THE IMPACT OF ARTIFICIAL INTELLIGENCE ON PRODUCT LISTING OPTIMIZATION IN MARKETPLACES

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Abstract. With the continued growth of online marketplaces, competition for consumer focus has become even more fierce, especially for product listings as they become the determining factor for consumers between sellers and platforms. As marketplaces grow in both size and complexity, traditional, online, and rule-based optimization become less effective in the face of dynamic consumer behavior, multi-modal content, and systematic, ranking algorithm variations. To engage with the most recent literature in e-commerce marketing, information systems, and machine learning, this study focuses on the application of AI technologies, such as machine learning, natural language processing, and computer vision, along with recommendation systems. The study analyzes the effects of these technologies on the listing processes of generation, evaluation, modification, and of the optimization process. AI optimization in product listings has the ability to increase visibility, engagement, and conversion. The study also highlights the possible negative effects of complete automation, content homogenization, algorithmic opacity, and the lack of transparency. The results indicate optimization of product listings via AI is the first of many steps to a continuous, data-driven, and adaptable approach to marketplace automation. The balanced governance of these systems still relies heavily on the insight of the users to maintain a level of transparency and fairness. Finally, the study attempts to improve seller and platform understanding of the automation processes and the anticipated shifts in market conditions as a result of AI.

Key Words: Artificial intelligence; product listing optimization; online marketplaces; e-commerce marketing; machine learning; natural language processing; personalization; conversion optimization.

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Introduction

Online marketplaces have shifted stages of e-commerce, showing how products can be found, assessed, and bought. Amazon, eBay, and Facebook Marketplace, among others, provide thousands of sellers and listings, developing a highly competitive market. Sellers have a lot of competitors, and then sellers have a lot of competitors, focusing on marketing presentations to influence purchasing outcomes. As marketplaces grow, the sellers compete on price and product quality, and representation within the algorithmically mediated environments [11].

In most cases, this is represented by the primary interaction between the buyer and the product. It is made of textual, visual, and reputational signals, like titles, descriptions, and images paired with pricing information and user reviews. Research in e-commerce marketing suggests product listings and algorithms serve two functions. A product listing must convince a buyer to purchase, and it will work to improve the ranking of the marketplace algorithms that dictate where the listing will be positioned among other competitors [2; 5]. The listing quality will have the most influence on listing performance with the most important metrics, like the click-through rate, dwell time, and probability to make a purchase.

Product listing optimizations have relied on manual or rule-based approaches even with the presence of artificial intelligence. Keyword stuffing, standardized templates, and heuristic-driven adjustments can all be seen from competitors. Although these methods may seem effective, there is still need for developing efficiencies on larger marketplaces. As algorithms and prices of competitors continuously change, so too should listing prices [18]. Sellers often have little information or understanding of marketplace systems. These systems rank products and conceal listing changes that could boost visibility and sales. Sellers often rely on instincts and experience that is built on years of observing and modeling the market [1; 9].

Structural systems built on artificial intelligence automate manual systems and reign true over the marketplace. Models built with machine learning, natural language processing, and computer systems automate listing evaluation. In contrast to these traditional methods, AI systems optimize and evaluate listings in real time in response to market conditions, consumer sentiment, and even the seller's own adaptive pricing and listings [3; 19]. AI introduces new innovative systems built on prediction and personalization to build a new marketplace.

Research shows that automated systems can enhance keyword optimization, produce meaningful descriptions, improve image ranking for visual relevance, and customize listings for various user categories [7; 16; Zhou et al., 2023]. Moreover, AI also controls how listings are ranked, tailored, and shown to customers, making it difficult to distinguish between algorithmic and user-centered optimization [8; 15]. This change fuels concerns about the effectiveness, transparency, equity, and over automation, especially given the increased use of generative models for automatic content creation [13].

Research Problem

Despite the growing adoption of artificial intelligence in e-commerce, the mechanisms through which AI influences product listing optimization and marketplace performance remain insufficiently systematized in academic literature.

Research Objective

The objective of this study is to analyze the role of artificial intelligence in product listing optimization within online marketplaces and to identify the mechanisms through which AI technologies influence listing performance and consumer engagement.

This study will analyze how AI impacts the optimization of product listings on online marketplaces. This study will take an expansive rather than algorithm or platform-specific approach. It will build on the integration of the various streams of literature in marketing, information systems, and machine learning. It will examine how AI impacts tech innovation in the optimization of (1) the process of optimization, (2) the data-driven listing management, and (3) the economic impacts such as conversion and sales (See Figure 1).

