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Trust and Social Presence as Mediators in the Acceptance of Ai-based Chatbots among Millennials: Evidence from the Service Industry

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Abstract

Chatbots are an innovative way for businesses to satisfy the requirements of millennial consumers. Chatbots are substituting human beings in several domains varying from education to manufacturing. The primary intention of the study was to know if the three identified antecedents namely Anthropomorphic cues, social presence, and empathy have a bearing on consumer acceptance of chatbots through trust and perceived interactivity in the realm of the service sector. We apply the theoretical framework stimulus organism response theory to test our hypotheses. A questionnaire was used to collect 400 responses from millennials, which were then examined by adopting structural equation modeling (SEM) approach.

The key outcomes indicate that social presence and trust mediated the relation between the three antecedents namely; anthropomorphic cues, perceived interactivity, responsiveness and the dependent variable, acceptance of chatbots among the users in the service industry. This study beefs up the Human-Computer literature by focusing on new interactive technology known as chatbots from the social lens. Unlike previous research studies that looked at AI-enabled chatbots in automated customer care situations solely from a technological standpoint, this research draws upon social and human perspectives by employing Stimulus-Organism-Response approach. The empirical research demonstrates the pivotal character of social presence and trust in chatbot adoption.

Keywords: *Family-owned business, restaurants, firm performance.*

1.0 Introduction

Organizations and customers have been ushering in a new digital world for the past decade. The increasing role of the internet and technical devices, which have encouraged electronic commerce, characterizes digitalization (Eeuwen, 2017). The nature of service delivery has changed rapidly as a result of technological advancements. Several high-touch and low-tech customer service activities are redesigned such that technology either complements or replaces human employees. The concept of automated conversational platforms can be linked back to Weizenbaum's work[38] in the 1960s. Developments in Artificial Intelligence (AI) based technologies and machine learning systems are substantially responsible for the recent surge in interest. The development of artificial intelligence in many e-commerce contexts has enabled communication with clients through live chat interfaces and is becoming a preferred mode for delivering real-time customer care. Moreover the use of AI in the service industry has become commonplace. Advanced digital technologies, particularly artificial intelligence, as well as the outbreak of the current Covid-19 pandemic, have accelerated the widespread use of AI-powered customer service to provide high-quality customer service with fewer in-personinteractions

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Artificial intelligence- enabled chatbots are considered more sophisticated to structured or devised chatbots because the former relies on advanced technologies like natural language processing (NLP), that improves chatbot performance[4], allowing it to comprehend more than just pre-established inputs. The more chats the virtual assistants encounter, the smarter they get owning to machine learning's learning skills, which have recently advanced with 'deep learning,' facilitating applications to intuitively recognize and comprehend things in the text, photos, sounds, or movies[13].

Since consumer concerns and queries were previously addressed mainly by human customer support, contemporary breakthroughs in artificial intelligence (AI) have sparked interest in deploying chatbots (text-based conversational agents) to perform these activities[33]. The Turing test, created by Alan (1950), inspired the thought of building a computer that can replicate human behaviour, and it is the foundation for chatbots[1]. Chatbots are an exciting new technology that has the potential to improve companies and daily life.

1.1 Research Problem

The majority of current chatbot research is focused on the technical aspects[30]. There are two goals to our research. First, this research aims to discover the social characteristics of chatbot services as viewed by users, which have rarely been investigated in the service industry context. This research looks into how different levels of humaneness namely anthropomorphism, perceived interactivity, and responsiveness of chatbots impact chatbot adoption through trust and social presence.

1.2 Research Objectives

Based on the above goal of the proposed study, the researchers have articulated the following research objectives to impart a specific direction and objectivity to the research.

- To analyze the role of human attributes, like anthropomorphic cues, perceived interactivity and responsiveness in chatbot adoption among millennials.
- To evaluate the character of social presence and trust as mediators in chatbot adoption among millennials.

2.0 Literature Review

The way people reply to chatbots is no longer only a widespread lookup subject matter in marketing, but it additionally has a lot of practical implications, due to the fact that the current technical advancements, mixed with constantly changing patron behaviour, are radically redefining client-company relations[27].

