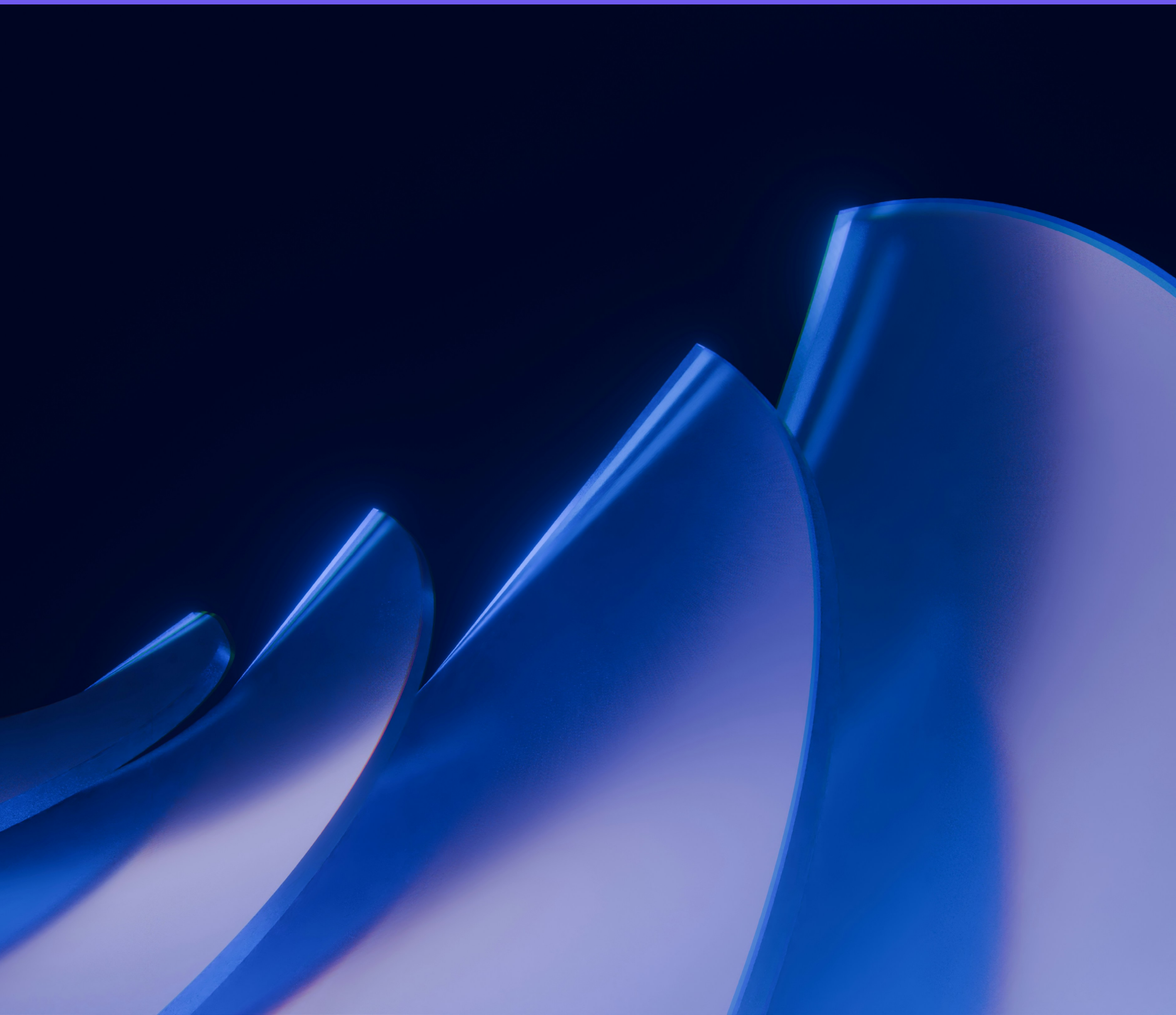
Buynomics

2026

The Evolution of Pricing From Simplistic to Simple



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01:

Introduction

Introduction

Pricing is one of the key levers of a company's financial success. For example, McKinsey claims that a 1% improvement in price yields a 6% improvement in EBITDA, while a 1% improvement in costs only increases EBITDA by 2%[1]. However, achieving improvements in pricing is notoriously difficult. This is, because the success of offer changes depends on how shoppers and competitors react.

Today, most companies collect a wide range of market data to assess customer preferences, their sensitivity to price changes, how competitors price their products, and how this affects market shares.

However, the results of these efforts are often fed into over-simplistic models such as those using price elasticities to capture the complexities of a market. This over-simplification can be very costly. Before switching to Buynomics , one client increased the price of a key product by 15% and saw sales drop by over 67% at a cost of over €25m. Their price elasticity model had predicted a sales loss of only 14% and a profit gain of €1m.

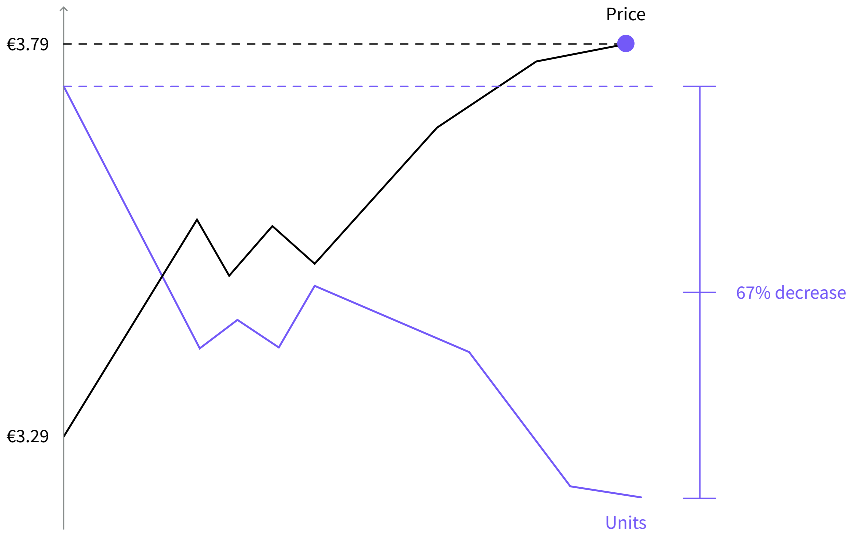


Figure 1: Price changes and resulting sales effect (source: Buynomics case example)

[1] Baker, W., Chopra, M., Nee, A., & Sinha, S. (2019). Pricing: The next frontier of value creation in private equity. McKinsey & Company. Retrieved December 1, 2025, from https://www.mckinsey.com/business-functions/marketing-and-sales/our-insights/pricing-the-next-frontier-of-value-creation-in-private-equity

Most of today's pricing tools such as price elasticity, price architectures, and competitor pricing come from a paper-and-pencil era to allow managers a quick ballpark assessment of the effects of price and product changes on sales. However, they are fundamentally inadequate for dealing with the complexities of differentiated price changes in a portfolio and assessing the interdependencies between different products.