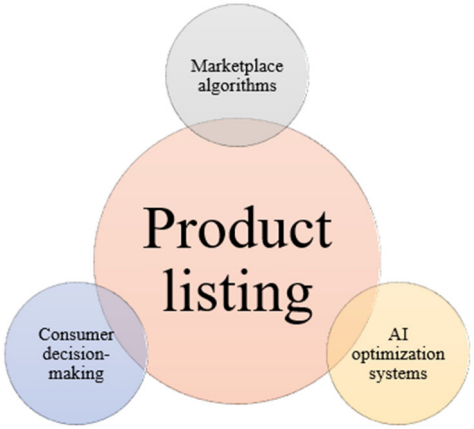

Figure 1. Conceptual positioning of product listings at the intersection of marketplace algorithms, AI optimization systems, and consumer decision-making

Literature Review

1 Product Listing Optimization: Concept and Challenges

Optimizing product listings involves making intentional changes to the various components of a listing to improve its position and conversion potential in the marketplace. A product listing contains a number of components that relate to one another: title, description, pictures and videos, price, promotions, and reviews [4; 5]. The combination of these components designs the evaluation from the system and perception from the user, which is why optimization of the listing is a complex process.

The listings serve the purpose of simplifying a consumer's process of making a decision by providing a quick snapshot of what the product is about. Research done in the field of e-commerce marketing suggests that how clear, relevant, and credible the contents of the listing are, effect the consumers trust and likelihood to purchase [6]. Additionally, the listing must follow the guidelines of the marketplace, which may include character limitations, category structures, image policies and other content guidelines. Therefore, the optimization must balance communication that is persuasive in nature and one that is algorithmically readable.

Listing optimization has generally been low-tech and consisted of manual keyword analysis, heuristically driven search engine optimization (SEO), copy and paste description frameworks, and A/B testing by small, incremental steps. Based on performance and ranking feedback, sellers field adjusted titles and descriptions, usually driven by best-case-scenario heuristics rather than predictive modeling [2]. These methods of optimization assisted in the

early growth of the marketplace, but in the present marketplaces, these methods carry large, structural deficiencies.

For one, traditional methods are outdated, and poorly equipped to facilitate the speed and growth of the marketplace. Large sellers will frequently have thousands, if not millions, of listings across different marketplaces. In these situations, the optimizing of listings traditionally, is simply not practicable [18]. In addition to this, traditional methods are primarily reactive and do not try to predict customer demand and marketplace/seller algorithm shifts. Fourth, 'traditional' methods of optimization assumes the search algorithms have not changed, which in today's marketplaces is not the case today [1; 9].

With each adaptive ranking system, or learning based system, traditional methods of optimization become increasingly obsolete. Moreover, marketplace algorithms applied additional complexities; product visibility is not simply contingent upon the relevancy of the listing description, but also on seller behavioral feedback, performance/sales metrics, customer personalization, algorithmic promotion, and paid promotion [8]. These promotion and visibility ranking systems are not neutral. They have a large influence over which listings are exposed to buyers and which are heavily filtered out from visibility [11].

Also, the logic behind marketplace rankings is usually unclear. Most platforms don't explain how ranking factors are weighed, and these factors could change over time due to constant testing and model updates [9]. This creates an information imbalance between platforms and sellers, forcing them to rely more on automated ranking pattern detection tools. Yet, conventional optimization approaches are not sophisticated enough to tackle complex systems.

Another challenge is the listing element interdependence. Changing one element, like the length of a title, may impact image visibility and other outcomes in unexpected ways. Traditional optimization frameworks often consider listing elements in isolation, missing interrelated components like text, imagery, and user behavior [7; 10]. This is an increasingly insufficient way of thinking about optimization as marketplaces continue to use more sophisticated ranking systems.

All of these factors indicate that the optimization of product listings has evolved from a tactical to a strategic, complex, and data-driven endeavor. The need for artificial intelligence has been clearly established due to the limitations of manual and rule-based methods (See Table 1). The role of artificial intelligence in listing optimization is framed by these foundational challenges.

Table 1. Core components of a product listing and associated optimization challenges (textual, visual, behavioral, and algorithmic).

Listing Component	Primary Optimization Challenge
Title	Balancing keyword relevance with readability and semantic clarity
Description	Ensuring semantic richness and alignment with user intent
Images	Achieving visual salience while avoiding excessive standardization
Pricing	Maintaining price competitiveness while preserving perceived fairness
Reviews	Managing sentiment bias and ensuring authenticity

2 AI Technologies Used in Listing Optimization

The optimization of product listing has made substantial progress thanks to the influence of artificial intelligence which can analyze extensive and varied datasets and adjust to changing conditions within the marketplace. Artificial intelligence in listing optimization is more than one type of technology. It encompasses numerous techniques, such as machine learning, natural language processing, computer vision, and recommendation systems. These techniques, in combination, alter the processes of listing creation, evaluation, and refinement [4; 19].

