ALIGNING CHATBOT FEATURES WITH INDUSTRY NEEDS: A COMPARATIVE STUDY OF USER EXPECTATIONS IN UTILITARIAN AND HEDONIC SECTORS FOR SMEs

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This study explores the optimal chatbot orientation—socially oriented (SO) or task-oriented (TO)—for small and medium-sized enterprises (SMEs) in hedonic versus utilitarian industries. Through a mixed-methods approach combining quantitative data from 166 participants and qualitative interviews, it examines user preferences for chatbot interaction styles, focusing on perceived ease of use (PEOU) and usage intention (UI). Findings highlight a strong preference for SO chatbots in hedonic contexts, emphasizing engaging, human-like interactions, while utilitarian industries showed no significant preference, with efficiency taking precedence. Correlation analysis revealed a robust link between perceived ease of use and usage intention for SO chatbots, underscoring their potential to enhance user engagement. The research provides actionable insights for SMEs to tailor chatbot designs to industry-specific customer expectations, aligning digital tools with business goals and customer satisfaction.

Keywords:
chatbot interaction design,
SME digital strategies,
hedonic vs utilitarian industries,
user-centric AI tools,
social vs task orientation

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1 Introduction

Businesses face a critical imperative: adapt to digital integration or risk obsolescence. With global retail e-commerce sales projected to rise from 6.3 billion in 2024 to 8 billion by 2027 (Statista, 2024), small and medium-sized enterprises (SMEs) must adopt AI tools like chatbots to meet customer demands for seamless, personalized, engaging and 24/7 accessible solutions (Adamopoulou & Moussiades, 2020). However, SMEs face barriers such as high costs and technical complexity, compounded by industry-specific expectations (Hansen & Bøgh, 2020; Alford & Page, 2015). As described in Table 1, in utilitarian sectors (e.g., banking), chatbot users prioritize efficiency and task-oriented functionality, whereas, in hedonic industries (e.g., hospitality), they demand personalized, engaging interactions (Haugeland et al., 2022). This dichotomy underscores that chatbots must be tailored to sector-specific needs—a critical consideration for resource-limited SMEs (Bedué, 2020).

While existing research has explored chatbot attributes, such as hedonic (entertainment-focused) and utilitarian (task-driven) qualities, it has largely overlooked their alignment with industry-specific contexts, particularly for resource-constrained SMEs (Haugeland et al., 2022). This gap is significant, as lack of the context-aware chatbot risks misaligned investments, leading to suboptimal user experiences and diminishes returns of AI adoption. Without systematic evidence linking chatbot orientation to industry-specific user expectations, such companies risk deploying generic solutions that fail to address distinct customer needs in hedonic (e.g., hospitality) versus utilitarian (e.g., banking) sectors.

This study addresses this critical oversight by investigating: *How do social-oriented (SO) and task-oriented (TO) chatbot designs align with user preferences in hedonic versus utilitarian industries for SMEs?* At the same time contributing to the emerging field of context-aware conversational agents (Følstad & Brandtzæg, 2017). By providing empirical insights into industry-tailored chatbot design, this research advances theoretical understanding of user-centric AI tools and offers practical guidance for SMEs or digital solutions companies to optimize customer engagement and competitiveness.

Table 1: Definition and interpretation of chatbot/scenario features

	Features identifies	Explanations	Reference
TO/SO	Orientation: Task- or Social-oriented	**Task-Oriented (TO):** Focuses on efficiency and goal completion; concise, direct responses to complete tasks quickly, minimizing unnecessary interactions; value speed, functionality, and efficiency in the interaction. **Social-Oriented (SO):** Prioritizes personalization and engagement; friendly, conversational responses, including small talk or emotional cues; more human-like, personalized experience, even if it sacrifices task efficiency.	(Sheth, 1976)
PEOU	Perceived Ease of Use	Degree to which an individual believes that using a system will be free of effort.	(Davis et al., 1986)
UI	Usage Intention	Extent to which an individual intends to engage with a system, in the future. Closely associated with system adoption metrics.	(Davis et al., 1986)
IND	Industry: Hedonic or Utilitarian	**Hedonic Industry:** These industries, such as hospitality, travel, and entertainment, focus on creating enjoyable, immersive and personalized user experiences. **Utilitarian Industry:** Industries like banking, logistics, and technical support prioritize efficiency, accuracy, and the completion of tasks.	(Babin et al., 1994)

