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Collaborative product innovation model with large language models and agentic systems

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Abstract. *Product innovation* is critical in strategizing business decisions in highly-competitive markets. For product enhancements, the entrepreneur must garner data from a target demographic through research. A solution to this involves qualitative customer feedback. The study proposes the viability of artificial intelligence (AI) as a co-pilot model to simulate synthetic customer feedback with *agentic systems*. Prompting with ChatGPT-4o's *homo silicus* attribute can generate feedback on certain business contexts. Results show that *large language models* (LLM) can generate qualitative insights to utilize in product innovation. Results seem to generate human-like responses through few-shot techniques and Chain-of-Thought (CoT) prompting. Data was validated with a Python script. *Cosine similarity* tested the similarity of datasets to quantify the juxtaposition of synthetic and actual customer feedback. This model can be essential in reducing the total resources needed for product evaluation through preliminary analysis, which can help in sustainable competitive advantage.

Keywords: product innovation, qualitative customer feedback, ChatGPT-4o, agentic AI systems, *homo silicus*, large language model, few-shot inferencing, cosine similarity

1 Introduction

Before delivering a product to the market, the entrepreneur must face a crucial element in their business: price [4]. Price perception involves how the customer reacts to current prices against competition. Certain deviations may affect future growth of the business, although it would be fallacious to assume that there is a direct relationship [11]. Pricing also induces psychological factors to product consumption. In [12], the noted difference between perceived value and actual market value will lead to criticisms from the price conscious customer. In retail, similar products are often placed beside each other in dedicated aisles. The competition may result in certain decisions made between price to product quality. In a broader sense, the market can determine if something is worth purchasing at certain prices [12,11].

Customer feedback is crucial in understanding how customers view their products, which can aid in innovation. Businesses can observe how their prices are weighed against competitors [25]. This can guide the entrepreneur in adjusting their competitive strategy and position. Through innovation management [7], the business is able to identify three driving factors: 1) competition, 2) market demand, and 3) advances in technology. To protect market position or increase presence, the business must be able to distinguish which decisions may result in the most optimal results. Pricing is then also critical in determining whether this can propel the innovation of their business model by lowering production costs, changing marketing and selling strategies, and increasing their contribution and profit margin [33,28]. The price sensitivity of a target demographic can assess the competitiveness of the idea or business model. Quantitative analysis entails measuring elasticity, a conjoint analysis of the customer *willingness-to-pay* (WTP), including the least squares regression model, and various sales-to-volume experiments, without investigating psychological factors behind such decisions [3,2,14,17]. Qualitative analysis entails looking into customer backgrounds, spending habits, opinions on price, and *value perception* [20]. This can be retrieved from focus groups, research surveys, and interviews. It provides a significant insight on what influences the demand for products [14].

Product innovation involves the process of continuously enhancing the product, from the ideation phase to product launch and commercialization. Entrepreneurs engage with customers to foster co-creation rather than treating them as mere numbers of market validation. Hence, the business is able to deliver better value to meet customer demands [24,29,15].

Large language models (LLM) serve as computational models to human decision-making. *Homo silicus* [6] is one attribute of LLMs that enables such to be endowed with preferences to explore behavior via simulation. It functions as an economic agent that can provide synthetic responses based on stimuli. Understanding price and competition calls for more intricate systems such as the *agentic systems* as they have the agency to make their own decisions and nuanced feedback [27]. Layers of endowment must be employed for the agents to perform strategic thinking and selection upon a given task [26].

1.1 Objectives and Research Questions

The study aims to determine GPT-4o's ability to simulate synthetic qualitative customer feedback to produce price, in relation to other business environments. The primary objective is to observe how LLM simulation can aid in product innovation. This entails that the product is already in the market. To increase their position, the business must act quickly and stay flexible to meet market demands [5].

RQ1) What general approach may be considered to prompt ChatGPT-4o to simulate synthetic qualitative customer feedback given a specific product's price point?

RQ2) How well can ChatGPT-4o simulate economic scenarios and use human-based language to perceive product value using context settings and psychological intuition?

RQ3) What are some notable considerations when simulating the synthetic qualitative customer feedback?