The present study draws upon the essence of multiple theories to develop and substantiate the framework used for the study. The Stimulus-Organism-Response framework is one of the most important ideas employed in the research. The SOR framework is excellent theoretical foundation for methodically examining the relationships among stimuli, organism, and response[8].

2.1 Anthropomorphic Cues

Chatbots can be regarded as self-service systems as they render customer care without the assistance of human beings. Anthropomorphism is an effort to ascribe human-like attributes to non-human creatures such as robots, animals, and other things[12]. Because humans have been ascribing human-like qualities and emotions to nonhuman agents, marketing research is gradually identifying anthropomorphism as a product design pattern and its underlying its psychological effects on its users. Anthropomorphic design cues have a four-fold larger impact than functional design signals. The existence of anthropomorphic elements in the interaction, such as the design and communication type, might elicit anthropomorphism perceptions[31,28]. Consumers have shown a greater propensity to respond to anthropomorphic forms of consumer products with increased moral concern and trust in nonhuman technical products like polygraph testing and driverless cars[37].

H1 "Anthropomorphic cues will have a significant influence on Trust".

H2 "Anthropomorphic cues will have a significant influence on social presence"

2.2 Perceived Interactivity

Artificial intelligence (AI) is a critical technology for constructing chatbots that can converse with clients and support them since it enables human-like engagements[39]. Although Computer-mediated-Communication (CMC) may readily establish message interactivity, the same cannot be said for HCI[31]. The measure to which a user perceives that there is reciprocal and bidirectional contact with another person is known as Perceived interactivity[20]. The perceived interactivity of chatbot services refers to the user's perception that communications with a chatbot are comparable to those with human agents[7].

H3 "Perceived Interactivity will significantly and positive influence on Trust"

H4 "Interactivity significantly and positively influences on Social Presence"

2.3 Responsiveness

For chatbot-related smart services, three dimensions from[26] are thought to be important: reliability, responsiveness, and assurance[6]. The most significant component of customer service is believed to be responsiveness (a service feature). Responsiveness is the capability to assist a client by giving them rapid access to services in order to give convenience.

H5 "Trust will be significantly and favourably influenced by responsiveness"

H6 "Responsiveness will have a statistically significant influence on Social Presence"

2.4 Trust

The vast array of research on trust spans subjects as diverse as social sciences to technology studiesfavorab[9]. Trust does have a favourable influence on consumers' intention[23] to buy products and services and many other aspects such as loyalty[3] and satisfaction[25], all of which impact business performance and is thus vital to consider when designing customer-facing chatbots. Technology acceptance and trust factors are crucial in determining the success of technology and its life cycle. Moreover, trust assumes a very important role, as it is molded by initial encounters and apparent social presence[24].

H7 "The adoption of chatbots will be significantly and favourably impacted by trust"

H8 "The association between anthropomorphic cues and chatbot adoption is mediated by trust"

H9 "Trust mediates the relationship between perceived interactivity and chatbot adoption"

H10 "Trust mediates the relationship between responsiveness and chatbot adoption"

Social Presence

The social dimensions of human–chatbot interplay, and consumers view of chatbots are influenced by social engagement. According to studies, online customers' views of social presence positively influence their eventual decision to buy from a commercial site, which is linked to the social presence theory[16]. Furthermore, many studies demonstrate perceived social presence has a favourable influence on online purchase intentions[19,10,23]. The mediating nature of social presence has been investigated in a variety of settings. In Human-Robotic-Interaction, social presence was found to be a powerful mediator[22].

H11 "Social presence has a positive influence on CA".

H12 "Social presence mediates the relationship between anthropomorphic cues and chatbot adoption"

H13 "Social presence mediates the relationship between perceived interactivity and chatbot adoption"

H14 "Social presence mediates the relationship between perceived Responsiveness and chatbot adoption"

2.5 Conceptual Model

A review of literature and further analysis of the gaps in the existing literature leads us to a conceptual model as depicted in Figure 1. The suggested model for the current study envisages validating the relationships as depicted below.

