This version of the contribution has been accepted for publication, after peer review (when applicable) but is not the Version of Record and does not reflect post-acceptance improvements, or any corrections. The Version of Record is available online at: http://dx.doi.org/10.1007/978-3-031-92823-9_14. Use of this Accepted Version is subject to the publisher's Accepted Manuscript terms of use https://www.springernature.com/gp/open-research/policies/accepted-manuscript-terms

Augmenting student startups' customer validation efforts through adaptive coaching using large language models

Lois Abigail To, Zachary Matthew Alabastro, Joseph Benjamin Ilagan, and Jose Ramon Ilagan

Business Insights Laboratory for Development, Ateneo de Manila University, Quezon City, Philippines
{lto,jbilagan,jrilagan}@ateneo.edu
zachary.alabastro@student.ateneo.edu,
WWW home page: https://www.ateneo.edu/

Abstract. Startup founders experience numerous barriers to venture creation. Customer development (CD), under the Lean Startup (LS) methodology, is a customer-centric process of refining business models to reduce startup failure. This paper explores the design of an LLM-based, adaptive coaching model that utilizes artificial intelligence's (AI) natural language processing (NLP) and continuous learning capabilities to formulate contextual responses that are suitable for the user's business context. Subsequently, the model generates synthetic customer insights to simulate customer interactions and strengthen CD competencies, creating more efficient systems for startup validation. Results suggest that the LLM-based adaptive coaching model is effective for startup validation and entrepreneurial education.

Keywords: Large language models · artificial intelligence · natural language processing · continuous learning · LLM adaptive coaching · LLM simulation · customer development · entrepreneurship

1 Introduction

Startups are temporary organizations seeking a scalable business model [4]. Known for their rapid growth despite ambiguous success factors, these early-stage companies face challenges related to finances, partnerships, human resources, and poor market understanding [2,21,29].

In contrast to traditional startups, Lean Startups (LS) rapidly gather feedback, test business hypotheses, and re-engineer their products, operating on continuous iteration rather than through a fixed business plan [4,6]. LS is a methodology that stimulates innovation while reducing the incidence of startup failure [4], and aligns with scholarly literature on entrepreneurship as an educational field and practice [6]. Under the LS methodology, Customer Development (CD) is the customer- and market-centric process of discovering, identifying, and validating the target market of a business, prior to developing a product. It

is divided into four steps: Customer Discovery, Customer Validation, Customer Creation, and Company Building. The first two steps focus on understanding customer problems and needs [5].

Customer validation involves continuous and agile enhancements by prioritizing customer interactions [6], which refine the initial prototype of the startup based on early feedback [11]. Furthermore, validation allows entrepreneurs to assess demand and strategize accordingly. Through a thorough investigation of market needs, startups can determine the strength of their product hypotheses, leading to a realignment between product and varying customer contexts.

Adaptive coaching has been shown to produce significant improvements within a team or organization, highlighting competitive scalability. In business, coaching has benefited the thinking mechanism of individuals looking to innovate and grow by combining knowledge, experience, support, and motivation [28]. A personal and close-contact approach also presents the dynamic demands of coaching as it strengthens its own contextual understanding of new requests or immediate needs [10]. In entrepreneurship education, knowledge-based methods alone may not entirely encapsulate the foundational skills required to start a business. To compose a holistic view of the entrepreneurial mindset, the mentor must be able to closely monitor the learning process of the student in designing their startup. This allows them to ask questions and develop a deeper attitude towards business [13]. Adequate interventions can also increase self-awareness, which can aid in the development of new perspectives towards the business. This is essential in retaining engagement and productivity through proper support as further iterations are made [8].

Artificial intelligence (AI) can leverage adaptive coaching through its memory storage and continuous learning capabilities [3]. As a direct and accessible model, students can seek input from such technologies to pursue entrepreneurial ideas more quickly and efficiently.

Although AI is a useful tool in accomplishing transactional tasks (e.g. sentence enhancements, summarization, or content generation), much has not been explored on its capabilities to serve as a mentor for startup entrepreneurs. AI as a means for personal and career mentorship has shown results on the abilities of such systems, underscoring its significant impact on startup development [22]. Such discoveries present AI as a primary coaching figure for CD, leveraging its adaptive and continuous learning capabilities on traditional startup development initiatives.

