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TAILORING AI CONVERSATIONS: CUSTOMIZED CHATBOT AGENTS

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Abstract: *In this conference paper, the authors are testing to what extend the customization of chatbot instructions, i.e. custom agents, is beneficial to increase the perceived quality of responses to different target segments of companies. This includes, for example, customers, employees, and suppliers. To this end, six custom agents were developed, tested, and evaluated by a panel of experts. The results suggest that targeted customization of chatbots that use generative artificial intelligence to respond to queries is beneficial in most cases.*
Key Words: ***Customization, Generative Artificial Intelligence, Custom Agents, Chatbot, Customer Segmentation***

1. INTRODUCTION

Customization and personalization have become a key driver of success across many business domains (Salvador et al. 2020) as well as in healthcare, education, and government. From marketing and e-commerce to customer service and human ressources, tailoring offerings to individual preferences has become an additional possibility to gain competitive advantage in a more and more digital world. The fact that generative artificial intelligence (GenAI) has become widely available and very present in both everyday life and in business, opens a new era of possibilities, with chatbots representing a central application of this transformative technology (Kecht et al. 2023).

While GenAI-powered chatbots have demonstrated impressive capabilities in natural language understanding and generation, their potential for delivering truly exceptional user experiences hinges on the degree of customization they can offer. This conference paper assesses the role of customization in enhancing the perceived quality of GenAI chatbots, exploring if and how tailoring these conversational agents to individual needs and preferences can elevate human-computer interaction.

2. LITERATURE REVIEW AND THEORY

2.1. Customization and Personalization Theory

The concepts of customization and personalization have been widely explored in marketing and consumer behavior research (e.g., Trentin and Salvador 2023, Coletti et al. 2023, Aichner et al. 2023) as well as in many other business domains. Customization allows consumers to actively tailor products or services to fit with their individual needs, preferences, and tastes (Trentin et al. 2020). It offers a sense of control and ownership (Shafiee et al. 2023), which can have a positive impact on customer satisfaction and their loyalty. Personalization, on the other hand, involves proactively tailoring offerings to individual consumers based on a deep understanding of their characteristics, behaviors, and preferences (Miceli et al. 2007). This tailored approach fosters a sense of relevance and value, strengthening the customer-brand relationship (Suzic and Forza 2023).

A cornerstone theoretical framework in this domain is the self-congruity model, which posits that individuals are more likely to be satisfied with products or services that align with their self-image (Chung et al. 2024). This model underscores the importance of personal relevance in consumer decision-making. Additionally, the value-based segmentation approach emphasizes the heterogeneity of consumer needs and preferences, highlighting the necessity of customized offerings. By tailoring products or services to specific value segments, organizations can create greater customer value and satisfaction (Schulz et al. 2023, Grosso 2023).

2.2. GenAI

GenAI has emerged as a transformative technology with the potential to revolutionize various industries. By leveraging vast amounts of data and complex algorithms (Huynh et al. 2023), these models can generate new content, including text, images, and music, that exhibits human-like creativity and quality. The underlying principles of GenAI are rooted in deep learning, particularly neural networks, which enable these models to learn complex patterns from data and generate novel outputs (Nah et al. 2023).

While the potential of GenAI is widely discussed since a few years and people are generally positive about it, it is essential to acknowledge the challenges and limitations. Issues such as accuracy and ethical considerations require careful attention (Ferrara 2023). Moreover, the interpretability of generative models remains an ongoing area of research. Despite these challenges, the rapid advancements in this field have opened up new possibilities for innovation and application across diverse domains.

2.3. Chatbots Based on GenAI

The integration of GenAI into chatbot development has marked a significant leap forward in human-computer interaction. Traditional rule-based chatbots often struggled to provide natural and engaging conversations, limiting their effectiveness (Haase and Hanel 2023). In contrast, GenAI-powered chatbots can generate more human-like and contextually relevant responses, enhancing user experience. These chatbots can access and process vast amounts of information, enabling them to provide comprehensive and informative answers to user queries.

Furthermore, GenAI-based chatbots can adapt to different conversational styles and user preferences, fostering a sense of personalization (Riemer and Peter 2024). By learning from user interactions, these chatbots can continuously improve their responses, creating a more dynamic and engaging experience. However, it is important to ensure that these chatbots are trained on high-quality data to avoid unwanted results and inaccuracies in their outputs.

2.4. Customization of Chatbots Using Custom Agents

To maximize the potential of GenAI-powered chatbots, the concept of custom agents has gained prominence. These agents are tailored to specific user segments or individual preferences, enabling highly personalized interactions (Vissers-Similon et al. 2024). By leveraging user data and behavior patterns, custom agents can deliver tailored information, recommendations, and support (Rahbar et al. 2022). This level of customization can enhance user satisfaction, loyalty, and engagement.

