



Publisher

<http://jssidoi.org/esc/home>



THE EFFECT OF ARTIFICIAL INTELLIGENCE ON THE SALES GRAPH IN INDIAN MARKET

Mithun S. Ullal¹, Iqbal Thonse Hawaldar², Suhan Mendon³, Nympha Joseph⁴

¹Department of Commerce, Manipal Academy of Higher Education (MAHE), Manipal, Karnataka, India

²Department of Accounting & Finance, College of Business Administration, Kingdom University, P.O. Box 40434, Building 287, Road 3903, Hajjath, Bahrain

³Manipal Institute of Management, Manipal Academy of Higher Education (MAHE), Manipal, Karnataka, India

⁴Department of Accounting and Finance, College of Administrative Sciences, Applied Science University, P.O. Box 5055, Building 166, Road 23, Al Eker, Bahrain

E-mails: ¹ mithun.ullal@rediffmail.com ; ² thiqbal34@gmail.com ; ³ suhan.mendon@manipal.edu ;
⁴ nympha.joseph@asu.edu.bh

Received 10 December 2019; accepted 7 April 2020; published 30 June 2020

Abstract. Artificial Intelligence (AI) has been the biggest revolution of the 21st century impacting every aspect of the business, sales being no different. The paper experiments the effect of marketing on 4500 customers using AI and humans. The outcomes of the research reveal the effectiveness of AI is the same as experienced salesmen and 2.7 times better than inexperienced salesmen is closing the sales calls. The sales graph experienced a dip by over 86.23% when it was revealed to the customer that the interface is with the machine, not humans and reduced the duration of the call substantially. The paper shows that Indians do not believe Artificial Intelligence and still prefer human interface as they do not trust machines over human emotions. The effectiveness of AI drastically reduces despite its superiority over humans in various aspects. The paper identifies the strategies to overcome the trust deficit that exists among Indian customers. The outcomes show how AI can be used, and how marketing could be done using AI in conservative markets such as India.

Keywords: Artificial intelligence; machines; sales; marketing; human resources

Reference to this paper should be made as follows: Ullal, M.S., Hawaldar, I.T., Mendon, S., Joseph, N. 2020. The effect of artificial intelligence on the sales graph in Indian market. *Entrepreneurship and Sustainability Issues*, 7(4), 2940-2954. [http://doi.org/10.9770/jesi.2020.7.4\(23\)](http://doi.org/10.9770/jesi.2020.7.4(23))

JEL Classifications: O31

1. Introduction

The paper aims to find out the scope for Artificial Intelligence (AI) in sales and marketing, to reveal what the benefits and costs are. It tries to find how efficient can AI be in comparison to humans who are experienced in selling. It also looks whether AI can replace humans in the long run, and, if so, at what cost.

The potential of Artificial Intelligence is enormous coupled with other latest technologies like data mining and machine learning. Artificial Intelligence is computer performing tasks, which need visual perceptions, decision making and speech recognition, which demands humans typically. Artificial Intelligence does the same through voice commands and chats. The latest Artificial Intelligence systems can fix appointments wherein the potential customers are unaware that they are in touch with machines and not humans (Ghassemi et al. 2019).

Artificial intelligence market is seeing exponential growth worldwide from \$100 million in 2012 to \$1.5 billion in 2025 (Martínez-López, Casillas 2013). More than 80% of youth in Western countries refer to Artificial intelligence for shopping (Del Valle 2018). The Indian market has seen users like Amazon, Facebook, Instagram use Artificial Intelligence (Srivastava 2018). The Artificial intelligence has provided the marketer with plenty of advantages such as services being automated and making sales pitch (Luo et al. 2019). Today's Artificial intelligence is capable of handling words spoken by customers and replying with compassion and emotion (Wilson et al. 2017). The superiority over humans lies in the fact that humans vary at the end of the day because of tiring out. In contrast, machines powered by Artificial intelligence are still the same with no loss of strength (Luo et al. 2019). The algorithm is also modified in some cases to suit sales needs (Dietvorst et al. 2016). The growth of IT and BPOS services in India has made the use of machines even more critical to handle the bulk of communications.

