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Article

A Strategy Framework to Boost Conversational AI Performance

Marketing Review St.Gallen

Provided in Cooperation with:

Universität St. Gallen, Institut für Marketing und Customer Insight

Suggested Citation: Hildebrand, Christian; Hundertmark, Sophie (2021) : A Strategy Framework to Boost Conversational AI Performance, Marketing Review St.Gallen, ISSN 1865-7516, Thexis Verlag, St.Gallen, Vol. 38, Iss. 4, pp. 10-16

This Version is available at:

<https://hdl.handle.net/10419/276147>

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Conversational Commerce

A Strategy Framework to Boost Conversational AI Performance

The development of conversational AI applications is often more tactical than strategic; more technology-focused than focused on the end user and the problem to be solved. This paper provides a strategy framework to structure the effective development of conversational AI in research and practice.

Prof. Dr. Christian Hildebrand, Sophie Hundertmark

Conversational AI is fundamentally changing how consumers interact with firms. With conversational AI ranging from text-based chatbots automating simple customer service tasks to digital voice assistants providing active recommendations during a shopping trip, conversational AI provides a scalable technology that is poised to create hyper-personalized and contextualized customer experiences that were unthinkable with traditional technologies (Hildebrand & Bergner, 2020; Zumstein & Hundertmark, 2018). As messaging platforms have become the digital de-facto standard for consumers to interact with their friends and families (Economist, 2016), consumers shy away from traditional consumer–firm communication modes and demand faster and more personalized ways of interaction. Recent industry reports highlight the strong cost-saving potential of conversational AI during the COVID-19 pandemic while academic research revealed that digital voice assistants can be engineered to be as effective as the top 20% of human sales representatives (Luo et al., 2019; Maruti Techlabs, 2017). However, consumers often experience frustration (e.g., due to a lack of understanding of what the consumer is saying), express privacy concerns, or experience heightened uncertainty when interacting with conversational AI applications (Hildebrand et al., 2020; Shumanov & Johnson, 2021; Thomaz et al., 2020). As illustrated in the examples in panels A and B of figure 1, despite all chatbots using non-human avatars, both Revolut and Helvetia provide the requested information in short, clear sentences, do not forward the user to a separate website, directly react and respond to the user input as a human would and with the appropriate tonality (even using emojis as a reaction to the positive user feedback in the Revolut example).

As these examples show, the design logic in current industry applications varies tremendously and significantly impacts the user experience. To address this issue, the current paper provides a strategy framework for developing more effective conversational AI applications. Specifically, we integrate prior work on the effective design of information systems and user-centric customer journeys to deliver more effective conversational AI experiences. This model offers a strategic perspective on the effective design of conversational AI, in contrast to the dominant technology focus in recent work on conversational AI (see Rapp et al., 2021), and mitigates common issues along the design, implementation, and deployment phases.

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The Six-Stage Model of Effective Conversational AI

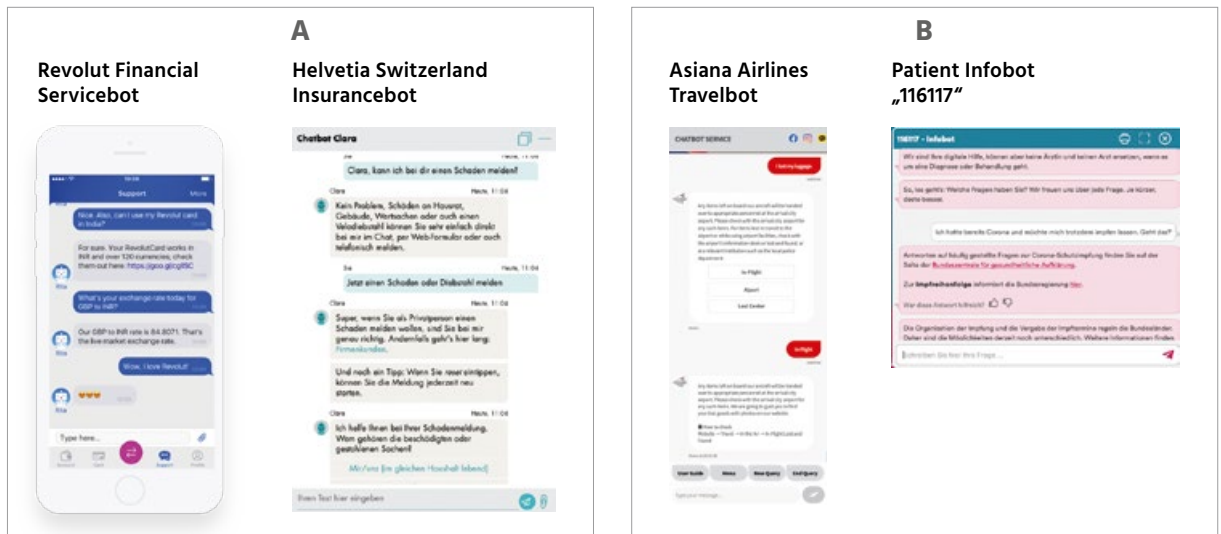
The model captures six distinct stages of effective conversational AI design summarized in this paper. It integrates prior work on the strategic design of information systems (Baptista et al., 2021; Gable, 2020) and the effective design of user-centric customer journeys in marketing (Lemon & Verhoef, 2016).