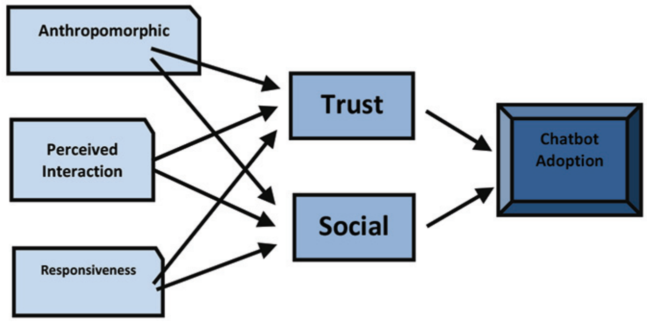

Figure 1: Conceptual Model

3.0 Methodology

Based on the extant literature, a structured questionnaire was designed. Those without any chatbot experience were filtered out. The questionnaires were delivered to 419 respondents who had prior experience with chatbots on various service delivery platforms across major Indian cities.

3.1 Sampling Procedure and Data Collection

To get responses from the specific target respondents, who are exposed and experienced with chatbot interaction on online service platforms, the snowball sampling method was adopted. 419 Millennials born from 1980 to 1995, across the major cities of India were selected to be part of the survey which was conducted from April 2021 to July 2021.

3.2 Measures

To come up with the measurements listed in Appendix A, researchers looked at a variety of papers, frameworks, and models. Measurements for all the constructs were developed based on the previously established scales.

The anthropomorphic scale was adapted based on Chen[6], whereas the Internet Privacy Concern measures are based on[11]. Ling et al Attitude Towards Mobile Advertisement measurements was adopted and adjusted (2010).

4.0 Results, Discussion and Findings

We undertook exploratory (EFA) to determine the factor structure. To verify the validity and reliability of the constructs, CFA approach was used. To verify the hypotheses and investigate the mediational analysis, SPSS and Amos were used to perform EFA and CFA respectively. After that, we got the average variance extracted (AVE) and Cronbach's alpha before, venturing into data analysis, preliminary EFA was undertaken to confirm the factor composition of all the factors (Anthropomorphic cues (AC), perceived interactivity (PI), responsiveness, social presence (SE), trust, and chatbot adoption (CA). Because the factors were a linear mixture of indicators, we employed principal component analysis and a rotating component matrix approach.

Table 1: Measurement Model Item

Construct and Items	
Social Presence	
SE1	"Sense of human touch with the chatbot"
SE2	"There is a personalized feeling with chatbot"
SE3	"User can Sense the feel of sociability with chatbot"
SE4	"Human warmth is present in the interaction with chatbots"
SE5	"users of chatbot perceive human sensitivity"
Trust	
Tru_1	"Chatbots are considerate to customer needs"
Tru_2	"The chatbots honors its commitment".
Tru_3	"Virtual assistants can provide the the consumer well-being"
Tru_4	"Chatbots are trustworthy"
Tru_5	"Virtual Assistants are dependable"
Anthropomorphic Cues (Ant)	
Ant_1	"I feel as though I am communicating with a person when I use this chatbot."
Ant_2	"I perceive sociability when using chatbots"
Ant_3	"I experience Human warmth with chatbots"
Ant_4	"I sense human contact when using chatbot"
Ant_5	"Chatbots replicate human interaction"
Perceived Interactivity (PI)	
PI_1	"I feel I am in control of things when interacting with chatbots"
PI_2	"chatbots are sensitive to personal needs"
PI_3	"I can freely responds with virtual assistants"
PI_4	"There is a feeling of personal touch with Chatbots"
Responsiveness (Res)	
Res_1	"Prompt assistance can be anticipated from chatbots"
Res_2	"Chatbots answers my inquiries right away"
Res_3	"This chatbot promptly gives services when I need them"
Chatbot Adoption (CA) (Venkateshetal, 2012)	
CA_1	"In the near future, I intend to use chatbots for all my service needs"
CA_2	"My interest in chatbots will grow"
CA_3	"chatbot usage is going to be commonplace"

Source : Author generated

4.1 Factor Analysis

The EFA confirmed the factor dimensionality with 6 factors emerging having an eigenvalue of more than one and explaining 86.31% variance (Table 2). The Kaiser–Meyer–Olkin (KMO) confirmed the sample's sampling adequacy; the KMO result was significantly higher than Kaiser's (1974) minimum criterion of 0.5 (Table 2).