Source: Own

2 Literature research

2.1 Effectiveness of Conversational Agents

The increasing integration of AI-driven chatbots into business operations is reshaping the way companies interact with their customers. Recent studies have shown that these agents are evolving to match human performance in certain areas of customer engagement, particularly in structured, task-oriented contexts. For instance, as Luo et al. (2019) report *"undisclosed chatbots (whose nature is not disclosed during the chat, so users assume they are human) are as effective as proficient workers and four times more effective than inexperienced workers in engendering customer purchases"* (p. 938). In a field experiment involving over 6,200 customers, these chatbots performed on par with experienced salespeople and significantly outperformed less experienced workers. This finding is extremely practical for such businesses, as it presents them with a great opportunity to streamline their budget into a reliable, cost-efficient and powerful system with measurable and proven performance.

However, the research also revealed a key caveat: when customers were made aware that they were interacting with a chatbot, purchase rates plummeted by 79.7%. This stark contrast between perceived and actual competence underscores the scepticism many consumers have towards AI-driven systems, despite their objective performance. The study offers insights into mitigating this bias, such as delaying the disclosure of chatbot identity and targeting customers with prior positive experiences with AI. These findings suggest that while chatbots have demonstrated their capabilities, businesses must strategically manage customer perceptions to fully leverage this technology.

2.2 User Motivation and Chatbot Effectiveness

Following on the previous section, it is extremely important to understand the origin of customer motivations that significantly influence how users interact with AI conversational agents. It was established that participants' interaction rates with AI models were positively correlated with purchasing functional (utilitarian) products (Ruan & Mezei, 2022). Conversely, when the product was perceived as experiential (hedonic), participants' satisfaction was lower if they received a consultation from a chatbot rather than from a human consultant. This finding indicates that there are differences in expectations toward chatbots based on users' motivations and the nature of the product or service.

While this study explored the relationship between the kind of service agent (chatbot or human) and user motivation, it did not delve into how specific chatbot features might impact user perceptions across different industry contexts. To address this gap, our research focuses on the type of industry in which service agents are used.

2.3 Aligning Features of Conversational Agents with User Expectations

This research builds upon established frameworks for understanding user attitudes and behavioral intentions, focusing specifically on the role of chatbot orientation in influencing PEOU and UI. Two significant studies provide the theoretical foundation for this approach. Firstly, Chuen et al. (2023) investigated how perceived usefulness and perceived ease of use (described in Table 1) impact usage intention in the context of a digital assessment system. The research ended up concluding that while PEOU may not significantly affect usage attitude directly, it remains a critical factor in shaping user behavior and intentions. Secondly, the widely adopted Technology Acceptance Model (TAM) developed by Davis et al. (1986) offers a robust theoretical framework linking system characteristics to user acceptance, emphasizing the role of perceived ease of use as a determinant of usage intention.

2.4 Implications for SMEs and Chatbot Design

Focusing specifically on small and medium-sized enterprises (SMEs), factors that lead to higher usage intentions of conversational agents were investigated within these organizations (Selamat & Windasari, 2021). Given the limited research on the adoption of such technologies by smaller businesses, this study fills a crucial gap by identifying elements that align with the unique needs of these companies. Notably, the study introduces the concept of "relationship marketing," which emphasizes the importance of social presence and feeling of personalization in fostering effective customer interactions (Yi, 2018).

This approach is particularly relevant for small enterprises, as they often rely on building strong customer relationships to compete with larger firms. The emphasis on relationship marketing suggests that these businesses can significantly benefit from implementing socially oriented conversational models that enhance personalization and human-like interactions.