2.1 Machine Learning and Predictive Analytics

Since predictive modeling of consumer behavior and marketplace performance is possible using certain machine learning (ML) techniques, it is possible to optimize contemporary listing systems. The historical data of supervised learning models is used to train outcomes such as click-through rate, probability of conversion, or possible ranking of specific listings for a given model [1; 8]. These predictions assist sellers and platforms in determining the possible outcome of listing revisions prior to listing changes.

This minimizes the need for testing through trial and error. Predictive analytics is also of great importance in listing optimization, which includes the awareness of ranking systems. Research shows that learning-based ranking models merge description relevance and behavioral metrics to influence the visibility of a product in search results [1].

Listing attributes can be adjusted by AI systems to meet implicit ranking goals in a manner that is not possible with traditional rule-based systems. Additionally, optimization decisions based on machine learning (ML) can be scaled. For instance, Lu and colleagues (2024) demonstrate that even in sponsored listings, algorithmic optimization frameworks can surpass heuristic-based ranking strategies, emphasizing the importance of data-driven decision-making in both organic and paid placements [9]. While such models are frequently created at the platform level, an increasing number of third-party services are supplying sellers with similar predictive capabilities.

2.2 Natural Language Processing for Titles and Descriptions

The development of large language models (LLMs) has greatly advanced the use of Natural Language Processing (NLP) tools for Listing Optimizations. Automated systems using LLMs can create, review, and edit product titles and descriptions and focus on the semantics, keyword targeting, and overall readability of each piece of content [7; 17].

While traditional SEO practices utilized the repetition of specific words, Modern SEO practices emphasize creating content that aligns with user intent. Therefore, SEO listings should be created with the desired intent of the user in mind when crafting listings. Modern techniques such as contextual embeddings paired with generative semantic indexing help models to achieve high retrieval rates and user satisfaction by going beyond strict keyword repetition [16]. This is especially important as customer queries become more conversational and intent-based, as opposed to transactional.

Generative models can produce and edit context descriptions, which can be tailored to attributes, user segments, or platform requirements (See Figure 2). In eCommerce, comparative analyses of LLMs have shown that these models can generate more informative content than traditional, template-based systems, especially when working with structured product data and customer reviews, [14]. These positive aspects have faulted LLMs in the

areas of bias, factual inconsistency, and other challenges, which need to be properly managed [13].

Figure 2. NLP-driven listing optimization pipeline: from query intent analysis to generative content refinement.

2.3 Computer Vision for Image Optimization

The ability of computers to 'see' is fundamental to optimizing listings driven by AI because visual content captures consumer attention and engagement. Computer vision models evaluate product images, assessing criteria such as quality, composition, background uniformity, and attention-grabbing power. They tend to evaluate images by comparison to other listings with dominant performance metrics in the same category. [10; 19].

AI gives sellers the tools to better engage shoppers through machine learning models that analyze images to identify visual characteristics, such as angle, lighting, and color contrast, correlated with high engagement or conversion rates. In many instances, systems of this kind integrate visual characteristics and other relevant text and behavioral data captured through the system to improve overall ranking and recommendation performance [7]. Listing optimization through computer vision and other innovative technologies is becoming more holistic and addressing each element of the listing simultaneously, rather than piecemeal.

Additionally, automated tools that select and improve images further decrease sellers' operational challenges while allowing them to innovate continuously. However, this increased reliance on computer vision may result in the same images and listing content being presented across multiple sellers because there is no standardization.

Methodology

1 Research Design

This study uses a qualitative analytical approach to examine the use of artificial intelligence (AI) in optimizing the product listings of sellers in online marketplaces. The focus of this research is on synthesizing what is currently known about e-commerce and technology in order to develop an understanding of the mechanisms by which AI improves the performance, visibility, and conversion of product listings. Due to the rapid pace of development of digital commerce technologies, this study uses an exploratory methodology that combines theories of e-commerce, data analytics, and artificial intelligence. The study does not rely upon primary empirical data; instead, it interprets how AI-based tools and algorithms are being used in marketplace settings to improve the process of optimizing listings for product offerings.

The conceptual model that guides this research includes three interrelated dimensions (See Figue 3):

1. AI based decision-making and data analysis,
2. Personalization and Dynamic Content Optimization and

3. The effect of the above mentioned factors on marketplace performance indicators including visibility, engagement and conversion rates.

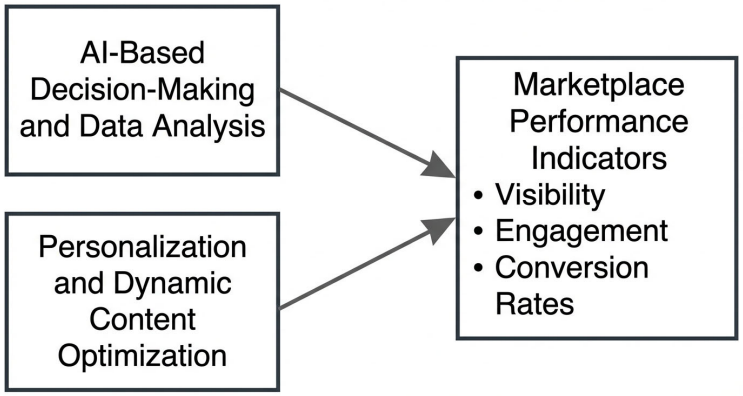

Figure 3. Conceptual Framework Design

Using this framework, we conducted a systematic evaluation of the functions that AI-based systems perform in digital marketplace ecosystems.