We first isolate the problem to be solved, followed by defining the expected target user. Next, we discuss the critical role of integrating different digital channels and the specific design decisions in the implementation and deployment phase. Finally, we outline the onboarding of the internal stakeholders and the selection of the appropriate technology stack. While this paper focuses on optimizing consumer–firm interactions, the model also applies to any other non-consumer setting (such as developing a conversational AI for internal processes). Figure 2 provides a visual illustration of the distinct stages and key questions in each development stage.

Stage 1 – WHAT: Define the User Problem

The first stage requires the definition of the specific task that should be automated by the conversational AI. Although this first stage sounds obvious, industry reports suggest a strong focus on the technology infrastructure, internal processes, and governance topics at the outset of a

Fig. 1: Selected Examples of Chatbots



Source: Own illustration.

project instead of focusing on the type of problem that should be solved for customers (Nguyen, 2017). We recommend analyzing the entire customer journey and critically evaluating in which stage conversational AI applications contribute to the existing objectives of the business. One dichotomy that helps with prioritization is to critically evaluate whether the trajectory of the business is focused on growth or cost-cutting. For example, if the COVID-19 pandemic requires a strong focus on costs, gaining management support for a pilot focusing on optimizing product information is less likely to receive approval compared to automating call center services through conversational AI to reduce service operation costs.

Our recommendation is to first outline a list of specific tasks with high potential for automation, then prioritize the selected use cases or tasks from a feasibility and business value standpoint. Suppose a company came up with three potential pilot projects in which options to solve the user problem ranged from (1) automating parts of the customer service process through a chatbot, (2) providing automated decision support by offering additional product information on a website through a chatbot, or (3) actively providing recommendations during the sales process through a chatbot. While the first project is arguably highly feasible, the expected business value is comparatively low. In contrast, the last project has a comparatively high business value but

lower feasibility as recommendations have to be highly individualized and contextualized. Finally, the clear articulation of the problem to be solved should also be closely tied to defining how the firm will track progress toward that objective (such as assessing customer acquisition costs before and after the pilot or the duration of customer service calls, depending on the key objective of the conversational AI). In summary, the first stage requires an exclusive focus on the problem that should be addressed from the user perspective.

Stage 2 – WHO: Define the Target User

The second stage is designed to define the envisioned target user. We recommend the use of methods already employed in prior work on customer journey mapping by defining the “archetypical user persona” (Lemon & Verhoef, 2016). Thus, the company should evaluate the predominant user of the conversational AI service for the defined problem (stage 1). The expected persona/s should be as specific as possible and cover both objective characteristics such as demographics (age, gender, marital status) and subjective characteristics such as the expected emotional state or important values of the user. Anticipating the emotional state of a user is critical as a negative experience of an already frustrated user can lead to a negative downward spiral and a negative evaluation of the firm. For

example, recent research by Hadi (2019) revealed that customers who were in a state of anger or frustration before entering the interaction with a customer service chatbot were even more frustrated after the interaction and evaluated the firm more negatively compared to a group of control customers. Thus, firms are advised to carefully define the expected target user and to incorporate the anticipated emotional state of the user.

