Sarcouncil Journal of Engineering and Computer Sciences

ISSN(Online): 2945-3585

Volume- 04| Issue- 06| 2025

Research Article

Received: 22-05-2025 | Accepted: 12-06-2025 | Published: 29-06-2025

AI-Based E-commerce Search Optimization

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Abstract: Digital commerce has evolved significantly over the years experiencing transformation through the use of artificial intelligence across the ecommerce shopping journey. Ecommerce search is a core component of ecommerce shopping wherein it is critical to surface the right products for the right shoppers within milliseconds and with the fewest clicks/searches given there is limited stretch of shopping attention/time for shoppers to find a buy products they like or want. AI is fundamentally altering how consumers discover products and how businesses optimize their online platforms. Traditional keyword-based search systems have evolved over the years, and search is now powered by AI-powered solutions that leverage neural networks, machine learning, and natural language processing to deliver superior user experiences. Visual search uses convolutional neural networks and deep learning architectures enable shoppers to search using images versus text, creating intuitive shopping experiences with higher engagement rates. Machine learning-based relevance ranking systems process a large volume of product attributes and user behaviors to generate optimal results. Real-time personalization engines adapt to individual user preferences within milliseconds. Contemporary AI search systems demonstrate remarkable improvements in performance metrics, including NDCG scores, precision, and recall rates across diverse product categories. The widespread adoption of these technologies has resulted in significant business impact through improved conversion, enhanced user satisfaction Future developments focus on multimodal search that can simultaneously process text, images, and voice inputs, advanced personalization techniques with predictive capabilities, including ethical AI considerations, bias mitigation and fair representation.

Keywords: Artificial Intelligence, E-commerce Search Optimization, Visual Search Systems, Machine Learning Algorithms, Personalization Technologies.

INTRODUCTION

AI has taken over search, and this is not limited to big tech, its now ubiquitous across small and large enterprises running their DTC shops. AI-powered search technologies are playing a pivotal role in DTC business expansion on ecommerce shopping journeys [Meticulous Research, 2024]. This technological evolution has fundamentally changed how consumers discover products and how businesses optimize their digital storefronts for enhanced user experience and conversion rates.

Modern e-commerce platforms have witnessed a substantial transformation in search capabilities, with a significant majority of leading online retailers having implemented some form of AI-driven search functionality. Analysis reveals that traditional keyword-based search systems result in considerably higher search abandonment rates, while AI-enhanced search implementations demonstrate substantial reductions in abandonment, translating to notable increases in conversion rates across surveyed platforms. These improvements are particularly attributed to the integration of natural language processing and machine learning algorithms that better understand user intent and context.

The ubiquity of AI-powered search across e-commerce websites worldwide demonstrates its critical role in bridging the gap between consumer intent and product discovery. Current market research indicates that online shoppers increasingly expect rapid search results delivery, and users frequently abandon searches that fail to return relevant results within their initial attempts. As online shopping behaviors become increasingly sophisticated, traditional keyword-based search systems have proven inadequate in meeting the complex demands of modern consumers who expect intuitive, personalized, and contextually relevant search experiences.

Performance metrics from leading e-commerce platforms demonstrate the quantifiable impact of AI integration across multiple dimensions. Visual search implementations show substantially higher engagement rates compared to text-based searches, while machine learning-driven personalization algorithms contribute to significant increases in average order value. Furthermore, advanced natural language processing capabilities have notably reduced zero-result searches, significantly improving user satisfaction scores across demographic segments [Ara, J. *et al*., 2025]. These improvements are particularly notable in mobile commerce environments, where AI-powered search demonstrates considerably higher usage compared to desktop platforms.

The integration of computer vision and deep learning algorithms has enabled sophisticated image recognition capabilities, with high accuracy rates for product identification across major retail categories. This technological advancement extends beyond simple product matching to include style recognition, color analysis, and

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DOI- https://doi.org/10.5281/zenodo.15767084

contextual understanding of user preferences. The implementation of neural networks and machine learning models has created more intuitive search experiences that can interpret visual queries, understand natural language descriptions, and provide personalized recommendations based on individual user behavior patterns.