Buynomics' proprietary Virtual Shoppers AI was developed to serve as the foundation for all shopper insight and commercial decision-making. It enables manufacturers to run agent-based simulations to predict shopper behavior with precision.

Virtual Shoppers AI integrates multiple data sources (including sales and transaction data, customer surveys) with advanced AI to understand shopper switching behavior and willingness-to-pay (WTP). Grounded in behavioral economics and decision theory, the Buynomics AI creates Virtual Shoppers that replicate shopper buying behavior, accounting for cannibalization and interactions with competitor products.

Leading Consumer Packaged Goods (CPG) manufacturers use Buynomics Virtual Shoppers AI to assess the effects of price, portfolio and promotion changes on sales, revenue, and profit. This allows them to make more predictable and profitable commercial decisions.

Buynomics is rapidly expanding into the retail sector, bringing its proprietary Virtual Shoppers AI to pricing challenges that traditional rule-based and price-elasticity tools struggle to handle. Instead of relying solely on aggregated historical elasticities, Virtual Shoppers AI learns from transaction and market data to create millions of virtual shoppers whose choices mirror real behavior.

With Buynomics, retailers can simulate price moves and see how shoppers are likely to switch between products, packs, and tiers and what that means for sales, profit, and price image. This lets them move beyond focusing only on key value items (KVIs) and manage the entire shelf with a single, consistent behavioral logic, always optimizing for the objectives they set whether that's profit, volume, or a sharper value perception for customers.

In this whitepaper, we provide an overview on current pricing methods and their shortcomings. Further, we will introduce the Virtual Shoppers technology that is the core of the next generation of pricing technologies, and we outline its benefits and applications.

Introduction

The pricing challenge

A company has two principal tasks: value creation and value capture. The former is performed across a range of departments from procurement to production, logistics, and others. The latter is guided by the company's strategy and largely implemented via its pricing – and it is the key to achieving the company's long-term profitable existence. Therefore, a well-executed pricing strategy supports the overall strategy of the company. For example, if a company is following a growth strategy, this would benefit from a pricing strategy that emphasizes increasing sales volumes over profit. In contrast, a company that is already close to its natural market share would benefit from a pricing that balances sales increase with profit growth.

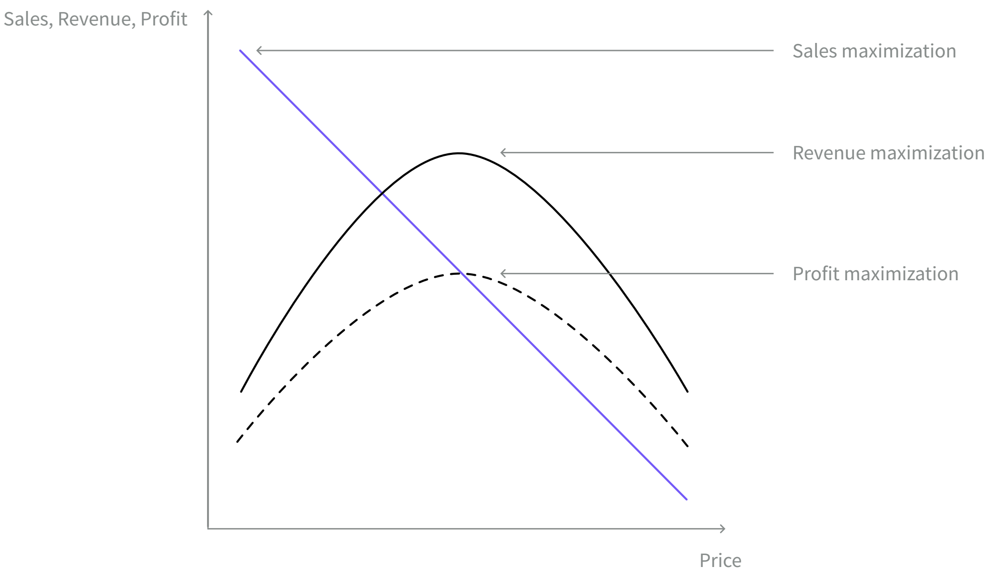


Figure 2: Principal pricing objectives (stylized)

It is useful to differentiate between three principal pricing objectives that companies can pursue (see Figure 2):

- Sales or market share optimization:
  This implies prices at the lower end of an industry to attract shoppers new to the market and from competitors. Sales maximization is not a sustainable strategy, as competitors often join in lowering prices igniting a price war – and this typically results in a money losing endeavor.

- Revenue maximization:
  This generally implies higher prices than sales maximization. However, very often a pure revenue maximization strategy is not profitable.

- Profit maximization:
  This objective generally leads to the highest price levels that can be justified. Few companies follow a pure profit maximization objective, as this often implies prices above the market level. Also, identifying the profit maximizing portfolio in a complex market environment is difficult.

In our experience, most companies aim for an objective between revenue and profit maximization, which is commonly termed a profitable growth objective. Depending on the overall strategy, this may be closer to the revenue or profit optimum.above the market level. Also, identifying the profit maximizing portfolio in a complex market environment is difficult.

The complexity of market dynamics makes achieving these objectives challenging in practice, as both buyers' and competitors' actions and reactions to price or product changes are difficult to anticipate:

- Buyers can decide to buy or not to buy a product. They choose between alternative products that differ in their quality, brand, or size based on their individual preferences. These preferences can differ greatly between shoppers.

- Competitors also offer products, run marketing campaigns, and change prices. Sometimes, they react to each other – sometimes, they adjust for other reasons.

Different methods have been used to address this complexity and help pricing managers make good decisions. To understand these, let's take a quick look at the roots of today's pricing methods and tools.

Introduction

The roots of pricing

Pricing is as old as money, and the question of how to set prices and offer products has long played a central part in people's lives. Early writings such as the code of Hammurabi (18th century BC) or the Bible emphasize the importance of fairness in price setting to ensure peace within the community. For example, Leviticus 25:14 states that "when we make a sale or buy from our neighbor, you shall not wrong one another."

Neoclassical economists such as Alfred Marshall developed quantitative models around the end of the 19th century to understand how supply and demand are matched[2].

Using the mathematics of calculus, these models allowed the study of the dynamics of markets in specific cases such as monopolistic (one supplier), oligopolistic (few suppliers), or polypolistic (many suppliers) competition. The price elasticity of demand ε, or just price elasticity, has its roots in these models, and it is of particular interest to pricing today. It measures how demand changes (ΔQ/Q) with price changes (ΔP/P):

$$\varepsilon = \frac{\Delta Q/Q}{\Delta P/P}$$

For example (see Figure 3), if the price of a product is increased by 1% and the demand reduced by 2%, then the price elasticity is -2. Generally, demand is called inelastic, if $0 \geq \varepsilon \geq -1$ and elastic if $\varepsilon \leq -1$. The price elasticity is useful, because it allows for a quick and easy assessment of the effects of a price change.

