Lucidworks

Quantifying the Impact of AI on B2C and B2B Commerce Search

Exploring ways business leaders can utilize generative AI in common search use cases and sectors, including impact and ROI.

A practical application guide from Lucidworks and Google

Lucidworks Google Cloud

In today's rapidly evolving digital landscape, artificial intelligence (AI) — including Generative AI powered by Large Language Models (LLMs) and machine learning (ML) — is reshaping how businesses approach search and product discovery.

This transformative technology has the potential to dramatically improve the leadership position of many companies within their sectors and change up the information discovery process, leading to improved relevance, higher return on investment (ROI), and enhanced user experiences.

In collaboration with Google Cloud, Lucidworks presents a practical application guide that explores the profound impact of AI, ML, and Generative AI (Gen AI) on common search use cases. This guide delves into the methods and strategies business leaders can employ to harness the full potential of AI, quantifying its effects on key performance indicators (KPIs) and ultimately driving business success.

Measuring and quantifying the impact of AI includes understanding industry-specific KPIs, collecting qualitative and quantitative metrics and analytics, conducting experimentation and testing to isolate and prove impact. It also includes utilizing attribution modeling to track influence across the user journey, and formulating economic impact metrics such as ROI.

For this guide, we have selected applying typical lift, return, cost reduction, or other typical outcome measures for AI, ML, and Gen AI to B2C and B2B commerce.

In the e-commerce industry, using AI, Large Language Models (LLMs), and Gen AI can add significant value to the e-commerce customer journey.

Global Study Reveals Businesses Are Rapidly Investing in Gen AI

Lucidworks conducted the most extensive global study of generative AI practices, involving over 6,000 participants from companies with 100 or more employees across 14 industries and nine functional departments. The study evaluated 80 generative AI best practices and identified four stages of generative AI development to help businesses create industry-specific, customized generative AI roadmaps.

A strong enthusiasm for the technology across various business functions drives the planned generative AI spending increase. Technology and Data Science departments lead the way, with 96% planning to invest more in generative AI, closely followed by Research or Product Development at 93% and the Finance or Accounting function at 92%. However, companies that do not plan to increase their generative AI spending have a much higher number of concerns, highlighting the importance of addressing these issues to foster confident AI adoption.

Key investment areas for businesses include improved customer experience, automation/efficiency, and overall business operations, as generative AI offers practical solutions for content creation, process optimization, and strategic decision-making.

Source: Lucidworks 2023, The State of Generative AI in Global Business

Using AI to Improve Personalized Search Relevance

Here, we explore a typical use case illustrating how AI, ML, and generative AI technologies can be applied in a B2C and B2B commerce situation:

USE CASE: An e-commerce company with a vast product catalog wants to improve the product search and discovery experience for its users. The goal is to increase user engagement, boost conversion rates, and drive revenue. The company leveraged AI, ML, and generative AI — including LLMs — to achieve this.

Five Ways AI Could Be Implemented to Personalize Search Relevance

Content Enhancement & Enrichment:

Generative AI and computer vision improve product content by adding additional attributes, meta-data, and context-specific descriptions derived from both internal and external unstructured content sources. These sources may include supplier content, third-party sites, reviews, and knowledge bases.

Audience Detection & Personalization:

As visitors interact with the brand, touchpoints use AI to determine visitor intent through searches and clicks, leveraging cohort and clustering behavior to present contextualized and personalized results. When purchase and interaction histories are available, use AI to develop detailed affinity vectors for the user to drive hyper-personalized results.

Search Optimization:

Generative AI models paired with vector search help improve search queries by incorporating complete natural language processing, suggesting relevant keywords, synonyms, and context-based recommendations. This ensures that users receive more accurate search results using their own words.

AI, Generative AI, and LLMs Defined

AI, or Artificial Intelligence, is the simulation of human-like intelligence in machines. It involves learning, reasoning, problem-solving, and decision-making, enabling machines to perform tasks that typically require human intelligence, such as understanding natural language, recognizing patterns, and making predictions. AI technologies include machine learning, neural networks, and natural language processing, and they find applications in various fields, from healthcare to autonomous vehicles and customer service.