Table 2: KMO and Bartlett's Test

Kaiser-Meyer-Olkin.		.872
Bartlett's test	Approximated Chi-Square	1.069E4
	Degree of freedom	276
	Significance	.000

Source: Author Generated

The outcome for KMO test showed a measure of 0.872 (Table 1), that was more than the often-recommended value of 0.6[32]. Further, Barlett's test generated a significant value that was less than .005 (Bartlett, 1954). Thus, both the tests indicate that factor analysis is appropriate and can be further probed. Principal Component Analysis (PCA) approach was used to measure variance. Rotation matrix confirmed that there were six constructs were involved in the study. The rotation component matrix (Table 3) reveals factor loadings and their contributions.

4.2 Confirmatory Factor Analysis: The EFA results published in the preceding

Section revealed the latent variables' dimensionality and confirmed the validity of the scales and its structure.

CFA was employed to analyze the overall goodness-of-fit of all the constructs to identify the measures' validity. The CFA was used to evaluate construct validity and unidimensionality, both of which are important aspects of measurement theory[2]. The presence of a unitary concept inheriting a set of observable variables is referred to as unidimensionality, and it is established when an empirical item is significantly related to the empirical depiction of a single construct[18]. Create the CFA, the researcher should have a good understanding of the concepts, factors, and other theoretical findings.

In order to clarify the interrelationships between the

Table 3: Rotated component matrix

	Component					
	1	2	3	4	5	6
Tru_3	.899					
Tru_4	.896					
Tru_5	.885					
Tru_2	.866					
Tru_1	.861					
SE_5		.918				
SE_4		.914				
SE_3		.903				
SE_2		.825				
SE_1		.804				
Ant_4			.931			
Ant_3			.924			
Ant_1			.911			
Ant_2			.894			
PI_3				.941		
PI_2				.935		
PI_4				.934		
PI_1				.843		
CA_2					.955	
CA_3					.952	
CA_1					.945	
Res_1						.906
Res_2						.895
Res_3						.872

Source: Author generated

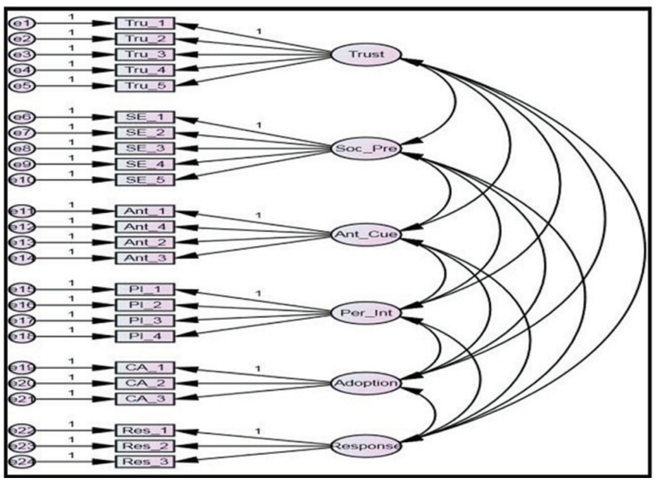

Figure 2: Confirmatory factor Analysis

Table 4: Model fit measures

Measure	Estimate	Threshold	Interpretation
CMIN	512.750	-	
DF	237.000	-	
CMIN(χ^2)/DF	2.164	Between 1 and 3	Excellent
CFI	0.974	>0.95	Excellent
SRMR	0.038	<0.08	Excellent
RMSEA	0.053	<0.06	Excellent
P Close	0.188	>0.05	Excellent

measured variables. In this study, chatbot adoption is both a theoretically and empirically researched phenomenon.

Confirmatory factor analysis tested the factor composition. There are numerous indices that can be referred to evaluate model fitness. The Chi-square (χ^2) statistic is used to determine how far a hypothesized model differs from the data. The root mean squared error of approximation (RMSEA) is another method for estimating the lack of fit to a saturated model. The proportion of variability in the sample variance-covariance matrix is shown by the goodness-of-fit index (GFI). The adjusted goodness-of-fit index (AGFI) can be used to account for GFI indexing by adjusting the index's value for the number of parameters[28].

