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Abstract. This study aimed to identify the various factors that may influence customer service representatives' perceptions of artificial intelligence (AI)-based conversational agents (CAs) for customer service. By analyzing 180 publications, a conceptual research model is developed for identifying the factors that may influence customer service representatives' perceptions of AI-based CAs for customer service. The underlying conceptual research model comprises ten factors. The study is grounded in the application of the Technology Acceptance Model 2 (TAM 2) approach. The research model is empirically evaluated with survey data from 128 participants. Our results show that the direct positive effect of subjective norm on customer service representatives' perception of using AI-based CAs in customer service decreases with increasing experience. Moreover, our results reveal new insights regarding trust. The results of this study provide an overview of the predominant characteristics of the influencing factors of customer service representatives' perceptions of AI-based CAs for customer service.

Keywords: empirical study, TAM 2, artificial intelligence, conversational agents, customer service

1 Introduction

It is significant for business success in today's growing competitive market to know what is appealing, what is satisfying, and what is neither from the customer's perspective [1], all of which can be obtained through customer service. Today's customers demand flexible, convenient, and personalized customer service, placing companies under increasing pressure to innovate [2]. Inadequate service could affect customer satisfaction and business growth [2]. Artificial intelligence (AI) is becoming increasingly important in companies, administrations, and everyday life, e.g., voice assistants [3]. AI characterizes computational systems that attempt to use aspects of human intelligence [4]. Amid the rise of customer-oriented and efficient customer service [5], a large number of companies now use conversational agents (CAs) such as chatbots, which optimize certain processes in customer service based on recent AI insights, especially in natural language processing (NLP) [6]. In various areas such as sales, customer service, and marketing, CAs nowadays provide 24/7 services [7]. The use of chatbots is expected to save service providers $8 billion annually by 2022 [8]. However, some studies (e.g., [9], [10]) have identified problems with CAs in customer service. For example, communication between humans and chatbots is described as lacking essential aspects of the extensive basic vocabulary present in a conversation between two humans [11], which can reduce the acceptance of the customer service representative in CAs. To address this issue, AI can be used as a key supporting technology for improving user perception (customer service representatives) of CAs for customer service. According to Damerji [12] and Ye et al. [13], AI-based CAs can help to increase productivity in the workplace (e.g., through robotic process automation, freeing up the customer service agent to focus on value-added activities) [12]. According to these contrasts, we are interested in the customer service representative's perception regarding AI-based CAs for customer service. This leads to the following research question (RQ): ***What are the main factors that can influence customer service representatives' perception of AI-based CAs for customer service?*** To answer this RQ, we follow the Technology Acceptance Model 2 (TAM 2) approach of Venkatesh and Davis [14]. We chose TAM 2 because it provides explanations of the main factors that precede judgments about perceived ease of use, which can explain up to 60% of the variance in these important factors that influence intention to use [14].

2 Literature Review

2.1 AI-Based Conversational Agents for Customer Service

AI can be differentiated between weak or strong AI. Strong AI can be understood as artificial general intelligence [15], [16], which equals or surpasses human intelligence [16]. Weak AI – also described as artificial narrow intelligence – deals with specific limited applications [15], e.g., chatbots and NLP [16]. When the term AI is used in the remainder of this paper, it refers to weak AI. CAs are increasingly used as service agents as they can support classical service tasks of human staff [2]. In addition, as a customer care technology CAs enable a cost-saving communication channel [2], increase service quality, and improve communication between providers and customers. CAs act as personal contacts for users and perform a wide range of functions, e.g., answering customer queries [7], [17]. In our study, we base our description of AI-based CAs in customer service on the definition provided in [18]. AI-based CAs are user interfaces that use NLP, machine learning, and/or AI to mimic communication between two humans (e.g., customer service representatives and customer) [18] in the context of customer service. Although AI-based CAs are already widely used in e-service, many users are still reluctant to use them due to difficulties in interaction and other issues [7].

