AI researchers, practicing marketers, and digital advertising specialists interested in understanding and practically implementing advanced approaches to the optimization of advertising creatives.***

Keywords: generative AI, large language models (LLM), multimodal AI, A/B testing, creative optimization, reinforcement learning (RL), click-through rate (CTR), hypothesis-driven AI, algorithmic bias, digital advertising

1.Introduction

The contemporary digital economy is characterized by unprecedented intensity and scale of interaction with the consumer, which radically increases the requirements for the effectiveness and the degree of personalization of marketing communications. Under these conditions, generative artificial intelligence (AI) appears not as a short term technological trend, but as a structural factor that fundamentally reshapes the logic of functioning of the creative industries. The economic significance of this shift is confirmed by empirical estimates: the volume of the global market for generative AI in creative sectors, which amounted to $3.08 billion in 2024, is projected to increase to $12.61 billion by 2029, which corresponds to a compound annual growth rate (CAGR) of about 32.5% [1]. The scale and speed of the penetration of these technologies into marketing practice also have an exponential character: it is expected that by 2025, 30% of outbound marketing messages of large companies will be generated using AI, whereas in 2022 the share of such messages did not exceed 2%. Already in 2024, 37% of specialists in the field of marketing and advertising declare active use of generative AI in their everyday activities [2]. Against the background of such rapid technological development, it becomes evident that traditional approaches to the evaluation and optimization of creatives, primarily classical A/B testing, face serious methodological limitations. The dominant model, which presupposes manual development of a limited number (as a rule, two to three) of creative variants and their sequential comparison, is characterized by low iteration speed, high production costs, and an extremely limited space of testable hypotheses [3]. By virtue of these features, it proves incapable of meeting the demands of contemporary digital marketing, which is oriented toward high speed, scalable, and deeply personalized optimization of creative solutions [5]. As a result, a critical gap is formed between the potential of traditional methods and the increased requirements of the market, which acts as a key catalyst for the implementation of generative AI.

Despite intensive discussion of the practical application of generative AI in marketing, a substantial gap remains in the academic discourse, associated with insufficient systematization of how new architectures (first and foremost multimodal models) and training methodologies (reinforcement learning, RL) transform not only the production of creatives, but also the very methodological and epistemological foundations of A/B testing. The existing studies predominantly focus on performance indicators, often ignoring the profound qualitative transformation of the experimental approach as such.

The aim of the study is to carry out a comprehensive analysis of the transformation of the methodology of A/B testing of creatives under the influence of generative LLMs and multimodal AI models, with the identification of key changes in processes, optimization paradigms, and the associated risks.

The scientific novelty of the study consists in the systematization and conceptual interpretation of the paradigmatic shift in A/B testing: from a predominantly empirical approach based on a simple enumeration of a limited set of variants to a hypothesis oriented, AI driven process into which domain knowledge is organically integrated for targeted testing and optimization.

Within the framework of this study, the following **authorial hypothesis** is formulated: the integration of generative models, especially multimodal architectures optimized by means of reinforcement learning, is not limited to accelerating and scaling existing A/B testing procedures, but leads to the formation of a fundamentally new scientifically grounded methodology oriented toward direct optimization of business metrics and the generation of profound behavioral insights.

2.Materials and Methods

The study is based on an interdisciplinary approach that combines several mutually complementary analytical procedures, ensuring a comprehensive examination of the stated research problem. The methodological core consists of a systematic review of scientific literature and content analysis of academic and industry publications, which makes it possible not only to inventory existing approaches but also to structure empirical and theoretical results along key dimensions.

To identify the dynamics of the processes under consideration and to compare their effectiveness, comparative analysis was employed. Its application made it possible, in an analytically rigorous form, to contrast the limitations of classical A/B testing procedures with the opportunities opened up by AI-driven methodologies. Verification of the theoretical assumptions and assessment of the practical impact of generative AI on key marketing indicators (KPIs) were carried out through case study analysis. This method made it possible to examine specific directions of the implementation of the corresponding technologies and to quantitatively evaluate their influence on CTR, ROAS, and conversion rate metrics.