The theoretical underpinnings of custom agents are grounded in the principles of personalization and user segmentation. By identifying distinct groups of users with similar needs and preferences, organizations can develop custom agents to cater to each segment's specific requirements. This approach allows for more targeted and effective communication, ultimately leading to improved business outcomes. While the concept of custom agents is promising, empirical research on their effectiveness is still evolving.

2.5. Custom Agents: Theory and Practice

In theory, custom agents offer a powerful approach to delivering personalized experiences through chatbots. By leveraging user data and advanced algorithms, these agents can create highly tailored interactions that resonate with individual needs and preferences. This alignment between user expectations and chatbot responses is expected to enhance user satisfaction, engagement, and loyalty.

However, realizing the full potential of custom agents requires careful consideration of several factors. The quality and quantity of user data are critical for developing accurate and effective agent profiles. Additionally, the algorithms used to create and manage custom agents must be sophisticated enough to capture the nuances of user behavior and preferences. Furthermore, the implementation of custom agents should be aligned with overall business objectives to ensure that personalization efforts drive desired outcomes.

While the theoretical foundations of custom agents are well-established (e.g., Dennis et al. 2023, Han et al. 2022), empirical evidence on their effectiveness is still emerging. While some studies have shown promising results in terms of improved user satisfaction and engagement (e.g., Namkoong et al. 2024, Hsu and Lin 2023), more research is needed to fully understand the impact of custom agents on various business metrics.

2.6. User Segmentation and Customization

User segmentation is a fundamental prerequisite for effective chatbot customization (Cao et al. 2022). By dividing the user base into distinct groups based on shared characteristics, behaviors, or preferences, organizations can develop targeted chatbot experiences. This approach ensures that users receive relevant and valuable information, enhancing their overall satisfaction.

Several segmentation criteria can be employed, including demographics (age, gender, location), psychographics (lifestyle, values, interests), behavioral patterns (purchase history, website browsing behavior), and firmographics (company size, industry). By combining these dimensions, organizations can create detailed user profiles that inform the development of custom agents.

For example, a retail website might segment customers based on purchase history (e.g., frequent buyers, occasional buyers, first-time buyers) and product preferences (e.g., fashion, electronics, home goods). This segmentation allows the chatbot to offer tailored product recommendations, personalized promotions, and relevant customer support.

Similarly, a B2B company might segment customers based on company size, industry, and purchase volume. This segmentation enables the chatbot to provide industry-specific information, tailored product demos, and customized pricing offers.

By understanding the unique needs and preferences of different user segments, organizations can create chatbot experiences that resonate with each group (Stöckl and Krauss 2024). This tailored approach fosters stronger customer relationships, increases customer loyalty, and drives business growth.

2.7. Research Question

Given the potential benefits of customization in enhancing chatbot performance, this study aims to investigate the following research question:

How does the performance of customized versus uncustomized GenAI chatbots vary across different user segments in terms of ease of understanding, information appropriateness, information specificity and response accuracy?

3. METHOD

To investigate the impact of customization on GenAI chatbot performance, a controlled experiment was conducted. The study compared the responses of seven chatbots in OpenAI ChatGPT-4o: six custom chatbots, each tailored to a specific user segment, and a control chatbot without targeted customization. The primary objective was to determine if customization enhances chatbot performance as perceived by representative users.

3.1. Chatbot Development

A total of seven custom agents were developed for the experiment. Six of these models were designated as custom chatbots, each trained on a dataset derived from the Dr. Schär website, a company selling food products, specifically gluten free food and foods for the dietary treatment of chronic kidney disease. These custom chatbots (see Table 1) were designed to simulate interactions with specific user segments: users/customers (V1), non-users/non-customers (V2), press/media (V3), nutritionists/doctors (V4), suppliers/partners (V5), and employees/potential employees (V6).