This paper describes the design of a large language model-based (LLM-based) simulation model for adaptive coaching, primarily focused on CD for startups. The proposed model aims to harness adaptive coaching using LLMs to draw realistic customer insights for startups, supporting real-world product or service validation. This study is only for coaching purposes and is not a replacement for human-based activities involving real customer feedback and validation.

The following research questions are explored in this study:

RQ1) What factors should be considered when designing an adaptive coaching simulator?

RQ2) How can adaptive coaching via LLM-based customer development simulators be designed and developed to aid the customer development process of early-stage startups?

RQ3) What measures can be used to evaluate the adaptability of the LLM-based customer simulator?

2 Review of Related Literature

Social and economic problems have continuously increased, creating a demand for more innovative approaches to problem-solving. While this opens opportunities, amateur entrepreneurs lack the proper skills and strategic intuition to analyze situations and provide the best results [14]. While many institutions provide coaching mechanisms, a more personalized approach remains lacking. [14] offers a recommendation on the usage of human-AI models to boost entrepreneurship through coaching and business development. Chatbots are also useful in professional coaching, allowing the user to receive possible solutions to existing strategic problems. It shows that chatbots are capable of narrowing tasks for goal attainment and direction, but an individualized approach to long-term coaching and alliance is still under-worked [20]. Although the design considerations are relevant, further understanding on its practical implications towards real human users must be analyzed.

AI coaching extends the benefits of coaching far beyond currently limited applications [27]. Studies have shown that it has the capability to transform aggregate interactions into valuable insights, support coaches all throughout the coaching lifecycle, promote skills development, and democratize coaching [26,27]. However, AI still lacks the empathy and emotional intelligence to replicate human coaching interventions [26].

LLMs, via natural language processing (NLP), provide enhanced user experiences across various industries and processes, such as entrepreneurial coaching [27], social systems [12], and market research [7]. Compared with traditional coaching methods, LLM-based coaching promoted increased effectiveness in delivering high-quality education in complex fields (e.g. negotiation) [23], as well as higher cost-efficiency and accessibility [27]. This advancement is achieved by fine-tuning the LLM with customized data and employing human-assisted design approaches [1]. LLMs also demonstrated the ability to autonomously adapt to multimodal engagement (i.e. voice and facial recognition) [25]. In studies involving economic simulation environments, LLMs formed realistic, humanlike decisions on macroeconomic phenomena [18]. When integrating LLMs as conversational agents, algorithm selection, interface design, and potential ethical issues should be considered [19,9].

In the fields of marketing and customer segmentation, understanding the customer base is crucial prior to product development and delivery. By understanding specific behavioral habits, demographics, and purchasing intentions, machine learning and artificial intelligence can be used to cluster data into specific groups [24]. This can be vital in matching specific problems or needs to solutions. [16] used the aforementioned approach to cluster and profile customers

based on a large dataset. This was useful in the context of digital startups to aid in business strategies. However, further research can be extended to analyze similar approaches using an interactive design (e.g. AI as a customer agent itself, AI as a coaching simulator for validation), allowing entrepreneurs to segment customers in a more holistic manner.

This study is part of a series of similar work involving the use of Generative AI in entrepreneurship education and use cases in management. It also pioneers the use of AI in democratizing adaptive coaching and contextualized technological education systems. Researchers create a simulated user experience that drives entrepreneurship education, rapid validation through an adaptive coaching mechanism, and enhanced CD for startups.

3 Methodology

In building the pilot customer development simulator, the researchers used OpenAI's Generative Pre-trained Transformer 3 (GPT-3) as the LLM. The simulation platform was deployed as a Telegram bot using a Python web stack and Postgres database for optimal user experience and accessibility. Conversational user experience principles such as NLP, continuous learning, and empathetic agent-modeling have been assimilated into the model design to deliver a meaningful CD coaching simulator.

The LLM agent fulfilled the role of a virtual CD coach with the following responsibilities: (1) provide constructive feedback on the startup's business model; and (2) simulate realistic customer conversations from the perspective of a target customer.

To assess the effectiveness of the simulation in augmenting customer development for nascent startups, a set of pre- and post-test questionnaires was distributed for feedback. Entrepreneurial intent and confidence were used as initial evaluation criteria. 300 students of an entrepreneurship program in a private university in the Philippines were invited to participate in the study as pilot users. The larger research initiative involving this study already has an ethical data mining protocol for collecting data involving the use of LLMs in a CITS setting [15], which was approved by the university's research ethics office. This protocol places a strong emphasis on ethical considerations and the effective use of LLMs in academic disciplines.