2.2 Systematic Literature Review

To present an overview of the current state of research and science focusing on customer service agents' perceptions towards AI-based CAs in customer service, a systematic literature review is presented here, following the guidelines of vom Brocke et al. [19] and Webster and Watson [20]. The retrieval of relevant articles was performed using the following two search strings: ("customer feedback" OR "customer complaint" OR "customer service" OR "customer satisfaction") AND (management OR system OR process OR workflow OR platform) and their German equivalents. To limit the number of results in the search phase, the analysis to identify related papers was limited to their title, abstract, and keywords within a specified time period from 2009 to 2020. A search of the EBSCOhost, ScienceDirect, and Google Scholar databases identified 7,451 scientific papers, which was followed by a forward and backward search, which enabled identifying twenty additional relevant publications. In order to maximize the significance of the results, frequency analysis [21] is used to examine the results. The preparation of data for frequency analysis is based on a proven flowchart [22] in which QDA Miner software [23] is used for technical support. In order to make the final sample selection, the 7,471 identified scientific publications were filtered according to the following inclusion criteria: a paper must (1) include in the title, abstract, or keywords the word stems "Artificial" OR "Intelligence" OR "Intelligent", (2) include relevant information especially on AI within the study, and (3) be written in English. Furthermore, we excluded studies that did not include original study data (e.g., editorials, and ongoing research) and studies that did not report relevant information (no AI). Overall, 180 articles were identified as relevant in this way. A compilation of the identified articles can be found at: https://tinyurl.com/44wemn96. The 180 papers were read in their entirety to identify potential publications that fit our focus topic of AI-based CAs for customer service. The majority of publications use AI in general to optimize business processes without the use of CA or chatbots, so they are not further considered in this study. However, thirteen publications were evaluated as relevant and considered for problem elaboration, motivation and derived knowledge.

2.3 Related Work

In the study by Przegalinska et al. [24], methods for tracking human-chatbot interactions and evaluating the performance of chatbots are developed, focusing on trust aspects. The authors demonstrate the importance of trust for human-chatbot interaction and analyze the extent to which trust needs to be defined as an essential property in using deep learning-based chatbots [24]. Furthermore, issues related to artificial conversation improvement are discussed in [25], security-related issues in [26], workload reduction issues for human advisors in [27], quality issues in [28] and [29], and customer response issues and implications for science and practice for AI in customer service in [30] and [31]. Despite multiple approaches to improve AI in the field of CAs, we consider that there is a lack of analysis regarding the different factors that may influence customer service representatives' perceptions towards AI-based CAs in customer service, which motivated our RQ.

3 Theoretical Background and Hypothesis Development

3.1 Theoretical Background on TAM and Related Theories

This study analyzes the factors of user perception (customer service representatives) towards AI-based CAs in customer service using the TAM 2 according to Venkatesh and Davis [14]. TAM ([14], [32-34]) examine the influence of different individual influencing variables in more detail. The constructs of *perceived usefulness (PU)*, *perceived ease of use (PEOU)*, and *intention to use (ITU)* of the TAM were extended in the TAM 2 by two further processes, namely the social influences (*subjective norm (SN)*, *experience (EX)*, *voluntariness (VO)*, and *image*) and the instrumentalized cognitive influences (*job relevance (JR)*, *output quality*, and *detectability of results*). The ten variables target the *user behavior (UB)* of the innovation [14]. Following previous studies (e.g., [35]), the perception of usage is not the same as the ITU, as it can be assumed that usage behavior is influenced by the perception of users (e.g., customer service representatives) based on the intention to use technologies (e.g., AI-based CAs) [36]. Given that TAM essentially only explains about 40% of the variance, additions are essential for specific RQs [37]. The integration approaches of TAM and *trust (TR)* according to Gefen et al. [38], *computer anxiety (CoA)* from the TAM 3 according to Venkatesh and Bala [34], and *willingness to investment (WTI)* according to Heyder et al. [39] and Theuvsen and Hollmann-Hespos [40] are used as the basis for these supplements. Thus, the constructs TR (in AI), CoA (towards AI), and WTI (in software/technology) are adopted, and nine hypotheses are derived as described in the following.