2 Data Sources and Literature Selection

The analysis for this report has been conducted through an academic and professional literature review, with respect to Artificial Intelligence (AI) application in E-Commerce and Digital Marketplace Optimization. Sources included, but not limited to: peer-reviewed journal articles, conference proceedings, scholarly books, industry reports, academic research and industry analysis for *AI*, *Machine Learning*, *Natural Language Processing*, *Computer Vision* and *Digital Marketing Technologies*.

Sources were selected based upon their relevance to the following thematic areas:

- Optimization of product listings within online marketplaces,
- Applications of artificial intelligence technologies in digital commerce,
- Algorithmic recommendation systems and consumer behavior analysis,
- Automated content generation tools and personalized content generation,
- Performance indicators including click-through rates, conversion rates, sales and other optimizations.

Studies focusing on technological mechanisms and strategic implications of the integration of AI into e-commerce platforms were prioritized in order to provide an analysis that represents both the academic community's views and emerging industry practices.

Table 2. Classification of Reviewed Literature

Ref.	Authors / Year	Source Type	Main Research Focus	Relevant AI / E-commerce Domain
1	Brenner et al., 2018	Preprint / research paper	Neural ranking systems for product search in e-commerce	Machine learning, search ranking, product discovery
2	Chodak & Błażyczek, 2023	Conference proceeding	Use of large language models for SEO in e-commerce	NLP, AI-driven SEO, listing optimization

3	Grewal et al., 2025	Peer-reviewed journal article	Impact of generative AI on marketing strategies	Generative AI, digital marketing, personalization
4	Haidar, 2024	Journal article	Overview of AI applications in e-commerce	AI technologies, digital commerce
5	Hasan, 2025	Academic article / proceedings	AI-powered SEO and digital marketing competitiveness	AI marketing optimization, marketplace strategies
6	Ibrahim & Zeebaree, 2025	Journal article (review)	Trends in e-commerce, consumer behavior and digital platforms	Marketplace systems, consumer analytics
7	Kathiriya et al., 2023	Research article	LLM-based generation of product descriptions and keywords	NLP, automated content generation
8	Lin et al., 2025	Research publication / technical paper	Machine learning ranking systems and personalization	Recommendation systems, ML personalization
9	Lu et al., 2024	Preprint / experimental study	Optimization of sponsored listing ranking algorithms	Marketplace ranking optimization
10	Mitchell, 2021	Journal article	Multi-modal AI combining text and visual data	Multimodal AI, computer vision
11	Papastamoulou & Antonopoulos, 2025	Peer-reviewed journal article	Comparative AI applications across e-commerce platforms	AI adoption strategies, marketplace analytics
12	Patil, 2024	SSRN working paper	Generative AI in marketing and consumer engagement	AI personalization, marketing automation
13	Ren et al., 2024	Preprint survey paper	Fairness and ethical challenges of LLMs in e-commerce	AI ethics, algorithmic bias
14	Roumeliotis et al., 2025	Journal article	LLM-based evaluation of product reviews	NLP, review analysis, consumer insights
15	Xi et al., 2025	Preprint / research paper	Synthetic data generation for marketplace search systems	LLMs, search optimization

16	Yang et al., 2025	Conference paper	Generative semantic indexing for product understanding	NLP, semantic search
17	Zhou et al., 2023	Research article	Large language models for enhanced product descriptions	NLP, automated product listing generation
18	Zhuk & Yatskyi, 2024	Journal article	AI and machine learning in e-commerce marketing	ML marketing analytics
19	Zumstein & Chodak, 2024	Conference proceeding / book chapter	Overview of AI applications, benefits and challenges in e-commerce	AI integration strategies

3 Analytical Approach

This research uses a qualitative analytical methodology combining conceptual synthesis with comparative evaluation of technological mechanisms for the application of Artificial Intelligence (AI) in Product Listing Optimization.

Analytical Process:

1. Stage One: Identification of core AI technologies being applied to product listing optimization; namely Machine Learning, Natural Language Processing, and Computer Vision.
2. Stage Two: Operational Mechanisms by which those technologies impact product listings, i.e., automated keyword analysis, interpretation of behavioral data, visual recognition of product images, and real-time adaptations to content presented in listings.
3. Stage Three: Evaluation of marketplace results resulting from the use of AI-Driven Optimization with respect to increased visibility, consumer interaction and conversion rates.