Generative AI, short for Generative Artificial Intelligence, refers to a subset of artificial intelligence techniques that generate new, original content based on patterns and examples found in existing data. The critical feature of generative AI is its ability to autonomously create content such as summaries of text, images, videos, music, text, and even entire virtual environments. This is achieved through sophisticated algorithms, typically based on deep learning models. These models learn to capture the underlying patterns and structures in the training data and can then generate new data samples that closely resemble the original dataset.

Generative AI is primarily based on using Large Language Models (LLMs). An LLM is an artificial intelligence (AI) model that processes and generates human language. LLMs are characterized by their extensive size, complex architecture, and ability to understand and develop text in natural language, such as English, without being explicitly programmed for specific language tasks. Currently, there are hundreds of commercial and open-source LLMs available for use.

An LLM embedding is like a digital fingerprint for words. It encodes their meaning, allowing AI to understand the context and relationships between words, making language models smarter in understanding and generating human-like text.

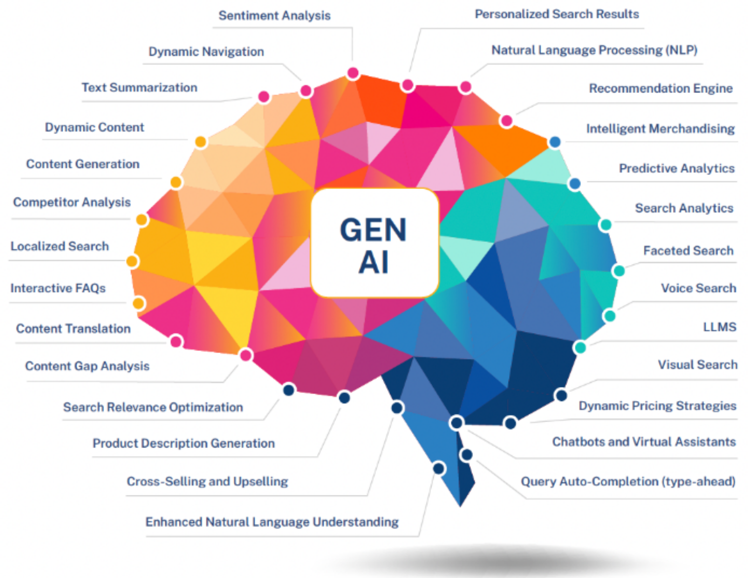
Recommendations:

AI-driven recommendation engines analyze user profiles and behavior to suggest additional searches, products, and topics that are likely to be interesting. LLMs can also help generate personalized product descriptions and reviews.

Insights:

LLMs pull data from internal and external sources, including community, social, transcribed support calls, chats, videos, and search engine results. This analysis informs product intelligence insights such as sentiment, pricing/promo, influential segments, attributes, placement, and merchandising strategies.

27 Applications of Generative AI to Accelerate Search Success



Accelerating relevance and improving the search experience (SX) is the primary goal of Lucidworks when working with any client. Improved relevance and SX directly lead to better conversion, purchases, and ROI.

In any e-commerce, workplace, or services/support environment, improving search performance is a worthy goal but not necessarily easy. Lucidworks is a pioneer in generative AI applications to improve search performance and make tasks easier through automation and intelligence.

Five Benefits of Using AI to Personalize Search Relevance

Reduced Purchase Friction:

Customers have a much shorter path to purchase due to showing the most relevant products and experiences for them at the moment.

Improved Conversion Rates:

Personalized product recommendations and tailored content generate higher conversion rates as users are likelier to purchase.

Increased Customer Engagement:

Users spend more time on the platform, exploring personalized product suggestions and engaging with dynamic content.