3.Results and Discussion

The first and most noticeable impact of generative AI on A/B testing practice consists in a radical removal of constraints on the scale and pace of experiments. In the traditional paradigm, the volume of creative variants under test was determined by human resources: teams were able to prepare and launch only a limited number of versions of ads, headlines, or descriptions, which made the experimentation cycle inertial, labor intensive, and financially costly. The emergence of generative models, primarily large language models (LLMs), has fundamentally changed this configuration: within minutes they are capable of generating hundreds and even thousands of alternative phrasings of advertising messages, headlines, product descriptions, and calls to action [20]. As a result, marketers gain the opportunity to move from linear, step by step testing of a narrow set of hypotheses to parallel, large scale exploration of entire spaces of creative solutions.

This qualitative shift is directly translated into economic effects. According to survey data, 46% of advertisers indicate acceleration of creative asset development, and 63% indicate an increase in overall campaign performance as key motives for integrating AI into their workflows [21]. Automation of routine aspects of content production effectively redistributes scarce temporal and cognitive resources of specialists in favor of higher level tasks: strategic campaign design, in depth analysis and interpretation of experimental results, as well as the formulation of new, more complex hypotheses [6]. In this sense, AI functions not as a replacement for human labor but as an amplifier of the expert's intellectual and creative potential. A conceptual scheme of the transformation of the A/B testing process is clearly demonstrated in Fig. 1.

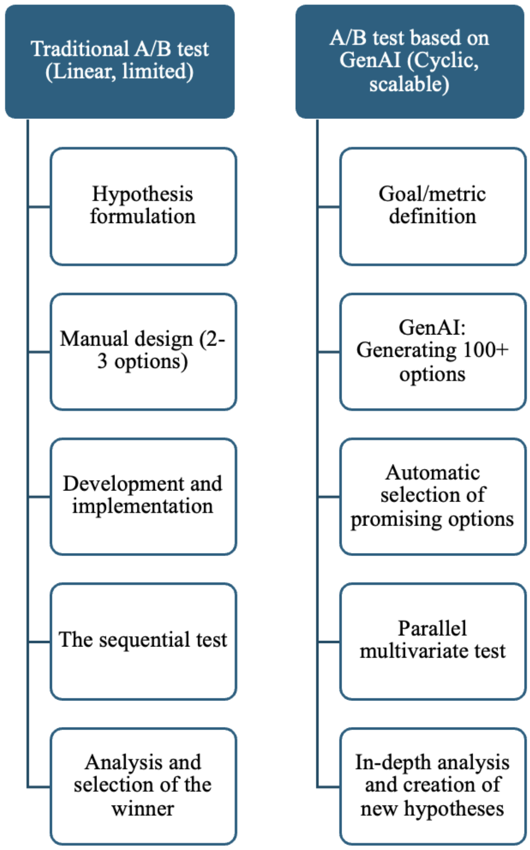

Figure 1: Conceptual diagram of the transformation of the A/B testing process (compiled by the author based on [4, 9, 19]).

As follows from the presented scheme, evolution proceeds from a slow, rigidly ordered and essentially sequential process to a high-speed, iterative and easily scalable pipeline. This involves not an incremental gain in efficiency, but a fundamentally different qualitative state in which it becomes possible to formulate and implement experimental tasks that previously lay beyond technological reach.

The next stage of this transformation is driven by the emergence of multimodal AI models. These are understood as systems capable of concurrently processing, aligning and generating information represented in various modalities: textual, visual, auditory and video [16]. Whereas classical architectures were oriented predominantly toward a single type of data (for example, LLMs toward text), multimodal solutions such as Google

Gemini or GPT-4V already possess the ability to interpret an image, read the text it contains and simultaneously capture the semantic and contextual layer of a video clip's audio track.

In the applied domain of advertising communications, this implies a shift of focus from local optimization of individual components (headline, visual) to optimization of the integral structure of the user experience. Multimodal AI is capable of reconstructing how the verbal and non-verbal components of a creative jointly form the audience's complex emotional response [23]. This, in turn, creates the prerequisites for the development of personalized advertising campaigns in which textual, graphic and video materials do not merely coexist, but are integrated into a single, internally consistent and well-substantiated communicative construct [16, 28].

