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Evaluation of a customer development simulator using large language model-based multi-agent system and synthetic respondents

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Abstract. Customer development (CD) is a Lean Startup (LS) methodology for startups to validate their business hypotheses and refine their business model based on customer feedback. This paper proposes designing a large language model-based multi-agent system (LLM MAS) to enhance the customer development process by simulating customer feedback. Using LLMs' natural language understanding (NLU) and synthetic multi-agent capabilities, startups can conduct faster validation while obtaining preliminary insights that may help refine their business model before engaging with the real market. The study presents a model in which the LLM MAS simulates customer discovery interactions between a startup founder and potential customers, together with design considerations to ensure real-world accuracy and alignment with CD. If carefully designed and implemented, the model may serve as a useful co-pilot that accelerates the customer development process.

Keywords: large language models, multi-agent systems, LLM-based multi-agent systems, GPT, ChatGPT, customer development, lean startup

1 Introduction

Customer development (CD) is the Lean Startup (LS) methodology of understanding customer needs and validating business hypotheses prior to launching a product [6,7,31]. Contrary to traditional product development, CD aims to develop an initial understanding of a company's potential customers, rather than creating a product then subsequently finding customers to sell it to [6]. CD is divided into four phases: Customer Discovery, Customer Validation, Customer Creation, and Company Building. The benefits of CD include reduced risk of startup failure, improved product-market fit, validated learning driving customer loyalty, and resource-efficiency [2,6,17,31]. Beyond business outcomes, customer involvement yields innovation [27].

While co-founders may launch products to market after development, involving customers in the innovation process may significantly enhance the product

by better aligning it with market demand. However, this approach is reliant on the company's financial resources [12]. To address this, startups can utilize pilots or *Alpha/Beta Testing* as a cost-efficient tool for early insights [6,26]. *Continuous deployment* and adoption further introduces rapid prototyping and dynamic feedback loops, accelerating the innovation process for those seeking to acquire early market validation [6,26].

Large language models (LLMs) can simulate customer feedback by using autonomous agents [15]. These agents are capable of simulating human-like decision-making. In pursuit of *Artificial General Intelligence* (AGI), progress entails the use of agents for CD [37]. Simulations complementing CD, regardless of the scenario, can be done at a faster and convenient rate, aiding in "getting out of the building" [6]. *Natural language processing* (NLP) and *understanding* (NLU) are attributes under AI that possess to the ability to identify the contextual meaning behind each word in an input, demonstrating AI's capacity to observe semantic relationships within an environment [10]. Advancements in these technologies have demonstrated its ability to conduct NLP and NLU tasks with *zero-shot prompting* [29]. LLMs can sufficiently simulate human language-based scenarios, instilling diverse and creative responses with clear directives towards the objective. With zero-shot prompting, LLMs can also generate responses without the influence of examples on question narrative [24]. This technique highlights the straightforward, independent, and flexible nature of LLMs in simulating realistic responses, resembling a "superposition of human authors" [30]. *Homo silicus* [18] explores the concept behind LLMs as agents for economic scenarios. This provides simulators with insights on synthetic agent behavior within controlled environments. In a startup context, LLMs are able to replicate conversations as a model that simulates human founders' and customers' abilities to validate ideas and share sentiments respectively [19,33].

A *multi-agent system* (MAS) is composed of autonomous rational agents that interact with each other, fulfill distinct tasks, and possess partial real-world perception [13,34]. Dividing labor among agents amplifies efficiency across cost, flexibility, and reliability [13]. Drawing from LLMs' communicative and specialized knowledge capabilities, *LLM-based multi-agent systems* (LLM MAS) introduce advanced applications for complex problem solving and real-world simulation [16]. In contrast to traditional LLM agents, LLM MAS exhibit diverse skills and capabilities that facilitate cross-agent collaboration, information retrieval or sharing, task efficiency, and action-oriented feedback mechanisms towards a shared objective [11,25,37], applicable in various areas of expertise and modern organizations [11]. Guided by NLP principles [23] and knowledge sources [22,32], these agents further exercise the ability to augment reasoning and communication to achieve consistency, reliability, and rationality [20]. Insights derived from NLP and LLMs proved to be useful in influencing strategic decisions and inculcating high customer satisfaction [1].