3.2 Hypothesis Development

SN influence ITU in TAM 2 by means of PU, whereby this process is referred to as internalization [41]. Wu et al. [41] describe that if the people (e.g., work colleagues) who have some relevance or importance to the subject person (customer service representative) contribute to the use of the system (e.g., AI-based CA) as appropriate, then the subject person will normally use the system. This leads to the following hypothesis: *H1: Subjective norm has a direct positive effect on customer service representatives' perception of using AI-based CAs in customer service (based on [14]).* Users (e.g., customer service representatives) can improve their efficiency at work if they are aware of their job-related knowledge [42]. JR refers to the extent to which a person (e.g., customer service representative) believes that AI technology is relevant to his or her work, and therefore it can be assumed that JR has a direct impact on PU [43]. Therefore, the following hypothesis can be derived: *H2: Job relevance has a direct positive impact on customer service representatives' perception of using AI-based CAs in customer service (based on [14], [43]).* PEOU corresponds to the degree to which potential users (e.g., customer service representatives) perceive the use of a particular technology as effortless, simplified, and enjoyable [44]. According to Damerji [12], PEOU has a direct impact on ITU in terms of the acceptance of a new technology (e.g., AI). Accordingly, the following hypothesis can be derived: *H3: Perceived ease of use* *positively affects customer service representatives' perception of using AI-based CAs in customer service (based on [12], [13], [45]).* According to Theuvsen and Hollmann-Hespos [40], EX and VO are considered moderating variables in TAM 2. However, Venkatesh and Davis [14] tested user acceptance at three different time points to analyze the effectiveness of EX as a moderator. The EX of employees (e.g., customer service representatives) with a new technology (AI-based CA) – regardless of their social and cultural background – significantly influences the impact on PU [46]. In the study by Oh et al. [47], it was presented that interaction between users (e.g., customer service representatives) and AI (e.g., in conjunction with a CA) leads to fun and new user EX. Therefore, the following two hypotheses arise: *H4: The direct positive effect of subjective norm on customer service representatives' perception of using AI-based CAs in customer service decreases with increased experience (based on [14]). H5: The direct positive effect of subjective norm on customer service representatives' perceptions of using AI-based CAs in customer service behaviorally is not significantly influenced by experience (based on [46], [48]).* TAM 2 theory shows that SN has a direct influence on the ITU technologies when use is mandatory but not VO [46]. Accordingly, VO (the extent to which potential users of the technology view the usage decision as non-mandatory) was declared as a moderating variable [46]. Regarding the construct VO, Goni and Tabassum [49] prove in their study that users rather prefer a communication channel with AI – e.g., a chatbot – than human contact. Accordingly, the following hypothesis is derived: *H6: Voluntariness does not significantly affect the effect of subjective norm on customer service representatives' perceptions of using AI-based CAs behaviorally in customer service (based on [14], [46]).* Based on previous studies (e.g., [38]), it is assumed that an increase in the level of TR – i.e., certain expectations of the technology in question (e.g., AI) – is in turn seen in connection with its increased ITU. According to Gefen et al. [38], TR has a positive impact on the perceived benefits. According to Siau and Wang [50], the creation of a TR base is a dynamic that implies an evolution from initial TR to ongoing TR growth. Further TR growth (e.g., of a customer service representative in an AI-based CA) is dependent on the AI's capability and intent [50]. Therefore, the following hypothesis emerges: *H7: Trust has a direct positive impact on customer service representatives' perceptions of using AI-based CAs in customer service behaviorally (based on [38]).* CoA (in relation to AI) describes the degree to which an affected person (e.g., customer service representative) has concerns and even fears about a computer application (e.g., AI) [51]. According to Igbaria and Iivari [52], users (e.g., customer service representatives) who do not experience fear of computers (e.g., AI-based CAs) are significantly more likely to use computer systems than those who experience greater fear of working with computers. CoA has been shown to have a negative effect on constructs corresponding to perceptions of usability [52], prompting the following hypothesis: *H8: Computer anxiety has a direct negative impact on customer service representatives' perception of using AI-based CAs in customer service (based on [34], [52], [53]).* Investments in technologies (e.g., AI) can not only benefit large companies through IT but also small and medium-sized enterprises. Furthermore, this technology can level the playing field in large companies, create independence of location and time, and improve communications [54]. Moreover, a smooth and deep integration of AI-based CAs into the company’s digital communication channels can significantly increase trust (e.g., of customer service representatives) towards these AI-based CAs [55], [56]. It can be argued that WTI (e.g., in AI-based CAs) and UB are related [57] and that users with a benevolent perception towards new technologies (e.g., AI-based CAs) have a stronger WTI in them. Accordingly, the followed hypothesis is proposed: *H9: Willingness to invest has a direct positive impact on customer service representatives' perceptions of using AI-based CAs in customer service (based on [39], [57]).* The demographic constructs are based on *gender*, *age group*, *function in the company*, *economic sector*, *company size*, and *experience with AI systems*. Against the background that the indicators are without exception not directly observable variables, a reflective measurement model is used [58]. Significantly, different indicators are added per construct, with Weiber and Mühlhaus [59] distinguishing the application almost exclusively to multiple items per construct for a multi-construct model. Item development is guided by [12-14], [43], [48], [53], [57], [60-67]. A compilation of the items per construct can be found at: https://tinyurl.com/44wemn96.