Table 1. *Individual instructions for each custom agent*

V1	**You are answering questions to Users/ Customers:** • **Description:** Everyday consumer who has purchased or is considering purchasing the specialized food product. • **Focus:** Making informed purchasing decisions and maximizing product enjoyment. • **Information Needs:** Practical details about purchasing, storage, use, and potential recipe ideas. • **Key Differentiator:** Seeks readily understandable information to solve everyday problems related to the product. Use a language style, a structure of your answer, and adjust the length of your answer that best fits with this type of user.
V2	**You are answering questions to Non-Users/ Non-Customers:** • **Description:** Individual with no prior experience with the product but may have some general interest in the category. • **Focus**: General curiosity about the product or the company. • **Information Ne**eds: Basic information about the product's purpose, differentiation, and company values. • **Key Differentiator**: Limited existing knowledge, seeking broad introductory information. Use a language style, a structure of your answer, and adjust the length of your answer that best fits with this type of user.
V3	**You are answering questions to Press/ Media:** • **Description:** Journalist, blogger, or other media professional creating content about food. • **Focus**: Creating compelling content about the product. • **Information Ne**eds: Detailed information about ingredients, health benefits, production methods, and company sustainability practices. • **Key Differenti**ator: Requires specific details to support their content and potentially conduct interviews. Use a language style, a structure of your answer, and adjust the length of your answer that best fits with this type of user.
V4	**You are answering questions to Nutritionists/Doctors:** • **Description:** Healthcare professional with expertise in nutrition and dietary needs. • **Focus**: Evaluating the product's suitability for specific dietary needs. • **Information Needs**: In-depth nutritional information, ingredient sources, allergen presence, and suitability for specific health conditions. • **Key Differentiator**: Highly specialized knowledge base, seeking detailed nutritional specifics. Use a language style, a structure of your answer, and adjust the length of your answer that best fits with this type of user.
V5	**You are answering questions to Suppliers/ Partners:** • **Description:** Company representative interested in supplying ingredients or collaborating on product development or other corporate partner. • Focus: For example, assessing product viability for business partnerships. • Information Needs: Specifications, logistics details like minimum order quantities, lead times, and potential private label options. • Key Differentiator: Industry knowledge with a focus on specific business needs for collaboration. Use a language style, a structure of your answer, and adjust the length of your answer that best fits with this type of user.
V6	**You are answering questions to Employees/ Potential Employees:**

	• **Description:** Someone currently working or interested in working for the specialized food producer. • **Focus**: Understanding the company culture and potential career opportunities. • **Information Needs**: Details about company values, work environment, and specific job requirements (if applicable). • **Key Differentiator**: Existing knowledge may vary, seeking insights into company culture and career paths. Use a language style, a structure of your answer, and adjust the length of your answer that best fits with this type of user.

The seventh model served as a control chatbot (V0), also trained on the Dr. Schär dataset but without any specific user segment targeting. This control chatbot was used as a baseline for comparison.

3.2. Data Collection

A standardized set of three questions was posed to all seven chatbots:

Q1: What needs to be considered when eating gluten-free?

Q2: How would you recommend Dr. Schär's products to a person who doesn't know them?

Q3: What is the most relevant aspect that I should know about Dr. Schär and its products?

The responses generated by each chatbot were recorded for subsequent analysis by selected experts (see next section).

3.3. Expert Evaluation

A panel of three experts, representing each all six target user segments, was assembled to evaluate the chatbot responses. Experts were selected based on their knowledge and experience with marketing automation, customization and GenAI.

The evaluation process involved assessing each chatbot response on a 10-point scale (1-10) across five dimensions (cf. Borsci et al. 2022), specifically one about perceived quality of chatbot functions (1 item) and perceived quality of conversation and information provided (4 items):

a) The chatbot's responses were easy to understand.
b) I find that the chatbot understands what I want and helps me achieve my goal.
c) The chatbot gives me the appropriate amount of information.
d) The chatbot only gives me the information I need.
e) I feel like the chatbot's responses were accurate.

The three experts made their evaluations individually and did not have access to the ratings of the other experts until they completed their own. The sequence was also the same for all experts, starting from V0 with V1, followed by V0 and V2, and so on.

Note that although the responses from the control chatbot were generated just once, they had to be evaluated a total of six times, for each of the six target segments. This is because the same response from the non-customized chatbot may fit well with one segment but not at all with another.

By comparing the average ratings of the six custom chatbots with the control chatbot without customization (V0), it was possible to determine the impact of customization on chatbot performance.

4. RESULTS

The average expert evaluations for each item and all questions are shown in Table 2, Table 3, Table 4, Table 5, Table 6, and Table 7. The difference between the average total value for each target segment is visualized in Fig. 1.