These aspects show the benefits of the machines powered by Artificial intelligence from the demand aspects of customers (Froehlich et al. 2018). Indian market is still consisting of conservative buyers who resist the use of machines in assisting them with their shopping. Indian customers consider the online transactions with devices as riskier as Indians considered machines devoid of emotions and empathy towards the buyer (Desai 2019). This has forced the players in the Indian market to hide the use of Artificial intelligence-driven machines from prospects. This severely limits the ability of Artificial intelligence because of the conservatism shown by Indian customers. In Western countries, customers wonder on whether they are talking to humans or machines on the other side, which is the ethical side of the business (Wise 2018; Hawaldar et al. 2016). Also, the privacy of customers data is a prime concern to the customers today (Federal Trade Commission 2017) In India, the recent trends of protecting their privacy is also an issue forcing the companies to reveal actual identities (Chaturvedi et al. 2008; Ullal and Hawaldar 2018).

The experiment was conducted on revealing the identity of the machine in case of a sales call. 4,500 customers were called by sales teams which consisted of machines driven by AI and salespeople. The identity of the caller was not revealed at all in 25% of the cases, in 25% of calls revealed at the beginning, in 25% of the calls after sales presentation, in 25% of the call the identity was revealed after the decision was taken. The effect of revealing Artificial intelligence on the customer can be identified, and comparison with the salesman can be made. The outcomes show that AI is as good as experienced salesmen and 2.7 times better than inexperienced salespeople in closing the sales call as per our results. The Indian customer strongly abstains any interaction with machines driven by AI. The outcomes are subjected to rigorous methods to double-check on the issues. The call duration was another finding where disclosure of devices reduced the call length by 71%.

The behaviours of consumers were mapped with the information from the survey and on chat records. The outcomes were that the Indian customers purchased less on revealing the identity of the machine as the conservative Indian think machines lack human emotions. The data mining of the messages exchanged in case of

experiments where the identity was not disclosed proves the effectiveness of devices is as good as an experienced salesman (Hawaldar et al. 2019a). The perception of average Indian effects the authenticity of the sales call. The article explores the strategies to overcome the opinions of Indians towards machines driven by AI and thus to increase spikes in sales graph. The timing of disclosure is found to be the most effective strategy to overcome this perception and thus drive on this experience to change the perception of AI based on the previous lesson. The article contributes to the field of sales and marketing by conducting experiments in actual settings and identifies the potential of AI in sales. The tests and the data mining have found evidence of the negative effect of machines driven by AI on Indian customers and revealed the reasons for the perceptions. The findings increase the knowledge about the tremendous potentials of the AI for usage in sales and marketing. The trust about AI in India can be built by companies through experience and change the attitude of the Indian customers about machines. The research sees the impact of machines on Indian customers and human salespeople on Indian customers and compares both in a genuine sense. Our results prove that replacing humans in sales and automation of the marketing process is a change which companies must accept as soon as possible. The only element stopping this could be the perception of the Indian customers against technology-driven machines. The companies currently ahead of the trend are trying to find the right balance between AI and humans in their sales teams across Indian markets. The BPO surge in India after the 1990s has created a vast market for AI based telemarketers in India which is still one of the primary methods used in sales (Hawaldar et al. 2019b). AI can assist in sales by relying on the vast repositories of knowledge in reply to questions which could best be done only by machines driven by AI. The repositories could of discounts and price comparison, which attract Indian customer (Hawaldar et al. 2019a).

2. Literature review

The positive aspects of AI have been well researched even in conservative and backward markets like Asia. Customers are tremendously affected by advertisements (Ullal and Hawaldar 2019). Analysis of stock is done through AI to trade (Trippi, Turban 1992). The recent mergers of Indian banks have opened huge potential for AI application in this field to identify the grey areas such as fraud and improve efficiencies through AI driven know how, as AI can increase banks effectiveness (Fethi, Pasiouras 2010). India has robust healthcare sector, the biggest in Asia, AI can help doctors in decision making thus helping in saving time in crucial decisions and overcome human error (Pinto et al. 2019; Esteva et al. 2017). The efficiencies of hospitals can increase manifold by the help of AI (Patel et al. 2009, Bennett, Hauser 2013). The empathy shown by the machines will be the crucial aspects about AI in marketing (Huang, Rust 2018). AI is all set to replace humans (Brynjolfsson, Mitchell 2017).