4 Methodology

To collect data for the empirical research study, an online survey [68] was conducted in Germany, Austria, and Switzerland. To ensure the validity and reliability of the questionnaire, a two-stage validation is performed. First, whenever possible, the pre-validated questions and the general accepted guidelines for instrument construction are followed per Boudreau et al. [69] and Straub [70]. The survey was created using Limesurvey software [71] after Nobata et al. [72], as it allows information preparation for subsequent statistical analysis using SPSS [73] and SmartPLS 3 [74]. In this survey, the Likert scale [75] was used by means of a five- or seven-point scale (e.g., 1: strongly disagree, to 7: strongly agree) [76] to structure the possible answers. For the purpose of refining the survey’s quality and content validity, a pre-test was conducted in advance with 37 subjects [77], [78]. The survey was shared on various platforms such as LinkedIn, XING and the German Association for Information Technology and Telecommunications, so that it was executable in anonymous form for participants from October 20, 2020, at 00:01 am to January 09, 2021, at 23:59 pm. In addition, the survey was distributed using Amazon Mechanical Turk (MTurk) to gather international opinions from Austria and Switzerland. Study participants were encouraged to answer all questions from a customer service representative’s perspective, except for the questions regarding WTI. At this point, we asked participants to place themselves in the role of a company decision-maker. Apart from the presentation-style items, there was a video about AI [79] and explanation of what we mean by AI in CA-based customer interaction [80], which ensured a consistent level of knowledge among the participants. Additional components of the online survey were an introductory text that informed about the incentives and procedure of the survey as well as the option to leave a comment at the end of the survey. Subsequently, 199 data records were examined and cleaned for completeness and credible response times. Plausibility checks were performed to achieve the highest possible data quality. For this purpose, the processing time was recorded and the survey was excluded if it fell below a realistic minimum duration [81] (average 12.2 minutes). In addition, we considered the dropout rate and only used surveys in which respondents completed [82] to page 5.

5 Results

The final sample comprised 128 terminated records used for analysis. Table 1 provides an overview of the demographic profile of the respondents. In terms of experience with AI systems, for this study we define that experience comprises the daily work of a customer service representative using AI. The quality of the measurement model is decisive for the future quality of the structural equation model. At this point, we focus on the validity and reliability of the measurement model. For this purpose, the common method bias (CMB) is tested by means of Harman's one-factor test [83].