In addition, multimodal models provide a fundamentally new level of work with arrays of unstructured data: customer reviews, social media content, video reviews, as well as recordings of interactions with contact centers [24]. The simultaneous analysis of textual content, prosodic features (tone and intonation of the voice) and facial expressions or behavioral reactions in video makes it possible to identify latent patterns of preferences and pain points of the target audience that remain inaccessible when only the textual component is considered. These identified insights then serve as the basis for generating more relevant and effective creatives. The economic significance of the technologies described is reflected in the accelerating growth of the corresponding market (Fig. 2).

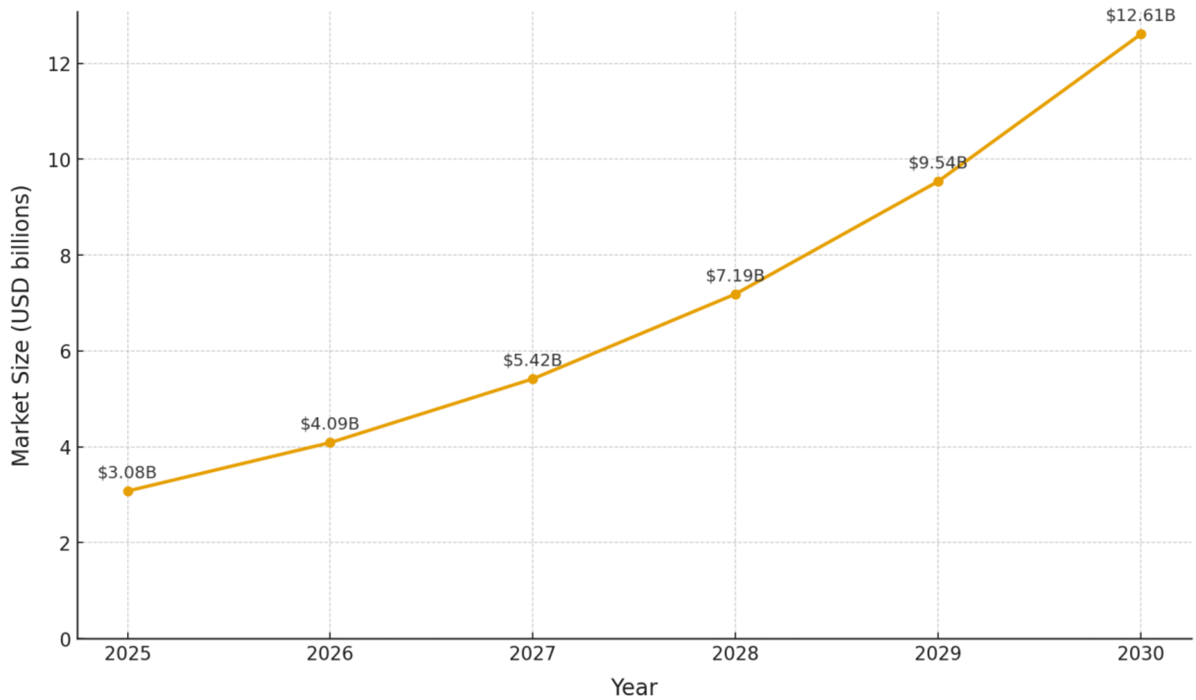

Figure 2: Forecast of growth of the global market for generative AI in creative industries (US billion) (compiled by the author based on [1]).

The most radical transformation of A/B testing is associated with a change in the very logic of optimization. Early generative architectures (such as GANs) were originally designed as tools for constructing visually plausible and aesthetically appealing content; their objective function essentially reduced to maximizing the likelihood of generated samples with respect to the distribution of real data. The modern generation of methods based on reinforcement learning (RL) is oriented not toward plausibility as such, but toward the direct optimization of quantitatively observable business indicators, such as click-through rate (CTR) or conversion rate [8, 25]. Within this new paradigm, creative content is considered not through the lens of its beauty or realism, but through the lens of its effectiveness with respect to a specific target business metric.