Stage 3 – WHERE: Define the Channel Integration Across Touchpoints

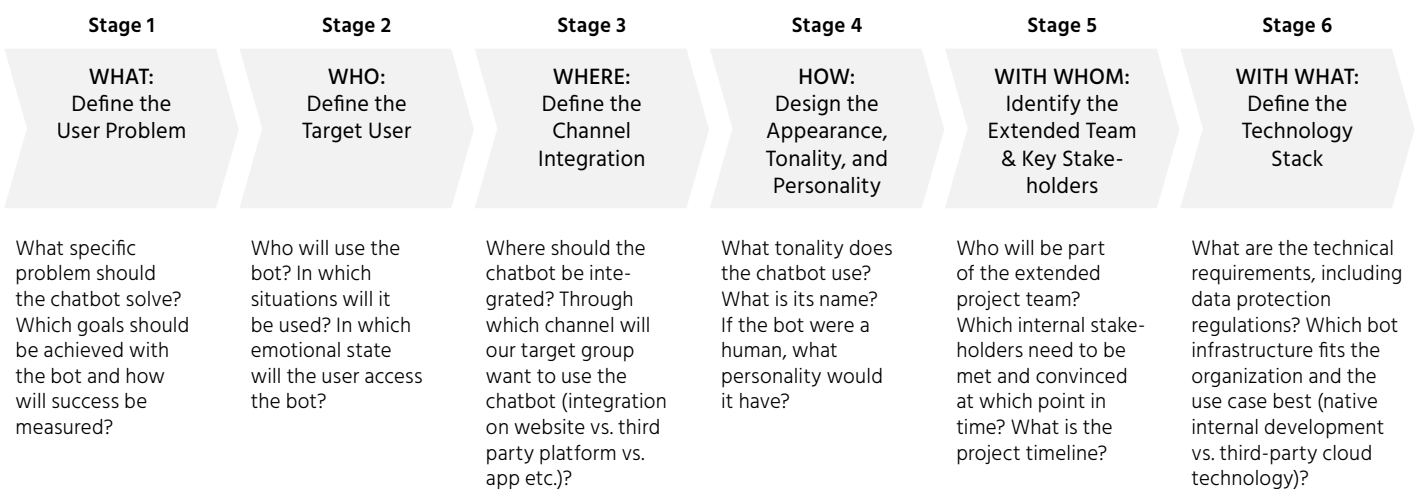
The third stage is designed to assess and decide how the conversational AI application should be deployed. This can range from integration on an existing website or within an existing third-party platform (WhatsApp, WeChat, Facebook, etc.) to deployment as a stand-alone App. This stage requires a decision regarding the core channel of operation and the question how channel switching should be handled across touchpoints. For example, a firm might decide to implement a conversational AI as part of their sales automation processes on the website. Thus, integration and deployment require a decision with respect to where on the website the conversational AI should be made available and what should happen in the case of failed intent matchings (i.e., when the conversational AI does not know how to answer or handle a prospect request). A failed intent matching should move a prospect or existing customer seamlessly from one channel of interaction to the

next. This could imply the seamless integration of human sales representatives taking over. Failed intent matching and ineffective channel integration are major sources of frustration for conversational AI users due to the reduced sense of goal attainment (Leung & Chan, 2020). Thus, objectives of the third stage are to decide which channel to focus on and to consider potential interactions across all channels and touchpoints. Companies are well advised to carefully assess failed intent matchings not only before or during a pilot phase but also at regular time intervals after the conversational AI application has gone live. The majority of conversational AI interfaces provides identifiers that explicitly flag failed interactions or intents in the backend, which can (and should) be carefully and systematically analyzed.

Management Summary

Conversational AI is fundamentally changing how consumers interact with firms. However, the design logic in current industry applications varies tremendously and significantly impacts the user experience. To address this issue, the current paper provides a strategy framework for developing more effective conversational AI applications. This model offers a strategic perspective on the effective design of conversational AI and mitigates common issues along the design, implementation, and deployment phases.