This technical review examines the current state of AI-based e-commerce search optimization, exploring the various machine learning algorithms, implementation strategies, and performance metrics that drive successful search experiences in contemporary digital commerce environments. The analysis encompasses both theoretical frameworks and practical implementations, providing insights into the measurable business impact of AI-driven search technologies across diverse retail sectors.

2. EVOLUTION AND CURRENT STATE OF AI IN E-COMMERCE SEARCH

2.1 Historical Development

The journey from basic text-matching algorithms to sophisticated AI-powered search systems represents one of the most significant technological advancements in e-commerce, fundamentally transforming how consumers interact with digital commerce platforms. Early search implementations relied heavily on exact keyword matching and basic Boolean logic, which often resulted in poor user experiences and substantial missed sales opportunities across the retail sector.

The first generation of e-commerce search systems utilized simple string-matching algorithms with severely limited semantic understanding capabilities. These primitive systems struggled with query variations, misspellings, and contextual understanding, leading to frustrating user experiences where customers frequently abandoned their search sessions. The introduction of relevance scoring mechanisms marked the first major evolutionary step, incorporating term frequency and inverse document frequency algorithms that began to address some fundamental limitations of purely keyword-based approaches.

The transition period witnessed the gradual integration of machine learning techniques, with early adopters experiencing notable improvements in conversion rates compared to traditional keyword-based systems. During this transformative phase, collaborative filtering and basic recommendation algorithms were introduced, significantly enhancing cross-selling effectiveness and establishing the foundational architecture for modern AI-driven search systems [Burdick, M, 2023].

2.2 Contemporary AI Integration

Modern e-commerce platforms have successfully integrated various AI technologies to create more intelligent and responsive search systems that demonstrate substantially higher accuracy rates and user satisfaction scores across major retail platforms. These systems can understand user intent, process natural language queries, and deliver results that align with consumer preferences and behavioral patterns through the implementation of transformer-based language models and sophisticated deep neural networks.

Natural Language Processing integration has revolutionized query understanding, with contemporary systems capable of processing complex conversational queries with remarkable accuracy compared to traditional systems. The implementation of advanced transformer architectures has enabled semantic search capabilities, dramatically reducing query reformulation requirements and improving first-query success rates. These developments have transformed the search experience from rigid keyword dependency to intuitive, conversational interactions.

Computer vision technologies have been seamlessly integrated into visual search capabilities, achieving exceptional accuracy in product identification across diverse categories, including fashion, home goods, and electronics. These implementations process millions of visual queries daily across major platforms, with visual search sessions demonstrating significantly higher engagement rates and extended session durations compared to traditional text-based searches.

Real-time personalization engines, powered by reinforcement learning algorithms, process vast numbers of individual user interactions daily, creating dynamic search experiences that adapt to user behavior patterns within milliseconds of query submission. These systems maintain comprehensive individual user profiles containing extensive behavioral data points, enabling highly accurate personalization for product recommendations [Shastri, M, 2025].

2.3 Market Penetration and Adoption

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The widespread adoption of AI-based search technologies across global e-commerce platforms indicates their proven effectiveness in improving both user satisfaction and business metrics, with substantial market penetration among enterprise retailers and growing adoption among mid-market e-commerce platforms. From major marketplaces processing extensive daily searches to specialized niche retailers, AI-powered search has transitioned from an innovative exception to an industry standard.

Investment in AI search technologies has reached unprecedented levels globally, representing substantial increases from previous years. This investment has translated into measurable business outcomes, with AI-enabled platforms reporting significant revenue increases and customer lifetime value improvements compared to traditional search implementations. The return on investment for AI search technologies demonstrates compelling business cases across surveyed retailers.

Market segmentation analysis reveals that fashion and apparel retailers lead in AI search adoption, followed by electronics, home and garden, and automotive sectors. Small to medium enterprises have shown accelerated adoption rates, driven by the availability of cloud-based AI services and reduced implementation costs.