The AI plays important role in depth analysis of diseases in healthcare sector (Esteva et al. 2017). The efficiency of AI in replacing salesman is commendable (Churchill et al. 1985). Online agents and AI also help new and existing customers adjust to different service contexts (Köhler et al. 2011). One of the greatest revolutions of AI is its ability to learn and adapt to new technologies (Monostori, Barschdorff 1992). Humans are affected by perceived crowding and job insecurities (Yoo et al. 2016). The managerial ability of AI is always questionable (Young, James E., Cormier, Derek 2014). AI can be a big chance in cancer diagnosis (Lachman, Merlino 2017). Recently customers have started trusting AI more than humans (Logg et al. 2019). AI is all set to create more jobs in future (Wilson et al. 2017). The presence of virtual agents in a commercial web site has a positive effect on the perceived interactivity which helps the marketing (Saad, Abida 2016). AI plays a vital role when the information is limited (Sivaramakrishnan et al. 2007). AI must customise websites and sales needs to be according to the profiles of the customers (Mimoun et al. 2017). This has resulted in AI financial deals crossing 1.5b \$ in 2019 (Desai 2019). The negative side of technology when identity is disclosed on sales is presented by actual field survey. The reactions to AI in sales calls is negative in conservative market like India even though AI is as competent as an experienced salesman in sales is shown in the paper. The research was limited to voice and

text-based sales calls. Voice calls are more dynamic to research as they reveal the tone and pitch which represents actual human emotions and feeling more than text-based messages (Luo et al. 2019). Also, in advertisements faces affect how a viewer reacts to an advertisement on the metrics that advertisers care about (Xiao, Ding, 2014). This research adds to the existing literature on AI in sales. Use of data and voice mining software's were used during the research to identify the human side of the voice which involves aspects like feelings and sentiments. The research aims to find sales numbers and purchases through experiments in actual sales settings. Also, this research focuses on learning data mining and voice mining to study the effect of behavior that has a negative influence on disclosure of machines backed AI on sales graph.

Timing of initial purchase of a new product is based on the number of previous customers who have made the purchases (Bass, 1969). Humans are more unpredictable than robots (Briggs, Scheutz, 2016). Personalisation of performance can be achieved by adapting to the behavior of the customers (Chung et al., 2016). Today the empowered customers decide what they want and get it delivered to their doorstep (Edelman, Singer, 2015). Customers retreat from unpleseant services enabled by technology as an interpersonal barrier (Giebelhausen, M., Robinson et al., 2014). Service provision is fundamental for the economic exchange to happen rather than the goods themselves (Vargo et al., 2014). Technology today can anlyse images and diagnose diseases (Leachman, Merlino, 2017). AI thus is reshaping service by performing various tasks and threatening jobs (Soucy, Pascal 2016). AI can be used to personalise the sales for individual customers (Vargo, Lusch 2014). Interpersonal elements of the service by providing control cues, raising social presence and working on human trust mechanism can gain more acceptance among customers rather than driving features of technology itself (Wünderlich et al., 2013).

3. Selection of companies and methodology

The experiment was conducted by one of the leading Chennai based data collection and experimentation agency which is ranked number 1 in India with over 7 million customers. This agency has been selected for its geographic reach and its technological acumen. All the customers were online buyers who used e-commerce portals frequently and were active users of social media. This company which takes up outsourced marketing contracts for leading companies in India, employs machines backed by AI and humans for sales. 4,500 responses were collected after filtering out all the calls which were not answered and not connected. The calls of discounts and offers, which are the regular way to attract sales hikes were made on Fridays and Saturdays considering the weekend mood of the regular Indian buyer. The company has software's to make calls and provide services that have a conversation in natural settings with customers. The machines here backed by AI are well trained to perform the routine tasks of experienced salespeople. The initial calls are pre-recorded because of the standard of presentation set by the clients of the company who want to reach their customers. In the first case, the identity of the caller was not disclosed, and a female voice with a neutral accent was used.