With the capability to produce quality synthetic data for market research, especially when context is provided [3,9], LLM MAS show promise in complementing and enhancing the customer development process of startups.

1.1 Objectives and Research Questions

This paper describes designing an LLM MAS for customer discovery. The study proposes a mechanism for testing business hypotheses via synthetic agents that assume the roles of a startup founder and customer, respectively, before actual validation with a real market.

RQ1) How can LLMs be utilized for their synthetic multi-agent and natural language understanding (NLU) capabilities to enhance the customer development process of startups?

RQ2) What considerations can be employed to ensure that interactions between LLM MAS agents yield high-quality data for refining startup ideas?

2 Review of Related Work

Startups struggle with assessing market demand for their business ideas, with no guarantee if their innovations for the market will prevail. Early customer discovery is optimal for lowering costs and increasing chances of success [28]. Research conducted on the health information technology (HIT) industry involved an eight-step approach: preparing the business model canvas (BMC), identifying interviewees, finalizing the business pitch, preparing interview questions, recruiting interviewees, conducting interviews, collating results, and revisiting the BMC [28]. Results showed that this eight-step methodology is useful in crafting successful idea implementation plans.

Idea validation is instrumental for developing roadmaps via market testing [21,4]. By asking potential target customers the right questions, a thorough understanding of market needs can be achieved. Machine learning (ML) and software engineering have been proven advantageous for idea validation [21]. The *Javelin Experiment Board* [38] handles business idea validation among startups. Through discussions with respondents, founders can assess product-market fit and evaluate an idea's usefulness to the target market. Although results suggest that this could minimize failure and validate the need for solutions, the method requires a considerable amount of resources to continue [38,8]. This framework builds upon actual human interactions, but can be used for synthetic customer validation and interaction. In this case, business idea validation using LLM MAS will be evaluated to determine if it could help minimize resources. Test results can help the co-founder pivot as needed and remain agile [7].

Customer discovery challenges startups to rapidly test business model hypotheses via out-of-the-building experiments. The goal is to accumulate feedback on all elements of the business model, such as product features, pricing, and distribution strategies, with a bias for nimble iterations or pivots [5]. This is done through two phases: (1) tests on customers' perceptions of the problem and problem importance; (2) initial showcase of MVP and its ability to address problem areas effectively.

LLMs have been tested as simulation tools for customer development [19]. Findings show that GPT-4 can generate *willingness-to-pay* (WTP) curves that resemble the law of demand, although its accuracy has yet to be validated. The paper thus argues that human co-founders could present their ideas to synthetic

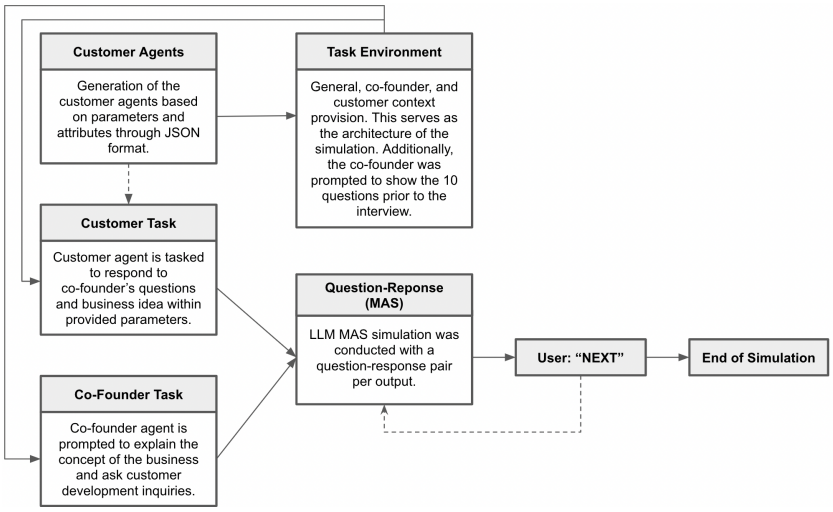
customer personas for initial market validation. However, the study only explored customer discovery with a single agent [19].