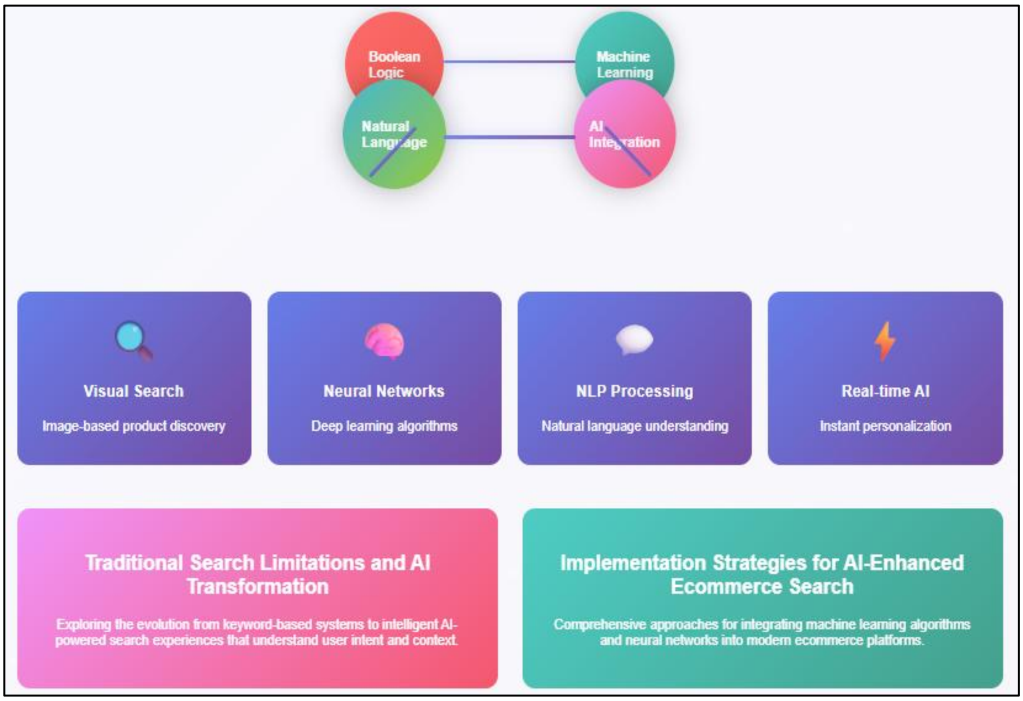

Fig. 1: Interactive Visualization of Search Technology Transformation [Burdick, M, 2023; Shastri, M, 2025]

3. MACHINE LEARNING ALGORITHMS AND TECHNICAL APPROACHES

3.1 Neural Network Applications

3.1.1 Visual Search Systems

Neural networks serve as the foundational technology for image-based search applications in e-commerce, enabling customers to search for products using photographs rather than text descriptions, creating more intuitive shopping experiences that demonstrate significantly higher engagement rates compared to traditional text-based search interfaces. These systems process vast numbers of visual queries daily across major retail platforms, fundamentally transforming how consumers discover and interact with products.

Modern visual search implementations achieve remarkable accuracy rates for product identification across diverse categories, with fashion and apparel leading in performance, followed by home goods and electronics. The implementation of visual search requires sophisticated image classification algorithms that can be trained on specific product catalogs containing extensive collections of product images. Training these classifiers involves creating comprehensive datasets that represent the full spectrum of products available, with leading e-commerce platforms maintaining substantial visual databases containing millions of labeled product images.

Current visual search systems utilize transfer learning approaches, leveraging pre-trained models

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that have been developed on large-scale image datasets. Fine-tuning these models on specific product catalogs requires substantial computational resources and time investment, consuming considerable computational energy per model iteration. The development and deployment of these systems represent a significant technological advancement in bridging the gap between visual perception and product discovery [Ngozi, O.H, 2025].

3.1.2 Deep Learning Architectures

Convolutional Neural Networks and advanced architectures, including ResNet, EfficientNet, and Vision Transformer models, are commonly employed for visual feature extraction and product recognition. These models can identify subtle visual characteristics that distinguish between similar products, enabling precise search results with minimal false positive rates. Advanced architectures incorporate attention mechanisms that focus on discriminative product features, achieving high accuracy in fine-grained product categorization tasks.