Fig. 2: Six-Stage Model of Conversational AI Design



Source: Own illustration.

Stage 4 – HOW: Design the Appearance, Tonicity, and Personality of the AI

The fourth stage encompasses all design-related decisions and involves the visual appearance and the conversational design (the structural and semantic properties of how the conversation between a human user and the AI is governed).

For example, the visual design in the context of chatbots involves the company or brand-congruent design of the digital avatar, the name of the avatar, the coloring and font type. The selection of the avatar and the appropriate naming are critical design choices (Miao et al., 2021) as they directly reflect the brand. The conversational design captures the structural and semantic properties of the conversation. The structural dimensions entail, for example, the frequency or extent of turn-taking (i.e., whether the conversational AI actively promotes a back-and-forth communication as in human-to-human communication). Recent research has demonstrated that a greater extent of turn-taking enhances trust and a more positive evaluation of the brand (Hildebrand & Bergner, 2020). The semantic dimension captures the tonality of the conversational AI and can range from a more formal to an informal tone of communication (using, for instance, more affect-rich language or emojis). The combination of the visual and conversational design ultimately defines the type of personality users will attribute to the conversational AI. For example, more affect-rich language can be used intentionally to engineer a more extraverted “personality” of the conversational AI. Such personality attributions can even be evoked by more subtle cues such as leaving longer pauses to indicate a greater sense of reflectivity on the part of the AI or increasing the variability of vocal frequency to indicate excitement (Hildebrand et al., 2020). In short, human users tend to attribute distinct personalities to the conversational AI, and the systematic visual and conversational design are key factors in engineering the envisioned personality profiles of the firm or brand (Nass & Moon, 2000; Nass et al., 1994).

Stage 5 – WITH WHOM: Define the Extended Project Team & Stakeholders

The fifth stage focuses on defining the extended project team and on actively onboarding internal stakeholders. The initiative typically resides in one functional organization (for example, the HR department when it comes to the use of a chatbot for internal trainings of employees or the marketing department regarding the use of a chatbot as part of their digital marketing activities to generate and convert leads).

This stage is essential for winning over the entire organization and extended project team (all internal stakeholders that will either directly or indirectly be involved in the project, such as the internal IT department). The fact that conversational AI applications are based on relatively recent technological developments can lead to internal resistance that needs to be actively managed. This stage is critical for avoiding false expectations while identifying strong internal promoters of the pilot project. It is vital to anticipate and respond to potential internal resistance. For example, it is recommendable to actively communicate how the success of the pilot is measured (for example, in the context of a sales automation project; this may involve the amount of traffic to key landing

Main Propositions

1. Conversational AI allows to build and nurture more personalized consumer–firm relationships.
2. To reap the benefits of conversational AI and to reduce the risk of project failure or low acceptance rates among users, we propose a structured process to develop conversational AI applications in research and practice.
3. We recommend to first define the intended use case, the target user, the digital touchpoints, the visual and conversational design characteristics, and finally integrate internal stakeholders and decide on the technology stack.

Lessons Learned

1. Start with the problem and end user in mind, not the technology.
2. Consciously design all user-relevant touchpoints and the integration of human employees and the conversational AI.
3. Design the tonality and personality to maximize a coherent brand experience for the user.
4. Actively integrate internal and external stakeholders. Define clear milestones, project timelines, and measures of success.

pages, actual conversion rates on those landing pages, or the number of pages visited before the key landing page).

Stage 6 – WITH WHAT: Define the Technology Stack

The sixth stage focuses on the selection of the most appropriate technology stack in view of all the preceding stages. The decision on the technology stack is positioned at the last stage of the model for two major reasons. First, the technology stack should be selected according to the specific use case, independent of the internal processes and already existing infrastructure. This sequence is designed to avoid narrowing down the options and distracting from the focal problem of the end user as opposed to the technology. Second, focusing on the technology after the requirements regarding the conversational AI helps to critically evaluate whether the envisioned use case requires a complex natural language processing engine or whether a simple rule-based conversational agent is sufficient.