Overall fitness indices were adequate and all of the values are higher than the standard index values (χ^2/df = 2.164, RMSEA = .053, GFI = .907, AGFI = .882, CFI = .974, IFI = .974, and TLI = .970 (Arbuckle 2003). With CR ratings of more than .70, all constructs achieved an acceptable level. The AVE values ranged from .721 to .934.

CFA was evaluated in the subsequent phase to look for reliability and validity (convergent and discriminate validity). The parameter estimations were used to determine the convergent validity. The composite reliability varied from 0.886 to 0.977, (Table 5) and the average variance extracted (AVE) values (Table 5) range from 0.743 to 0.934, implying all items have strong convergent validity.

Discriminant validity establishes that a construct is distinect in its measurement and does not have any collinearity with the other constructs involved in the study[21]. Furthermore, the average variance extracted from the components was greater than the squares of its correlation with other constructs, indicating that there is adequate discriminant validity[14]. Discriminant validity analys is reported that the AVE of all the constructs involved in the analysis were above than the squared correlations of that construct to others

The model shown in Figure 1 was analyzed using AMOS 22. The results are shown in Table 7. With CMIN = 386.512, df = 161, CMIN (χ^2)/ DF = 2.400, RMSEA =.055 (RMSEA 0.06), SRMR= 0.068 (SRMR 0.08), and CFI =0.968 (CFI

Table 5: Convergent Validity

	CR	AVE	MSV	Max R(H)
Chatbot_Adoption	0.977	0.934	0.079	0.980
Trust	0.953	0.801	0.132	0.957
Social_Presence	0.935	0.743	0.091	0.951
Anthropomorphic_Cues	0.957	0.848	0.132	0.963
Perceived_Interactivity	0.957	0.849	0.104	0.969
Responsiveness	0.886	0.721	0.061	0.902

Source: Author Generated

Table 6: Discriminant Validity

Chatbot Adoption	Trust	SP	AC	PI	Resp
0.966					
0.261	0.895				
0.215	0.301	0.862			
0.211	0.363	0.151	0.921		
0.281	0.322	0.221	0.213	0.922	
0.118	0.121	0.035	0.247	-0.017	0.849

Source: Author Generated

Table 7: Structural Model Fit Indices

Measure	Estimate	Threshold	Interpret
CMIN	386.512		
df	161		
CMIN (χ^2)/ DF	2.400	Between 1 and 3	Excellent
RMSEA	.055	>0.06	Excellent
SRMR	.068	<0.08	Excellent
CFI	.968	<0.95	Excellent

>0.95), the structural model exhibited good fit indices, with all indices greater than the suggested cut off values.

The fitness indices for the structural path were in line with that of the generally recommended. The adherence to the standards allows for further verification of the path relationships. As observed in Table 8, all the paths except for two were found to be significant. Responsiveness of the chatbots was found not to be having any significant influence on social presence and trust.

The mediating function of trust and social presence in the linkages between anthropomorphic cues, responsiveness, perceived interactivity, and chatbot adoption was investigated in order to meet the study's goal.

The following Table 9 is a summary of the bootstrap analysis test for mediation.

Investigate the hypothesized indirect effect, weusedan AMO Suser-defined estimands as recommended[15]. As evident from the mediation analysis (Table 9), social presence was found to be significantly mediating the relations between anthropomorphic cues and chatbot adoption; perceived interest and chatbot adoption;