Simulations, as described in [14], serve as design and analytical tools for understanding reactivity to various environmental stimuli. The study presents MAS experiments that examine agents' reactive properties within a system. Numerous research and business applications support the significance of MAS implementation [13,14]. Users can also act as evaluators during the analytical stage of simulations, with results potentially contributing to advancements in future research or ventures.

3 Experimental Design

The researchers used OpenAI's Generative Pre-trained Model 4 (GPT-4) as the LLM in designing the simulation. To maintain consistency among results, memory retention for prompts was enabled. The design follows the customer development framework, focusing on customer discovery [5]. The MAS serves as a co-pilot for startup founders in facilitating customer discovery, designed to support real customer research activities. For this simulation, the MAS was given a business idea: a digital order-and-pay system enabling bars to maximize sales.

Fig. 1. Proposed design of LLM MAS simulation model.



Prompts were provided contextual information for better output. Prior to customer discovery interview simulations, GPT-4 was prompted to create 10 customer personas with realistic attributes, as seen in Table 1.

Table 1. Prompt used to formulate customer personas.

Objective	User Prompt
To create a JSON file of 10 customer personas which will be used in each conversation.	Generate a list of 10 random persona records in JSON format from a sample population and assign a value for the following attributes: {"Persona Number": [Number], "Age": ["18-24", "25-34", "35-44", "45-54", "55+"], "Gender": ["Male", "Female", "Non-binary"], "Income Level": ["Less than ₱20,000", "₱20,000-₱39,999", "₱40,000-₱59,999", "₱60,000-₱79,999", "₱80,000-₱99,999", "Over ₱100,000"], "Occupation": ["Student", "Professional", "Entrepreneur", "Freelancer", "Retired", "Unemployed"], "Customer Segment": ["Bar Goer", "Bar Owner"] "Frequency of Bar Visits": ["Never", "Rarely", "Monthly", "Weekly", "Daily"], "Tech Savviness": ["Low", "Moderate", "High"], "Payment Preferences": ["Cash", "Credit/Debit Card", "E-wallet", "Online Banking"], "Drinking Preferences": ["Non-Alcoholic", "Beer", "Wine", "Cocktails", "Spirits"], "Social Behavior": ["Solo", "Small Group", "Large Group", "Event Attendance"], "Dining Preferences": ["Eats at bars", "Doesn't eat at bars", "Prefers bar snacks", "Prefers full meals"], "Type of Bar or Restaurant": ["Small bar", "Medium bar", "Large bar", "Fine dining", "Casual dining", "Fast food"]}
Continuation	Ensure that there are an equal number of personas per customer segment. To the best of your knowledge, ensure the values are realistic and consistent with the other attributes. Not all of these attributes are independent from the others. For example,...but that is not true all the time.

Figure 1 illustrates the design of the LLM MAS simulation model. The co-founder agent was prompted to understand the customer's pain points and validate the business idea, while the customer agent was prompted to provide constructive feedback. The user input 'NEXT' prompted subsequent conversation pairs until all 10 questions were asked. CoT [35] and zero-shot [29] prompt

engineering techniques were used to structure conversations and prevent hallucination. Other prompting patterns were taken from [36]. The *persona* pattern managed the characteristics of both agents, whereas the *recipe* pattern was used with constant memory updates to build on existing knowledge. The *context manager* technique covered the entire process, resulting in a derivative of the flipped interaction pattern. Instead of asking the user questions, the MAS asked itself questions and formulated new insights based on its own past generated responses. A continuous cycle can be formed, unless the user states otherwise.

4 Results

Table 2 illustrates a selected sample of the results obtained from the LLM MAS simulations. It must be noted that this does not generalize other results. The simulations were split into two customer segments: bar goer and bar owner.