4 Research Limitations

Several limitations need to be recognized. The first limitation is that the research uses secondary data and conceptual analysis as opposed to conducting an original, empirical investigation. Therefore, the results are based upon the researcher's analytical interpretations as opposed to measuring actual performance indicators using data from individual marketplaces.

The second limitation is that artificial intelligence continues to evolve rapidly, therefore; new AI-based optimization methods and algorithms will continue to be developed, and could exceed the scope of the research covered in this study.

Despite the two limitations identified, the research methodology has provided a thorough and analytical review of all currently available AI-optimization mechanisms and aids to our understanding of how artificial intelligence impacts the operational aspects of digital markets.

Findings and Results

1 AI-Driven Data Analysis and Decision-Making

The effectiveness of AI-driven product listing optimization is deeply ingrained in data analysis as a capability. Marketplaces create and maintain huge amounts of structured and unstructured data which include search queries, clicks, time spent, conversions, and competitive data. AI assists in converting these data be used as insights. With this, listing optimization evolves from intuition-based adjustments to evidence-based changes [5; 19].

1 Search Query and Keyword Intent Analysis

Optimizing a marketplace involves understanding user search intent which remains one of the most complicated aspects. Traditional keyword analysis techniques focus on keyword hit rates and positive and negative keyword correlational relevance which would not capture the intent the query holds. AI models, especially NLP and semantic embedding, offer more comprehension of search behaviors as they focus on queries and concepts as attributes of a product rather than as isolated words [2; 16].

Generative semantic indexing methods aid more product intent descriptions and better user need encapsulation than user seller description encapsulation [16]. AI helps users align descriptions with consumer language as they point to seller's title and description changes. Changes of this nature help to yield better search results and foster better user engagement, especially with ambiguous long-tail searches, which have been proven [15].

Intent modeling analysis allows sellers to focus on repositioning the listings strategic rather than mindlessly increasing keyword saturation. This is a qualitative change in the logic of optimization where success is not measured in keyword count, but relevance, understanding, and leaving the query open to interpretation.

2 Behavioral Data Interpretation

Market place ranking and recommendation systems are becoming increasingly dependent on behavioral analytics such as click through rate (CTR), dwell time, bounce rate, and conversion probability [1; 8]. These analytics systems powered by artificial intelligence are constantly evaluating listing analytics and making inferences about the relationship between the attributes of a listing and the behaviors of customers.

Out of the available behavioral data, machine learning models are proficient in identifying and capturing complex non-linear behavior patterns that go unnoticed in a manual analysis. Artificial intelligence systems, for instance, can analyze phrases used in the title of a listing and the images used in the listing and predict the impact on the amount of time the user may spend looking at the listing. Similarly AI-systems can analyze price indicators and predict conversions based on the amount of traffic a listing is receiving. These systems can generate minute behavioral and analytical optimizations at scale that would otherwise be highly impractical to implement [9].

A critical aspect of behavioral analysis in this case goes beyond measuring performance. It involves an automated iterative decision making loop (See Figure 4) where the listings are changed based on the analysis and feedback, making the systems self-optimizing to user behavior [11]. These systems, while becoming more efficient, also add on a dependence for automated decision making systems that may not align with the brand or the strategic goals of the company.