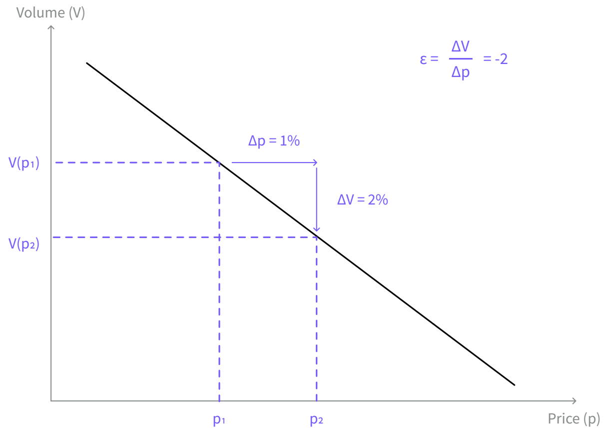


Figure 3: Visualization of price elasticity

[2] Marshall, A. (1890). Principles of Economics. London: Macmillan and Co.

Another key pricing concept, value, can also be traced back to its neoclassical roots. In the early 19th century, David Ricardo studied the implications of differently productive resources on the profitability of competitors[3]. Specifically, he looked at how more fertile land that produced more crops with the same effort allowed farmers to generate a profit (a Ricardian rent) compared to farmers with less fertile land. This offered an economic explanation for why more fertile land was more valuable. It is noteworthy that neoclassical works generally focused on commodities.

> Nowadays people know
> the price of everything
> and the value of nothing.
> Oscar Wilde, The Picture of Dorian Gray

Therefore, the concept of value was first attached to specific scarce resources that allowed for cheaper production and not to differentiate products.

The emphasis on customers valuing different products differently came later with the emergence of branded products and with shoppers preferring products from specific regions or countries or manufacturers over others. The tools to assess such differences are rooted in psychology, particularly conjoint analysis[4]. Conjoint analyses are widely used to measure shoppers' willingness-to-pay for products and their features (see Figure 4).

Which of these smartphones would you buy?

Brand	**iPhone**	**Samsung**	**Sony**	**None**
Screen Size	5”	6”	5.5”	-
Color	Silver	Turquoise	White	-
Price	$1,200	$1,100	$1,000	-
	Choose	Choose	Choose	Choose

Figure 4: Conjoint Analysis

[3] Ricardo, D. (1817). On the Principles of Political Economy and Taxation. London: John Murray.
[4] Green, P.E. and Srinivasan, V. (1975). “Conjoint Analysis in Consumer Research: Issues and Outlook,” Journal of Consumer Research, 5(2), pp. 103-238.

Conjoint Analysis

Conjoint analysis is a statistical technique to determine how people value different product attributes that make up an individual product or service. To determine how they value specific attributes, survey participants are asked to choose between product variations that consist of varying attribute selections.

The last key influence on pricing is behavioral economics, which – starting in the 1960s – emphasizes the role of people's decision-making heuristics and how they affect their decisions. Examples of such heuristics relevant for pricing are[5]:

- Substitution: A complex decision is replaced with a simpler one. For example, complex products that consist of hundreds of attributes are reduced to a simple decision between brands and a few key features. For pricing, this can be exploited by optimizing a product with a focus on these key features.

- Anchoring: For people, it is much easier to evaluate something in relation to something known. For example, if shoppers must come up with their willingness-to-pay for some product that they don't know, their assessment can be anchored with a reference price (e.g., "list price: €99").

These different roots are often difficult to reconcile in actual pricing, because they are based on different assumptions. Take behavioral pricing and price elasticity as an example. While price elasticities are based on the assumption of rationality and atomistic demand to allow for the use of differential calculus, the starting point of behavioral pricing is the acknowledgement that people are not rational and make inconsistent decisions. With that in mind, the next section will address current pricing methods that have evolved from the roots just outlined.

[5] For a general overview on behavioral economics see: Daniel, K. (2017). Thinking, fast and slow. For an overview on behavioral pricing see: Chen, H., Hardesty, D., Rao, A., & Bolton, L. E. (2021). "Introduction to special issue on behavioral pricing," Journal of the Association for Consumer Research, 6(1), pp. 4-9.

02:

Traditional pricing methods

Out of these roots, five main approaches have developed that are employed – either individually or in combination – by most pricing professionals.

Traditional pricing methods

Cost-plus pricing

As everyone who has ever priced a product knows, finding the right price is not easy. A very simple way to set a price is cost-plus pricing. It describes the practice of setting the price based on the marginal cost of producing a good or service and adding a mark-up. The mark-up is often based on what is considered usual in the industry, and it assures that the resulting price is comparable to competitor offers. Also, it allows – to some extend – to account for differences in the quality of inputs as these are often reflected in different costs. For example, a larger product variant uses more material, therefore costs more and is sold at a higher price. A prominent example is the food pricing by restaurants that widely apply a 300% markup on their wholesale costs, which implies a 75% margin before rent, labor, and other fixed costs.

Cost-plus pricing is often unjustly mocked for only looking at cost and not at competition or value to the shopper[6]. However, it is arguably in line with the traditional view on pricing that focuses on fairness and often works well in established and stable markets. Further, price increases triggered by cost increases are automatically passed on and they are often more accepted by customers.

It does not work well in dynamic markets with many price changes or promotions by competitors, or for products with high capital and low marginal costs such as software or in telco or hospitality.

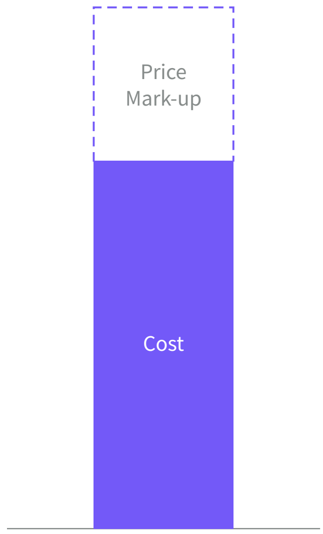


Figure 5: Cost-plus pricing

[6] Dholakia, U. M. (2018). "When Cost-Plus Pricing Is a Good Idea," Harvard Business Review. Retrieved November 30, 2025, from https://hbr.org/2018/07/when-cost-plus-pricing-is-a-good-idea

Traditional pricing methods

Competitive pricing

Competitive pricing is similar to cost-plus pricing in that it marks-off from a reference point (see Figure 6).

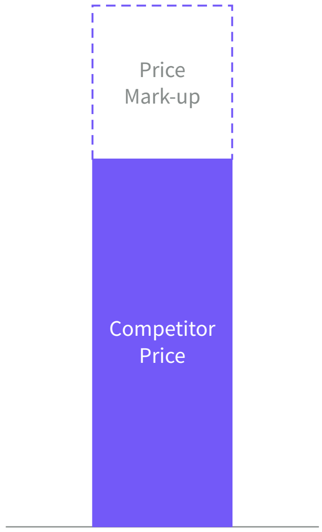


Figure 6: Competitive pricing

Here, the reference point is the competitor price. In practice, this might either be the average price of key competitors or the price of a market leader. The latter is often called the price leader – for example, the firm that sets the industry's price and all others follow. The obvious advantage of competitive pricing is that it saves a lot of effort, because once the reference competitor price is identified, only the mark-up or -down needs to be decided. In most practical cases, firms decide on the mark-up or -down based on their assessment of how premium their products are versus the benchmark. For smaller companies that operate in a market with transparent competitor prices and clear price leadership by some dominant competitor, this can be a good approach.