Higher Revenue:

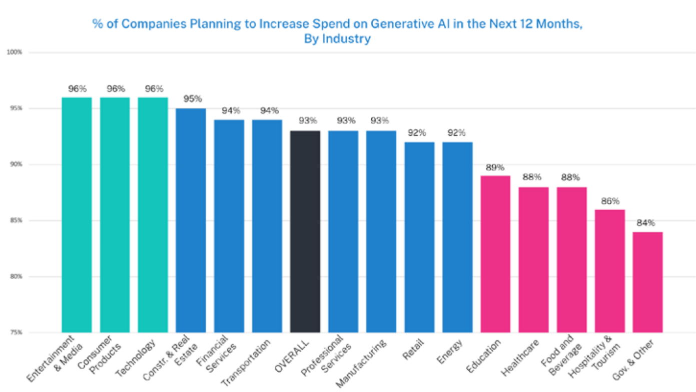
The combination of improved user experience and conversion rates leads to increased revenue for the e-commerce platform.

Reduced Cart Abandonment:

AI helps address user concerns, answer questions, and provide relevant product information, reducing cart abandonment rates.

AI, ML, LLMs, and generative AI technologies can improve the product search and discovery process in e-commerce by providing personalized recommendations, optimizing search queries, and dynamically generating content.

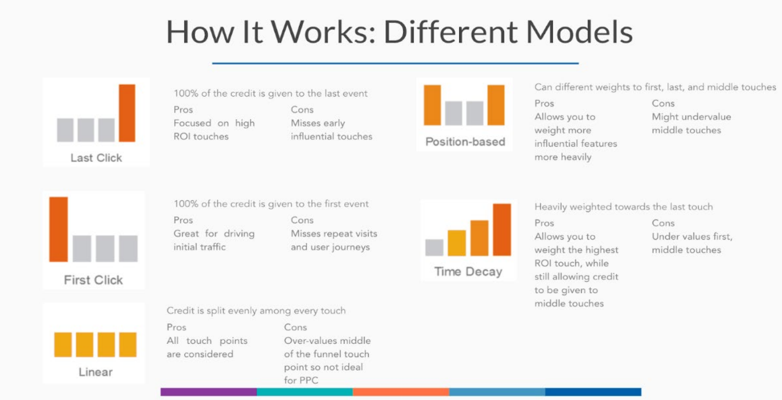
Every Industry Will Spend More on Gen AI



2023 Global AI Study from Lucidworks

Impacting Typical Commerce KPIs Using AI

Before getting into the numbers, understanding how to get there is essential. Attribution modeling is a well-recognized method to link a capability or feature to its ultimate impact. In the case of generative AI use cases, this may be connecting a generative AI-powered search or chat dialogue session to a conversion and revenue event. For example, embedding CTAs (Calls to Action) within or around generative AI results, such as including a product add-to-cart or category link to measure corresponding checkout value.



Pros and Cons of Using Different ROI Metrics in Commerce Search and Product Discovery

Context is another essential factor in measuring impacts. Shopper behaviors vary widely by context; therefore, including this in your analysis is highly recommended.

Typical B2B KPIs for merchandising and search product discovery in e-commerce that focus on incremental impacts for a given time frame include:

Adoption/Usage:

Measures the increase in usage of a specific feature such as search traffic. This also includes a relative increase against other touchpoints such as browse and chat. This primary metric is the basis of most other metrics, which are based on/close to, and a good indicator of how well your experience is performing. Measuring adoption across your keyword distribution and growth rates on tail vs. head keywords indicates more confidence users have in your search.

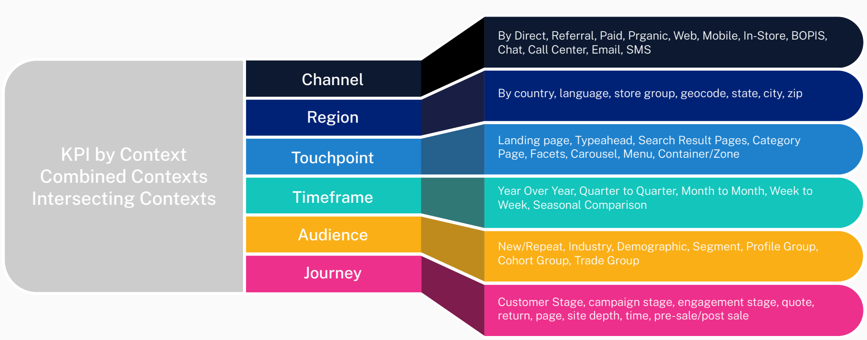
Relevance:

Measures the percentage of product click events — click-through rate (CTR) and click-through position (CTP) — on a product listing page, such as a search or category result. A high CTR shows that outcomes are appealing and relevant. The associated CTP is also essential. For example, a higher frequency of clicks occurring on the first ten results indicates better rank relevance and corresponding value vs. clicks occurring lower in the result list. CTR behavior by touchpoints such as mobile vs. desktop yields an essential perspective as the variation in the amount of screen real estate and corresponding experience generally impacts these metrics significantly. It is, therefore, necessary to ensure that the result is visible (impressions are occurring) to the user, such as above the fold (ATF). The CTP metric is relative to the number of visible results/impressions on a page. Heatmap tools can also be used to facilitate the collection of this metric.

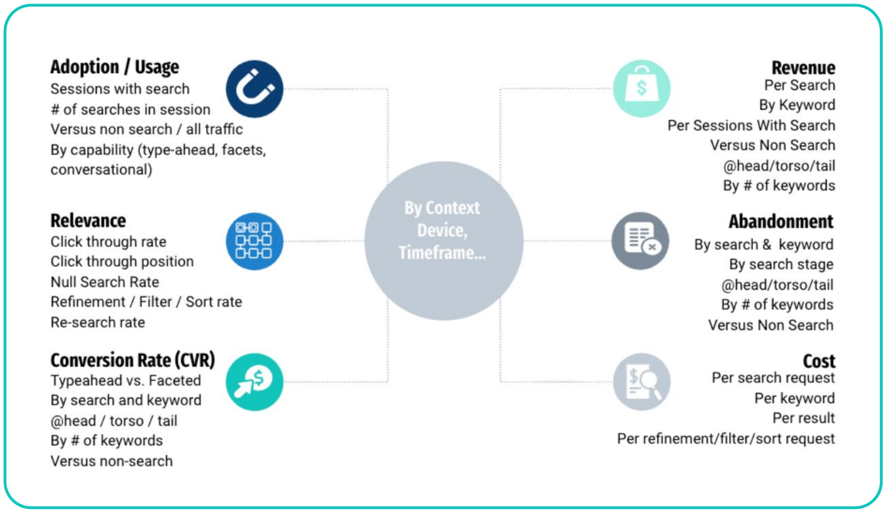
Conversion Rate (CVR):

Measures the percentage of website visitors who purchase due to interaction, for example, the search conversion rate for purchases attributed to search results, keyword conversion to measure keyword performance, and category/landing page conversion for navigation-related conversion. Standard CVR metrics include CVR for sessions with search, keyword CVR, head/torso/tail CVR, and CVR based on the number of terms. For conversational applications, CVR by chat or conversational session would be

Measurement Contexts Used in Analysis



used. When using AI-driven browse, category and node conversion rate is used. Facet conversion rate, where the use of facets leads to a conversion event, should also be considered. Intersecting conversion rates, such as keyword by page, gives a much more precise level of insight and attribution. A higher conversion rate indicates more effective overall merchandising strategies, such as the combination of using AI to position a product(s) at the right time, right place, right price, and availability for that given customer shopping moment.



Revenue:

Revenue per search and revenue per keyword track the average amount a customer spends in a single transaction attributed to a search and specific keywords/phrases or a conversation thread. Effective product discovery can lead to higher AOV. It is also essential to track revenue influence at a line item level where possible to help more precisely measure the impact of a specific search or conversational session on that product purchase.