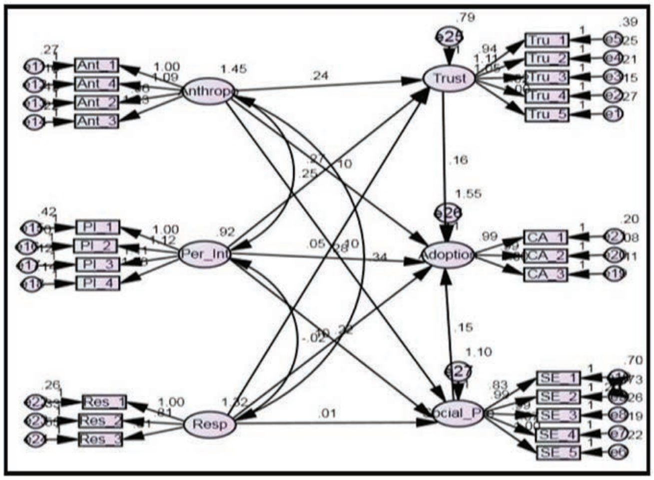

Figure 3: Path coefficients

Table 8: Path Relationship and Hypothesis Results

Parameter	Esti	SE	CR	P	Result
Trust ← AC	.244	.042	5.857	***	HI Supported
SP ← AC	.098	.048	2.023	.043	H2 Supported
Trust ← PI	.270	.051	5.337	***	H3 Supported
SP ← PI	.223	.059	3.800	***	H4 Supported
Trust ← Resp	.045	.043	1.047	.295	H5 Not Supported
SP ← Resp	.007	.051	.130	.896	H6 Not Supported
CA ← SP	.147	.061	2.400	.016	H7 Supported
CA ← Trust	.164	.072	2.266	.023	H8 Supported

Source: Author generated

Table 9: Mediation Analysis

Parameter	Estim	Lower	Upper	P
CA ← Trust ← Ant	.040	.002	.095	.040
CA ← SE ← Ant	.014	.001	.041	.027
CA ← Trust ← PI	.044	.003	.105	.038
CA ← SE ← PI	.033	.008	.078	.008
CA ← Trust ← Resp	.007	-.004	.037	.186
CA ← SE ← Resp	1.028	.203	1.910	.015

responsiveness and chatbot adoption. Similarly, trust was found to be mediating the relationship between anthropomorphic cues and chatbot adoption; perceived interest, and chatbot adoption. But trust did not mediate the relationship between responsiveness and chatbot adoption.

5.0 Practical Implications and Contributions

The outcome of our empirical study corroborated that Anthropomorphism is very essential to create a positive influence on Trust. As Anthropomorphism is an endeavor to ascribe human-like attributes to non-human creatures such as robots, animals, and other things and nowadays it is used as a product design pattern, researchers have started to investigate the psychological ramnifications of interacting with anthropomorphic elements.

Some of the outcomes of the present research are in accordance with past studies and findings. Moreover, it has validated the presence of a noteworthy and significant influence between anthropomorphism and social presence.

Above all, this research study also revealed that perceptions of social presence and trust are integral to the acceptance of chatbots. Further, the current work also substantiates that social presence and trust are indeed paramount determinants of acceptance of chatbots in an interaction with a virtual assistant. Finally, this study draws some pivotal inferences. First, we were able to establish that humaneness or human-like characters are essential to accomplish chatbot acceptance, especially in the service sector.

This study adds to our knowledge of how humanness works in eliciting trust and social presence which eventually leads to user acceptance of chatbots in the service industry.

This research adds to the body of knowledge in a number of ways. First, we present an overview of current research, providing scholars with a broad understanding of the phenomena and relevant factors related to AI-enabled technologies. We identify and describe factors that contribute to user acceptance, as well as its implications, allowing us to have a better understanding of how to induce trust and social presence and thereby user acceptance.

6.0 Conclusions

Artificial intelligence (AI) and other digital technologies have fundamentally changed how businesses operate, promoting sustainable growth by generating benefits for stakeholders, customers, and the environment. Artificial intelligence and digital technology have developed quickly in recent years, which has enhanced the pro-activeness in adopting novel consumer and organizational tactics in a sustainable manner. The distinction between humans and non-humans is becoming increasingly hazy as a result of recent advancements in technology. We propose that, despite the complexity underlying consumers' psychological, cognitive and behavioural reactions to chatbots, there is a willingness evinced by the customer to adopt the chatbot technology provided it has certain human characters ascribed to it. This study is unique in its efforts as the researchers have tried to rope in factors such as anthropomorphism, perceived interactivity, and responsiveness. Moreover, the relationship between these antecedents gets intense with the intervention of trust and social presence. So, we conclude that an ideal mix of human characters coupled with trust and social presence would increase the probability of chatbot acceptance in the service industry among millennials.