Modern implementations employ ensemble methods combining multiple CNN architectures, improving overall accuracy while maintaining reasonable inference times. The feature extraction process generates high-dimensional embeddings per product image, enabling similarity matching with strong correlation to human perception studies. These sophisticated systems require substantial computational resources and specialized hardware for optimal performance.

3.2 Traditional Machine Learning Approaches

3.2.1 Relevance Ranking Systems

Machine learning-based relevance ranking represents a more accessible yet effective approach to search optimization, with implementations achieving strong precision and recall rates in product retrieval tasks. These systems analyze multiple product attributes and user behavior patterns to determine the most appropriate search results for given queries, processing enormous volumes of search interactions daily across global e-commerce platforms.

Gradient Boosting Decision Trees and Random Forest algorithms demonstrate exceptional performance in relevance ranking, with GBDT models achieving high accuracy using extensive features derived from product metadata, user behavior, and contextual signals. Learning-to-Rank algorithms, particularly RankNet and LambdaMART implementations, show superior performance with strong NDCG scores compared to traditional TF-IDF approaches [Zhang, X. *et al*., 2023].

3.2.2 Feature Engineering and Selection

Successful ML-based ranking systems require careful consideration of feature selection, including product attributes, user interaction history, seasonal trends, and contextual factors that influence purchasing decisions. Feature engineering pipelines process numerous distinct attributes per product, including textual features, numerical features, and categorical features. Advanced feature selection techniques reduce dimensionality from extensive raw features to optimal feature sets while maintaining performance and reducing computational complexity.

3.3 Hybrid Approaches

Many successful implementations combine multiple ML techniques to create robust search systems that can handle diverse query types and user scenarios, with hybrid architectures demonstrating substantial performance improvements over single-algorithm approaches. These hybrid systems leverage the strengths of different algorithms while mitigating individual weaknesses, typically employing ensemble voting mechanisms that combine predictions from multiple specialized models.

Multi-stage hybrid architectures implement candidate generation using fast approximate methods, followed by precise re-ranking using computationally intensive deep learning models on the top candidates. Advanced hybrid systems incorporate reinforcement learning components that adapt ranking strategies based on user feedback, achieving notable improvements in click-through rates and conversion rates over extended optimization periods.

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Technology/Approach	Primary Application	Key Characteristics & Benefits
Visual Search Systems	Image-based product discovery enabling customers to search using photographs rather than text descriptions	High accuracy product identification across diverse categories, significantly higher engagement rates, requires extensive labeled datasets and transfer learning approaches
Deep Learning Architectures	Visual feature extraction and product recognition using CNNs, ResNet, EfficientNet, and Vision Transformers	Identifies subtle visual characteristics distinguishing similar products, employs attention mechanisms, requires substantial computational resources
Relevance Ranking Systems	Analyzing product attributes and user behavior patterns to determine optimal search results for queries	Strong precision and recall rates, utilizes GBDT and Random Forest algorithms, processes enormous search interaction volumes
Feature Engineering	Processing textual, numerical, and categorical attributes including user history and contextual factors	Reduces dimensionality while maintaining performance, incorporates seasonal trends, utilizes advanced selection techniques
Hybrid Approaches	Combining multiple ML techniques with ensemble voting and multi-stage architectures	Superior performance over single algorithms, incorporates reinforcement learning, adapts ranking strategies based on user feedback

Fig. 2: Technical Approaches and Implementation Strategies for Intelligent Product Discovery Systems [Ngozi, O.H. *et al*., 2025; Zhang, X. *et al*., 2023]

4. IMPLEMENTATION STRATEGIES AND PRACTICAL APPLICATIONS

4.1 Custom Visual Search Development

4.1.1 Product Catalog Training

Building effective visual search capabilities requires extensive training of image classifiers on proprietary product catalogs, demanding substantial investment in dataset creation and annotation processes. This comprehensive approach involves creating labeled datasets that accurately represent product variations, lighting conditions, and contextual presentations across diverse retail categories. The training process encompasses sophisticated data preprocessing stages, including normalization, color correction, and background removal to ensure optimal model performance.