3 Methodology

To investigate the research questions, this study examines three primary variables: Chatbot Orientation—whether the chatbot is Socially Oriented (SO) or Task Oriented (TO); Perceived Ease of Use (PEOU); and Usage Intention (UI). The Chatbot Orientation serves as the independent variable, while PEOU and UI are the dependent variables, with constructs defined in Table 1. The research aims to examine the relationship shown in Figure 1.

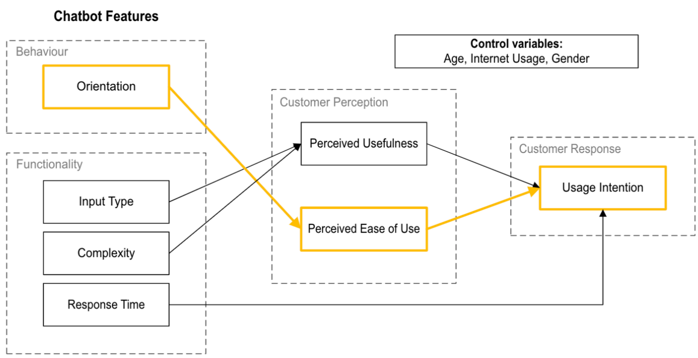

Figure 1: General research model (highlighted area is the scope covered by this research paper)
Source: Own

H$_1$: SO chatbots are perceived as significantly easier to use than TO ones across both industries, suggested by a difference in means of PEOU.

Socially oriented (SO) chatbots, designed to mimic human-like interactions (Selamat & Windasari, 2021), likely align naturally with users' intuitive expectations of communication.

H$_2$: Participants are significantly more likely to choose SO chatbots for hedonic industrial contexts, while TO agents are preferred more in utilitarian scenarios, reflecting an industry-dependent preference.

Ruan & Mezei (2022) found users prefer human consultants for hedonic products due to social interaction, suggesting SO chatbots better meet these needs. TO chatbots' efficiency suits utilitarian contexts, where task completion is prioritized (Haugeland et al., 2022).

H$_3$: A positive correlation can be established between PEOU and UI for SO chatbots among all industry types (Yi, 2018; Selamat & Windasari, 2021).

Selamat & Windasari (2021) and Yi (2018) emphasize relationship marketing in SMEs, where SO chatbots' ease of use in social interactions likely strengthens UI, as social temperament is critical for customer retention.

3.1 Participants and Sampling

Table 2: Sample demographics information

Characteristic	Distribution	
Sample size	168 (through Prolific: 151, convenience sample: 17) 156 (after cleaning and eliminating inattentive responders, explained in section 3.2)	
Age	Range: Mean: Median: Std:	19-67 years 29.61 26 9.88
Sex	male: female:	43% 57%
Chatbot usage	Every day At least 10 times a month At least once a month Less than once a month	22.2% 26.7% 35% 16.1%

Source: Own

3.2 Research design

The research utilized a mixed-methods approach, combining quantitative questionnaires with qualitative interviews to enrich the data collection. The within-subjects design, involving scenario-based experiments, was chosen to allow participants to experience both chatbot orientations, enhancing the comparison reliability, minimizing individual variability and increasing data robustness (Charness et al., 2012).

Four scenarios were crafted, representing two hedonic industries (karting, board game store) and two utilitarian industries (IT solutions, car garage). To ensure ecological validity, scenarios were based on real-world SME customer interactions and direct input from sector-specific business owners (e.g., hospitality managers, IT support staff). Dialogues reflected authentic user queries—such as reserving a karting slot or resolving software issues—with hedonic scenarios using engaging, conversational tones and utilitarian scenarios prioritizing clarity and efficiency.