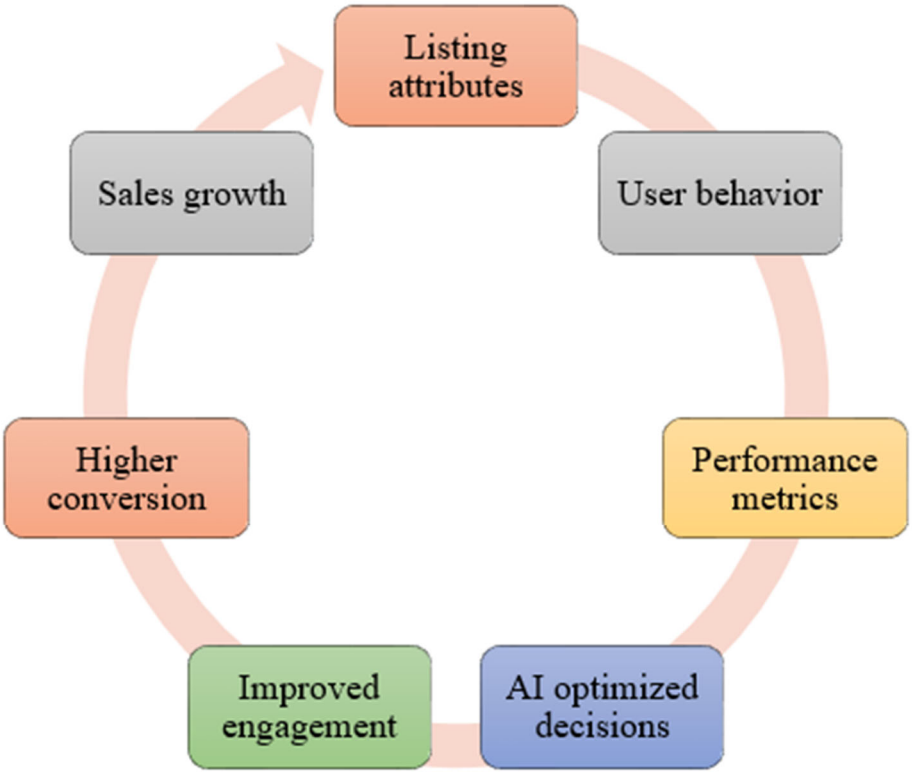

Figure 4. Feedback loop between listing attributes, user behavior, and AI-driven optimization decisions

3 Competitive Benchmarking through AI Tools

AI also provides systematic competitive benchmarking so sellers can see how their listings compare to competing products in the same category. Computers can use vision and NLP models to extract competing listings—such as semantic positioning, image/style, pricing, and review sentiment— to find gaps in performance and ways to differentiate [4; 7].

AI tools do this automatically and look at large competitions sets, as opposed to manual benchmarking, which has scope and frequency limitations. This is helpful in saturated markets where small improvements to listing can improve visibility and ultimately, sales [5]. Nevertheless, there are systemic problems to consider with the adoption of AI benchmarking. As sellers listings become increasingly algorithmically "optimized," there is less diversity in the listings which can lead to a decrease in the consumer experience. The reliance on AI for a "quick" optimization illustrates the lack of diversity it can lead to, and the risk associated with it.

2 Personalization and Dynamic Content Optimization

The evolution of artificial intelligence in product listing optimization is not without controversy, but perhaps the most transformational is personalization. Given the ability of AI systems to recognize individual user tastes, settings, and behavior, listings transform from being static to dynamic, becoming tailored to the user [11]. This shift changes the product representation and the marketplace environments definition of success optimization.

1 Adaptive Product Descriptions and Visuals

AI personalization technology adjusts product descriptions and images based on predicted user intent, user browsing history, and user demographics. Systems based on

natural language processing (NLP) can create multiple versions of product descriptions. These versions can focus on one of many attributes, such as price, functionality, sustainability, or aesthetics, and be used for targeted marketing to different customer segments [12; 14; 17]. Likewise, computer vision can be used to identify and prioritize images based on user preferences, such as lifestyle images for exploratory shoppers and specification images for goal-directed shoppers [10].

From an optimization perspective, adaptive content is more relevant and engaging, which leads to improved click-through and conversion rates relative to standard listings [5]. However, adaptive content creates complications for measurement, as the outcome of the personalization and the outcome of listing quality dictate different performance metrics (See Table 3). Therefore, the idea of a "best" listing no longer holds, and the focus shifts to performance across different user segments.

Table 3. Forms of AI-driven listing personalization and associated performance indicators.

Personalization Type	Primary Performance Indicator
Adaptive product descriptions	Conversion rate
Dynamic image selection	Click-through rate
Personalized pricing cues	Revenue per user
Targeted promotional cues	Engagement duration

2 AI-Driven Pricing and Promotional Adjustments

AI systems also adapt pricing and promotional text in product listings. Some machine learning models can suggest and/or automatically carry out pricing changes based on demand elasticity, competition, inventory, and user price sensitivity [4; 11]. Based on predicted price sensitivity, users can also get tailored promotional messages like discounts, urgency, and suggestions to buy a set of products instead of just one.

Even though personalized product listings and dynamic pricing might improve immediate revenue, they also raise concerns from a business strategy and ethics perspective. Customers may experience frustration and feel less trust in the business offering personalized pricing and/or products when they can't see the personalization strategy behind it, especially in the long run [13]. Any pricing strategy involves a gap between the need to optimize immediate revenue and the need to solve this tension in the long run.

3 The Personalization versus Standardization Dilemma

Although it has its benefits, personalization also creates an optimization dilemma with respect to consistency. While consistent brand compliance and policy/ regulatory alignment may be eroded by hyper-personalized listings (which may optimize engagement in the short term, excessive personalization reinforces behavioral biases, limits consumer choice, and increases algorithmic discrimination [13].

Personalization research points to a middle ground in the form of hybrid models, where some elements remain constant while a few are chosen [8]. Such approaches allow sellers to retain their brand, messaging, and market position strategies while accessing the relevance of AI. Personalization should be viewed as an optimization strategy that has constraints, as a result of a lack of governance, opacity, and misalignment with objectives, etc.

When assessing the impact of listing optimization, the further the objectives are from these constraints, the more likely the AI's deployment will result in focus shifts. These will be commercially focused in the section that follows.