We acknowledge, however, that this stage also has to incorporate the organizational requirements such as previously used technologies, existing data protection regulations, and other project resources. The presented model may be seen as an ideal archetype, and the actual implementation of a project may require several iterations, going back from the technology to earlier stages. As the number of conversational AI providers continues to grow (ranging from Amazon, Google, Microsoft, and IBM to smaller, more specialized solution providers), we recommend to regularly monitor the development on the technology side. As with any corporate information systems project, large companies usually offer highly scalable but more standardized solutions whereas smaller providers are often more actively involved and offer a better, customized fit.

Future Directions in Research and Industry Practice

We see four fruitful directions for future work in research and practice. First, future work could further explore the interactions between the individual stages highlighted in this paper. Specifically, future work may further assess the interplay between the users' psychological predispositions and their specific design preferences of the conversational AI. For example, users with higher levels of extraversion might prefer a conversational agent with a larger number of affect-rich, emotional cues (from emojis in written language with text-based chatbots to greater vocal variability in digital voice assistants) (Hildebrand et al., 2020).

Second, future work may further explore the role of adaptive user interfaces (de Bellis et al., 2019) and the importance of more contextualized interactions. For example, a user with higher levels of extraversion might prefer a more emotional voice assistant when searching for a new fashion item or screening a new movie on Netflix. However, the same user may prefer a less emotional voice assistant when searching for a mortgage or optimizing their financial portfolio. Thus, future work could further explore the importance of dynamically adapting the conversational AI to the context or task.

Third, future work could further explore the dynamics of the strategic framework provided in this research over time. Specifically, the type of problems that a bot is expected to han-

Effective conversational AI
is not a fixed product or
service but in constant flux
with changing user demands.

dle is a 'moving target' and may change in both scope and complexity over time (stage 1). Due to the implementation across multiple channels the end user base is often becoming more diverse, and consumer expectations are likely to increase as well (stage 2). Also, the digital channel landscape is continuously evolving, raising the question of effective channel integration across touchpoints (stage 3). Finally, consumer expectations and legal frameworks may require developers in the future to use non-humanized avatars to avoid the impression that the agent is a human as opposed to a machine (stage 4).


Fourth, the framework does not specify an explicit "monitoring stage" but in practice this part is of critical importance. Specifically, companies must not forget to monitor the conversational assistant and improve it on the basis of important performance metrics such as bounce rate, user feedback, and the questions received (particularly those that lead to a dysfunctional outcome or dead end for the user). Effective conversational AI is not a fixed product or service but in constant flux with changing user demands. Usually, a chatbot does not cover all of the users' relevant questions immediately after the launch. These must be supplemented with further iterations. If the company has decided on a very distinctive chatbot personality, this must also be critically scrutinized after a certain operating time and possibly adapted depending on user reactions.

Finally, the majority of emerging work on conversational AI in marketing and related areas has focused on studying

relatively narrowly defined contexts such as specific customer service tasks (Hadi, 2019; Hildebrand & Bergner, 2020; Thomaz et al., 2020). There are ample opportunities for more conceptual work based on the current paper to help synthesize the emerging effects into broader organizing frameworks and design principles. This work would help both to integrate and synthesize the quickly emerging empirical work into larger conceptual frameworks and to highlight potential blind spots in empirical research and give directions for future research.

Conclusion

Conversational AI is fundamentally changing how consumers search, shop, and express their preferences. Despite the opportunity to deliver cost-effective and highly scalable user experiences, emerging research and industry findings

are mixed and range from greater user satisfaction to heightened frustration and reluctance to engage in future use of conversational AI due to privacy concerns and poor intent matching. This paper provides a strategic framework for developing more effective conversational AI based on prior work on the effective design of information systems. We provide a structured process that is designed to mitigate common issues in the design, development, and deployment phase by first clarifying the intended use case, then defining the target user, the integrated digital channels, the visual and conversational design characteristics of the conversational agent, the onboarding phase with internal stakeholders, and finally the envisioned technology stack. We hope that this research inspires future work in the quickly developing field of conversational AI at the intersection of marketing, information systems, and the user-centric design of conversational AI applications. 

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