Participants accessed the survey via Qualtrics through Prolific. After informed consent, each was randomly assigned two scenarios (one hedonic, one utilitarian), each presenting SO and TO chatbot interactions side-by-side. Participants selected their preferred interaction style and rated Perceived Ease of Use (PEOU) and Usage Intention (UI) on a 5-point Likert scale (1 = "Strongly Disagree," 5 = "Strongly Agree"):

Perceived Ease of Use (PEOU):

- **PEOU1:** "I found the chatbot easy to use during this interaction."
- **PEOU2:** "The chatbot was clear in guiding me through the process."
- **PEOU3:** "It was simple to complete the required task with the chatbot."
- **PEOU4:** "It was rather difficult to understand the solution from the chatbot."

PEOU4 was intentionally phrased negatively to assess participant attention and response consistency. This reverse-coded item helps identify inattentive respondents and improves the reliability of the data.

Usage Intention (UI):

- **UI1:** "I would use this chatbot again if I needed similar assistance."
- **UI2:** "I would prefer using this chatbot over other available options."
- **UI3:** "I am likely to recommend this chatbot for similar tasks."

This process was repeated for both assigned scenarios, resulting in each participant providing data on two industries and their corresponding chatbot preferences. Randomization of scenarios and chatbot presentation order was implemented to minimize order effects and biases.

3.3 Interview component

To complement the survey data, qualitative interviews were conducted with 5 participants with ages ranging from 19 to 71, providing a deeper understanding of user expectations and preferences across different industry contexts in addition to the survey. The interviews presented participants with chatbot interaction examples for both hedonic and utilitarian industries. Participants were asked to reflect on these examples, discussing how tone, style, and the use of emojis or casual language influenced their perception of the chatbot's appropriateness and effectiveness within each industry type.

4 Results

4.1 Measurement Model Assessment

Table 3: Assessing the measurement model for reliability and convergent validity of latent variables to ensure robustness of the findings

Variable	Cronbach`s alpha	Composite Reliability	Difference	AVE
PEOU	0.804	0.815	0.011	0.635
UI	0.872	0.889	0.027	0.775

Source: Own

The reliability analysis showed strong internal consistency for both Perceived Ease of Use (PEOU) and Usage Intention (UI), with Cronbach's alpha (PEOU: 0.804; UI: 0.872) and Composite Reliability (PEOU: 0.815; UI: 0.889) exceeding the 0.70 threshold. Convergent validity was confirmed, as all Average Variance Extracted (AVE) values surpassed 0.5 (PEOU: 0.635; UI: 0.775). Discriminant validity was established using the Fornell-Larcker criterion, with the square root of AVE for both constructs (PEOU: 0.797; UI: 0.880) exceeding their correlation (0.450), confirming their distinctiveness. These results mean that **these constructs, while related, are conceptually distinct**, which validates the reliability and validity of the measurement model (Fornell & Larcker., 1981).

4.2 Hypotheses testing

Paired t-tests assessed H_1, which proposes that social-oriented (SO) chatbots are perceived as easier to use than task-oriented (TO) chatbots across industries. In the general context, SO chatbots ($M = 4.437$, $SD = 0.62$) outperformed TO chatbots ($M = 4.307$, $SD = 0.65$), with a mean difference of 0.130 ($t(309) = 1.8529$, $p = 0.065$, $d = 0.21$). This small effect size suggests a slight trend favouring SO chatbots' ease of use, though not significant at $p < 0.05$. Similarly, small effects were observed in hedonic (mean difference = 0.131, $t(154) = 1.3894$, $p = 0.167$, $d = 0.22$) and utilitarian contexts (mean difference = 0.103, t(153) = 0.9803, p = 0.328, d = 0.16), with no significant differences. These modest effects, potentially influenced by a ceiling effect in PEOU ratings (see Figure 3), indicate limited differentiation in perceived ease of use between chatbot types.