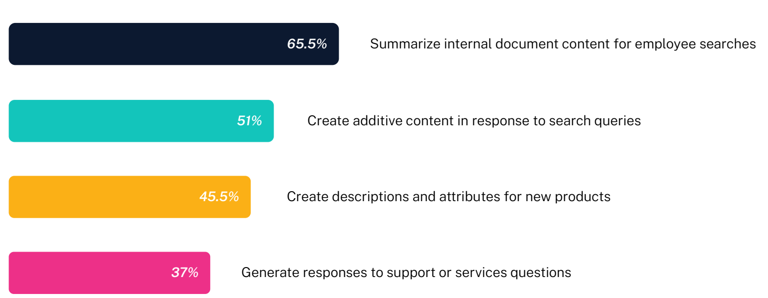
Abandonment Rate:

Abandonment rate should be tracked by every touchpoint/module powered by the AI. This tracking should be at the component level to better isolate the source of the abandonment. For example, for components that use search, including typehead, facets, or carousels with search, the search abandonment rate tracks the percentage of users who initiate a search but don't click on any products. Similarly, if using an AI-powered search for browse pages, browse abandonment would be tracked. For product detail pages (PDP) and checkout where recommenders may be used, product abandonment and checkout abandonment would be used. Search / Browse exits & bounces could also be included in this metric, though Lower abandonment rates indicate successful search experiences.

Cost:

To complete any monetary impact analysis, granular cost input data is required. In the search case, understanding the total price at a request level, such as at a query level, is ideal. Through an attribution model, you can then link the cost with the revenue. For example, connecting a query to the associated product and its final price in a checkout event. Standard cost variables that are used for AI-driven search include query volume, query type, query size or # input tokens/prompts, result side or # output tokens, the size of the index (ex. # of document), size of documents, how frequently they are updated, and how they are updated (ex. Attribute level, or entire record). Backend costs, such as the cost to index and train models, should be included. Measuring human resource costs such as manual merchandising rules, engineering, maintenance, and support need to be accounted for as well.

How would your search and/or knowledge discovery department(s) use AI in the next 12 months?



2023 study from Lucidworks and Google Cloud of B2B manufacturing professionals

These KPIs help B2C and B2B e-commerce businesses assess the effectiveness of their product discovery and merchandizing strategies, enabling them to make data-driven improvements and enhance the overall shopping experience for customers.

Use-Case Deep Dives and Expected Outcomes

Now, let's explore five ways that AI, ML, and generative AI could be used to improve the commerce search and product discovery experience and possible costs and outcomes.

#1 Product and Content Enrichment Using AI

AI Measurement by e-Commerce Search Use Case

Proposed Use Case	How to Measure	How to Estimate Costs	Expected Outcomes
Product and content enrichment.	Ideally, maintain the unenriched and enriched product or content record version at the individual attribute level. Randomly route traffic to one version vs. the other through A/B test, query pipelines, or experimentation framework that can track metrics such as click-through conversion, revenue, and returns resolution rate of each version.	Cost factors include the number of documents/records to be enriched, the number of fields to be enriched, and the type of enrichment (e.g., visual enrichment vs. Generative AI enrichment, the size of each enrichment, such as the number of tokens or embeddings.	Recall and relevance improvement leading to lifts in clickthrough conversion rate, search revenue, increased longtail exposure and revenue, SEO (organic acquisition growth), service improved resolution rate, deflection rate, reduced returns rate, and abandonment rate. Improved merchandising control and performance due to additional attribution/ tagging: increased depth and granularity of analytics and insights.

e-Commerce Search ROI and Outcomes Scenario:

In a fictional scenario, a B2B e-commerce company invested $1.5 million in AI and ML technologies to enhance their product and content enrichment strategies. They aimed to improve merchandising control, enhance performance attribution, and gain deeper insights through increased data granularity. With AI-driven content tagging and enrichment, the company could tag products with color, size, style, and more attributes. This precise tagging allowed for more effective product display categorization, filtering, and customization.

The company observed a significant 12% increase in the conversion rate and revenue growth of $10 million over the year as more visitors turned into paying customers. It also reduced manual content tagging efforts and saw a 30% reduction in labor costs associated with data enrichment. These results indicate a 6x return on investment.