In the experiment, the company exactly divided the customers into two parts, 50% each, and assigned one lot to machines and another to human salesmen. The number of calls was limited to 1 and randomly allotted to one of the experimental conditions.

The experimental conditions are explained below in figure 1. The first condition call made by machine backed by AI which revealed its identity after customer has taken purchase decision. The second condition is machine backed by which reveals the identity after the offer presentation but before the customer purchase decision. The third condition was machine supported by AI, which discloses its identity before the offer presentation. The fourth condition is to use AI without revealing its identity. The fifth condition is the call from an experienced salesman with over 5 years in the industry. The sixth condition is the calls from the non-experienced salesmen. The fourth, fifth and sixth conditions had the same line for the introduction. All the conditions follow the same standard

procedure of sales. Purchase includes agreeing to buy and make the transactions within 48 hours with e-commerce portals.

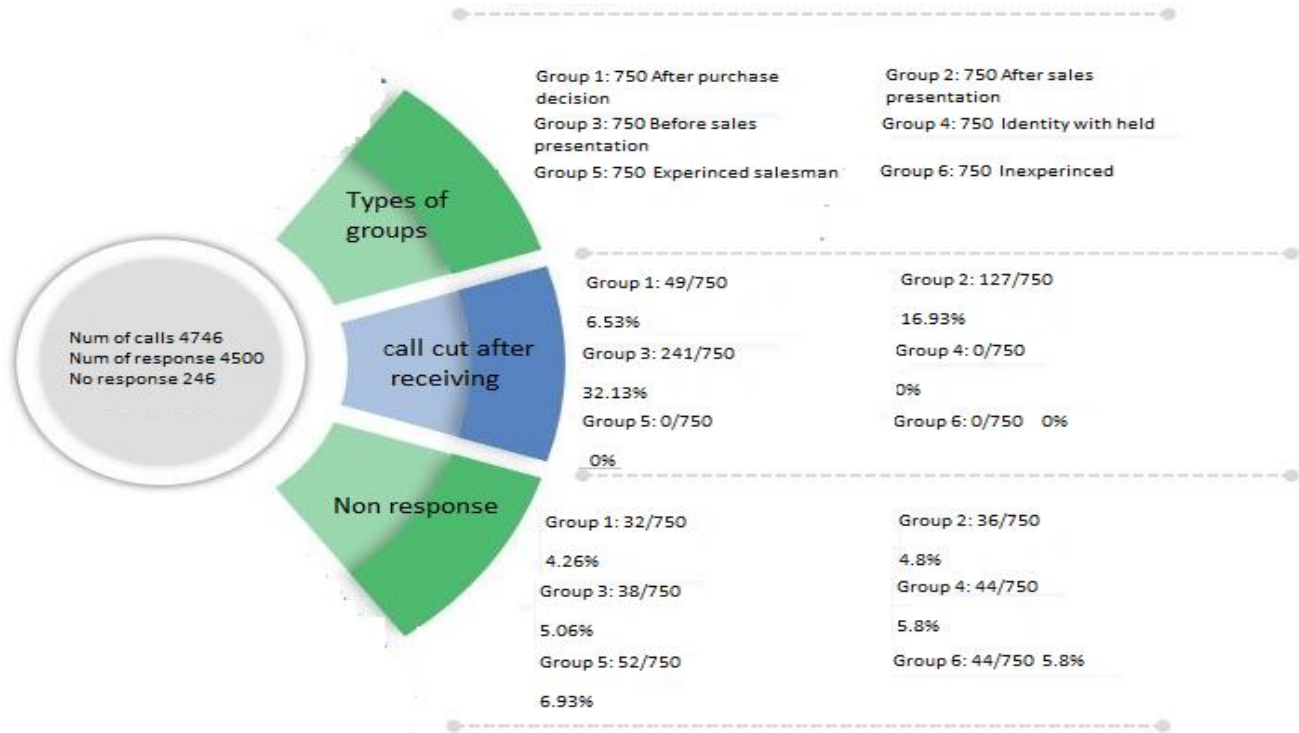


Figure 1. Call details

Table 1. Descriptive Statistics of calls

Figure Variables	Description	Minimum	Maximum	Mean	25 th percentile	50 th percentile	75 th percentile	90 th percentile
Male/Female	Male M Female F	NA	NA	0.672	M	M	M	M
Age	As mentioned by the customer	21	45	31.76	22	26	35	43
Education	1 = Graduate 2 = Postgraduate	1	2	2.832	1	2	2	2
Purchases in numbers	Made in year	1	7	1.36	1	2	2	3
Purchase amount spent in 30days	Made in one single transaction after receiving the call	1800	4600	3200	1891	3122	3788	3789
Amount spent in a year	Six months before and after the call	8110	16488	12299	8820	13100	17600	21200