3 Impact on Conversion Rates and Sales Performance

AI-driven product listing optimization helps businesses improve their overall commercial performance. The literature surrounding e-commerce outlines visibility, relevance, engagement, and most importantly, conversion rate and sales, showing the strategic importance of AI beyond operational efficiency [5; 11].

1 Correlation Between AI Optimization and Commercial Outcomes

AI-driven listing products consistently outperform traditionally optimized listings. Listings paired with machine-learning ranking and optimization tools yield better outputs, improving alignment with internet user queries and content, resulting in increased click-through and engagement rates [1; 8]. The previously mentioned behavioral metrics contribute to the improvement of marketplace performance and ranking algorithms to create a feedback loop to optimization, visibility, and performance.

Natural Language Processing (NLP) improvements of title clarity and relevance of the description have proven in particular categories to increase the likelihood of conversion [7; 17]. Computer vision (CV) image optimization reinforces a consumer's first impression, critical to consumer decision-making. AI-driven optimization product listings along with the other categories mentioned improve a business's overall commercial performance. As a result, AI-driven optimization improves a business's commercial performance [10].

AI's ability to optimize products improves the overall AI commercial performance of a business and provides resilience in revenue during the marketplace volatility. AI helps businesses adapt to seasonal and competitive challenges. Advanced versions of AI improve the iteration speed of market signals. AI improves marketplace responsiveness and improves revenue resilience [19].

2 Risks of Over-Automation

The risks involved with the commercialization of AI-driven optimization are, however, not without advantages. Too much automation can lead to short-term optimization at the cost of strategic differentiation. As AI systems are likely to achieve the same performance-maximizing configuration, listings will likely become more and more uniform, and therefore will lead to more brand dilution and less of a differentiated consumer offering [4; 11].

To make things worse, optimization systems reinforced with historical-performance systems are likely to entrench existing inequalities in the marketplace by favoring successful products and neglecting new and niche products. Because of this, the systems will erode the quality of competition and the diversity of the market, especially when ranking algorithms assign more weight to engagement measures that are the result of prior engagement [1].

From the perspective of these risks, the most critical need to be more than a tool of optimization, and broader strategic guidelines, remain in place. AI should be viewed as a decision-support tool, and not a substitute for the human factor, especially when the issue being dealt with is more strategic in the longer term, and more ethical in the longer term.

3 Ethical and Transparency Considerations

AI listing visibility shaping raises ethical and governance issues. If unchecked, generative models used in listing creation may incorporate bias, and be factually incorrect or

emphasize the wrong things [13; 14]. Also, personalization means the criteria upon which offers are made is hidden, restricting consumer knowledge and choice. Marketplace visibility democracies notwithstanding, the opacity of the algorithms sellers do have to optimize and the curated products consumers see poses the greatest transparency problems. These issues cannot be resolved with technology alone; they also require institutional mechanisms for accountability, explainable systems, and fairness to be woven into the fabric of the optimizing systems [13; 19].

Conclusions

The role of Artificial Intelligence (AI) in transforming online marketplaces by optimizing product listings has been analyzed, placing AI as a structural countermeasure to the scale, intricacy, and competitiveness of digital commerce. The research proves AI's comprehension of listing optimization by predictive, adaptive, and data-driven reasoning beyond the boundaries of traditional manual and rule-driven systems.

Text, image, and behavioral AI – be it machine learning, natural language processing, computer vision, or recommendations – offer a new frontier to the relevance and effectiveness of product listings. Recent literature cites AI optimization as a factor in attaining visibility, engagement, and conversion. Furthermore, AI impacts the ranking of online marketplaces and tailoring of product exposer algorithms [1; 8; 17].

The research findings also center criticism and concern. The loss of long-term strategic differentiation, fairness, consumer confidence, and trust, through automation, result in a loss of authenticity, and the algorithms employed in adaptive content and personalization are opaque. These concerns exemplify the need to consider AI as a form of technology that is not purely technical. AI technology, as a purely technical solution, remains a digital marketplace governing systems commercial paradigm.

As a primary consideration, sellers should implement AI-driven optimization in a more controlled manner, using automation and human involvement to keep a consistent brand and stay within ethical boundaries. Marketplace platforms, in reverse order, must also bear responsibility regarding transparency and fairness in systems of algorithmic ranking and personalization. The more relevant and upcoming research interest should shift from focusing on performance metrics to understanding the longer-term effects—possibly at the market level—of AI-driven listing optimizations, particularly the effects on the competitive landscape, market diversity, and consumer welfare. Moreover, more data-based research is necessary to identify the governance models that succeed in AI-enabled marketplaces at the intersection of personalization, standardization, and accountability.