#2 Improve Search Query Understanding Using AI

AI Measurement by e-Commerce Search Use Case

Proposed Use Case	How to Measure	How to Estimate Costs	Expected Outcomes
Improve query understanding.	Measure refinement, re-query rate, synonym usage rate, click-through conversion rate, and time/steps to outcomes such as transaction or resolution. Measure the number of rules and time spent maintaining rules, and test the impact of existing rules against no rules in this scenario. Evaluate this against the existing incumbent query pipeline.	Number of queries, size, or number of tokens/queries. Number of calls/requests per query, size of response returned. Depending on the approach, if using embeddings or other semantic enhancement on ingest/indexing documents, cost inputs would include the number of documents, size of documents, the number of sections in a document, etc.	Reduced search abandonment and improved search-attributed and long-tail revenue. Dramatic reduction in manual rules and corresponding overhead.

e-Commerce Search ROI and Outcomes Scenario:

In a fictional scenario, a B2C retailer invested $100,000 in Gen AI and LLMs to enhance query understanding for its online store — the result is a 20% boost in conversion rates. With the improved search experience, customers found products more efficiently and made more purchases. The retailer estimates that this increase in conversion equates to an additional $12.7 million in gross revenue, surpassing the LLM investment by 4x in total profit from the improvement.

#3 Improve Intent Detection and Personalization Using AI

AI Measurement by e-Commerce Search Use Case

Proposed Use Case

Improve intent detection and personalization.

How to Measure

Map out all contexts and touchpoints of the customer journey to be impacted by personalization. For example, the impact of personalizing a new customer landing page or paid ad landing page.

Measure and attribute at the page/screen component level where personalization is enabled (e.g., Slot, Recommenders, Carousel, Zone, Listing Grid, Facets, Navigation, Content Zone, Chat).

Measure changes in engagement rate, click-through, conversion, and revenue attributed to the component to eliminate influence from other components.

Measure the click-through position, particularly above the fold, and click distance from the first result.

Measure purchase friction through steps/path and time to purchase, including subsequent keywords, filters, sorts, pagination, scrolling, and click position distance from existing rank.

If personalizing other components of the experience, such as facets and navigation, measure facet usage rate, facet click position, drill downs, and conversion rates.

How to Estimate Costs

Personalization can incorporate numerous systems such as a customer data platform, marketing platform, e-commerce, search, recommenders, email, and more.

Summarize cost across all systems used to service a personalization request. These will include the type of request (for example, a personalized prompt for an LLM vs. typeahead vs. personalized search results vs. category landing page vs. a recommender).

The type of personalization model used can influence cost, such as a clustering model vs. a regression model.

Choosing a time frame such as real-time individualized personalization vs. batch-segmented personalization can also dramatically influence the cost basis.

Expected Outcomes

From a topline perspective, personalization can improve return on ad spending, campaign spending, revenue, AOV per visit, engagement rate, click-through rate, conversion rate, abandonment rate, retention rate & customer lifetime value.

From a bottom-line perspective, personalization can reduce the cost of campaigns by reducing the amount of unnecessary targeted/qualified touches, and generative AI such as LLM can minimize input and output tokens through more efficient personalized prompts and more focused responses.

From a customer service perspective, reducing time and steps to resolution improved resolution rates and increased self-service adoption.

e-Commerce Search ROI and Outcomes Scenario:

In a fictional scenario, a prominent e-commerce company embarked on a journey to enhance its customer experience by implementing AI and ML-driven search intent detection and personalization. The company allocated $2 million to implement advanced AI and ML technologies for improving search intent detection and personalization. They tailored the online shopping experience based on customer preferences, previous interactions, and real-time behavior. With better search intent detection, personalized ad campaigns became more effective. This reduced the budget allocated to irrelevant ad placements and optimized the targeting of high-intent customers. This led to:

Improved return on ad spending (ROAS) and a 20% reduction in campaign spending. Enhanced personalization drove a 15% increase in revenue.

The average order value (AOV) per visit was also substantially boosted. Visitors were more likely to interact with the website and complete purchases.