As it is shown in table 1, 72% of the customers were men with a mean age of 34.8 years, and all were above college degree in education. The prospects for the research were tech-savvy young people who use e-commerce portals and shop online. Buying averages was 2.71 online in the last 30 days, with an average of Rs 12,299 spent over the year and Rs 3200 spent in the previous 30 days. Randomisation checks were conducted with background variables. The outcomes as shown in Table 3 show that the variables are not significantly different in six conditions on conducting f-test.

Revealing Artificial Intelligence identity

The six conditions based on table 2 and table 3 show that revealing AI at the beginning of the sales call reduced the purchase rate, had more call drops and reduced the duration of the call by 80%. Econometric models were applied to test the impact as we have randomised experiments aimed at identifying causal effects. The logistic regression model is used, which determines the unnoticed chance of purchase as a logistic regression function of randomised condition.

$$\text{Chance of purchase} = \frac{\text{Exp}(N_i)}{\text{Exp}(N_i) + 1}$$

$$N_i = a + a_1 \times \text{Non experienced salesman} + a_2 \times \text{Undisclosed} + a_3 \times \text{beginning presentation} + a_4 \times \text{after conversation} + \text{After purchase decision} + \text{Controls} + e_i(1)$$

Table 2. Randomisation

Group	N	Age	Education	Purchase Numbers	Purchase in 30 days	Purchase in a year
After purchase decision	750	31.86	1.387	1.34	3214	12299
After sales presentation	750	31.87	1.388	1.36	3321	12311
Before sales presentation	750	31.94	1.389	1.38	3412	12344
Identity withheld	750	31.99	1.381	1.39	3211	12129
Experienced salesman	750	32.01	1.386	1.36	3110	12186
Inexperienced salesman	750	31.91	1.384	1.34	3127	12292

Table 3. Outcomes

Group	N	Call response		Call cut	Call duration	Purchase
		in %	in %			
After purchase decision	750	95.74	6.53	82	0.324	
After sales presentation	750	95.20	16.93	79	0.184	
Before sales presentation	750	94.94	32.13	12	0.045	
Identity withheld	750	94.20	0.00	81	0.327	
Experienced salesman	750	93.07	0.00	72	0.323	
Inexperienced salesman	750	94.20	0.00	36	0.047	

N_i shows hidden use of making a purchase and the dependent variable of purchase is whether the customer has made a purchase. The independent variables are dummy variables with experienced salesmen comparison baseline. Control is a control variables vectors which represent the demography of customers who purchase and the purchase data such as the number of purchases and amount purchased. Feelings, pitch and frustration, was

noted by SoftMax Python software. Effects on purchase are incremental in nature. Columns 1 and 3 in Table 5 shows all the calls made in the logical regression model, probit model and OLS model. The outcomes prove that purchase decision is negative when the identity of the AI is revealed before the sales presentation ($p < 0.01$). The extent of the impact is given in figure 2. When the AI identity is withheld condition is compared with the identity revealed before a sales presentation, the purchase rate reduces by 86%. (From 0.241 to 0.038).

Testing of Robustness: The AI used for the research is trained by the recorded conversations of the trained salesmen with over 5 years of experience with performance mapping.