The core problem here is that this method does not provide a consistent order of magnitude for the mark-up or -down, nor does it explain which products are perceived by shoppers as relevant alternatives. Also, the method does not answer the question of how a change in reference price or mark-up affects sales.

Finally, we must not underestimate the risk involved if competitors reference price each other without considering constraints relative to cost or value to the customer. Figure 7 demonstrates this in the example of an obscure biology book on Amazon ("The Making of a Fly"), which was offered by two sellers that had automatically and continually reset their price relative to the other. This had gone on unnoticed until the price of the book had reached $23.7 million.

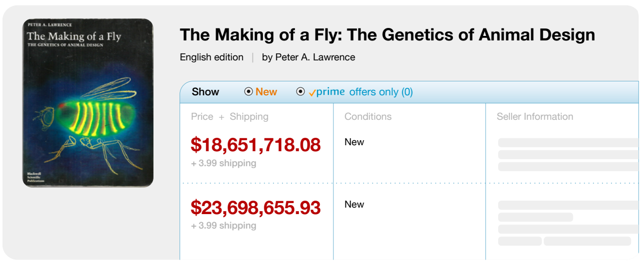


Figure 7: Price of "The Making of a Fly"

Traditional pricing methods

Price elasticity-based pricing

The use of price elasticities introduced in the previous section is straightforward. If a pricing manager knows a product's price elasticity, they can easily model the effects of a price change on sales, revenue, and profit for that product. Furthermore, if only the price of one product needs to be optimized, the profit optimum can be calculated using this formula:

$$\varepsilon \cdot m = -1,$$

where ε is the product's price elasticity and m its margin (p−c)/p. For example, if a product's price elasticity is -2, then a margin of 50 percent maximizes the profit. With unit costs of €100, the profit-maximizing price is then €200. Further, the revenue-maximizing price is at a price elasticity of -1.

Price optimization using price elasticities in a portfolio, for example, in a good-better-best offer, where prices and sales between products interact, is much more difficult. In most cases, no analytical solution is easily available. Because a share of the sales that are lost if the price of one product is increased will stay within the portfolio, prices in a portfolio can be higher than if products are optimized individually. Therefore, in a portfolio[7].

$$\varepsilon \cdot m \leq -1$$

[7] To measure cross effects between two products, that is how the sales of one product changes with the price change of another, pricing theory offers the concept of the cross-price elasticity. However, in practice the cross-price elasticity is very difficult to measure, and it changes massively with price changes in either product.

Price elasticities are widely used in practice, because they reduce the complexities of market dynamics into a single number that can easily be used for pricing decisions. There are different ways to determine price elasticities ranging from survey to sales data analysis[8]. Most common are regression-based analyses of the price-sales relationship using historical sales data. Figure 8 shows a typical example of such an analysis. The graph shows weekly sales and price data that indicate a general trend such that sales decrease with price, after the data have been corrected for effects such as seasonality, weather, or competitor promotions.

There are several challenges with such analysis. These include the choice of the demand function (e.g., linear or exponential), the identification and exclusion of "outliers" that do not support the expected relationship between price and sales, and the way the price elasticity is computed from the regression line – as the price elasticity varies along the curve. Furthermore, such models often suffer from poor fit quality, as typical regression models – linear or otherwise – do not capture well the dynamics and customer choices that determine sales in a market. Therefore, in practice such price elasticity analyses are often tweaked to support the expected result.

To sum up, price elasticities are a bit like sausage, everyone likes them, but no one wants to know how they are made.

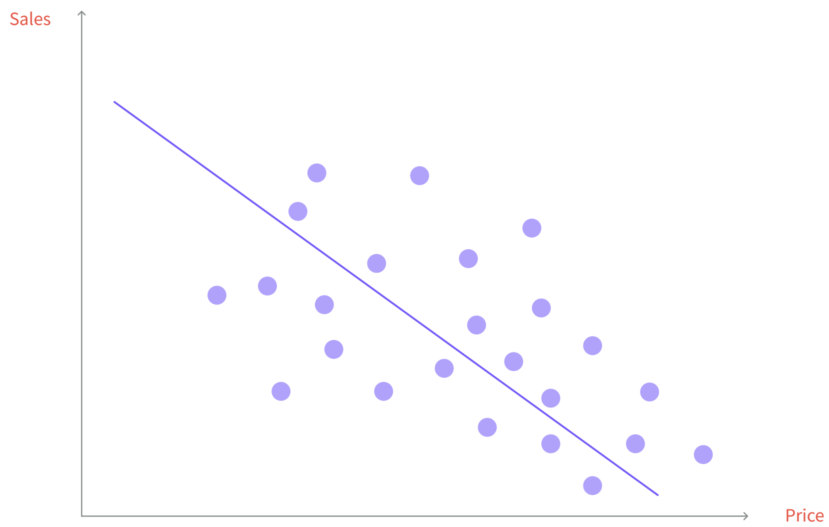


Figure 8: Regression-based price elasticity analysis

[8] The example is based on an actual case, but the values are anonymized.

Traditional pricing methods

Value-based pricing

The core idea of value-based pricing is to price products based on their value to shoppers. If there is only one shopper who has a maximum willingness-to-pay of €10 for a certain product – and that is known to us –, then value pricing suggests that we should ask for €10. Further, if we add a feature to that product that is worth €5 to that shopper, then the total value-based price is €15. In general, with value-based pricing, the total value of a product can be determined by aggregating the individual values of the product features. This can also be used to define a product architecture for a range of products. Figure 9 shows an example of value pricing for ski jackets. There can be variations of how attribute values are computed, but the additive model shown here is most common. A multiplicative aggregation using markups is also common in practice. If in the ski jacket example, the mark-up for down filling is 20% and the mark-up for water column > 15,000mm is 20%, then the price for the blue jacket is €250 * (1+0.2) * (1+0.2) = €360.

Therefore, a multiplicative aggregation leads to more extreme prices at the upper and lower price range.