This resulted in a 10% increase in engagement rates, a 25% boost in click-through rates, and a 12% rise in conversion rates.
The company reduced cart abandonment rates by 18% by providing personalized product recommendations and content during shopping. By tailoring the shopping experience to individual customers, they experienced a 20% growth in CLV. With AI-powered chatbots for customer service, they reduced resolution time and simplified issue resolution.

The $2 million investment yielded a revenue increase of $50 million over the year, significantly reducing campaign costs.

#4 Providing Conversational Search Experiences Using AI

AI Measurement by e-Commerce Search Use Case

Proposed Use Case	How to Measure	How to Estimate Costs	Expected Outcomes
Provide conversational search experiences to improve engagement and collect more relevant information. NOTE: Conversational search is a free-form bi-directional dialogue that carries context from one interaction to another, such as through a conversational loop in a chat or virtual assistant, or could be embedded in the keyword search. This allows customers to express themselves more naturally and in more detail than a simple keyword search. A more significant deal of the customers' intent and context is divulged this way, improving several performance measures. This applies to several areas in commerce, including product findability, discovery, Q&A, customer service, quoting, and more.	More sophisticated measurements include feedback first/feedback after and cost based on corresponding gain. Measure adoption/usage rate, task completion rate, task completion time, task completion steps (e.g., roundtrips/clarifications), quote creation and completion rates for B2B, conversion and revenue/conversational sessions such as a chat, resolution rate, time to resolution, and deflection rate for customer service. More sophisticated measurements include feedback first / feedback after and cost based on corresponding gain. Source	Training and tuning costs, model hosting costs, type of conversational engine (e.g., intent-based vs. generative-based), cost per Q&A request, Q&A token size (prompt), cost for additional input of non-text types such as speech, telephony, cost for additional response types such as speech synthesis, cost of additional search types within a dialogue such as products, content, reviews, etc., and amount of data required both size and records.	Increased sales transactions due to decreased purchase friction (path and time to purchase). Increased revenue/higher AOV due to selling based on customer goal; increased goal detection through dialogue vs. single product need. For example, selling all the items required for a repair goal, such as a kit, or completing the look in apparel, cross-sells, and next-sells/next-best. The increased narrative from customers also reveals additional preferences such as price/discount propensity, urgency, and quality, for example, which can be used for personalized conversational responses that increase both conversion and revenue. Improved customer lifetime value due to higher repeat purchase rate and improved experience. Reduced returns through improved purchase accuracy due to more verbose needs collection. Deflection for support and sales calls while accelerating productivity scores for support and sales staff when used.

e-Commerce Search ROI and Outcomes Scenario:

In a fictional scenario, a forward-thinking e-commerce retailer invested in AI to improve conversational search and personalization. By allocating $2.5 million, they achieved the following improvements:

Decreased Purchase Friction:

Customers could engage in natural, dialogue-based interactions, leading to a 25% increase in sales transactions due to reduced purchase friction.

Higher Average Order Value (AOV):

Personalized conversations allowed the company to sell based on customer goals, detecting the entire scope of customer needs resulting in an AOV increase of 15%.

Cross-Sells and Next-Sells:

Identified opportunities for related products and next-best offers, leading to a 10% increase in revenue from this effort.

Personalized Conversations:

Conversational interactions also revealed additional customer preferences, such as price sensitivity, urgency, and quality expectations, increasing conversion rates by 18%.
Reduced Returns: Conversational search collected more verbose customer needs, leading to greater purchase accuracy and reduced returns by 12%.

The $2.5 million investment resulted in a revenue increase of $30 million over the year and significant cost savings due to reduced returns.

#5 Using Multiple LLM Models for Gen AI Search Experiences

AI Measurement by e-Commerce Search Use Case

Proposed Use Case

Using multiple LLM models.

NOTE: Applying the right tool for the job also applies to AI. Hundreds of public and commercial models solve certain use cases — for example, selecting the correct model type based on the data type.

There are models for text, such as LLMs; images, such as Computer Vision; and voice, such as speech models. There are domain-specific models within each of these model types, such as industry-specific ones.