References

1. Brenner, E., Zhao, J., Kutiyanawala, A., & Yan, Z. (2018). End-to-End Neural Ranking for eCommerce Product Search: an application of task models and textual embeddings. *arXiv preprint arXiv:1806.07296*. https://doi.org/10.48550/arXiv.1806.07296

2. Chodak, G., & Błażyczek, K. (2023, December). Large language models for search engine optimization in e-commerce. In *International Advanced Computing Conference* (pp. 333-344). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-56700-1_27

3. Grewal, D., Satornino, C. B., Davenport, T., & Guha, A. (2025). How generative AI is shaping the future of marketing. *Journal of the Academy of Marketing Science*, *53*(3), 702-722. https://doi.org/10.1007/s11747-024-01064-3

4. Haidar, I. (2024). Applications of artificial intelligence in E-commerce. *Journal of Artificial Intelligence General science (JAIGS) ISSN: 3006-4023*, *5*(1), 32-38. https://doi.org/10.60087/jaigs.v5i1.151

5. Hasan, R. (2025). Enhancing market competitiveness through AI-powered SEO and digital marketing strategies in e-commerce. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 465-500. https://doi.org/10.63125/31tpjc54

6. Ibrahim, I. Y., & Zeebaree, S. R. (2025). Emerging Trends in E-commerce: A Review of Consumer Behavior, Marketplaces and Digital Platforms. *Asian Journal of Research in Computer Science*, *18*(4), 45-58. https://doi.org/10.9734/ajrcos/2025/v18i4607

7. Kathiriya, S., Mullapudi, M., & Karangara, R. (2023). Optimizing ECommerce Listing: LLM Based Description and Keyword Generation from Multimodal Data. *Int. J. Sci. Res.(IJSR)*, *12*, 2123-2130. https://doi.org/10.21275/SR24304113521

8. Lin, E., Berlowitz, D., & Guo, O. (2025). Machine Learning Driven Ranking to Control Degree of Personalization in Search Results. https://www.tdcommons.org/dpubs_series/8435

9. Lu, H., Zhang, L., & Zhu, Y. (2024). The Power of Linear Programming in Sponsored Listings Ranking: Evidence from Field Experiments. *arXiv preprint arXiv:2403.14862*. https://doi.org/10.48550/arXiv.2403.14862

10. Mitchell, A. (2021). Multi-Modal AI Models: Combining Text, Vision, and Speech. *International Journal of Artificial Intelligence and Machine Learning*, *4*(3).

11. Papastamoulou, P., & Antonopoulos, N. (2025). Artificial Intelligence in E-Commerce: A Comparative Analysis of Best Practices Across Leading Platforms. *Systems*, *13*(9), 746. https://doi.org/10.3390/systems13090746

12. Patil, D. (2024). Generative artificial intelligence in marketing and advertising: Advancing personalization and optimizing consumer engagement strategies. *Available at SSRN 5057404*. https://dx.doi.org/10.2139/ssrn.5057404

13. Ren, Q., Jiang, Z., Cao, J., Li, S., Li, C., Liu, Y., & Chen, Y. (2024). A survey on fairness of large language models in e-commerce: progress, application, and challenge. *arXiv preprint arXiv:2405.13025*. https://doi.org/10.48550/arXiv.2405.13025

14. Roumeliotis, K. I., Tselikas, N. D., & Nasiopoulos, D. K. (2024). LLMs in e-commerce: A comparative analysis of GPT and LLaMA models in product review evaluation. *Natural Language Processing Journal*, *6*, 100056. https://doi.org/10.1016/j.nlp.2024.100056

15. Xi, R., Ba, H., Yuan, H., Agrawal, R., Tian, Y., Kong, R., & Prakash, A. (2025). Aug2Search: Enhancing Facebook Marketplace Search with LLM-Generated Synthetic Data Augmentation. *arXiv preprint arXiv:2505.16065*. https://doi.org/10.48550/arXiv.2505.16065

16. Yang, H., Xie, Q., Zhang, Q., Yu, C. L., Zou, H., Lian, C., & Zheng, B. (2025, November). GSID: Generative Semantic Indexing for E-Commerce Product Understanding. In *Proceedings of the 2025 Conference on Empirical Methods in Natural Language Processing: Industry Track* (pp. 1113-1121). https://doi.org/10.48550/arXiv.2509.23860

17. Zhou, J., Liu, B., Acharya, J.N., Hong, Y., Lee, K., & Wen, M. (2023). *Leveraging large language models for enhanced product descriptions in e-commerce*. *Transactions on Machine Learning Research*. https://doi.org/10.48550/arXiv.2310.18357

18. Zhuk, A., & Yatskyi, O. (2024). The use of artificial intelligence and machine learning in e-commerce marketing. *Technology audit and production reserves*, *3*(4 (77)), 33-38. https://doi.org/10.15587/2706-5448.2024.305280

19. Zumstein, D., & Chodak, G. (2024, October). Artificial Intelligence in E-Commerce–Overview of Applications, Benefits and Challenges. In *International Scientific-Practical Conference* (pp. 1-15). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-88052-0_1