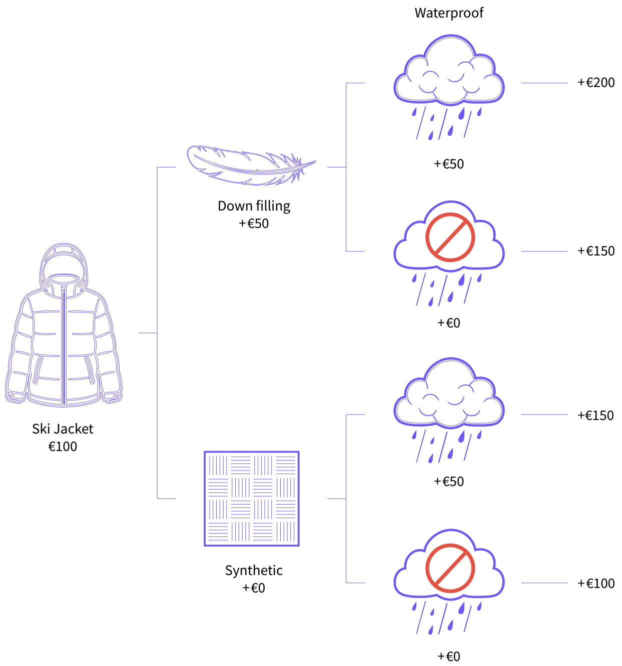


Figure 9: Value-based pricing example

[9] Dholakia, U. M. (2016). "A quick guide to value-based pricing," Harvard Business Review. Retrieved November 30, 2025, from https://hbr.org/2016/08/a-quick-guide-to-value-based-pricing

If there is more than one shopper, and each shopper has a potentially different willingness-to-pay, then value-based pricing becomes a bit more difficult. If selling to a mass market as in the ski jacket case, then practitioners often work with averages across the market or within subsegments to determine the mark-up or -down for specific features. For example, after conducting a market study, a pricing manager might conclude that the overall average willingness-to-pay for down vs. synthetic filling is €50, or that within the segment of shoppers who prefer down to synthetic, their willingness-to-pay for down is €50.

This example already shows that while the basic idea of value-based pricing is simple, its application is not and leaves room for different approaches. Herein also lays a key problem with value pricing. Where price elasticity-based pricing makes a prediction on how sales will react to price changes that can be tested in practice, value-based pricing makes no similar prediction, and it is now straightforward to test, if a value-based price was successful or not. In general, there is a very broad range of approaches that are called value-based pricing, that differ in how values are determined and aggregated.

It is noteworthy that value-based pricing is not limited to B2C applications, but it is also used for B2B pricing. In the latter case, it is often used to determine customer-specific prices, rather than market prices as in the B2C case. This requires that pricing managers can determine if – for example – shoppers from industry A are willing to pay more or less than shoppers from industry B.

Traditional pricing methods

Behavioral pricing

Unlike the other methods, behavioral pricing does not offer a full recommendation, but rather it is used in combination with other methods such as value-based pricing.
For example, a price computed via value-based pricing is adjusted to the nearest price threshold using behavioral insights.

The starting point of behavioral pricing is the recognition rooted in behavioral economics that shoppers are not rational but rather use a range of simplifying heuristics to make purchasing decisions. For example, a pricing manager might decide to add a third product to a product range to serve as a decoy to make the other products appear cheaper.

Figure 10 shows a well-known example case. First, a wine vendor only offered the two bottles priced at €10 and €20. In this case, most shoppers go for the €10 bottle, because they are risk-averse and do not want to spend more than needed. If then the €50 bottle is added, the €20 bottle looks much more reasonable to most people, and they switch from the €10 to the €20 bottle. This behavior is considered irrational, because the preference between the €10 and €20 bottle should not be affected by the addition of the €50 bottle. However, it can be very profitable to consider such common and empirically stable behavioral patterns in setting up an offer.

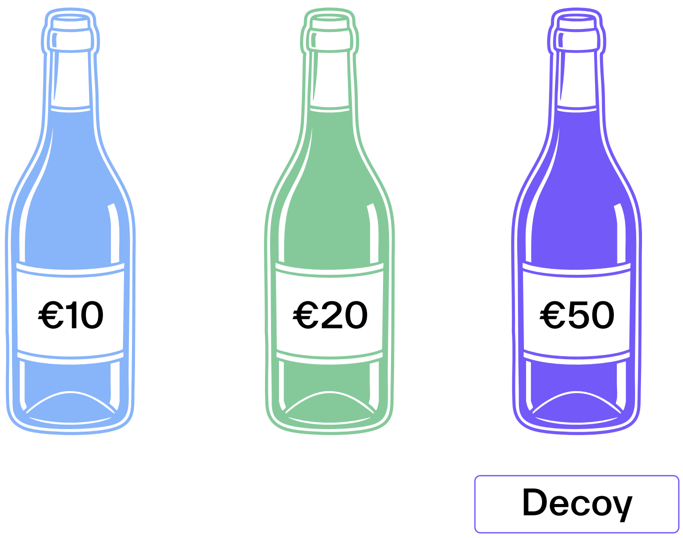


Figure 10: Example of decoy pricing

Figure 11: Overview of behavioral pricing effects

There are many behavioral effects that have been identified and can be used for pricing. Figure 11 provides an overview. The key problem with behavioral pricing as it is applied today is that it is not a consistent method but rather a selection of anecdotes and specific cases. For example, the above wine decoy example cannot be transferred into every industry. If shoppers have a good understanding of their requirements, they cannot be much influenced by a decoy. Also, behavioral pricing does not offer specific pricing advice. For example, should the decoy wine be priced at €40, €50, or €60? In sum, many behavioral pricing tools are available, but there is no consistent guidance on how to best use them.

Traditional pricing methods

Integration of pricing methods

Most practitioners use the above pricing methods in combination. For example, the base price in a portfolio is determined via price elasticity analysis, and the product variants are then differentiated using value pricing – and the price is finalized using some behavioral pricing cosmetics (e.g., €9.99 instead of €10.00).

The problem with this approach is that the different methods are based on different assumptions, which makes it difficult to combine different methods. For example, value-based pricing looks at "the" shopper to assess the value of a product. Price elasticities imply that the value of a product differs between shoppers, as only some – and not all – will not buy a product anymore if the price is increased. Further, price elasticities with their roots in classical economics assume shoppers who make rational decisions based on their preferences. Behavioral pricing on the other hand is based on irrational shoppers. One common difficulty that arises from this conflict is the way price elasticities are used at price thresholds. Often, the price elasticity is simply increased if a price change crosses a price threshold – for example, from -2 to -3, so that the effect of the threshold depends on the magnitude of the price change, when at the price threshold actually a certain percentage of shoppers is lost, independent of how large the total price changes is.

In sum, the different pricing methods cannot be integrated into a consistent method that is more than just the average of the results of incompatible methods. One of the companies that now uses Buynomics, had previously worked with a consulting firm that had produced recommendations using cost-plus, competitive, value-based, and price elasticity-based pricing. For an example product, the recommendations from the different methods were: €8, €12, €17, and €25. The consultants recommended just taking the average (see Figure 12) .

We at Buynomics find that these traditional methods are of great importance to learn about pricing and to understand the principal market mechanics using simplified case studies. However, they should no longer be used for actual and high-impact pricing decisions.

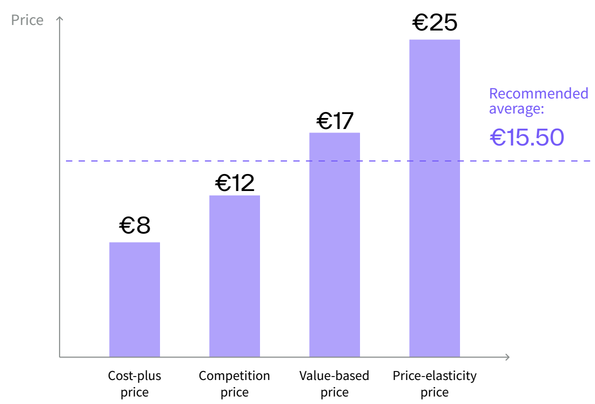


Figure 12: Price recommendations from different methods

03:

The current technology solutions

The current technology solutions

In practice, the above pricing methods are mostly used within an Excel environment (example in Figure 13). Based on our experience, that is true across industries and companies. Excel spreadsheets have been around since the 1980s.