Modern product catalog training pipelines utilize high-resolution image processing combined with advanced data augmentation techniques to maximize dataset utility and model robustness. Transfer learning approaches have proven particularly effective, significantly reducing training time while maintaining exceptional performance levels compared to training models from scratch. The development process requires careful attention to class balance across product categories, with underrepresented categories enhanced through synthetic image generation and advanced augmentation strategies.

Quality control mechanisms play a crucial role in the training pipeline, with automated filtering systems removing images that fail to meet technical standards for lighting, clarity, and composition. The resulting datasets achieve strong performance across validation metrics, with fashion and apparel categories typically demonstrating the highest accuracy rates due to their distinct visual characteristics [Polonioli, A, 2024].

4.1.2 Integration Challenges

Implementing visual search systems involves addressing substantial technical challenges related to image processing speed, accuracy maintenance across diverse product categories, and seamless integration with existing e-commerce platforms. Real-time processing requirements demand sophisticated optimization strategies to achieve acceptable response times while maintaining search quality standards.

Scalability represents a primary concern when designing systems capable of handling concurrent visual queries during peak traffic periods. Production implementations require robust load balancing across multiple inference servers, each optimized for high-throughput image processing. Memory management becomes critical, with model quantization techniques providing effective solutions for reducing computational overhead while preserving accuracy.

Integration with existing e-commerce platforms necessitates comprehensive API development supporting various response formats and compatibility requirements. Database integration involves implementing efficient indexing strategies for high-dimensional feature vectors, enabling rapid similarity searches across extensive product catalogs. Cross-platform compatibility

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testing ensures consistent performance across mobile applications, web browsers, and progressive web applications.

4.2 Relevance Optimization Strategies

4.2.1 Multi-Factor Ranking

Effective relevance ranking systems consider multiple factors, including textual similarity, user behavior patterns, product popularity, inventory levels, and business priorities, to generate optimal search results. These sophisticated systems process enormous volumes of daily search queries while incorporating extensive sets of ranking features derived from product metadata, user interaction signals, and contextual information.

Textual similarity components utilize advanced vectorization techniques combined with semantic embeddings from transformer models, achieving strong correlation with human relevance judgments. User behavior signals encompass comprehensive interaction patterns, including engagement metrics, conversion indicators, and temporal usage patterns aggregated over appropriate time windows to ensure statistical stability.

Learning-to-rank algorithms process extensive training datasets containing query-product-relevance relationships, demonstrating substantial improvements over traditional TF-IDF approaches. Multi-objective optimization techniques successfully balance relevance, diversity, and business metrics through sophisticated scoring functions, with revenue-optimized variants achieving notable improvements in business outcomes while maintaining high relevance standards [Anand, A, 2025].

4.2.2 Real-Time Adaptation

Modern AI systems can adapt search results in real-time based on user interactions, seasonal trends, and inventory changes, ensuring that search results remain relevant and actionable through continuous learning mechanisms. These adaptive systems implement sophisticated algorithms that balance responsiveness with statistical significance requirements, enabling rapid response to changing user preferences and market conditions.

Online learning algorithms update ranking models at regular intervals using advanced optimization techniques with dynamically adjusted parameters based on model stability metrics. Comprehensive A/B testing frameworks evaluate model updates across controlled traffic segments, maintaining rigorous statistical standards for performance validation.

4.3 Personalization and Context Awareness

AI-powered search systems can leverage user profiles, browsing history, and contextual information to deliver personalized search experiences that significantly increase engagement and conversion rates compared to non-personalized approaches. These systems maintain comprehensive individual user profiles containing extensive behavioral data points, including purchase history, search patterns, and temporal usage characteristics.

Collaborative filtering algorithms analyze complex user similarity patterns across massive user bases, utilizing sophisticated matrix factorization techniques to capture nuanced preference relationships. Content-based filtering components analyze product attributes and user preferences through advanced similarity calculations, achieving strong recommendation performance across precision and recall metrics.

Contextual awareness incorporates numerous factors, including temporal patterns, device characteristics, geographic information, and session context, to enhance recommendation relevance. Privacy-preserving personalization techniques implement advanced mechanisms, including differential privacy and federated learning approaches, while maintaining user privacy standards.