It must be emphasized that the proposed simulation model does not intend to substitute real human feedback observed by sales teams and analysts. Instead of a replacement, the LLM is considered a co-pilot to aid in improving efficiency. This can aid in conducting preliminary feedback analytics for product innovation.

2 Review of Related Work

As presented in [15], product innovation was tested on its correlation with sustainable competitive advantage. Sample space results in a specific food product industry suggest that product innovation has a positive impact on competitive advantage. This entails gradual, but consistent product enhancements as a strategic endeavor to strengthen market position. These findings serve beneficial to the need of businesses to improve their product offerings [15].

Research conducted in [9] exhibited the ability of GPT-4.0 to generate a demand curve through the provision of price points towards a service business in a local school campus. The LLM was prompted to simulate customer WTP and generate some demand curve. [9] suggested that the agent-based modeling systems (ABMS) can be used for the simulation, but much is yet to be known about the psychological implications of their decisions. This does not discuss underlying factors behind price consciousness. By understanding the qualitative elements of expectations, the business can improve on delivery [19,18]. The law of demand is a theory that connects these concepts together [23]. By understanding all the implicit behaviors behind customer movement, entrepreneurs can identify the current pace of the market. This can place the observed demand in a more specific context and adjust both the product and business model further.

LLMs are able to find associations when fed with small amounts of information. This can allow the model to distinguish patterns and generate outputs in line with the data. The *few-shot inferencing* technique, as opposed to zero-shot inferencing which focuses on base prompting, [16,30] focuses on seeking relevant examples to train the LLM on. Including this can potentially increase its performance through more refined reasoning from data. [16] experimented on the LLM to generate text sentiments through few-shot prompting, and the results exhibited its potential use cases, however more room is still needed to improve accuracy. *Chain-of-thought* (CoT) prompting [32] can also be applied to give the LLM time to process information through its memory, understand associations, and simulate human interactions [9]. This can help prevent instances of hallucinations from various amounts of data. Although results depend on the LLM and prompting techniques, CoT can support higher level reasoning tasks [32].

Certain human tasks can be made more efficient with the use of LLMs, without the latter replacing the former. A study was conducted on the viability of a human-LLM collaborative approach [31]. This interaction was facilitated on

a data annotation task, showing that LLMs can be utilized as a supplementary tool to explain the rationales behind such given labels. Human decision-making must still be employed, as re-annotations can ensure more accuracy and validity [31]. Further studies can be geared towards increasing synthetic reliability in order to maximize task efficiency.

Experiments conducted in [8] compared synthetic feedback with real-world data by employing precision and recall analysis to provide medical diagnosis through document classification. Results showed that the ChatGPT-3.5 was not able to perform accurate classification using the ICD-10 coding system [8]. Further studies must be tested on its ability to classify other types of document and text [13]. In relation to customer feedback, LLMs can still be tested on their ability to rationalize given certain market contexts. Similar tools as precision testing can be employed to see comparison between synthetic and real feedback datasets. This can test the viability of AI in validation.

3 Methodology

The simulation shall be conducted with ChatGPT-4o. ChatGPT has been pre-trained on large sets of data, and is capable of natural language processing [1,34]. Moreover, the GPT-4o model is proposed to be more capable of complex tasks and natural human-computer interactions as the newer model [10]. Qualitative price sensitivity analysis shall be performed by prompting the LLM to generate a list of 70 customer sentiments based on certain parameters.

Three trials shall be tested on three businesses; two are real-world, and one is hypothetical. The personas shall provide feedback on the latter, which serves as the business of the user. This set-up could determine if agentic systems can propel innovation through insight. For purposes of this study, the researchers shall focus on skincare products. This was selected based on personal observations in the local market context.

Fig. 1. Proposed prompting framework to simulate customer feedback.