Such a shift in focus transforms A/B testing from a predominantly diagnostic tool that answers the question of which of the already prepared variants demonstrates the best results, into a tool of prescriptive optimization that addresses the question of how to synthesize the variant that will be optimal. Whereas previously a human was responsible for generating candidate solutions and the model for their comparative evaluation, the model now learns to construct variants that are highly likely to exhibit the desired behavioral advantage. In this way, the testing procedure becomes an embedded component of the generation process rather than an external stage of subsequent validation.

A representative implementation of this approach is the CAIG method (CTR-Driven Advertising Image Generation), proposed for the automated generation of advertising images [13]. Its architecture, shown in simplified form in Fig. 3, is built around two key stages.

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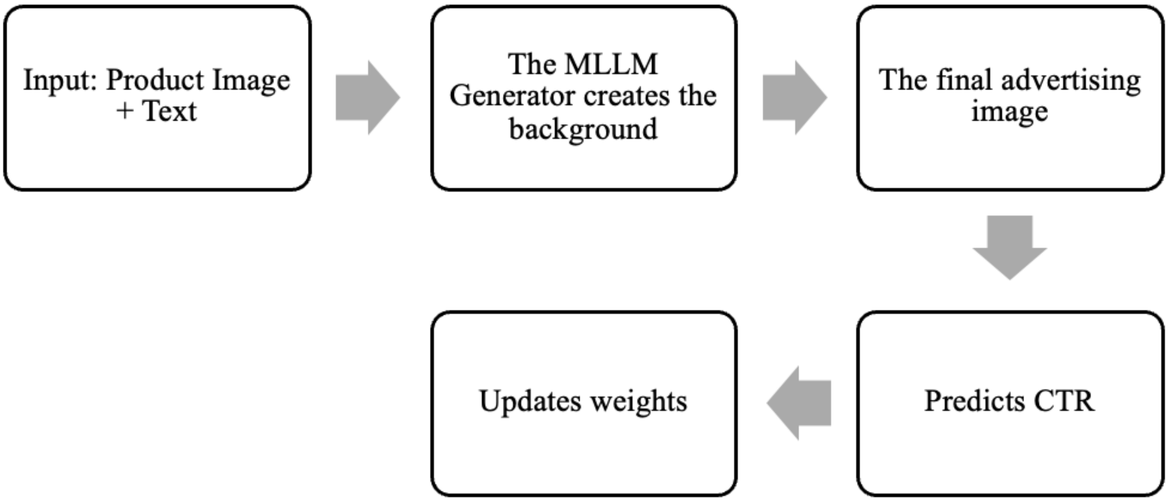

Figure 3: Simplified architecture of the CAIG method based on reinforcement learning (compiled by the author based on [8, 13]).

At the first stage, the Reward Model (RM) is trained. For this purpose, a large-scale set of real behavioral data (click logs) is used, on the basis of which the model is trained to predict which of two advertising images is more likely to initiate a click. Formally, such a model becomes a digital twin of the aggregated preferences of the target audience, since it encodes in its parameters the empirical regularities of user choice.

At the second stage, the generator is optimized using RL. A multimodal language model (MLLM) synthesizes various variants of the background environment for the product image, after which the generated variants are fed into a frozen Reward Model that returns a scalar signal, the predicted reward in the form of the expected CTR. This signal is used as the objective function for updating the parameters of the MLLM by means of a reinforcement learning algorithm. As a result, the model iteratively shifts the distribution of generated images from random visual variants to those that have a higher probability of being clickable [11, 12].

To prevent the emergence of visually inappropriate creatives, even if they are potentially effective in terms of CTR (for example, a sports background for a cosmetic product), an additional strategy PCPO (Product-Centric Preference Optimization) is integrated into the CAIG method. This strategy forces the generative model to explicitly take into account the characteristics of the product itself when synthesizing the background context, thereby ensuring semantic relevance and visual coherence of the final advertising image [13].

The effectiveness of the described methods has been empirically verified in a number of case studies: the accumulated data demonstrate a significant increase in key marketing metrics compared to classical approaches, which is clearly reflected in Table 1.

Table 1: Summary data on the impact of generative AI on key marketing metrics (compiled by the author based on [5, 8, 10]).