Table 4. Effect of revealing AI identity on purchase decision

	Calls made			No response			Call cut		
Purchase rate	OLS	Logit	Probit	OLS	Logit	Probit	OLS	Logit	Probit
After Purchase Decision (1)	-0.024 (0.021)	-0.124 (0.121)	-0.052 (0.048)	-0.018 (0.016)	-0.127 (0.123)	-0.05 (0.054)	-0.022 (0.019)	-0.129 (0.118)	-0.058 (0.056)
After sales presentation (2)	-0.132*** (0.018)	-1.061*** (0.132)	-0.603*** (0.072)	-0.153*** (0.021)	-1.073*** (0.133)	-0.615*** (0.074)	-0.146*** (0.022)	-1.011*** (0.135)	-0.593*** (0.076)
Before sales presentation (3)	-0.218*** (0.018)	-2.321*** (0.196)	-1.151*** (0.091)	-0.161*** (0.052)	-1.794*** (0.401)	-0.911*** (0.197)	-0.172*** (0.057)	-1.695*** (0.412)	-0.889*** (0.202)
Identity Withheld (4)	-0.016 (0.018)	-0.091 (0.116)	-0.054 (0.062)	-0.019 (0.019)	-0.094 (0.118)	-0.055 (0.063)	-0.019 (0.018)	-0.095 (0.119)	-0.056 (0.063)
Experienced Salesman (5)	NA	NA	NA	NA	NA	NA	NA	NA	NA
Inexperienced Salesman (6)	-0.198*** (0.019)	-1.891*** (0.172)	-1.012*** (0.084)	-0.181*** (0.028)	-1.701*** (0.227)	-0.881*** (0.118)	-0.188*** (0.032)	-1.862*** (0.239)	-1.104*** (0.123)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.298*** (0.081)	-0.765 (0.562)	-0.483 (0.322)	-0.027 4.231	-1.236 38.891	-1.702 20.012	0.572 4.801	2.123 36.112	0.902 19.882
Log	NA	-2446.021	-2.452.809	NA	-2422.483	-2402.192	NA	-2236.912	-2241.792
R ²	0.064	0.102	0.103	0.068	0.105	0.106	0.058	0.076	0.078
N	4746	4746	4746	4500	4500	4500	4083	4083	4083
F-value									
2-3	21.011***	34.902***	37.887***	0.091	4.022***	2.456	0.374	2.941*	2429
1-2	67.181***	55.781***	57.087***	66.114***	56.614***	57.886	54.891***	49.815***	52.071

The effect of disclosing the identity of AI on purchase are shown above. Outcomes are based on 4746 calls, and 4500 calls received. Outcomes are 4,083 calls. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

The effect of disclosing the identity of AI on purchase are shown above. Outcomes are based on 4746 calls, and 4500 calls received. Outcomes are 4,083 calls. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Effect of revealing AI identity on purchase decision

The table 4 above shows that the sales presentation by experienced salespeople and sales call by machines driven by AI with identity withheld has the same purchase rates ($p>0.10$). This gives no scope to the argument that sales lost by AI is because of poor quality rather than disclosure of identity. The salesmen with less experience have low sales closure rates 0.05 ($p<0.01$). This is mainly because of the low-quality salesmen who lack experience. The disclosure of identity after purchase decision has been taken is no different from that of experienced salespeople as the customers have already made the decision.

The insignificant coefficient after the customer has taken the decision is given in table 4 to check for its robustness.

Dealing with no response

Every customer in no response code was called again. The random sampling was limited to receiving the call but receiving was uncontrolled variable. So 2777 calls were not received as call were made during weekdays on working hours which could be the reason behind a large number of customers preferring to ignore the sales calls an add to that the number beyond coverage, numbers switched off and those which come under do not disturb numbers and those who cut the call on coming to know that it was a sales call. The figure shows that the center part, the number of no response is 2777, which had a response rate of 66.40% which is a good rate in the noisy towns of India. The rate of no reaction in six categories are in the range between 28.8% to 39.1% as shown in figure1 and table 2. The experiments are done after removing all the non-responses. The outcomes are shown in table 4, column 4 and 6 show that outcomes are tested against falsifications. So, selection effects from non-response cannot explain the results. The data about several people who cut the call with 2 seconds of informing that it was a sales call. The number of such calls was 241. The calls cut after disclosing the identity of the machines backed by AI was 127 and when disclosure was done after the conversation was 49. The rest of the conditions had no such call cuts. Then the models are run to further explain the purchase rate after cutting out all no responses. In table 4, 7 and 9 columns show that the outcomes are strong after excluding the calls which go cut. The strength is also tested by the seconds taken to cut the call after disclosure of the identity of the AI. On examining the calls that were cut because disclosure of the AI identity pushed the research towards examining the duration of the call.