For data analysis, Braun and Clarke's thematic analysis framework was employed to systematically identify, analyze, and distill themes within the dataset [17]. ChatGPT 4o, OpenAI's latest LLM, was utilized as a supplementary tool to apply the six-phase framework, organizing data, generating initial codes, searching themes, reviewing themes, providing preliminary thematic groupings, and generating a report. The themes were critically reviewed and refined by the researchers to ensure accuracy, with further cross-checking against source tables facilitated by ChatGPT for consistency.

Quantitatively, a Python script was used to test the survey responses using the paired two-sample t-test. This specific tool was used because the sample set of participants is the same (or overlapping) for both the pretest and the post-

test. Furthermore, this test is more accurate for comparative analysis [30]. With the help of the *scipy* Python library, the test was conducted. Both the p-value and the test statistic were retrieved per customer discovery metric. A sample size of 57 participants was included in the test.

4 Results

A thematic analysis of the pilot simulation showed positive results. The respondents indicated that the CD simulator is effective for startup validation and entrepreneurial education, particularly in the following areas: evaluating business models, obtaining a nuanced understanding of market needs, improving product-market fit, enhancing the customer development process, and cultivating critical entrepreneurial skills. The table below summarizes key themes found in respondents' evaluation of the simulator.

Table 1. Thematic analysis of responses.

Theme	Definition	Key Supporting Points
Valuable Customer Insights	Participants found the customer discovery process highly valuable, gaining meaningful insights that aligned with their expectations. However, further refinement is required to address nuanced customer behaviors and evolving needs.	– Understanding customer needs and pain points. – Refining segmentation for targeted marketing strategies. – Adjusting assumptions based on customer behavior insights. – Leveraging data analytics for deeper insights. – Aligning feedback with actionable business goals.

Theme	Definition	Key Supporting Points
Improved Business Model and Product-Market Fit	Participants indicated progress in aligning their products and business models with market needs. They recognized the need for strategic refinements to ensure a stronger product-market fit and value proposition clarity.	– Adapting business models to match evolving customer expectations. – Refining core product offerings to maximize relevance. – Addressing differentiation challenges within competitive markets. – Conducting continuous market validation. – Enhancing product usability based on customer feedback.
Highly Effective and Scalable Simulation Platform	The simulation platform was found to be highly effective in providing structured feedback and insights, but participants highlighted the need for enhanced personalization to address specific business contexts.	– Effectiveness of real-time validation of business assumptions. – Need for deeper, industry-specific feedback. – Desire for increased interactivity and flexibility. – Integration of scenario-based learning. – More detailed breakdowns of market trends.
Development of Entrepreneurial Soft Skills	Participants reported growth in their soft skills, particularly in empathy and customer engagement. They recognized the importance of practical application opportunities to further enhance their confidence in real-world scenarios.	– Improved ability to connect with customers through active listening. – Need for strengthening negotiation and problem-solving skills. – Applying soft skills in high-pressure entrepreneurial situations. – Enhancing teamwork and collaboration. – Building resilience through feedback adaptation.

Theme	Definition	Key Supporting Points
Strong Enthusiasm for Platform Enhancements to Improve User Experience	Participants provided positive feedback regarding the platform and expressed enthusiasm for future enhancements. Their suggestions focused on improving user experience, customization, and integration capabilities.	– Additional customization options for tailored feedback. – Improved user interface and faster response times. – Integration of advanced analytics for deeper insights. – Enhanced accessibility for diverse users. – Expansion of learning modules for different business stages.

While the simulation model shows promise for adaptive coaching, respondents highlighted areas for improvement. Their suggestions include the integration of advanced analytics, improved accessibility for diverse users and modal challenges, strengthened adaptive learning capabilities for increased personalization, and the availability of use cases and language options at scale.

More than half of the metrics shown exhibited a statistically significant improvement in areas of customer discovery, including customer empathy, negotiation, market research, business model iteration, lean canvas concepts, business model evaluation, and enhancing customer development processes. The following criteria was used to determine such interpretations:

- T-statistic is negative: Mean of the pretest scores are lower than the post-test scores.
- P-value is less than 0.05: Test is statistically significant.