Table 1. Demographic characteristics of respondents

	Gender	Age group	Function in the company
N (%)	M = 107 (84%), F = 18 (14%), D = 3 (2%)	I = 23 (18%), II = 98 (77%), III = 7 (5%)	TM = 11 (9%), PM = 8 (6%), DiM = 7 (5%), DM = 11 (9%), TL = 28 (22%), Em = 56 (44%), Ot = 7 (5%)

M: Male; F: Female; D: Divers; I: 18 to 24 years; II: 25 to 44 years; III: 45 to/over 67 years; TM: Top Management; PM: Plant Management; DiM: Division Management; DM: Department management; TL: Team Leader; Em: Employee; Ot: Other

	Economic sector	Use AI systems
N (%)	a = 4 (3%), b = 13 (10%), c = 17 (13%), d = 19 (15%), e = 38 (30%), f = 5 (4%), g = 12 (9%), h = 20 (16%)	Y = 53 (41%), N = 53 (41%), Ns = 22 (18%)

a: Agriculture, forestry, fishing; b: Manufacturing excluding construction; c: Construction; d: Trade, transport, hospitality; e: Information and communication; f: Financing, real estate, corporate service providers; g: Public service providers, education, health; h: Other providers; Y: Yes, we are using.; N: No, we are not using it.; Ns: Not specified.

Therefore, all 29 indicators are analyzed in a factor analysis, leading to the extraction of a factor explaining 39.664% of the variance. Since this is below < 50%, a CMB is unlikely [84]. Additionally, an exploratory factor analysis (EFA) per construct is conducted to assess unidimensionality using SPSS software. As a result of the UB being scenario-based and measured by only one item, it is omitted from further analysis [85]. The items meet the established thresholds for measure of the sampling adequacy (MSA) > .5; communalities > .5; Kaiser-Meyer-Olkin criterion (KMO) > .6; and Bartlett's test < .05 [86] (for more detailed statistical analyses, contact us e.g., EFA per construct, verification of the method bias, and square root of AVE). Because the items CA4 (.425), TR1 (.491), TR3 (.501), and TR6 (.166) do not meet or are only slightly above the threshold for commonality within their item group, and TR7 (.569[a]) has the lowest value for the MSA, they are dropped from further analyses. Omitting an item from the reflective measures does not affect the significance of a construct [87], [88]. In addition to the EFA per construct, a simultaneous EFA is performed for all 29 indicators to confirm their assignment to the appropriate constructs. For this purpose, it is necessary to select the factors that have an eigenvalue > 1 [89], which is true for six factors that explain 71.683% of the total variance. Moreover, the values for KMO (.891), Bartlett's test (.000), MSA (> .626[a]), and communalities (> .579) are consistently acceptable. Consequently, after subtracting items CoA4, TR1, TR3 TR6, and TR7 (cf. Section 3.2), one-dimensionality can be assumed.

Table 2. Internal consistency reliability

Construct	CISC Range	IIC	CrA	CR	AVE
UB	Scenario-based single point measurement				
CA	.619 - .805	.664	.856	.905	.760
ITU	.591 - .753	.595	.855	.902	.698
JR	.814 - .891	.783	.935	.954	.837
PEOU	.607 - .713	.567	.840	.893	.676
PU	.683 - .717	.634	.839	.903	.756
SN	.688 - .747	.621	.868	.910	.716
TR	.673 - .701	.622	.832	.893	.736
WTI	.808 - .818	.761	.905	.941	.841

CISC: Corrected Inter-Scale Correlation; IIC: Inter-Item Correlation; CrA: Cronbach's Alpha; CR: Composite Reliability; AVE: Average Variance Detected