Figure 2. Purchase rates

Examining the duration of the call

The Indian customers are unwilling to talk to a machine which leads to call being cut and reduces the purchase. If the above explanation holds truth, then the duration of the call revealing the identity of AI should be shorter than the calls where withholding of identity was done. The graph on call duration supports this assumption. The length of the call is taken as the dependent variable. Outcomes exhibited in table 5 with OLS models show a negative effect of disclosure at the beginning of the call, excluding non-received calls and calls that were cut. Further experiments are conducted further to understand the behaviours of the customers.

More experiments based on cancellation

Customers feel cheated when they come to know that they were talking to a machine and not a human. When the identity is revealed at the beginning of the call.

Table 5. Effect of disclosure of AI on call duration

Call duration	Calls made		No response		Call cut	
	OLS	Tobit	OLS	Tobit	OLS	Tobit
After purchase	-0.246 (0.588)	-0.264 (0.592)	-0.156 (0.289)	-0.158 (0.288)	-0.164*** (0.289)	0.164** (0.288)
After sales	-0.144 (0.588)	-0.154 (0.592)	-0.016 (0.289)	-0.017 (0.288)	0.664*** (0.298)	0.665** (0.291)
Before sales	-52.347*** (0.588)	-52.321*** (0.594)	-54.572*** (0.289)	-54.572*** (0.288)	-50.223*** (0.387)	-50.223*** (0.387)
Identity withheld	0.136 (0.587)	0.119 (0.593)	0.284 (0.289)	0.284 (0.288)	0.296 (0.289)	0.296 (0.288)

Experinced	NA	NA	NA	NA	NA	NA
Inexperinced salesman	-24.564*** (0.586)	-24.561*** (0.592)	-25.040*** (0.289)	-24.040*** (0.288)	-24.793*** (0.289)	-24.793*** (0.288)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Constant	61.332*** (2.881)	-61.141*** (2.956)	-186.831** (78.996)	-186.831** (78.996)	-164.221** (81.181)	-164.221* (81.181)
Log	NA	-24352.377	NA	-21242.221	NA	-19542.181
R ²	0.772	0.142	0.964	0.311	0.906	0.262
N	4746	4746	4500	4500	4083	4083
F-value						
2-3	9,143.811***	8,872.973***	36,764.235***	36,346.967***	19,829.185***	19,834.644***
1-3	8,942.440***	8,893.675***	36,114.241***	35,745.681***	19,625.768***	19,542.579***

Impact of disclosure of AI on call duration is shown in the above table. Outcomes are based on 4746 calls made 4500 calls which were received and 4083 conversations. ***p<0.01, **p<0.05, p*,0.10

Psychology of customers in case of disclosure of AI

Subjective information from an analysis of calls along with objective voice data analysis from voice recorded during the call is used. The experiment includes all customers who receive and cut the calls and are asked to answer a questionnaire based on the sales acumen of the salesman. The outcomes of mediation with 3000 copies in bootstrapping (Preacher, Hayes 2004) is shown in figure 3. The outcomes suggest that non-disclosure of AI before sales presentation decreases the faith towards AI and its ability to understand human needs and thus reduces the call duration and purchase decisions (p<0.01). But voice mining of calls where identity was not withheld shows that AI is as proficient salesman as an experienced human in the field of sales. So, the perception of Indian customers about AI is the reason for non-performance despite its abilities which are comparable to the best salesman in the job.

So, the perception in the conservative markets like India is against the AI is responsible for no purchase rather than the feeling of being cheated. Voice mining of the calls could not identify feelings that are negative across all six categories about the feeling of being cheated. Also, no complaints were received or orders that were cancelled by customers on revealing the identity of AI in sales calls.