Furthermore, the following hypotheses were established as part of the t-test statistical analysis:

1. H_0 (Null): There is no significant difference in respondents' customer validation performance before and after using the simulation platform.
2. H_1 (Alternative): There is a statistically significant difference in respondents' customer validation performance before and after using the simulation platform.

Table 2. Statistical analysis of metrics using the paired two-sample t-test.

Metric	**T-Stat.**	**P-Value**	**Sig.**	**Interpretation**
Customer Empathy	-2.11199	0.036323	Yes	Statistically significant improvement in customer empathy.
Negotiation	-2.22654	0.027449	Yes	Statistically significant improvement in negotiation skills.
Market Research	-4.97159	1.77E-06	Yes	Highly statistically significant improvement in market research skills.
Business Model Iteration	-3.39085	0.000888	Yes	Statistically significant improvement in business model iteration.
Application of Lean Canvas Concepts	-4.55183	1.08E-05	Yes	Highly statistically significant improvement in applying Lean Canvas concepts.
Evaluating Your Business Model?	-3.02057	0.002961	Yes	Statistically significant improvement in evaluating business models.
Deeper Understanding of the Target Market?	-1.9727	0.050344	No	Slight improvement, but not statistically significant.
Providing Realistic Feedback from the Perspective of Target Customers?	-1.29751	0.19642	No	No significant improvement in providing realistic feedback.
Aiding You in Validating Assumptions?	-1.43296	0.153922	No	No significant improvement in validating assumptions.
Refining Strategies	-0.40003	0.689697	No	No significant improvement in refining strategies.
Enhancing Customer Development Process	-2.81368	0.005546	Yes	Statistically significant improvement in customer development processes.

Metric	T-Stat.	P-Value	Sig.	Interpretation
Improving Customer Engagement Skills	-1.31638	0.190027	No	No significant improvement in customer engagement skills.

However, some outliers include the metric on a deeper understanding of the target market, which showed no significant difference. Metrics on realistic customer feedbacks, validating assumptions, refining strategies, and improving customer engagement did not show statistically significant improvements. Overall, 7 metrics rejected the null hypothesis, while 5 did not reject the null hypothesis using an alpha of 0.05.

5 Discussion and Conclusion

This section addresses the research questions of the study:

RQ1) What factors should be considered when designing an adaptive coaching simulator?

Designing a Chain of Thought (CoT) prompt that integrates contextualized learning outcomes, entrepreneurial background, and conversational history enables the creation of an adaptive coaching environment where feedback is optimally tailored to the user's needs. The simulation platform should adopt an empathetic coaching agent persona, trained with real-world coaching scenarios, validated entrepreneurial insights, and adaptive learning algorithms that dynamically adjust responses based on self-generated profiles and conversational progress. In addition, it is necessary to prioritize strong ethical and data privacy standards.

In some cases, respondents noted that the simulator lacked real-world complexity, personalization, and diversity. We found that implementing changes based on the factors mentioned in the paragraph above improved results significantly. Thus, a simulator's configurations and design must undergo critical analyses and enhancements prior to release.

RQ2) How can adaptive coaching via LLM-based customer development simulators be designed and developed to aid the customer development process of early-stage startups?

The simulation model generates adaptive responses by incorporating feedback from ongoing conversations and past interactions. To aid early-stage startups in the customer development process, the model should be designed with a prompt framework that incorporates adaptive feedback learning, problem interrogation, and context awareness to develop a realistic representation of the startup's context. This enables the simulator to provide tailored coaching at different stages of customer development, while dynamically refining its approach based on accumulated insights. Furthermore, incorporating continuous learning and agent-based modeling enhances the platform's ability to simulate diverse

roles in CD interactions and handle complementary support in related activities.

RQ3) What measures can be used to evaluate the adaptability of the LLM-based customer simulator?

Having concrete metrics such as those shown above can help evaluate the adaptability and usefulness of the customer simulator. By collecting both qualitative and quantitative data from the participants, the analysis can use prior knowledge and experience, as well as baseline performance to determine their capabilities. A self-assessment of confidence in performing different customer discovery tasks is a possible way to achieve such. Post-simulation queries can also determine any developments in co-founder character and confidence through Likert-scale ratings. By quantifying such perceptions, the data can then be analyzed through the relevant statistical tools such as the t-test.