To assess internal consistency reliability, Cronbach's alpha (CrA), inter-item correlation (IIC), and corrected inter-scale correlation (CISC) are calculated in a further analysis (see Table 2). The constructs regarding CrA can be considered reliable with a value of .7 or .75 [90] or they are considered very acceptable > .9 [86], which is true for the majority of the constructs. Regarding IIC, a value > .3 is considered adequate, and this is also confirmed for all constructs [91]. For the CISC, all items are above the threshold of > .5 [92]. Against the background that the three criteria provide satisfactory results, the internal consistency reliability is fulfilled. The second-order reliability and validity of the constructs with respect to their quality criteria is assessed by determining the indicator reliability (IR), composite reliability (CR), and average variance observed (AVE). Likewise, the thresholds of IR > .4 (> .741), CR > .6, and AVE > .5 are achieved [93], as shown in Table 2. Hereby, the premises of convergent validity in the context of construct validity are confirmed. Furthermore, we investigate the discriminant validity with respect to the square root of the AVE according to the Fornell-Larcker criterion [94], where it is shown to be true for values. Consequently, the constructs are suitable as a good basis for testing the hypotheses. This part of the research study examines the nine hypotheses and the conceptual model. Hair et al. [95] recommend using the partial least squares structural equation modeling (PLS-SEM) verification procedure, which is performed using SmartPLS 3 software [88], since the PLS-SEM procedure is used as a common method for determining (complex) path models with latent variables and their interrelationships [96]. For this purpose, model fit is first investigated using three parameters: standardized root mean square residual < 0.08 [97]

(.088), normed fit index > .90 [94], [98] (.679), and exact model fit (bootstrap-based statistical inference) < HI 95% of dULS and HI 95% of dG [99] (dULS (4.318) and dG (1.995)). With values of dULS (4.318) and dG (1.995), this fit criterion is not fully met, resulting in only a partial accurate model fit. Nevertheless, the overall model should not be rejected, as borderline results may be justified by minimal model weaknesses (e.g., small effect size in two paths) or the limited sample size [85]. Furthermore, thresholds are subject to controversy even outside of the IS discipline [100]. Due to only minor discrepancy, the model is rated as acceptable. The structural equation model (cf. Fig. 1) analyzes the beta values of the path coefficients and the coefficients of determination (R^2 values). The significance of each path is estimated using the bootstrap procedure [101] using 5,000 replicate samples, which tends to provide reasonable standard error estimates [102]. It can be confirmed that SN has positive direct influences on ITU ($\beta = .080$, $p < .001$) and PU ($\beta = .061$, $p < .01$). Direct positive influences can be confirmed for JR ($\beta = .352$, $p < .01$) and PEOU ($\beta = .287$, $p < .05$) on PU. Similarly, a direct positive influence is shown for PEOU on ITU ($\beta = .246$, $p < .01$). A significant negative influence is seen with TR on ITU ($\beta = -.068$, $p < .05$). A direct positive influence exists for PU on ITU ($\beta = .191$, $p < .001$) and for ITU on UB ($\beta = .016$, $p < .001$). Likewise, WTI shows a strong positive influence on UB ($\beta = .425$, $p < .01$). CoA shows a direct negative influence on PEOU ($\beta = -.062$, $p < .05$). EX ($\beta = -.031$, $p < .01$) has a significant negative interaction effect of SN on PU. EX ($\beta = -.033$, $p < .01$) shows a non-significant positive moderating effect of SN on ITU. VO ($\beta = -.040$, $p < .001$) shows a negative moderating significant effect of SN on ITU.