Table 4: Studying H_1 by assessing the significance of differences in ease of use among industries and chatbot types

Construct + IND	Chatbot Type						Result
	SO	TO	Mean diff	T-score	P-value	df (Cohen's d)	
PEOU (General)	4.437	4.307	0.130	1.853	0.065	309 (0.22)	Not supported
PEOU (Hedonic)	4.492	4.361	0.131	1.389	0.167	154 (0.23)	Not supported
PEOU (Utilitarian)	4.368	4.265	0.103	0.980	0.328	153 (0.16)	Not supported

source: own

Table 5: Testing H_2 by comparing the choices of the participants for the preferred interaction style, given the industry scenario

	Orientation	SO	TO	Total
Industry				
Hedonic		93	63	156
Utilitarian		74	81	155
Total		167	144	311

Source: Own

The chi-square analysis (χ^2 = 3.94, p = 0.047) reveals a statistically significant association between chatbot orientation (SO vs. TO) and industry context (hedonic vs. utilitarian). This result, significant at the 0.05 level, indicates that the distribution of preferences for SO and TO chatbots varies depending on the context, suggesting that user orientation choices are context sensitive.

To further investigate these preferences, z-tests were conducted to compare the proportions of SO choices within each context. For hedonic industries, the z-test yielded a statistic of 2.45 (p < 0.014), indicating a significant preference for SO chatbots. This suggests that users in hedonic contexts are more inclined to choose chatbots emphasizing social interaction.

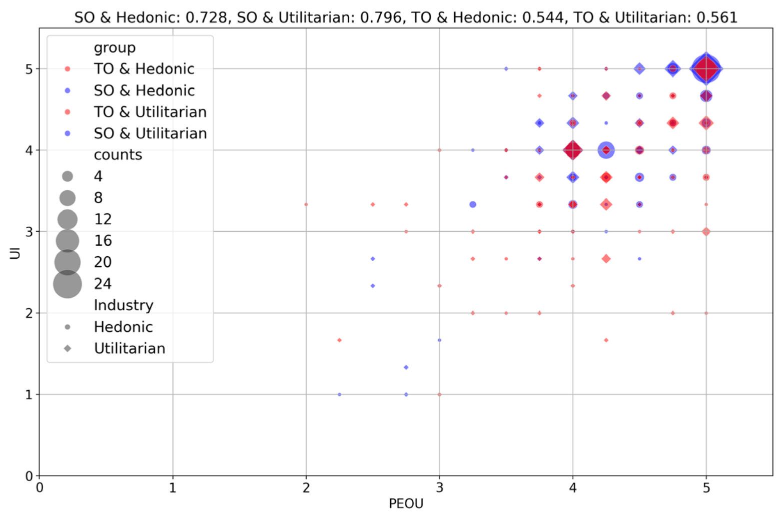

Figure 2: H_3 Correlation combinations of industry and agent types
Source: Own

Conversely, the z-test for utilitarian contexts yielded a non-significant statistic (z =-0.57, p = 0.57), suggesting no strong preference for either SO or TO chatbots within utilitarian settings, with no apparent inclination toward one interaction style over the other. Overall, these findings highlight a clear preference for socially oriented chatbots in hedonic contexts, while preferences in utilitarian contexts remain neutral. For SO chatbots, the correlations are particularly robust, with values of 0.728 (hedonic) and 0.796 (utilitarian), indicating that users who find SO chatbots easy to use are significantly more likely to intend to use them again. This supports H3, suggesting that SO chatbots' design enhances user adoption intentions. For TO chatbots, the correlations are weaker but still positive (0.544 for hedonic and 0.561 for utilitarian), implying that while efficiency is valued, it may not drive usage intention as strongly as the social and relational aspects of SO chatbots. These findings underscore the importance of aligning chatbot design with user expectations, particularly in hedonic contexts where SO chatbots excel, while utilitarian contexts show more balanced preferences.

However, the ceiling effect (see Figure 2) likely tempered these correlations, especially at higher levels of perceived ease of use, where further differentiation becomes challenging.

5 Discussion, Limitations and Future Work

Based on the hypotheses tested and the literature referred to, the findings highlight that technology adoption depends on aligning the interaction style of CAs with industry expectations. Firstly, the clear preference for socially oriented (SO) chatbots in hedonic industries suggests that human-like interaction enhances user experience, with interviewees emphasizing the importance of friendly language and emojis in hospitality and entertainment (Ruan & Mezei, 2022). In contrast, utilitarian industries showed no strong preference, indicating that efficiency matters more than social presence (Haugeland et al., 2022). Similarly, interview results stressed professionalism, suggesting that overly casual chatbots may harm credibility in technical or service-driven fields.

