Assessing Algorithmic Versus Generative AI Pricing Tools

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The use of pricing algorithms, and especially the impact of this practice on competition and consumer protection, has been of interest for some time.

The Federal Trade Commission, for example, has investigated possible roles played by pricing algorithms for nearly as long as algorithms have been employed. In a March blog post, it restated its view that "price fixing by algorithm is still price fixing."

The advent of large language models, or LLMs, that are powering generative artificial intelligence tools, such as ChatGPT developed by OpenAI, opens a new era in the field of algorithmic pricing.

These off-the-shelf tools can be used to perform a wide variety of tasks, including designing pricing recommendations, without requiring advanced technical expertise like pricing optimization methodologies, and importantly, without the need to acquire and maintain expensive market data for training the pricing models.

By potentially providing cheap and effective tools, LLMs hold the promise of decreasing barriers to entry and improving competition in several industries.

At the same time, given their relative newness, several important questions emerge. Can LLMs be used to generate sufficiently high-quality pricing recommendations? What are the pros and cons of using LLMs for pricing recommendations? Given the easy access to such tools, should regulators and practitioners be concerned about the competitiveness of market outcomes when managers use LLM-based pricing recommendations?

Businesses, regulators and litigators will need to understand what is different — and what is not — when relying on LLMs to price products or services.

What Is a Pricing Algorithm?

Experienced managers understand how to optimize prices if they have firsthand industry experience and high-quality data. However, information-gathering and processing consumes time and resources in an era when pricing strategies must adapt quickly — often in real time — to rapidly evolving competitive landscapes.

With careful calibration and testing, algorithms can make that process almost instantaneous. A pricing algorithm is a bespoke model specifically designed to make pricing recommendations based on inputs and explicitly defined objectives, such as profit maximization.

They can generate pricing recommendations at speeds and capacities humans cannot attain. Some also allow for continual learning, becoming more precise and efficient over time. In addition, they can be constructed so that they are less prone to biases that may taint human decision making.

The use of pricing algorithms is common nowadays in numerous industries, including e-commerce, travel and hospitality, and ride-sharing. Typically, pricing recommendations in industries such as these have multiple dimensions — e.g., regular price, dynamic adjustments, personalized discounts and incentives — and require methodologies and assumptions of varying complexity.

For instance, while some basic algorithms employ simple logic-based rules — if-then-else statements — others use sophisticated machine learning and optimization methods.

The universe of potential pricing algorithms includes naive algorithms, economic modeling-based algorithms, price-testing experiments and advanced proprietary algorithms. Algorithms vary in their complexity and degree of sophistication, and their results vary according to their intended use, the quality and quantity of available data, and the targeted industry.

What Is an LLM?

An LLM is a computational model capable of understanding and generating human-like language. These models are trained on vast amounts of text data and can identify and utilize statistical relationships within the language. Users can write prompts to off-the-shelf LLM applications like ChatGPT for a specific task and receive an answer.

These features allow the LLM to be a flexible tool, as the guidelines or instructions are tailored to each prompt and not hardwired into a set framework, as in other algorithmic pricing tools. Consequently, a business manager could write prompts explaining their business setting and asking the LLM to generate pricing recommendations for their products or services within that context.

With an LLM, all the knowledge required to answer the prompt is embedded in the model parameters. An LLM provides answers and insights based on the data that was ingested and used during its training phase.

LLMs are easy to access and, with some basic information about a market and its consumers, can potentially provide data-driven pricing recommendations.

For example, one could provide an LLM with information on a product's marginal cost, as well as past market prices and volumes, and explicitly ask the LLM for a pricing recommendation that maximizes the long-term profits. One can also take this exercise to the next level by adding contextual information — data about inventory levels, supply chain information, etc. — in the prompt with the hope of receiving a more refined answer.

While LLMs can increase access to AI technologies and yield procompetitive market outcomes, the quality of the prompt plays an important role in the quality of the answer. More specific and tailored prompts will likely generate more accurate and precise price recommendations. Thus, pricing differentiation may be driven by the ability to provide the most appropriate prompt containing the most pertinent information.

Comparing Traditional Pricing Algorithms and LLM-Based Pricing

Although LLM-based price recommendations are algorithmic and iterative by nature, they differ in many ways from other algorithmic pricing tools. The table below provides an item-by-item comparison of typical algorithmic pricing tools and LLM-based pricing tools.

	Algorithmic Pricing Tools	Large Language Models
Licensing and Deployment	▪ Typically, proprietary software sold by vendors or developed by individual firms using proprietary data.	▪ Publicly available generative AI models that can be used to provide immediate pricing recommendations without requiring long lead times or customization.
Input and Data	▪ Historical market data such as prices, volumes, inventory levels, and other macroeconomic factors that may affect demand. ▪ Rules and parameters embedded ("hard-wired") in the model to optimize prices within a specific, set framework.	▪ Prompts written by users, which optionally may use high-quality historical market data for better-quality pricing recommendations. ▪ Knowledge of the industry is essential because the quality and the precision of the prompts will have a direct impact on the accuracy and the precision of the pricing recommendations.
Advantages	▪ Precise, sophisticated, and efficient, when the modeling is done right and the quality and quantity of the data are appropriate. ▪ Can implement complex pricing strategies that would be difficult to accomplish manually. ▪ Can operate rapidly and at a large scale (e.g., personalized prices that vary dynamically). ▪ Can validate the quality of the pricing recommendation before deployment. ▪ Reproducible; produce reliable and consistent prices given the same inputs.	▪ Pre-trained, off-the-shelf models are turnkey to use, therefore lowering cost and barrier to use, which may accelerate their adoption. ▪ Can democratize pricing as LLMs don't require technical expertise. ▪ Not imposing a preset framework allows exploration of new, innovative pricing strategies.
Risks	▪ Assumptions of preset framework for the market can be a limitation in complex non-stationary scenarios where pricing needs to consider other nuanced factors. ▪ Lack of transparency and explainability; risks annoying customers if basis for price changes is not clear. ▪ Can have biases, if not designed appropriately. ▪ Costly to hire internal resources to address potential biases and transparency considerations.	▪ Design is generalized and not specialized to the task of pricing. ▪ Logic behind LLM recommendations is opaque, not easily understandable, and can make it challenging to justify pricing decisions to stakeholders or regulators. ▪ Outputs of LLMs depend on the training data, so specific contexts (e.g., geographies or industries) may be over-represented, hence leading to biases. LLMs rely on established AI technology providers to address potential biases. ▪ May not necessarily produce reliable and consistent pricing

A Pricing Tool for the Masses?

LLMs offer a cheap and effective tool for designing pricing recommendations, as minimal technical expertise is required from managers, and they incur no development costs. In addition, proprietary data isn't required, unlike most other pricing algorithms. LLMs thus provide small firms access to a new tool that can help with pricing decisions.

However, the use of these tools for pricing is likely to also be scrutinized by policymakers, as is happening with other algorithmic pricing tools.

Importantly, LLMs can improve competitiveness through democratization of access to advanced tools. At the same time, the quality of the prompts is likely to emerge as a key differentiator in terms of the quality of pricing recommendations.

By providing access to companies that could not afford customized, expensive pricing tools otherwise, LLMs may offer the potential to increase competitiveness in markets where gathering pricing intelligence and being reactive to market dynamics is difficult or expensive.

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