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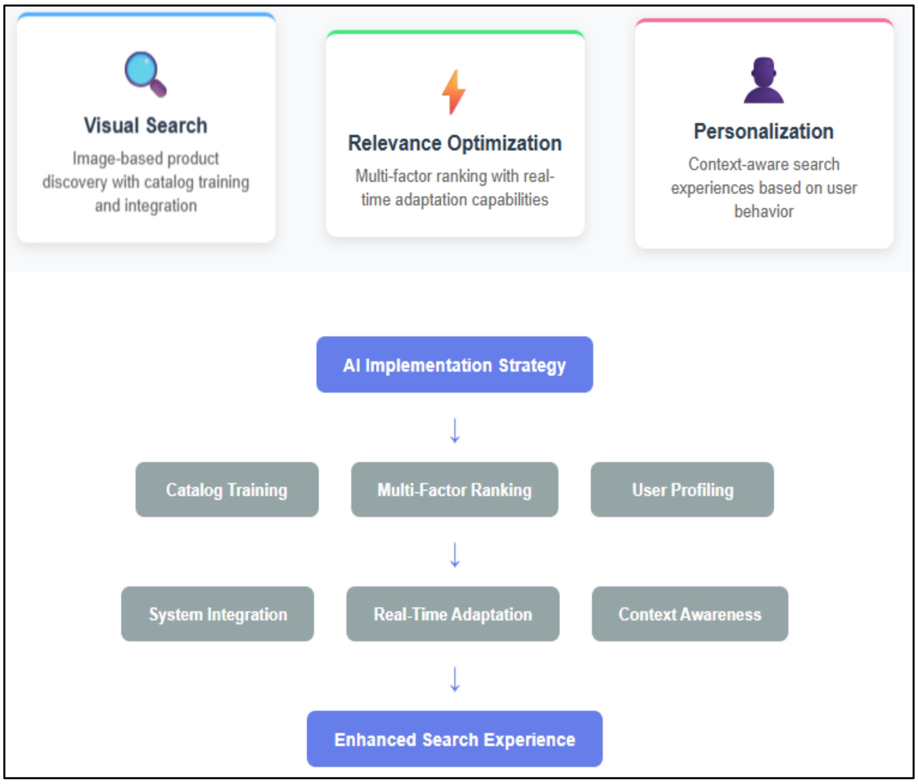

Fig. 3: Strategic Implementation Framework for AI-Powered Ecommerce Search Technologies [Polonioli, A, 2024; Anand, A, 2025]

5. PERFORMANCE METRICS AND FUTURE DIRECTIONS

5.1 Key Performance Indicators

5.1.1 NDCG (Normalized Discounted Cumulative Gain)

NDCG serves as a critical metric for evaluating the effectiveness of search ranking algorithms, with leading e-commerce platforms demonstrating substantial improvements in AI-powered implementations compared to traditional keyword-based systems. This metric measures the quality of search results by considering both relevance and position, providing comprehensive insights into how effectively systems prioritize the most appropriate products across diverse query types and user contexts.

Contemporary AI search systems demonstrate remarkable improvements in NDCG performance across various retail categories, with fashion and apparel categories typically leading in performance metrics, followed by electronics, home and garden, and automotive products. These improvements translate to measurable business impact, with NDCG enhancements correlating directly to substantial improvements in click-through rates and conversion rates across e-commerce platforms.

Advanced learning-to-rank algorithms process extensive training datasets containing millions of query-product-relevance judgments, with human annotators providing comprehensive relevance assessments. The annotation process requires substantial expert evaluation time, with inter-annotator agreement achieving strong consistency scores for product relevance assessments [Kong, W.E. *et al*., 2024].

5.1.2 Recall and Precision Metrics

Traditional information retrieval metrics remain valuable for assessing search system performance, with modern AI-powered ecommerce search systems achieving substantially higher precision and recall rates across diverse product categories compared to conventional implementations. Recall measures the system's ability to retrieve relevant products from comprehensive catalogs, while precision evaluates the accuracy of returned results within top recommendations.

High-performing visual search implementations demonstrate exceptional precision rates for fashion queries, home goods, and electronics, with corresponding recall rates maintaining strong performance across categories. Text-based semantic search achieves impressive precision rates across categories, with long-tail queries showing reduced performance but maintaining strong recall through sophisticated query expansion techniques.