7.0 References

1. Almansor, E.H. and Hussain, F.K. (2019): "Survey on intelligent Chatbots: State-of-the-art and Future Research Directions", Advances in Intelligent Systems and Computing, pp. 534–543.
2. Anderson, J.C. and Gerbing, D.W. (1988): "Structural equation modelling in practice: A review and recommended two-step approach"., *Psychological Bulletin*, Vol. 103 No. 3, pp. 411–423.
3. Bilgihan, A. (2016), "Gen Y customer loyalty in online shopping: An integrated model of trust, user experience and branding", *Computers in Human Behaviour*, Vol. 61, pp. 103–113.
4. Candela .E, (2018): Consumers' perception and attitude towards chatbots' adoption. A focus on the Italian market.
5. Chen, Q., Clifford, S. J., & Wells, W. D. (2002): Attitude Toward the Site: II. *New Information. Journal of Advertising Research*, 42(2), 33–45.
6. Chen, J.S., Le, T.T.Y. and Florence, D. (2021): "Usability and responsiveness of artificial intelligence chatbot on online customer experience in e-retailing",

International Journal of Retail & Distribution Management, Vol. 49 No. 11, pp. 1512–1531.
7. Cho, W.C., Lee, K.Y. and Yang, S.B. (2019): "What makes you feel attached to smartwatches? the stimulus– organism–response (S–O–R) perspectives", *Information Technology & People*, Vol.32 No.2, pp. 319-343.
8. Chung, M., Ko, E., Joung, H. and Kim, S.J. (2020): "Chatbot E-service and customer satisfaction regarding luxury brands", *Journal of Business Research*, Vol. 117, pp. 587–595.
9. Corritore, C.L., Kracher, B. and Wiedenbeck, S. (2003): "Online trust: concepts, evolving themes, a model", *International Journal of Human-Computer Studies*, Vol. 58, pp. 737-58. Delgado-Ballester
10. Cyr, D., Hassanein, K., Head, M. and Ivanov, A. (2007): The role of social presence in establishing loyalty in E- service environments. *Interacting with Computers*, 19(1), 43–56. https://doi.org/10.1016/j.intcom.2006.07.010
11. Dinev, T. and Hart, P. (2004): Internet privacy concerns and their antecedents - measurement validity and a regression model. *Behaviour & Information Technology*, 23(6), 413–422. https://doi.org/10.1080/01449290410001715723
12. Duffy, B. R. (2003): Anthropomorphism and the Social Robot. Robotics and Autonomous Systems, 42(3-4), 177–190. https://doi.org/10.1016/s0921-8890(02)00374-3
13. Khan, R., & Das, A. (2018): Build better chatbots: A complete guide to getting started with Chatbots. A press. "The Delone and McLean Model of Information Systems Success: A ten-year update". (2003), *Journal of Management Information Systems*, Vol. 19 No. 4, pp. 9–30.
14. Fornell, C. and Larcker, D.F. (1981): Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. https://doi.org/10.2307/3151312
15. Gaskin, J. and Lim, J. (2016): Model fit measures. AMOS Plugin. Gaskination's Stat Wiki. Goh, S.C. and Richards, G. (1997). Benchmarking the learning capability of organizations, *European Management Journal*, 115(2), 575-88.
16. Gefen and Straub. (2003): "Managing user trust in B2C e-services", *e-Service Journal*, Vol.2 No.2, p.7.
17. Go, E. and Sundar, S.S. (2019): "Humanizing chatbots: The effects of visual, identity and conversational cues on humanness perceptions", *Computers in Human Behaviour*, Vol.97, pp.304-316.
18. Hair, J.F. (2010): Multivariate Data Analysis: A Global Perspective, Pearson Education, Upper Saddle River, NJ.
19. Hassanein, K. and Head, M. (2005): The impact of infusing social presence in the web interface: An investigation across product types. *International Journal of Electronic Commerce*, 10(2), 31–55. https://doi.org/10.2753/jec1086-4415100202
20. Kang, L., Wang, X., Tan, C.H. and Zhao, J.L. (2015): "Understanding the antecedents and consequences of live chat use in electronic markets", *Journal of Organizational Computing and Electronic Commerce*, Vol. 25 No. 2, pp. 117–139.
21. Kline, R.B. (2016): Principles and Practice of Structural Equation Modelling, The Guilford Press, New York..
22. Lee, J. D. and See, K. A. (2004): Trust in automation: Designing for appropriate reliance. Human Factors, 46, 50–80.
23. Lu, B., Fan, W. and Zhou, M. (2016): "Social Presence, trust, and Social Commerce Purchase Intention: An empirical research", *Computers in Human Behaviour*, Vol. 56, pp. 225–237.
24. Ogonowski, A., Montandon, A., Botha, E. and Reyneke, M. (2014): "Should new online stores invest in social presence elements? the effect of social presence on Initial Trust Formation", *Journal of Retailing and Consumer Services*, Vol. 21 No. 4, pp. 482–491.
25. Papadopoulou, P. (2006): "Applying virtual reality for trust-building e-commerce environments", *Virtual Reality*, Vol. 11 No. 2-3, pp. 107–127.
26. Parasuraman, A., Zeithaml, V.A. and Berry, L.L. (1988): Servqual: A Multiple-Item Scale For Measuring Consumer Perceptions of service quality. *Journal of Retailing*, 64(1), 12-40. (4) .
27. Rust, Roland & Huang, Ming-Hui. (2014): The Service Revolution and the Transformation of Marketing Science. *Marketing Science*. 33. 206-221. 10.1287/mksc.2013.0836.
28. Sah, Y. J. and Peng, W. (2015): Effects of visual and linguistic anthropomorphic cues on social perception, self- awareness, and information disclosure in a health website. *Computers in Human Behaviour*, 45, 392–401. https://doi.org/10.1016/j.chb.2014.12.055
29. Shah, R. and Goldstein, S.M. (2005): "Use of structural equation modelling in Operations Management Research: Looking Back and Forward", *Journal of Operations Management*, Vol.24 No.2, pp. 148–169.
30. Sheehan, B., Jin, H.S. and Gottlieb, U. (2020): "Customer service chatbots: Anthropomorphism and adoption", *Journal of Business Research*, Vol. 115, pp. 14–24.
31. Sundar, S.S., Bellur, S., Oh, J., Jia, H. and Kim, H.-S. (2014): "Theoretical importance of contingency in