Table 2. *Experimental results for users/customers (V1)*

Question and item	V0	V1	Difference
Q1, a)	8.3	9.3	1.0
Q1, b)	8.3	8.7	0.4
Q1, c)	8.0	8.0	0.0
Q1, d)	6.7	8.0	1.3
Q1, e)	8.7	8.3	-0.4
Average Q1	8.0	8.5	0.5
Q2, a)	9.3	9.3	0.0
Q2, b)	9.3	9.3	0.0
Q2, c)	8.7	10.0	1.3
Q2, d)	8.3	8.7	0.4
Q2, e)	9.3	8.0	-1.3
Average Q2	9.0	9.1	0.1
Q3, a)	9.3	9.3	0.0
Q3, b)	8.0	9.3	1.3
Q3, c)	8.7	8.7	0.0
Q3, d)	7.7	8.7	1.0
Q3, e)	9.3	9.3	0.0
Average Q3	8.6	9.1	0.5
Total	**8.5**	**8.9**	**0.4**

Table 3. *Experimental results for non-users/non-customers (V2)*

Question and item	V0	V2	Difference
Q1, a)	7.0	9.3	2.3
Q1, b)	7.3	9.3	2.0
Q1, c)	6.7	8.3	1.6
Q1, d)	5.3	8.0	2.7
Q1, e)	8.0	8.7	0.7
Average Q1	6.9	8.7	1.8
Q2, a)	9.3	9.3	0.0
Q2, b)	9.0	10.0	1.0
Q2, c)	8.7	8.7	0.0
Q2, d)	8.3	9.3	1.0
Q2, e)	9.3	10.0	0.7
Average Q2	8.9	9.5	0.6
Q3, a)	9.3	9.3	0.0
Q3, b)	9.0	9.3	0.3
Q3, c)	8.3	8.3	0.0
Q3, d)	8.7	10.0	1.3
Q3, e)	9.3	9.3	0.0
Average Q3	8.9	9.3	0.4
Total	**8.2**	**9.2**	**1.0**

Table 4. *Experimental results for press/media (V3)*

Question and item	V0	V3	Difference
Q1, a)	7.0	9.3	2.3
Q1, b)	6.3	8.7	2.4
Q1, c)	6.3	9.3	3.0
Q1, d)	5.3	10.0	4.7
Q1, e)	7.3	8.7	1.4
Average Q1	6.5	9.2	2.7
Q2, a)	8.7	10.0	1.3
Q2, b)	7.7	8.7	1.0
Q2, c)	8.0	9.3	1.3
Q2, d)	7.0	9.3	2.3
Q2, e)	8.0	9.3	1.3
Average Q2	7.9	9.3	1.4
Q3, a)	8.7	10.0	1.3
Q3, b)	7.0	8.7	1.7
Q3, c)	7.0	9.3	2.3
Q3, d)	6.3	9.3	3.0
Q3, e)	7.3	8.7	1.4
Average Q3	7.3	9.2	1.9
Total	**7.2**	**9.2**	**2.0**

Table 5. *Experimental results for nutritionists/doctors (V4)*

Question and item	V0	V4	Difference
Q1, a)	8.3	9.3	1.0
Q1, b)	7.3	9.3	2.0
Q1, c)	7.0	9.0	2.0
Q1, d)	5.3	8.7	3.4
Q1, e)	7.3	9.3	2.0
Average Q1	7.1	9.1	2.0
Q2, a)	8.7	10.0	1.3
Q2, b)	7.0	8.7	1.7
Q2, c)	7.3	8.0	0.7
Q2, d)	6.3	10.0	3.7
Q2, e)	7.3	9.3	2.0
Average Q2	7.3	9.2	1.9
Q3, a)	8.7	9.3	0.6
Q3, b)	6.3	10.0	3.7
Q3, c)	6.3	9.0	2.7
Q3, d)	5.7	10.0	4.3
Q3, e)	6.7	9.3	2.6
Average Q3	6.7	9.5	2.8
Total	**7.0**	**9.3**	**2.3**

Table 6. *Experimental results for suppliers/partners (V5)*

Question and item	V0	V5	Difference
Q1, a)	7.0	9.3	2.3
Q1, b)	6.7	9.3	2.6
Q1, c)	6.3	8.7	2.4
Q1, d)	4.7	8.7	4.0
Q1, e)	7.3	10.0	2.7
Average Q1	6.4	9.2	2.8
Q2, a)	8.7	9.3	0.6
Q2, b)	7.3	9.3	2.0
Q2, c)	8.0	9.3	1.3
Q2, d)	6.7	10.0	3.3
Q2, e)	8.0	10.0	2.0
Average Q2	7.7	9.6	1.9
Q3, a)	8.7	10.0	1.3
Q3, b)	6.0	9.3	3.3
Q3, c)	6.0	9.0	3.0
Q3, d)	5.3	8.7	3.4
Q3, e)	6.7	10.0	3.3
Average Q3	6.5	9.4	2.9
Total	**6.9**	**9.4**	**2.5**