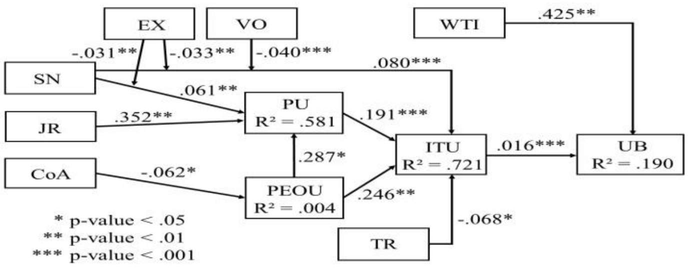

Figure 1. Investigated hypothesis model with path coefficients and R^2 values

In terms of the coefficient of determination, R^2 values of $\approx .33$ correspond to a moderate explanation of a construct, and R^2 values of $\approx .67$ correspond to a substantial explanation of a construct [103]. The direct influences of SN and JR on PU together with the direct influences of PEOU (which mediates the indirect influence of CoA on PU through PEOU) and the moderating influence of EX with SN on PU explained 58.1% of the variance in PU ($R^2 = .581$). The direct influence of PU on ITU (which mediates the indirect influences of SN and JR on ITU through PU), in parallel with the moderating influences of EX with SN and VO with SN, together with the direct influences of PEOU (which mediates the indirect influence of CoA on ITU through PEOU) and TR on ITU account for 72.1% of the variance in ITU ($R^2 = .721$). The direct influence of CoA on PEOU explains 0.4% of the variance in PEOU ($R^2 = .004$). The influence of ITU on UB (which mediates the indirect influences of SN, JR, PU, CoA, PEOU, and TR, along with the moderating influences of EX with SN and VO with SN on UB through ITU), in parallel with the direct influence of WTI on UB explains 19.0% of the variance in UB ($R^2 = .190$). All hypotheses except H7 can be confirmed.

6 Discussion

6.1 Theoretical Contributions and Implications

Similar to Venkatesh and Davis [14], this study shows that SN has a direct positive effect on PU. Consequently, hypothesis H1 is supported. Regarding cognitive instrumentalized influences, JR shows a significant positive effect on PU. Thus, hypothesis H2 can be confirmed, again leading to agreement with the results of Venkatesh and Davis [14]. Similar to previous studies (e.g., [12]), PEOU shows a direct positive effect on ITU, confirming hypothesis H3. It is striking about the research results that the social influence processes that are shown to be effective in TAM 2 [14], [46] are partially true when transferred to the AI context in customer service. Venkatesh and Davis [14] found that EX significantly moderates the influence of SN on PU and ITU, such that increasing EX with a system (e.g., AI) has a direct positive influence of SN on PU and ITU. Our results refute these claims and confirm our hypotheses H4 and H5, namely that as EX increases, the customer service representative’s perception of AI-based CAs in customer service reduces the direct positive influence of SN on PU (H4), and similarly that EX does not significantly moderate the customer service representative’s perception of AI-based CAs in customer service concerning the positive influence of SN on ITU, thus proving hypothesis H5. Furthermore, it is shown that there is no effect of VO on the effect of SN on ITU, making H6 true. By contrast, Venkatesh and Davis [14] found an interaction of VO with respect to the influence of SN on ITU. The negative influence can be interpreted as an indicator that in the AI context, people with EX (e.g., customer service representatives) tend to be less influenced by the opinions of others about the PU [46] of AI-based CAs in customer service. No direct positive effect can be seen for TR on ITU, which is why hypothesis H7 does not hold. Following previous studies (e.g., [38]), we found no agreement regarding the assumption that TR variables contribute to ITU (e.g., AI-based CAs in customer service). Similarly, in previous studies (e.g., [52]) CoA has been shown to have a direct negative impact on PEOU, confirming hypothesis H8. Accordingly, AI has a direct negative influence on customer service representatives’ perceptions concerning the use of AI-based CAs in customer service. Consistency with existing studies (e.g., [39]) shows WTI leading to a direct positive significant effect on UB, and therefore H9 is supported.

6.2 Implications for Practice

The results of this research not only include a theoretical contribution but also hold interesting practical implications for e.g., online platform providers and those considering the implementation of AI-based CAs in customer service (e.g., [2]) [6].