There are also purpose-built models based on how they will be used,, such as enriching data vs. supporting conversational applications.

How to Measure

Identify and select models.

Create test pipelines for each model to route and measure evaluation metrics.

Incorporate both implicit and explicit signals to generate your metrics. The signals will vary by use case. Gen AI will depend on the use case and feedback mechanisms.

Evaluation metrics include:
-Accuracy
-Precision
-Recall
-F1 score
-AUC-ROC

The standard metrics, such as click-through rate, position, keyword conversion, and revenue, apply in the case of LLM-enhanced search. For LLM, use cases like conversational apps (e.g., virtual assistants) include the above mentioned metrics.

How to Estimate Costs

Training and tuning costs, model hosting costs, type of conversational engine (e.g., intent-based vs. generative-based), cost per Q&A request, Q&A token size (prompt), cost for additional input of non-text types such as speech, telephony, cost for additional response types such as speech synthesis, cost of additional search types within a dialogue such as products, content, reviews, etc., and amount of data required both size and records.

Expected Outcomes

Improve industry contextual responses, category specificity, search performance, quality, and accuracy.

Improved contextual understanding, resulting in higher converting and revenue-generating responses.

Improved performance, such as reduced response latency and higher scalability, due to handling more sophisticated tasks efficiently.

Reduced cost due to using a lean or distilled vs. general-purpose model.

Increased accuracy due to reduced noise in using a more generic model.

Reduced hosting/infrastructure cost.

Increased control over compliance and security requirements, such as running a private vs. public model.

e-Commerce Search ROI and Outcomes Scenario:

In a fictional scenario, a B2B technology e-commerce company leveraged multiple Large Language Models (LLMs), including finely-tuned models, to improve their industry-specific contextual responses, search performance, and quality. They invested $3 million in the effort. By using finely tuned LLM models, they achieved a 30% improvement in industry-specific contextual responses. This improved the quality and relevance of customer information and led to higher converting and revenue-generating responses. The utilization of advanced LLMs reduced response latency and increased scalability so the company could efficiently handle more sophisticated tasks and complex queries, resulting in a 20% boost in search performance. By transitioning from a general-purpose LLM model to more lean and distilled models, they realized a 15% reduction in operational costs. Their $3 million investment yielded a revenue increase of $50 million over the year, primarily driven by improved contextual responses, higher converting responses, and enhanced search performance.

Conclusion

In today's dynamic digital landscape, Generative AI powered by LLMs, AI, and ML are reshaping how B2C and B2B commerce businesses approach search and product discovery. The case for improved personalization, conversational search, search query intent detection, and product detail enhancement all impact the search and buy experience profoundly. In each case, it is possible to explore reasonable ways to begin small and execute with the intention of a realistic positive ROI, including growth and savings elements. These use cases showcase the potential of AI to transform the e-commerce landscape by enhancing user experiences, increasing conversion rates, and driving significant revenue growth.

Start Now

The commerce search experience is changing quickly, and those companies that wait to embrace that change (driven by AI) may need to catch up. In a recent global survey of executives, those involved in AI decision-making shared their intent to invest in Gen AI in the next 12 months, as captured below, with an average of 92% across all industries.

In a recent study from Lucidworks and Google Cloud of B2B manufacturing professionals, respondents indicated how generative AI will be used to improve the search and product discovery process in the future.

Get an assessment of using AI to improve your search and product discovery experience.

Lucidworks Google Cloud

Use AI to Improve Search Experiences with Solutions from Lucidworks and Google Cloud.

Lucidworks and Google Cloud deliver a complete solution for commerce companies looking to improve and measure the search and product discovery process using AI. With Lucidworks and Google Cloud, search professionals get a scalable, complete, best-of-industry solution through a proven partnership and delivery model. Lucidworks Fusion customers get an open, composable, enterprise-ready search experience platform powered by hyper-modern Neural Hybrid Search and AI. Google Cloud customers gain additional ways to utilize Google Cloud spend through an expanded array of joint solutions on the Google Cloud Marketplace.