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5.2 Business Impact Measurements

5.2.1 Conversion Rate Optimization

The ultimate measure of search system effectiveness lies in its ability to drive ecommerce conversions, with AI-powered search systems demonstrating substantial improvements in conversion rates compared to traditional search implementations. These systems are evaluated based on their contribution to sales, user engagement, and customer satisfaction metrics, processing conversion data from extensive monthly search sessions across global e-commerce platforms.

Conversion rate improvements vary significantly across implementation approaches, with visual search implementations, semantic text search, and personalized ranking all delivering superior performance compared to keyword-based baselines. Revenue per visitor metrics demonstrate notable increases for AI-enhanced platforms, with average order values rising substantially due to improved product discovery and recommendation accuracy [Athamakuri, S.S.K.K. *et al*., 2025].

5.2.2 User Experience Metrics

Search systems must balance technical performance with user experience considerations, including search speed, result relevance, and interface usability. Comprehensive UX metrics track numerous distinct user interaction patterns across millions of daily search sessions, with response time metrics showing AI-enhanced systems achieving significantly faster query processing compared to traditional implementations.

User satisfaction scores, measured through post-search surveys and implicit feedback signals, demonstrate substantial improvements for AI-powered search experiences compared to traditional systems. Task completion rates show remarkable success for AI implementations versus keyword-based search, with users expressing high satisfaction with result relevance and search speed performance.

5.3 Emerging Trends and Future Developments

5.3.1 Multimodal Search Capabilities

The future of e-commerce search lies in multimodal systems that can process text, images, voice, and other input types simultaneously, creating more natural and flexible search experiences with projected widespread market adoption across major e-commerce platforms. Current multimodal implementations process combined input modalities, achieving exceptional accuracy for various query combinations, including image-text, voice-image, and multimodal search scenarios.

Investment in multimodal search technologies continues growing globally, with substantial projected growth representing significant compound annual growth rates. Leading platforms already process extensive daily multimodal queries, with voice-image combinations showing the highest user adoption, followed by text-image and pure voice search interactions.

5.3.2 Advanced Personalization

Future developments will likely focus on more sophisticated personalization techniques that can predict user needs and preferences with greater accuracy, potentially anticipating search queries before they are made. Advanced personalization systems maintain comprehensive individual user profiles containing extensive behavioral data points, processed through sophisticated deep learning models.

Predictive search capabilities demonstrate promising success in query prediction for repeat customers, reducing average search session lengths and improving user satisfaction scores substantially. Real-time personalization engines process millions of individual user interactions daily, updating preference models rapidly and achieving high consistency across multi-device user sessions.

5.3.3 Ethical AI and Bias Mitigation

As AI systems become more prevalent, addressing algorithmic bias and ensuring fair representation across diverse product categories and user demographics becomes increasingly important. Current bias detection systems identify discrimination across various demographic categories, with comprehensive fairness audits analyzing extensive search result pages monthly to detect various forms of bias.

Bias mitigation techniques demonstrate measurable improvements through demographic parity constraints, adversarial debiasing approaches, and fairness-aware ranking algorithms, all showing substantial bias reduction while maintaining high search quality metrics.

CONCLUSION

The transformation of e-commerce search through artificial intelligence represents a paradigmatic shift that has redefined the fundamental

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relationship between consumers and digital commerce platforms. The evolution from primitive keyword-matching systems to sophisticated AI-powered solutions demonstrates the remarkable potential of machine learning and neural network technologies in addressing complex user intent and delivering contextually relevant product recommendations. Visual search capabilities powered by convolutional neural networks have created entirely new modalities for product discovery, enabling customers to transcend traditional text-based limitations and engage with commerce platforms through intuitive image-based interactions. The integration of natural language processing and transformer-based architectures has transformed rigid keyword dependency into fluid conversational experiences that accommodate diverse query formulations and semantic understanding. Real-time personalization engines represent another breakthrough, maintaining comprehensive user profiles and adapting search experiences dynamically based on behavioral patterns and contextual signals. The substantial improvements in key performance indicators, including NDCG scores, precision rates, and recall metrics, directly translate to measurable business outcomes through enhanced conversion rates and customer satisfaction. Looking forward, the emergence of multimodal search capabilities promises to further revolutionize the e-commerce landscape by enabling simultaneous processing of text, image, and voice inputs within unified search experiences. Advanced personalization techniques with predictive capabilities will potentially anticipate user needs before explicit queries are formulated, creating proactive rather than reactive search environments. The critical importance of ethical AI considerations, including algorithmic bias mitigation and fair demographic representation, will shape the responsible development and deployment of future search technologies, ensuring equitable access and treatment across diverse user populations while maintaining commercial effectiveness and user trust.