Table 3. Main findings, implications, and propositions

RQ: What are the main factors that can influence customer service representatives' perception of AI-based CAs for customer service?
MF1: In contrast to previous studies (e.g., [14]), direct positive influences are found for SN on PU and PEOU on ITU regarding customer service representatives' perceptions of using AI-based CAs in customer service, suggesting that the associated level of usage is less crucial for customer service representatives in mid- or high-performance organizations.
I1.1: Companies should identify how time-consuming and difficult it is for their customer service representatives to learn how to use AI-based CAs for customer service (**identify complexity level of training)**.
I1.2: Companies should identify which training opportunities exist for service representatives to learn how to use AI-based CAs for customer service (**explore training opportunities**).
MF2: The social influence processes that have been shown to be effective in TAM 2 (e.g., [14]) do not apply in the context of customer service representatives' perceptions of using AI-based CAs in customer service: EX does not significantly moderate the positive impact of SN on PU and ITU; VO does not significantly moderate the impact of SN on ITU.
I2.1: Companies should promote the development of customer service agents in terms of EX with AI-based CAs for customer service, as these users are less likely to be influenced by the opinions of others in terms of PU [45] (**promote employee development**).
I2.2: Companies should develop understanding not only at the level of service representatives, but also at higher levels (e.g., customer managers, management) (**promote management development**).
MF3: There is no direct positive effect of TR on ITU, as in previous studies (e.g., [104]).
I3: Companies should not only pay attention to making it useful and easy to use for all users (customer service representatives, etc.), but should also include trust-building features in AI-based CAs for customer service (**introduce trust-building properties**).
MF4: However, we can confirm the claim that CoA has a direct negative impact on customer service representatives' perception of using AI-based CAs in customer service.
I4.1: Companies should individually enable all users (customer service representatives, customer managers, etc.) to undertake appropriate training according to their skills and self-confidence (**offer employee training**).
I4.2: Companies can reduce users' (customer service representatives, customer managers, etc.) anxiety about AI-based CAs in customer service based on careful software selection or appropriate work situations (**analyze work situation**).
MF5: A direct positive significant effect is seen in the WTI on UB.
I5: Companies should consider their own specific market situation – e.g., regarding competitive pressure – before estimating the investment volumes in AI-based CAs for customer service (**conduct market and competitive analysis**).
MF: Main findings; Is: Implications and propositions

This paper explores and presents the main factors that may influence customer service representatives’ perceptions of AI-based CAs in customer service and their main implications. Table 3 summarizes the results. Since all but one hypothesis is supported, it can be concluded that the TAM 2 – including its extensions – within this research study is an acceptable instrument for analyzing the main factors regarding customer service representatives' perceptions of AI-based CAs.

6.3 Limitations and Future Research Direction

The results presented in this research study require considering certain limitations. One limitation is that we purely focused on weak AI in this study without reference to strong AI. Since the survey was conducted online, it is necessary to consider the limitations of web-based surveys [105]. Moreover, we used MTurk to generate the survey data, whereby this sampling platform has limitations regarding data reliability and validity. However, we followed data quality assurance guidelines from Hunt and Scheetz [106] to ensure that we accessed qualified MTurk participants and validated our collected data. Another limitation may be the topic of AI or CA itself, as these topics may only be foreign words for many companies or individuals due to the current maturity level. Since the answers to the questions were taken from the perspective of a customer service representative or regarding investment readiness from the perspective of the decision-maker role of an entrepreneur, it may be the case that the results are limited to these scenarios. At the same time, the change of role to the decision-maker function can be seen as a limitation, as presumably not every study participant can place themselves in this role. For future work, this study suggests several approaches. Among other things, there is a lack of knowledge about user trust in AI-based CAs, specifically systematically-derived design knowledge, which affects the diffusion of CAs.

7 Conclusion

To gain a better understanding regarding customer service representatives' perceptions of AI-based CAs in customer service to increase user satisfaction, we developed a model for the interaction between humans and AI-based CAs. Although technologies for collaboration between humans (e.g., customer service representative) and AI-based CAs enable high efficiency and expediency, this technology can occasionally contribute to a sense of dissatisfaction among users when their needs and expectations are insufficiently met [7]. One of the most significant findings of this study is that the direct positive effect of SN on the PU of AI-based CAs in customer service decreases with increasing EX. Therefore, we suggest that companies should emphasize increasing the maturity level of customer service employees in terms of their EX with AI-based CAs for customer service to promote the employees' development with them. Another important finding can be made regarding trust in AI-based CAs, as no direct positive impact of TR on ITU was found. Accordingly, we suggested that enterprises should not only ensure that AI-based CAs are useful and easy to use for all users (customer service representatives), but also that AI-based CAs have trust-building features.

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