Table 7. *Experimental results for employees/potential employees (V6)*

Question and item	V0	V6	Difference
Q1, a)	7.3	10.0	2.7
Q1, b)	6.3	9.3	3.0
Q1, c)	6.0	8.3	2.3
Q1, d)	4.7	9.7	5.0
Q1, e)	7.3	9.3	2.0
Average Q1	6.3	9.3	3.0
Q2, a)	8.7	9.3	0.6
Q2, b)	7.7	9.7	2.0
Q2, c)	8.0	9.3	1.3
Q2, d)	7.0	7.7	0.7
Q2, e)	8.0	8.7	0.7
Average Q2	7.9	8.9	1.0
Q3, a)	8.7	9.3	0.6
Q3, b)	6.3	9.0	2.7
Q3, c)	6.3	8.3	2.0
Q3, d)	5.7	10.0	4.3
Q3, e)	6.7	10.0	3.3
Average Q3	6.7	9.3	2.6
Total	**7.0**	**9.2**	**2.2**

It can be noted that all custom agents performed better based on the expert evaluations. The smallest difference is to be found for users/customers (V1), which is also the only target segment with single items that were rated better for the non-customized chatbot, specifically Q1, e) and Q2, e). On average, the custom agent only received a rating that was 0.4 higher, which is neglectable.

For all other target segments, the differences are notably larger – with values ranging from 1.0 (V2) to 2.5 (V5).

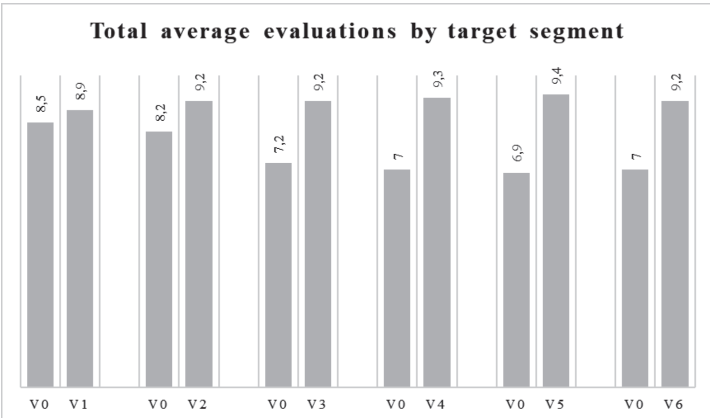

Fig. 1. *Total average evaluations by target segment*

5. DISCUSSION AND CONCLUSION

This study indicates that tailoring chatbots to specific user groups enhances their effectiveness and the perceived quality of the responses to specific questions as compared to non-customized chatbots.

When chatbots are designed with particular user needs and preferences in mind, they provide superior support and information. This is evident in our findings, which show that custom-built chatbots generally outperformed a standard chatbot across most user groups.

While a general-purpose chatbot can adequately address the needs of standard customer inquiries, our study indicates that for specialized user groups, such as press/media or employees/potential employees, a customized approach yields substantially better results. It is likely that users in these groups will be more satisfied with the response and feel that the chatbot better understood their needs.

While it is relatively simple to create custom agents for many different target segments, the challenge for companies may be to correctly identify who is visiting their website or using the chatbot. One way is to implement a straightforward user identification process, such as a simple selection menu, which can then improve chatbot performance. By understanding the user's role or needs upfront, chatbots can be dynamically adjusted to provide more relevant and helpful information.

Another possibility could be to dynamically customize the agents to the previous behavior or interactions with the company. This means that rather than having, for example, six custom agents, the chatbot itself reprograms itself based on the knowledge and experiences of the user. This is possible both if the user is unknown – but in a limited way – and especially if the user is logged in and the chatbot has access to a broad range of historical data, e.g. about purchases, complaints, and other types of interactions of the user with the company and his behavior on the website both in the current and previous sessions.

To advance our understanding of chatbot customization, future research should explore the optimal number of user groups for maximum effectiveness. Using real users rather than experts to evaluate the response quality will also provide a more detailed and more accurate picture. Using experts could be seen as a limitation of this study. This also applies to the fact that the chatbots were evaluated in the same order rather than in a random order, leading to a potential learning effect over time. Additionally, investigating the long-term implications of customization on user behavior and satisfaction would be interesting to grasp additional benefits and challenges of this approach.

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DISCLAMER

The authors of this article used OpenAI ChatGPT-4o and Google Gemini as part of their research, specifically to program and test custom agents, to suggest customization items, to rewrite text passages and for proofreading purposes.

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