Qualitative data analysis can be retrieved by utilizing open-ended questions and analyzing them through thematic analysis. This groups similar responses into themes, which can be interpreted based on their corresponding metrics. By understanding the psychological aspect or thought process of the users, researchers can determine its impact on customer development processes.

However, it is important to ensure the realistic environment of the customer simulator. This ensures that the data resembles real-world attributes, and is not arbitrarily determined. The bot must also possess dynamic adaptability as to recognize and adjust to the variations or requirements set by the user (i.e. context, customer tone, responses, etc.). Regardless of the complexities in customer discovery questions, it must answer properly, with minimal to no hallucinations. Temperature settings can also be adjusted to account for randomness and creativity. The bot must also provide direct feedback, which can both save time and token usage due to clarifications. The entire interaction must adhere to the realism required by the user, allowing for complex responses, but maintaining clarity and efficiency.

Preliminary results suggest improved confidence in entrepreneurial competencies, and a generally positive feedback. However, discrepancies may arise due to the open-ended nature of qualitative responses, offering respondents more freedom for input and critique, in contrast to the fixed options of the Likert scale. The sample size of 57 is a relatively small sample size for a comparison of pre- and post-test results using a paired two-sample t-test. Respondents' diverse backgrounds and varying perceptions of startup and customer discovery could influence the quantitative analysis. The qualitative analysis, however, allows respondents to provide insights based on their experiences, which can be grouped into themes.

6 Future Work

Human-agent collaboration may be incorporated to further reflect real-world nuances and personalization in simulated interactions, with human feedback as a potential training source and evaluation metric. The researchers aim to strengthen grounding to minimize unintended consequences of inherent biases in

the LLM. Future iterations may also involve customer retention, adaptive coaching enhancement mechanisms, modality exploration (e.g. human-agent audio interviews), and multi-agent systems fine-tuned for CD-specific research methods, focusing on creating augmented customer discovery experiences for enhanced customer development.

Acknowledgments. We would like to thank Ateneo de Manila University through the John Gokongwei School of Management (JGSOM) and the Business Insights Laboratory for Development (BUILD) for enabling our participation and future presentation of this study.

References

1. Arakawa, R., Yakura, H.: Coaching Copilot: Blended Form of an LLM-Powered Chatbot and a Human Coach to Effectively Support Self-Reflection for Leadership Growth. In: ACM Conversational User Interfaces 2024. pp. 1–14. ACM, Luxembourg Luxembourg (Jul 2024). https://doi.org/10.1145/3640794.3665549, https://dl.acm.org/doi/10.1145/3640794.3665549, 0 citations (Crossref) [2024-10-18]
2. Bhaskar, D.P., K, P.G., V, P.V.: A Study On Challenges Faced By Entrepreneurs. Journal of Positive School Psychology **6**(10), 3871–3879 (Nov 2022), https://journalppw.com/index.php/jpsp/article/view/14000, number: 10
3. Billiot, T.: Continuous learning and advancing technologies: a framework for professional development and training in artificial intelligence. Development and Learning in Organizations: An International Journal **37**(3), 28–31 (Mar 2023). https://doi.org/10.1108/DLO-04-2022-0064, https://www.emerald.com/insight/content/doi/10.1108/dlo-04-2022-0064/full/html, 0 citations (Crossref) [2024-12-19] Publisher: Emerald Publishing Limited
4. Blank, S.: Why the Lean Start-Up Changes Everything. Harvard Business Review (May 2013), https://hbr.org/2013/05/why-the-lean-start-up-changes-everything
5. Blank, S.: The four steps to the epiphany: successful strategies for products that win. John Wiley & Sons (2020), https://books.google.com/books?hl=en&lr=&id=7p_ODwAAQBAJ&oi=fnd&pg=PR5&dq=customer+development+blank&ots=0K6cxEm0io&sig=pitbgX_2TIqTssNgY55MvyufLRc
6. Blank, S., Eckhardt, J.T.: The Lean Startup as an Actionable Theory of Entrepreneurship. Journal of Management p. 01492063231168095 (Apr 2023). https://doi.org/10.1177/01492063231168095, https://doi.org/10.1177/01492063231168095, 17 citations (Crossref) [2024-12-19] Publisher: SAGE Publications Inc
7. Brand, J., Israeli, A., Ngwe, D.: Using LLMs for Market Research (Jul 2024), https://www.hbs.edu/ris/Publication%20Files/23-062_ed720ebc-ec4d-4bc3-a6ba-bad8cfbd9d51.pdf
8. Brinkley, M.L., Le, R.I.l.: Coaching as a support function for potential entrepreneurs. The Southern African Journal of Entrepreneurship and Small Business Management **10**(1), 1–12 (May 2018). https://doi.org/10.4102/sajesbm.v10i1.99, https://journals.co.za/doi/abs/10.4102/sajesbm.v10i1.99, 8 citations (Crossref) [2024-12-19] Publisher: AOSIS
9. Cebrián, J., Martínez, R., Rodríguez, N., D'Haro, L.F.: Considerations on creating conversational agents for multiple environments and users. AI Magazine **42**(2), 71–86 (2021). https://doi.org/10.1609/aimag.v42i2.7484, https://onlinelibrary.