Their benefits are clear:

- Flexible modelling, low cost of use, easy access and fast when making rough calculations. However, 40 years later they seem like an ancient tool closer to the paper-and-pencil era.
- They are not integrated with any other data models, they are impossible to scale across an organization, they lack predictive capacity, they are limited by your laptop's computing power, and the are unable to leverage self-learning algorithms.

Price elasticity based pricing

Price elasticity - 2,0

				Current				Target				
Product	Current Price	Cost	Price elasticity	Units	Revenue	Profit	Margin	Margin	Price	Units	Revenue	Profit
Own Peanut Brand 1000g	16,99 €	9,00 €	- 2,0	2.655	45.108 €	21.213 €	47%	50%	18,00 €	2.365	42.577 €	21.289 €
Own Peanut Brand 750g	12,99 €	6,00 €	- 2,0	725	9.418 €	5.068 €	54%	50%	12,00 €	850	10.195 €	5.097 €
Own Peanut Brand 500g	9,99 €	4,50 €	- 2,0	575	5.744 €	3.157 €	55%	50%	9,00 €	708	6.376 €	3.188 €
Own Peanut Brand 250g	6,99 €	2,50 €	- 2,0	3.400	23.766 €	15.266 €	64%	50%	5,00 €	6.645	33.225 €	16.612 €
Competitor A 1000g	12,05 €		- 2,0	1.855					12,05 €	1.855		
Competitor A 500g	9,62 €		- 2,0	15					9,62 €	15		
Competitor B 1000g	12,49 €		- 2,0	1.510					12,49 €	1.510		
				7.355	**84.036 €**	**44.704 €**				**10.568**	**92.373 €**	**46.187 €**

									ice Decision
									16,99 €
Own	750g	6,00 €	5,00 €	3,00 €	14,00 €	12,99 €	12,00 €	14,00 €	**12,99 €**
Own	500g	6,00 €	5,00 €	2,00 €	13,00 €	9,99 €	9,00 €	13,00 €	**10,99 €**
Own	250g	6,00 €	5,00 €	1,00 €	12,00 €	6,99 €	5,00 €	12,00 €	**8,49 €**
A	1000g	6,00 €	3,00 €	5,00 €	14,00 €	12,05 €			
A	500g	6,00 €	3,00 €	2,00 €	11,00 €	9,62 €			
B	1000g	6,00 €	2,00 €	5,00 €	13,00 €	12,49 €			

Figure 13: Example Excel pricing tool

For the past decade, rules-based software has been developed by numerous providers that basically employs Excel-logic in a nicer interface – and are often cloud- based. Such tools come with most benefits of Excel while making usability and computing power less of a concern. But the fundamental framework of thinking about pricing remains the same. They lack predictive capacity and do not consider the customer view sufficiently. Mostly, they use the traditional methods described above and automate these based on simple rules like “if the price of competitor product A rises, raise the price of my own product B by X%”. A similar system was responsible for the above Amazon book example (see Figure 7).

More recently, automated price elasticity engines have emerged, that claim to employ machine learning algorithms to automate and improve the process of elasticity-based pricing. Given sales data, these solutions constantly calculate price elasticities and make automatic price changes.

However, being based on price elasticities, they typically ignore both the interaction between products stemming from buyers’ switching, and they are unable to properly include other important factors such as promotions, pack sizes, product features. All in all, these tools simply automate the use of a flawed concept, price elasticity. However, speed alone does not achieve sustainable profitability. Further, these price elasticity-based tools only focus on assessing price changes, and they cannot evaluate the effects of portfolio changes such as changes in product features, delisting of products, or the introduction of innovations. Given this status quo, it is obvious that a fundamental change is needed. This is where the story of Buynomics begins.

04:

The new paradigm: Virtual Shoppers

The new paradigm: Virtual Shoppers

Idea

The pricing methods described in the previous section build on mathematical tools that were developed to facilitate computations with only paper and pencil. While these methods are extraordinarily clever, they are not well suited to capture the complexities of actual market dynamics with dozens of products shoppers can choose from and the resulting interdependencies between different products. For example, research at Buynomics shows that a product's own price changes are typically only responsible for about 50% of the product's sales volume changes after correcting for seasonality and other effects that affect the whole market. The rest of the sales variations is caused by changes in other products in the market.

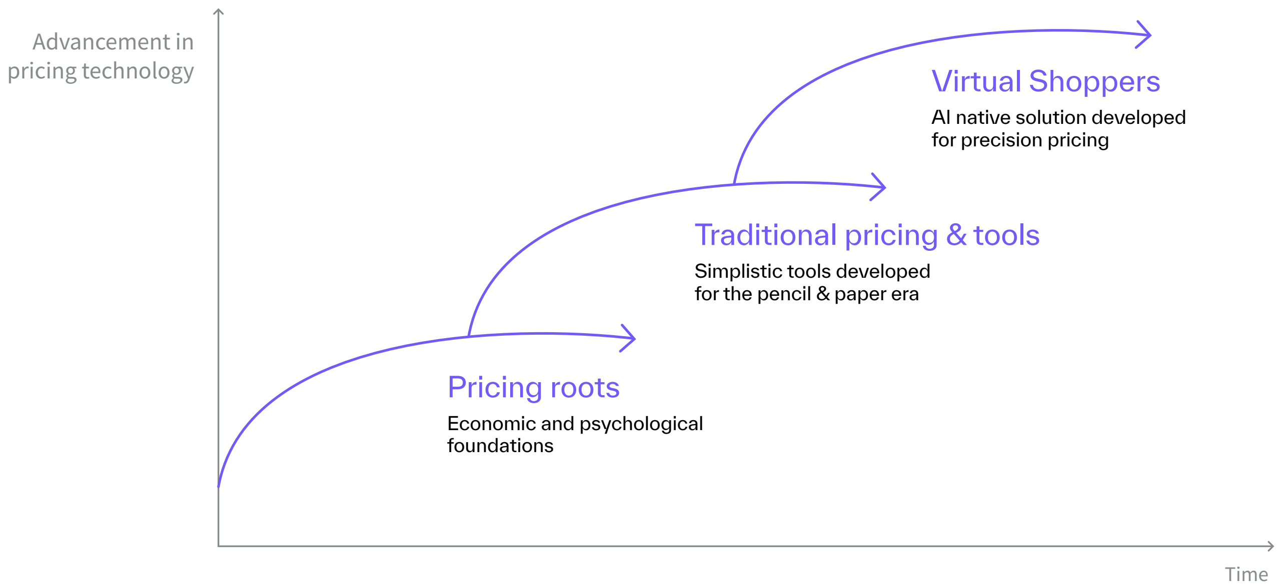


Figure 14: The advancement in pricing strategy

Using a computer to estimate a price elasticity does not make the result better or more useful than when it is computed by hand – it only produces the result faster. To make the best use of currently available technologies, a different approach is needed. Therefore, we at Buynomics have developed a new method that builds on large-scale simulations of shoppers' buying decisions to model how demand reacts to – for example – changes in product features or prices. This technology is called Virtual Shoppers AI , and the basic idea is that the buying behavior of actual shoppers in a market is replicated using Virtual Shoppers (see Figure 15). These have the same product preferences and behaviors as their real-life counterparts, and when shown real product offers, replicate the actual buying decisions of real shoppers with very high precision. Demand reactions to changes in an offer (e.g., a price increase) are then computed by counting the number of Virtual Shoppers who buy each product before and after the offer change. This allows the Virtual Shoppers AI precisely model how changes in an offer affect sales volumes across all products. If needed, price elasticities, cross-price elasticities, and other measures of market dynamics that help pricing professionals to manage their portfolio can be computed using Buynomics Virtual Shoppers AI .