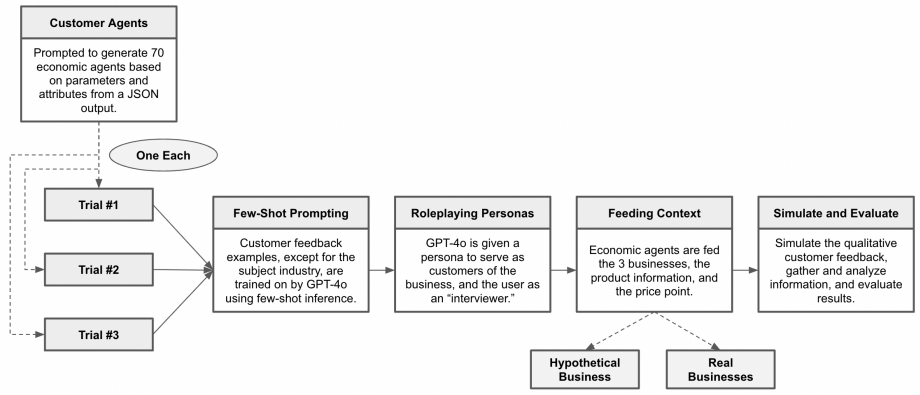


Figure 1 illustrates the prompting framework to conduct the experiment with the LLM. Patterns were retrieved from the prompting catalog [34] to increase LLM performance and avoid hallucinations. The personas are first generated as part of agentic systems, and are then assigned attributes that are dependent with one another. Temperature is set to one (1) to balance randomness and predictability, which can set customer distinctions. Customer attributes include age, gender, income level, education, degree, occupation, skin type, ethnicity, buying motivations, shopping method, and health consciousness.

A set of examples showcasing some usual customer feedback are provided. An informal Google search on 'customer feedback on products,' except for skincare products, yielded examples which were fed to GPT-4o for few-shot prompting. The LLM is given a *persona* to act as a regular skincare product customer. They may explain or simply provide feedback on different aspects of the product. Given the *context*, the LLM is asked if it understands the businesses and their products. This ensures that the LLM is able to process the information accordingly prior to the simulation. Using the *recipe* method, GPT-4o is able to look back into the conversation memory and cross-check the qualitative feedback results with the personas and the products [34].

Table 1. Example of the hypothetical business for purposes of the simulation.

Business	Description
Business Model	**Price**: Php 995 for 200ml; Php 1,795 for 400ml **Product Description**: Introducing our enhanced Shea Body Butter, the ultimate solution for dry skin. This moisturizer...donations from stakeholders. **Properties**: Deeply moisturizes and nourishes very dry skin. Provides lasting hydration for up to 96 hours. Infused with a pleasant nutty scent. Formulated with 97% naturally derived ingredients. Vegan certified and dermatologically tested. **Ingredients**: Butyrospermum parkii butter, water, yellow-5, citric acid, theobroma cacao seed butter, ..., and fragrance **Usage Instructions**: After proper cleansing and exfoliating, towel dry skin. Take a scoop of the Body Butter and apply generously or as needed to extremely dry areas of your skin, such as the knees, elbows, and feet. Allow the product some moments to properly absorb before dressing. Use daily to maintain nourished, smooth, and protected skin.

For purposes of the paper, the actual description in the user prompt was shortened. Entrepreneurs must conduct extensive market research to identify their competitors. Real products were retrieved from online search results on 'skincare products', serving as competitors to the hypothetical model:

- CeraVe PH Moisturizing Cream
- The Body Shop Moisturizing Cream

Prices were converted to Philippine Pesos (PhP) for this study. The synthetic business and product was formed from online search results of skincare products. This ensured a realistic depiction of the business in the simulation.

4 Results

A Python script, involving OpenAI's GPT-3.5 Turbo API, was programmed to conduct the *cosine similarity* test with synthetic feedback from all trials on actual human feedback for a skincare product that resembles the same hypothetical one above. It was done by calculating the cosine angle between two non-zero vectors, outputting a value from -1 to 1 [22]. For purposes of analysis, a similar high similarity threshold of 0.65 shall be employed [21]. The trials show following similarity scores:

Table 2. Similarity scores from all three hypothetical trials on real business 1.

Tool Used	Trial 1	Trial 2	Trial 3	Average
Cosine Similarity	60.47%	61.73%	59.45%	60.55%

In general, customer feedback generated nuanced opinions: positive, neutral, and negative. This proves useful to analyze different perspectives of the product.

Table 3. Examples of synthetic customer feedback from the hypothetical trials.