human- computer interaction", *Communication Research*, Vol.43 No.5, pp.595–625.

32. Tabachnick, B.G. and Fidell, L.S. (2001): Using Multivariate Statistics. 4th Edition, Allyn and Bacon, Boston.
33. Tuzovic, S. and Paluch, S. (2018): Conversational commerce – a new era for service business development? Service *Business Development*, 81–100. https://doi.org/10.1007/978-3-658-22426-4_4
34. Van den Broeck, E., Zarouali, B. and Poels, K. (2019): Chatbot advertising effectiveness: When does the message get through? *Computers in Human Behaviour*, 98, 150–157. https://doi.org/10.1016/j.chb.2019.04.009
35. Van Doorn, J., Mende, M., Noble, S.M., Hulland, J., Ostrom, A.L., Grewal, D. and Petersen, J.A. (2016): "Domo Arigato mr. Roboto", *Journal of Service Research*, Vol. 20 No. 1, pp. 43–58.
36. Van Eeuwen, M. (2017): Mobile conversational commerce – messenger chatbots as the next interface between businesses and consumers, http://purl.utwente.nl/essays/71706 (retrieved on 10.08.2017).
37. Waytz, A., Heafner, J. and Epley, N. (2014): The mind in the machine: Anthropomorphism increases trust in an autonomous vehicle. *Journal of Experimental Social Psychology*, 52, 113–117. https://doi.org/10.1016/j.jesp.2014.01.005
38. Weizenbaum, J. (1966): "Eliza—a computer programme for the study of natural language communication between man and Machine (1966)", Ideas That Created the Future, pp. 271–278.
39. Zheng, J., Veinott, E., Bos, N., Olson, J.S. and Olson, G.M. (2002): "Trust without touch", Proceedings of the SIGCHI Conference on Human Factors in Computing Systems Changing Our World, Changing Ourselves - CHI '02, available at:http://doi.org/10.1145/503376.503402.