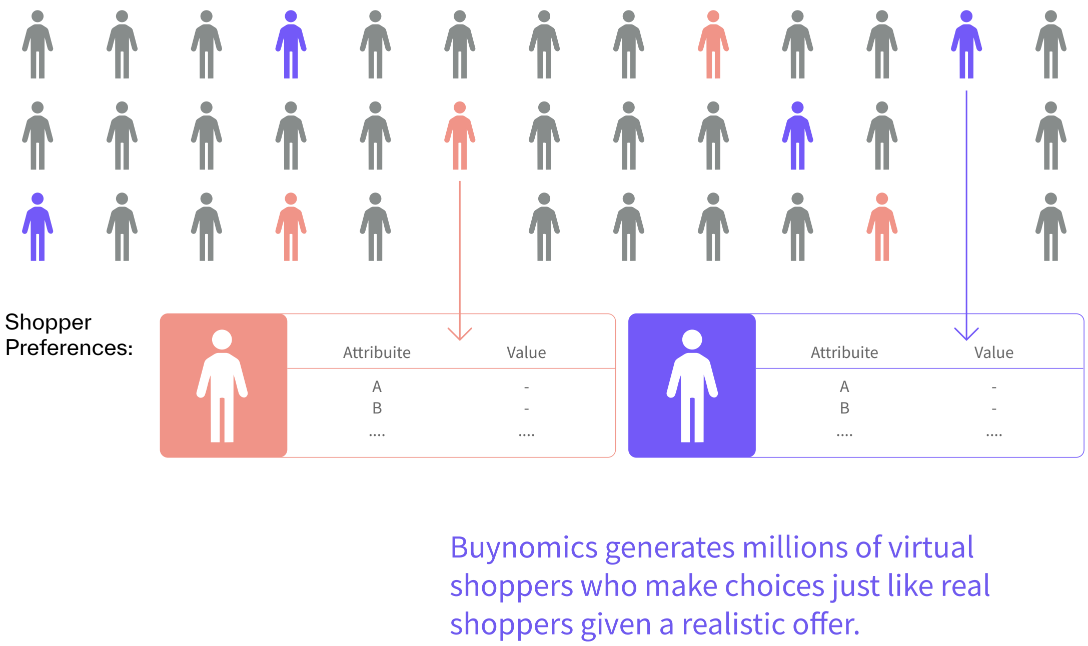


Figure 15: Virtual Shoppers

To demonstrate the workings of the Virtual Shoppers AI technology, we use the three-wines example from the previous section (see Figures 10 and 16). At prices of €10, €20, and €50, sales to the Virtual Shoppers of the three bottles are 100, 350, and 20 bottles. If now the price of the middle bottle is increased to €30, sales change to 130, 270, and 30. That means that the middle wine loses 80 bottles of sales. Of those, 30 go to the €10 bottle, 10 to the €50 bottle, and the remaining 50 bottles are lost because of the price increase. These changes result from each Virtual Shoppers's specific preference and purchasing decision.

The benefits of this approach are obvious. Where traditional methods such as price elasticities or shopper segmentations are overly simplistic in how they model reality, the Virtual Shoppers can precisely replicate actual sales dynamics in a market, if they are able to behave like real shoppers. With this, not only the effects of price changes can be predicted, but also the effects of any offer changes such as the removal or addition of a product or the change in a product's features, such as its size. Also, the cross-effects between products are easily identified, as the above wine example shows. Further, this technology does not require rational or irrational shopper behavior. Rather, it shows the different market outcomes if customers are rational or irrational. Therefore, Virtual Shoppers do not suffer from the incommensurability problems of traditional methods highlighted before.

The key challenge of the Virtual Shoppers AI technology lies in how they are created. At Buynomics, we have developed a larger set of techniques to assess key data sources and integrate them into a coherent Virtual Shoppers AI model that can then be used to answer specific questions. The available data sources typically differ between industries. They include sales data, pricing study data (e.g., conjoint studies, van Westendorp, Gabor-Granger), expert judgement, and data bases such as the Buynomics behavioral pricing effects data base.

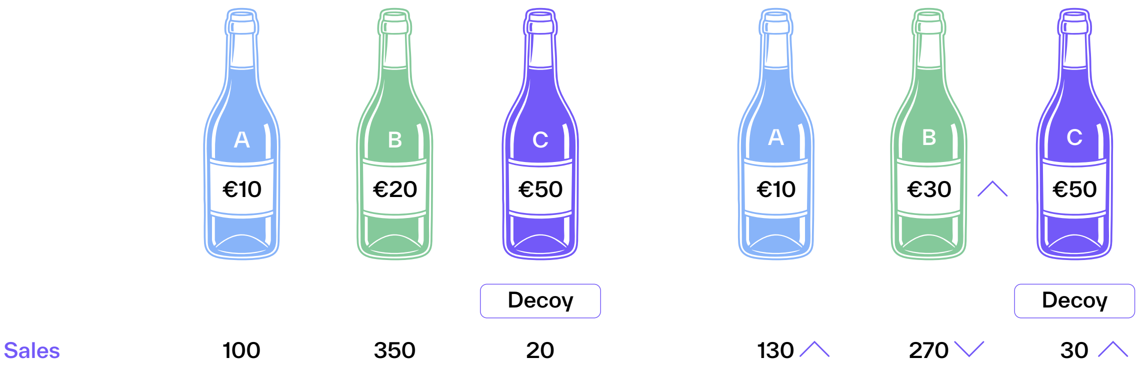


Figure 16: Changes in the units sold resulting from price change of the middle bottle