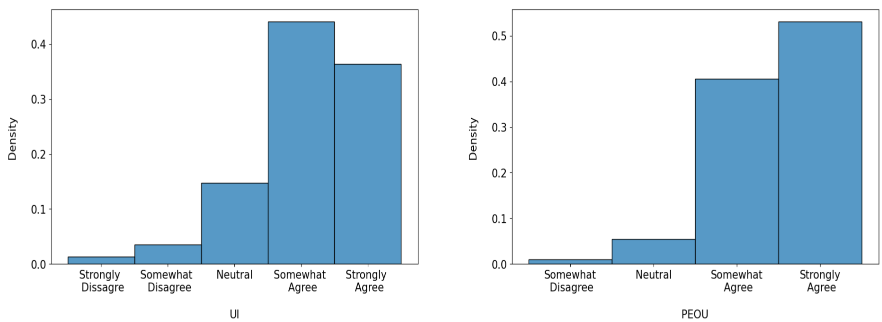

Figure 3: Density Distribution of UI and PEOU
Source: Own

These results extend the Technology Acceptance Model (TAM) by demonstrating that perceived ease of use (PEOU) and usage intention (UI) are moderated by industry context, contributing to the field of context-aware conversational agents (Følstad & Brandtzæg, 2017). Specifically, the preference for SO chatbots in hedonic settings underscores the role of contextual factors in shaping user-centric AI design, offering a theoretical foundation for adaptive conversational systems.

For SMEs, these findings provide actionable guidance: SO chatbots enhance engagement in hedonic industries, while utilitarian contexts benefit from TO or neutral designs. Strategic implementation, including careful management of chatbot disclosure, is critical to optimizing user acceptance and business outcomes.

During the study, it became evident that the responses for the constructs Perceived Ease of Use (PEOU), and Usage Intention (UI) exhibited a ceiling effect. This clustering of responses (shown in Figure 3) complicates the analysis, making it challenging to derive nuanced insights regarding user perceptions and preferences. To add regarding the limitations of this study: a) study sample from Prolific may be biased towards more tech-aware demographic group; b) cultural interpretation of "friendliness" or emojis could differ among populations; c) reliance on hypothetical scenarios with chatbot may not fully represent the real-world interactions. Future research could address these by diversifying samples, examining cultural factors, testing live chatbot interactions, and expanding industry contexts.

In the qualitative analysis, participants revealed distinct preferences based on industry context. In hedonic scenarios, a socially oriented chatbot—characterized by the strategic use of emojis, casual language, and emotional expressions—was consistently perceived as engaging and more likely to encourage future use. In contrast, for utilitarian contexts, respondents favoured a more professional, task-oriented tone, noting that excessive social cues, particularly emojis, could seem unprofessional and off-putting in serious situations. Although one respondent mentioned that removing emojis might make a social approach acceptable, the consensus emphasized that a balanced, restrained communication style is essential to maintain credibility in utilitarian interactions.

6 Conclusion

In conclusion, this research provides targeted insights into how chatbot orientation—social versus task-oriented—aligns with industry-specific user expectations in hedonic and utilitarian contexts for small and medium-sized enterprises (SMEs). The study's findings reveal a distinct preference for socially oriented chatbots within hedonic industries enhancing engagement and personalized interactions. In contrast, utilitarian industries prioritize functionality over interaction style. Additionally, a notable correlation between perceived ease of use and usage intention highlights the influence of chatbot design on user acceptance, with stronger correlations observed for socially oriented chatbots across both industry types. This research contributes to the field by filling the knowledge gap concerning industry-specific chatbot preferences and offering actionable recommendations for SMEs aiming to adopt chatbots in alignment with their customer engagement goals. The combined quantitative and qualitative data reinforce these conclusions, underscoring the importance of tailoring chatbot orientation to the unique needs of each industry.

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