Metric	Improvement indicator	Context
CTR (Click-Through Rate)	+6.7%	Large-scale test of an LLM trained with reinforcement learning
CTR (Click-Through Rate)	Up to 2 times higher	Comparison of AI-optimized creatives with manual ones
ROAS/ROI	Increase of 20–30%	Companies actively using AI in marketing
ROAS/ROI	Increase up to 50%	Individual business cases
Conversion rate	Significant improvement	Dynamic real-time customization of advertising
Accuracy of success prediction	90% (AI) vs. 52% (human)	Prediction of creative effectiveness prior to launch

The cumulative transformation of the scale, pace, and target objectives of optimization is leading to the emergence of a more mature research paradigm, hypothesis-driven A/B testing. In fact, this entails a shift in the conceptual frame: from traditional AI, used primarily to identify latent statistical regularities in data, to hypothesis-driven AI [14, 22]. The key novelty of the latter lies in the fact that domain knowledge and scientific hypotheses are initially embedded into the architecture and logic of the algorithms, making it possible to purposefully test causal relationships rather than merely record associations.

In marketing practice, this means abandoning the mechanical enumeration of hundreds of headline variants automatically generated by an LLM in favor of the deliberate construction of a limited set of testable hypotheses. These hypotheses are grounded in the principles of behavioral psychology, data on audience segments, and the accumulated experience of previous experiments. For example: For the segment of new users, employing the principle of scarcity in the headline will lead to a 15 % increase in conversion, or Changing the color scheme of the button to green will strengthen the sense of safety and increase CTR among users older than 45 years [14]. Thereafter, the AI does not simply generate arbitrary creatives but purposefully produces variants specifically designed to test these pre-formulated hypotheses.

This approach provides three key advantages:

Interpretability. The results of A/B tests acquire a higher level of explainability. Not only is the fact that variant B outperforms variant A in terms of the target metric recorded, but at the same time we obtain empirical confirmation or refutation of the underlying hypothesis behind variant B. This clarifies the mechanisms by which this variant achieves a better outcome [14].

Resource efficiency. Traffic, time, and financial resources are concentrated on testing the most well-founded and potentially significant ideas [14].

Knowledge accumulation. Each test conducted becomes a contribution to the formation of a structured knowledge base on audience behavior and preferences. This creates the conditions for the step-by-step construction of increasingly accurate and nuanced models of consumer patterns, in contrast to an approach in which each experiment yields only local tactical optima without a long-term effect on the overall picture.

Large experimentation platforms such as Optimizely are already evolving in this direction, integrating AI agents capable of autonomously formulating hypotheses, designing testing plans, and even generating program code for their implementation [7, 18]. At the same time, the widespread introduction of generative AI into A/B testing practice is accompanied by substantial risks that require careful reflection on the part of both the research community and practitioners.

One of the most problematic aspects is algorithmic bias. Generative models are trained on large-scale data corpora from the Internet, which inevitably contain and often reinforce existing social stereotypes and prejudices (gender, racial, cultural, etc.) [15, 26]. In advertising creatives, this is manifested in the reproduction of stereotypical images: for example, when prompted with engineer, the model is more likely to generate an image of a white man, whereas for the prompt nurse it is more likely to generate an image of a woman [27]. In the context of A/B testing, such bias leads to the system optimizing CTR systematically generating and promoting creatives that work best for the dominant demographic group while simultaneously ignoring or even alienating members of minorities. This not only artificially narrows the potential market reach but also reproduces existing forms of social inequality [17, 29]. A consolidated classification of the main types of such biases is presented in Table 2.

Table 2: Classification of types of algorithmic biases and their manifestation in A/B testing of creatives (compiled by the author based on [26, 29]).

Type of bias	Description	Example of manifestation in GenAI A/B testing
Data Bias	The training data are non-representative or contain historical stereotypes.	The AI generates variants for the test that depict CEOs only as men, because in the training data most CEOs are men. The system optimizes the creative for this stereotype, demonstrating worse results on the female audience.
Algorithmic Bias	The algorithm unfairly weights certain features or uses incorrect proxy variables.	An RL algorithm that optimizes conversion discovers a correlation between high income (target feature) and postal code (proxy). As a result, it starts to favor creatives that perform better in affluent areas, discriminating against audiences from other locations.
Human Bias	Subjective prejudices of the developer or marketer affect system design or the interpretation of results.	The marketer chooses engagement (likes, reposts) as the optimization metric, which may be higher for provocative or stereotypical content, while ignoring the long-term impact on brand reputation.