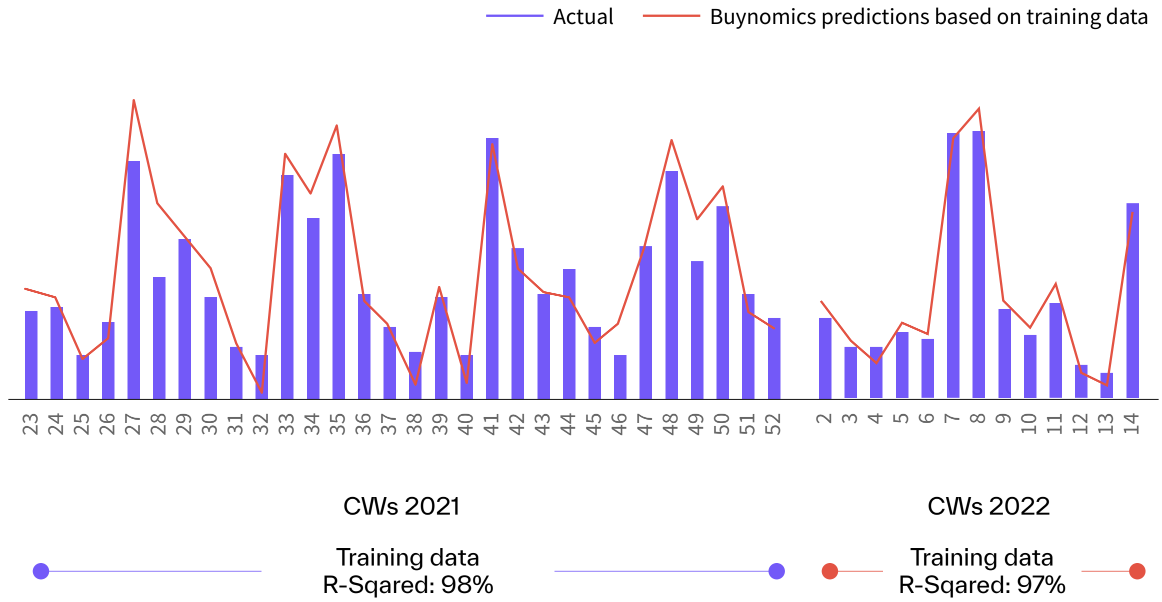


Figure 17: Training Virtual Shoppers - Actuals vs. Buynomics predictions (excerpt Buynomics case example, anonymized)

A great benefit of the Virtual Shoppers AI technology is that the different data sources can be integrated seamlessly, and the Virtual Shoppers can be updated with – for example – new sales data to account for changes in preferences over time or the effects of inflation on purchasing decisions. Using these data, the Buynomics tool generally achieves a more than 95% forecast accuracy.

Figure 17 shows the example of how Buynomics' Virtual Shoppers are trained with past sell-out data to forecast future sales. The data shown are for one product out of a category over time. The modeled sales for this product are based on the buying decisions of a trained sample of Virtual Shoppers that choose each week between all the products in the category given their prices, availability, promotions, etc.

The model also determined the sales of all the other products in the category, and it can determine the effect on all products if – for example – the promotion of one product is changes in one week. This allows net revenue managers to optimize their offer by identifying the optimal portfolio structure, prices, and promotions. The precision of this model is exceptionally high with a 97% accuracy in the testing period*.

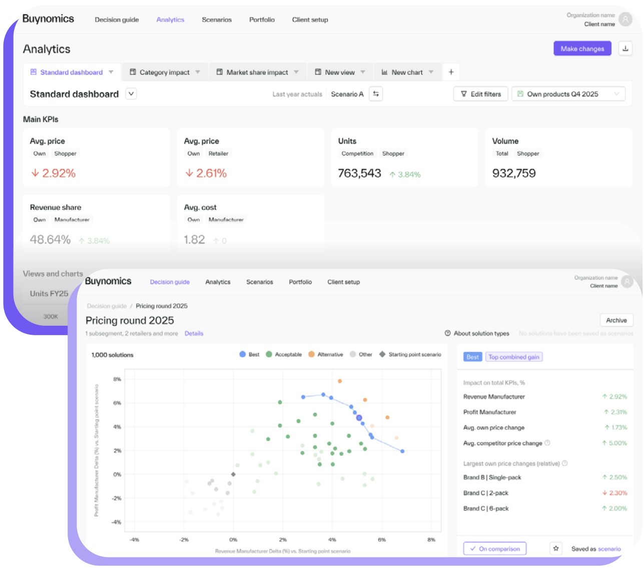
*Depending on data quality and completeness

The new paradigm: Virtual Shoppers

Benefits of the Virtual Shoppers AI technology

The Buynomics Virtual Shoppers AI technology comes with many advantages. Here, we list the most important ones:

- Unprecedented accuracy: Virtual Shoppers make decisions just like real shoppers. They consider the entire category including your other products and competing ones. This results in up to 95% forecasting accuracy[12]!



- Immense speed-to-insight: Virtual Shoppers can be asked about their purchasing decisions millions of times within seconds. This allows users to find the optimal portfolio combination in the blink of an eye.
- Better scalability: Virtual Shoppers react exactly like their real counterparts even in new channels and markets. This allows the solution to be deployed in any context, in any market by any team. Try doing that with the Excel model built 3 years ago.
- New way of working: Virtual Shoppers empower teams to engage in a fully digitized way of working. With their immense speed-to-insight users can answer more hypotheses in a shorter amount of time. Instead of waiting for the results of an 8-week market study, revenue managers can iterate their hypotheses in minutes to get more insights faster.
- Reduced data needs: Unlike other methods, Buynomics works with a very limited amount of readily available data. No need to add an endless number of studies or A/B tests to finetune the model. Get more with less.

[12] Depending on data quality and completeness.

The new paradigm: Virtual Shoppers

The first shopper centric retail pricing solution

Pricing is an immensely important profit lever for any company. But existing methods and solutions are stuck in the past, which leads to expensive mistakes and inefficiencies. Buynomics allows you to make informed decisions and develop shelf pricing with confidence, knowing how your shoppers will react.

Behavioral pricing is at the core of Buyomics software, providing recommended shelf prices based on how customers actually switch—not just on elasticities or rules of thumb. Built on switching and basket impact, our recommendations scale beyond Key Value Items (KVIs) while respecting guardrails and delivering clear expected impact.

Run agent-based simulations with Buynomics' Virtual Shoppers AI, accounting for switching behavior and basket effects, and turn them into shelf prices with clear, expected impact on volume, revenue, profit, and price index. All you have to do is bring the assortments, processes, data, and your expertise and we bring the proprietary Buynomics Virtual Shoppers AI, proven success, and deep pricing expertise.

Virtual Shoppers in action

Buynomics Virtual Shoppers AI learns how shoppers choose, switch, and build baskets from your transaction data and competitor snapshots. It then recommends shelf prices that respect your guardrails and price architecture, with clear expected impact on volume, revenue, profit, and price index.

Turn Data into Actions

Buynomics Virtual Shoppers AI is trained on your transactional data and competitor snapshots. The model is calibrated to your shoppers and your market, not a generic benchmark.

Predict Shopper Choices

It allows you to predict switching and basket impact across substitutes, complements, and price families, not just SKU level effects.

Optimize for Profit

Get price recommendations that maximize your companies targets while respecting KVIs, ladders, guardrails, and price perception targets.

Book a demo

and build the next generation of retail pricing, powered by Virtual Shoppers AI.

Peter Opzondek

Head of Retail Growth and Strategy at Buynomics

peter.opzondek@buynomics.com

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www.buynomics.com