wiley.com/doi/abs/10.1609/aimag.v42i2.7484, 1 citations (Crossref) [2024-10-18] _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1609/aimag.v42i2.7484
10. Cushion, C.J., Stodter, A.: Developing (adaptive) coaching expertise. In: Science and Soccer. Routledge, 4 edn. (2023), num Pages: 14
11. Ghezzi, A., Cavallo, A.: Agile Business Model Innovation in Digital Entrepreneurship: Lean Startup Approaches. Journal of Business Research **110**, 519–537 (Mar 2020). https://doi.org/10.1016/j.jbusres.2018.06.013, https://www.sciencedirect.com/science/article/pii/S014829631830300X, 338 citations (Crossref) [2024-12-19]
12. Gurcan, O.: LLM-Augmented Agent-Based Modelling for Social Simulations: Challenges and Opportunities (May 2024), http://arxiv.org/abs/2405.06700, arXiv:2405.06700 [physics]
13. Gustafsson-Pesonen, A., Remes, L.: Evaluation of entrepreneurial development coaching: changing the Teachers' thinking and action on entrepreneurship. Annals of Innovation & Entrepreneurship **3**(1), 17211 (Jan 2012). https://doi.org/10.3402/aie.v3i0.17292, https://doi.org/10.3402/aie.v3i0.17292, 15 citations (Crossref) [2024-12-19] Publisher: Taylor & Francis _eprint: https://doi.org/10.3402/aie.v3i0.17292
14. Huang, E.J.: Human-AI Collaboration For Entrepreneurship Coaching: Leveraging a Cognitive Model and an LLM to Provide Proactive, Adaptive, and Differentiated Support. Ph.D., Northwestern University, United States – Illinois (2024), https://www.proquest.com/docview/3145310767/abstract/B4D8029E6B3240FFPQ/1, iSBN: 9798346858669
15. Ilagan, J.B.R., Ilagan, J.R.S., Rodrigo, M.M.T.: Ethical Education Data Mining Framework for Analyzing and Evaluating Large Language Model-Based Conversational Intelligent Tutoring Systems for Management and Entrepreneurship Courses. In: International Congress on Information and Communication Technology. pp. 61–71. Springer Nature Singapore Singapore (2024), https://library.oapen.org/bitstream/handle/20.500.12657/93274/1/978-981-97-4581-4.pdf#page=78
16. Kasem, M.S., Hamada, M., Taj-Eddin, I.: Customer profiling, segmentation, and sales prediction using AI in direct marketing. Neural Computing and Applications **36**(9), 4995–5005 (Mar 2024). https://doi.org/10.1007/s00521-023-09339-6, https://doi.org/10.1007/s00521-023-09339-6
17. Lee, V.V., Lubbe, S.C.C.v.d., Goh, L.H., Valderas, J.M.: Harnessing ChatGPT for Thematic Analysis: Are We Ready? Journal of Medical Internet Research **26**(1), e54974 (May 2024). https://doi.org/10.2196/54974, https://www.jmir.org/2024/1/e54974, company: Journal of Medical Internet Research Distributor: Journal of Medical Internet Research Institution: Journal of Medical Internet Research Label: Journal of Medical Internet Research Publisher: JMIR Publications Inc., Toronto, Canada
18. Li, N., Gao, C., Li, Y., Liao, Q.: Large Language Model-Empowered Agents for Simulating Macroeconomic Activities (Oct 2023). https://doi.org/10.2139/ssrn.4606937, https://papers.ssrn.com/abstract=4606937, 2 citations (Crossref) [2024-10-18]
19. Passmore, J., Diller, S.J., Isaacson, S., Brantl, M.: The Digital and AI Coaches' Handbook: The Complete Guide to the Use of Online, AI, and Technology in Coaching. Taylor & Francis (Jun 2024), google-Books-ID: XwEIEQAAQBAJ
20. Plotkina, L., Ramalu, S.S.: Unearthing AI coaching chatbots capabilities for professional coaching: a systematic literature review. Journal of Management Development **43**(6), 833–848 (Sep 2024). https://doi.org/10.1108/JMD-06-2024-0182, https://www.emerald.com/insight/content/doi/10.1108/jmd-06-2024-0182/full/html, publisher: Emerald Publishing Limited