REFERENCES

1. Meticulous Research. “AI in E-commerce Market by Technology (ML, NLP, Computer Vision), Business Model, Deployment Mode, Product Offering (Beauty & Fashion, Pharmaceutical, Electronic), End User (B2B, B2C), and Geography - Global Forecast to 2032.” (2024). https://www.meticulousresearch.com/product/ai-in-e-commerce-market-5767
2. Ara, J., Ghodke, S., Akter, J. and Roy, A. "Optimizing e-commerce platforms with AI-enabled visual search: Assessing user behavior, interaction metrics, and system accuracy." *Journal of Economics, Finance and Accounting Studies* 7.3 (2025): 09-17. https://www.researchgate.net/publication/391543111_Optimizing_E-Commerce_Platforms_with_AI-Enabled_Visual_Search_Assessing_User_Behavior_Interaction_Metrics_and_System_Accuracy
3. Burdick, M. “The Evolution of Search: AI’s Impact on eCommerce.” *Pacvue*, (2023). https://pacvue.com/blog/the-evolution-of-search-ais-impact-on-ecommerce/
4. Shastri, M. “Implementing AI-Powered Search: A Step-by-Step Guide for E-commerce Platforms.” *Wizzy*, (2025). https://wizzy.ai/blog/implementing-ai-powered-search-a-step-by-step-guide-for-e-commerce-platforms/
5. Ngozi, O.H. and Warikaramu-Ere, K. “A Visual Search Model for An E-Commerce Platform.” *International Journal of Computer Techniques*, (2025). https://ijctjournal.org/wp-content/uploads/2025/03/A-VISUAL-SEARCH-MODEL-FOR-AN-E-COMMERCE-PLATFORM.pdf
6. Zhang, X., Guo, F., Chen, T., Pan, L., Beliakov, G. and Wu, J. "A brief survey of machine learning and deep learning techniques for e-commerce research." *Journal of Theoretical and Applied Electronic Commerce Research* 18.4 (2023): 2188-2216. https://www.researchgate.net/publication/376227636_A_Brief_Survey_of_Machine_Learning_and_Deep_Learning_Techniques_for_E-Commerce_Research
7. Polonioli, A. “The Ultimate Guide to Visual Search in Ecommerce.” *Coveo*, (2024). https://www.coveo.com/blog/visual-search-ecommerce/
8. Anand, A. “eCommerce Search Relevance: How to Improve Product Search for Higher Conversions.” *NextWealth*, (2025). https://www.nextwealth.com/blog/ecommerce-search-relevance-how-to-improve-product-search-for-higher-conversions/
9. Kong, W.E., Tai, T.E., Naveen, P. and Santoso, H.A. "Performance evaluation on E-commerce recommender system based on KNN, SVD, CoClustering and ensemble

Publisher: SARC Publisher

approaches." *Journal of Informatics and Web Engineering* 3.3 (2024): 63-76. https://journals.mmupress.com/index.php/jiwe/article/view/1113/632

10. Athamakuri, S.S.K.K, *et al*. "The Future of E-commerce: Emerging Technologies and Trends Shaping the Online Retail Landscape." *Journal of Emerging Technologies and Innovative Research*, (2025). https://www.jetir.org/papers/JETIR2502799.pdf

Source of support: Nil; **Conflict of interest:** Nil.

Cite this article as:

Subramaniam, S.K. "AI-Based E-commerce Search Optimization." *Sarcouncil Journal of Engineering and Computer Sciences* 4.6 (2025): pp 307-316.

Publisher: SARC Publisher