	Selected Feedback
Samples	**1.** Effective on my dry skin but it's a bit greasy. The scent is too strong for my liking. **2.** The moisturizing effect is good, but it leaves a greasy residue. **3.** I appreciate the natural ingredients and subtle scent, but I wish it absorbed quicker. It's good, but not great for my daily use. **4.** The product is good, but the price is a bit high for my budget. **5.** This body butter has helped my very dry skin a lot. I highly recommend it.

The feedback showcased the customers' value perception toward the product, albeit not much was said about its relation with competition. Results, however, offer some suggestions and comments which the entrepreneur can use for further enhancements. Initially, the study was conducted with the only parameter being the price of the product. However, as businesses become more complex, other factors must be considered about the model to help the entrepreneur improve on their existing strategies. Customer feedback was simulated based on the value perception of the generated personas.

5 Discussion

Results from the simulation yield the following discussion points:

RQ1) What general approach may be considered to prompt ChatGPT-4o to simulate synthetic qualitative customer feedback given a specific product's price point?

Prompt engineering is a crucial approach to inducing GPT-4o's response given a product. To maximize the LLM's homo silicus nature, the users must create a realistic task environment and hypothetical market scenario. This allows the LLM to generate economic agents that are attuned to the current market. Few-shot prompting appears to be essential. While LLMs generally attempt to think and write similarly to humans, few-shot prompting can refine the manner of decision-making, tone, and feedback. This may help increase similarity scores to the feedback desired by the user. Prompting GPT-4o to assume specific customer personas with preferences and purchase levers allowed the LLM to simulate feedback that is both realistic and up-to-date. Furthermore, the user can provide different price points, allowing the LLM to give a list of newer feedback from synthetic customers. This can then be utilized to generate insights on potential reactions to perceived product value, which is useful for innovation.

RQ2) How well can ChatGPT-4o simulate economic scenarios and use human-based language to perceive product value using context settings and psychological intuition?

Based on the scores above, the proposed framework can still be greatly improved. An average of 0.6055 does not yet imply a high similarity score with real human feedback, and therefore cannot be deployed in business development. Nonetheless, this serves as a significant headway in leveraging AI for product innovation. Further prompting tweaks and LLM capabilities can introduce the user to new features that can aid in increasing competitive advantage, and bring the numbers closer to 1.

RQ3) What are some notable considerations when simulating the synthetic qualitative customer feedback?

Considerations include the dependencies of the customer attributes. It must be ensured that the characteristics match other attributes (i.e. there is a correlation between the age and income level or occupation of the customer). The provided business models and price points should be comprehensive. Without this, the agents will not be able to produce human-like behavior based on the psychological implications of such prices. The user must consider the possibility that feedback may appear repetitive or patterned. In this case, further prompting techniques must be employed to avoid such. It is crucial to understand that AI-generated feedback must still be interpreted intently using human knowledge and intuition. Synthetic feedback may not always be "accurate" towards the business situation, as is the case with possible outliers. Regardless, they still provide relevant information that could lead to efficiency in product innovation.

6 Conclusion

ChatGPT-4o appears to replicate qualitative customer feedback with few-shot learning and agentic systems. Preliminary observations present the existence of psychological implications behind the responses, albeit more research needs to

be performed. The LLM is capable of simulating synthetic customer feedback generations through pre-trained data, but there is no certainty that it fully understands human interactions with existing businesses. NLP attributes and homo silicus can be explored using OpenAI's more recent releases of ChatGPT and other chatbots. Brand ambassadorship and presence could also be a relevant discussion, as customers tend to perceive value based on public figures that promote such products. As a note to future studies, different purchase levers may be explored, such as quantity, innovative features, marketing and communications strategy, among others. All these levers are relevant for businesses in driving sales and competitive advantage. Vertically, researchers can identify other aspects of a product that can further justify certain price points. Aspects such as laboratory tests and FDA approvals can help modify initial value perceptions. Alternatively, researchers can assess ChatGPT's capacity to create feedback on other industries, and see if there are differences in the feedback generated per industry. Down the line, researchers may pursue studies on further applications of value perception as done by LLMs. This can include the efficacy of AI-generated value perception for use cases like strategic planning, marketing and communications integration.

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