21. Salamzadeh, A., Kawamorita Kesim, H.: Startup Companies: Life Cycle and Challenges. SSRN Electronic Journal (2015). https://doi.org/10.2139/ssrn.2628861, http://www.ssrn.com/abstract=2628861, 74 citations (Crossref) [2024-12-19]
22. Sharma, M., Kumari, A., Jyotsna: AI-Based Deep Learning Chatbot for Career and Personal Mentorship. In: 2023 IEEE 3rd International Conference on Technology, Engineering, Management for Societal impact using Marketing, Entrepreneurship and Talent (TEMSMET). pp. 1–6 (Feb 2023). https://doi.org/10.1109/TEMSMET56707.2023.10149907, https://ieeexplore.ieee.org/abstract/document/10149907?casa_token=CNnvIXYkzpAAAAAA:ZII_wu1Nc8ldto7cYPZQlAlGDhRFli6DSB0NP3SM0NeHTryBmVdaicCtBeJkfrhHSSZ1Yv29z5oR, 4 citations (Crossref) [2024-12-19]
23. Shea, R., Kallala, A., Liu, X.L., Morris, M.W., Yu, Z.: ACE: A LLM-based Negotiation Coaching System (Oct 2024), http://arxiv.org/abs/2410.01555, arXiv:2410.01555
24. Sofiati, N.A., Trimurti, C.P., Widodo, R.E., Ariyani, F., Pahrudin, C.: Concept and Implementation of Business Model Canvas in Startup Companies: Relationship with Customers, Customers Segments and Market Trends. | EBSCOhost (Aug 2024). https://doi.org/10.38035/dijdbm.v5i5, https://openurl.ebsco.com/contentitem/doi:10.38035%2Fdijdbm.v5i5?sid=ebsco:plink:crawler&id=ebsco:doi:10.38035%2Fdijdbm.v5i5, iSSN: 2715-419X Issue: 5 Pages: 1029 Volume: 5
25. Spitale, M., Axelsson, M., Gunes, H.: VITA: A Multi-modal LLM-based System for Longitudinal, Autonomous, and Adaptive Robotic Mental Well-being Coaching (Dec 2023), http://arxiv.org/abs/2312.09740, arXiv:2312.09740
26. Terblanche, N., Molyn, J., de Haan, E., Nilsson, V.O.: Comparing artificial intelligence and human coaching goal attainment efficacy. PLoS ONE **17**(6), e0270255 (Jun 2022). https://doi.org/10.1371/journal.pone.0270255, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9212136/
27. Terblanche, N.H.: Artificial Intelligence (AI) Coaching: Redefining People Development and Organizational Performance. The Journal of Applied Behavioral Science **60**(4), 631–638 (Dec 2024). https://doi.org/10.1177/00218863241283919, https://doi.org/10.1177/00218863241283919, publisher: SAGE Publications Inc
28. Vidal-Salazar, M.D., Ferrón-Vílchez, V., Cordón-Pozo, E.: Coaching: an effective practice for business competitiveness. Competitiveness Review: An International Business Journal incorporating Journal of Global Competitiveness **22**(5), 423–433 (Sep 2012). https://doi.org/10.1108/10595421211266302, 26 citations (Crossref) [2024-12-19]
29. Vinoth Kumar, V., Indumathi, N.: A study on challenges faced by students to starting an own business. International Journal of Science Academic Research **05**(05) (2024)
30. XU, M., FRALICK, D., ZHENG, J.Z., Wang, B., TU, X.M., FENG, C.: The Differences and Similarities Between Two-Sample T-Test and Paired T-Test. Shanghai Archives of Psychiatry **29**(3), 184–188 (Jun 2017). https://doi.org/10.11919/j.issn.1002-0829.217070, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5579465/