Table 2. Sample set of question-response outputs from a conversation.

Co-founder Agent Response	Customer Agent Response
Hello, thank you for taking the time to speak with us today. I'm the co-founder of [Startup], a startup that aims to revolutionize the bar experience by allowing customers to order and pay via their smartphones using a digital menu. Our system is designed to integrate seamlessly with existing bar operations to improve service speed and customer satisfaction. Given your experience with bars, I'd like to know: Can you describe a typical night out at a bar for you and what aspects you find most frustrating?	Hi, I appreciate the chance to share my thoughts. Well, as a retired individual who occasionally goes out to bars with a small group, I find that the biggest issue tends to be the slow service. Since I'm not very tech-savvy, I usually prefer to pay in cash, which sometimes complicates things, especially when it's busy. Bars that are smaller and more intimate tend to get crowded, and it's a hassle to get the bartender's attention. Plus, since I drink non-alcoholic beverages, sometimes I feel like I'm not given as much priority. So, any solution that could streamline this process and make it more efficient would be interesting to me, though I admit I'm a bit cautious about using new technology.

Continued on next page

Table 2. (Continued) Sample set of question-response outputs from a conversation.

Co-founder Agent Response	Customer Agent Response
That's very insightful, thank you. Given your preferences for simplicity and efficiency, have you encountered any problems with ordering or paying at bars? Could you share those experiences?	Yes, there have been a few instances. Often, I find the process of flagging down a waiter or waiting to pay at the counter quite cumbersome, especially during busy nights. There have been times when the noise and crowd made it difficult just to place an order. As someone who prefers to pay with cash, I also face the inconvenience of ensuring I have the correct change or waiting for change to be returned, which can slow down the evening. If there was a way to streamline these interactions, perhaps through a more direct ordering and payment system, it might alleviate some of the typical frustrations I face at bars.
That sounds like a valuable improvement. To further understand your needs, can you share how you think a digital order and payment system could change your bar experience?	I think a digital system could really streamline the entire evening. Not having to physically wave down a server to place orders or pay would reduce a lot of the stress associated with busy nights. It would be more relaxing to know that I can handle everything from my phone, especially in terms of payment security and not having to carry much cash. Also, the ability to see a running total of my tab on my phone would help me manage my spending better throughout the night. This kind of system could definitely make me feel more in control and potentially enjoy my outings more.

5 Discussion

This section examines the research questions of this study:

RQ1) How can LLMs be utilized for their synthetic multi-agent and natural language understanding (NLU) capabilities to enhance the customer development process of startups?

The simulation revealed that LLMs' MAS and NLU capabilities, combined with CoT prompt engineering, produce realistic customer discovery sessions. LLM MAS possess the ability to process diverse customer personas and subsequently generate contextualized and nuanced feedback on prompts aligned with customer discovery objectives. NLU complements this by fostering a humanlike conversational flow between agents and by selecting optimal responses based on analyses. Through these, valuable preliminary insights can be drawn to guide customer discovery, or used to enhance the customer development process.

RQ2) What considerations can be employed to ensure that interactions between LLM MAS agents yield high-quality data for refining startup ideas?

To ensure real-world accuracy and alignment with CD, the LLM MAS should be given comprehensive context about the business model, including real business assumptions, variable customer segments, and other critical components of the business idea. Attributes attached to customer agent personas must also be interdependent to ensure authenticity, reflecting nuanced problems present in actual market environments. When applied to the LLM, CoT prompting and conversational memory recall further yield optimal reasoning and dynamic learning mechanisms for quality simulations. However, it is important to note that guardrails must be set to mitigate bias and hallucination.

6 Conclusion

Early results of the proposed LLM MAS simulation model for customer discovery indicate consistency, but are subject to further evaluation. Outputs generated by co-founder and customer agents were thorough and consistent with human feedback, reflective of persona context and pain points. Future work may include testing the proposed design with real founders and customers and incorporating feedback in following iterations. Fine-tuning methods, varying MAS setups (e.g. one-to-many), and latter stages of customer development may also be explored.

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