Creative homogenization constitutes another fundamental source of risk. Algorithmic systems that are rigidly oriented toward optimizing a single short-term metric (for instance, CTR) gradually begin to converge toward a limited set of proven creative formats that have demonstrated effectiveness in the past. As a result, advertising messages lose novelty and conceptual diversity, turning into predictable and stereotypical templates, which in the long term leads to the erosion of brand differentiation and a decline in perceived brand value.

In addition, there is an evident fundamental tension between the logic of short-term optimization and the necessity of maintaining long-term consumer trust. Empirical data indicate that advertising which users identify as created with the help of AI can elicit skepticism and distrust. This distrust has clearly measurable consequences: a 14% decrease in purchase intention and a 17% decline in the brand's premium rating [10]. Thus, a paradox emerges: creative content that is maximally tailored to achieving peak click-through performance today can simultaneously undermine trust in the brand and devalue it tomorrow. Uncritical, blind implementation of AI solely for the sake of KPI growth, without taking this effect into account, is fraught with impressive short-term gains coupled with potentially catastrophic long-term costs. All of this underscores that, under conditions of AI expansion, strategic managerial control and human judgment do not lose their importance but, on the contrary, may become even more critical.

4. Conclusion

The study conducted demonstrates that the emergence of generative and multimodal AI models is initiating a paradigmatic shift in the methodology of A/B testing, radically transforming it along four key dimensions:

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Scale and speed: There is a transition from manual construction and sequential comparison of a limited number of variants to systematic, highly parallel experimentation with hundreds and thousands of creative assets automatically generated by AI models. As a result, A/B testing is transformed from a pointwise optimization tool into a continuous, scalable process of searching through hypotheses and creative configurations in a mode close to real time.

Depth of analysis: The introduction of multimodal models enables a shift from discrete optimization of individual components of communication (textual formulations, visual elements, etc.) to an integral, synthetic conceptualization and construction of creative as a single, indivisible communicative act. The analytical focus shifts from local characteristics of individual elements to their joint impact in the context of a holistic user experience.

Optimization objective: There is a shift from a predominantly diagnostic approach, in which the task was reduced to identifying the best option from a predefined set of variants, to a prescriptive paradigm focused on the direct generation of an optimal solution. This generation is governed by reinforcement learning methods and aimed at maximizing clearly defined business metrics, which makes it possible not only to measure effectiveness but also to purposefully manage it.

Methodology: A hypothesis-oriented approach is being formed, shifting the emphasis from empirical search and heuristic testing to scientifically grounded hypothesis testing. This increases the interpretability of experimental results, contributes to the systematic accumulation of long-term knowledge, and turns A/B testing into an instrument for developing the organizational analytical memory rather than merely a tool for operational optimization.

Taken together, the results obtained allow us to conclude that the author's hypothesis is fully confirmed. The integration of advanced AI models is not limited to the automation and acceleration of existing procedures but leads to the formation of a qualitatively new methodology of A/B testing, which is characterized by higher speed, scalability and, crucially, greater intellectual richness and purposiveness.

The practical significance of the study lies in the fact that it provides marketers and analysts with a conceptual framework for rethinking and re-engineering their own experimental processes. For AI system developers, the research emphasizes the importance of designing interpretable, hypothesis-oriented and ethically sound tools, as well as the need for a purposeful approach to addressing algorithmic bias and the tendency toward creative homogenization.

Future research directions should reasonably be focused on several key areas. First, the development and empirical validation of robust methods for identifying and mitigating algorithmic bias in the domain of creative solutions is required. Second, there is a need for the design of more complex and context-sensitive reward models for reinforcement learning systems that would take into account not only short-term performance indicators (CTR, conversion) but also long-term indicators of brand sustainability (brand equity, customer lifetime value, level of trust). Finally, a promising avenue is the study of the cognitive and organizational aspects of the interaction between the human marketer and the AI system in the joint process of generating and testing hypotheses, which is the key to creating effective human–machine tandems in the field of creative analytics.

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