Suggestions to negate the perceptions against AI

The first suggestion is that a comparison of coefficients show that purchase increases when identity is revealed after the purchase decision (p< 0.01). So, experimental learning on AI can overcome perceptions against revealing its identity. When the identity of the AI is revealed before during or after the call, the purchase rates drop. The rate of drop is slightly lesser when the identity is revealed at the end of the call. So, the result here is to win the trust of a conservative but educated Indian customer in the few initial discussions and overcome the negative perceptions. Next to the experience of the customers with AI if any before also impacts the perceptions about AI. The data also was collected about any AI apps that are used by the customer before. Table 6 shows that experience with AI makes customers purchase increase. Coefficient of interaction before AI x before a sales call is positive and significant (p<0.01) indicating that AI experience reduces the impact of revealing AI identity.

Table 6. Effect of disclosure of AI on call duration

Purchase rate	Calls made	No response	Call cut
After decision (1)	-0.005 (0.132)	-0.006 (0.132)	-0.006 (0.132)
After sales presentation (2)	-0.988*** (0.168)	-0.992*** (0.168)	-0.871*** (0.168)
Before sales presentation (3)	-2.829*** (0.291)	-2.189*** (0.436)	-2.246*** (0.521)
Identity withheld (4)	-0.059 (0.132)	-0.071 (0.133)	-0.071 (0.133)
Experienced salesman (5)	NA	NA	NA
Inexperienced salesman (6)	-1.812*** (0.198)	-1.582*** (0.252)	-1.675*** (0.254)
Previous experience	1.912*** (0.187)	1.915*** (0.187)	1.915*** (0.187)
Inexperienced and prior experience	-0.291 (0.392)	-0.281 (0.392)	-0.288 (0.392)
Identity withheld and prior experience	0.192 (0.272)	0.197 (0.272)	0.192 (0.272)
Before sales presentation and prior experience	0.942** (0.412)	0.912** (0.412)	1.268** (0.542)
After sales presentation and prior experience	-0.322 (0.313)	-0.321 (0.314)	-0.275 (0.316)
After purchase decision and prior experience	-0.158 (0.275)	-0.150 (0.275)	-0.151 (0.275)
Control variables	Yes	Yes	Yes
Constant	-0.994* (0.594)	-35.504 (36.996)	-30.012 (37.382)
N	4746	4500	4083
Log	-2,245.658	-2,118.005	-2,112.087
R ²	0.189	0.189	0.155

***p<0.01, **p<0.05, *p<0.10

Conclusion and further research

The study analyses the importance of AI, which is the future of business. The various conditions examined shows that disclosure of the identity of AI reduces purchase chances drastically. Analysing the data also shows that purchase rates dip and calls are disconnected when the identity of AI is revealed as Indians perceive AI as less capable and has less knowledge which cannot understand human feelings and requirements. One of the limitations of the research was the research being a two-way communication which may not always be interactive. This further allows researching in future. Differences in two-way communication among AI and customers with salesman and customers could be researched further. Also, the research could be extended to inbound calls. Researchers can also study various other methods of disclosure of AI. One such approach could be offering lower costs to customers as the benefits of having no labour cost could be passed on to the customers in India who prefer talking to machines backed by AI. AI will make business smooth and easy, and in some crunch situations,

humans in sales could be used. Also, customers interact with AI; differently, some are well behaved; some are not so nice (Thompson 2018). The difficulty level of sales tasks and the preference of the customers may give scope to future research on allowing customers to choose between salesman and AI, which could increase sales. Indians have accepted Google Alexa and Apples Siri, which makes us believe that they will also take AI in future for other more important aspects of daily decision making. The researchers strongly recommend more study in the area to identify various applications of AI for sales and marketing.

References

- Bass, Frank M. (1969). A New Product Growth for Model Consumer Durables. *Management Science*, 15(5), 215-227.
- Briggs, G., & Scheutz, M. (2016). The Case for Robot Disobedience. *Scientific American*, 316(1), 44–47. <https://doi.org/10.1038/scientificamerican0117-44>
- Bennett, C. C., & Hauser, K. (2013). Artificial intelligence framework for simulating clinical decision-making: A Markov decision process approach. *Artificial Intelligence in Medicine*, 57(1), 9-19. <https://doi.org/10.1016/j.artmed.2012.12.003>
- Brynjolfsson E, Mitchell, T. (2017). What can machine learning do? Workforce implications. *Science*, 358(6370), 1530–1534.
- Chaturvedi, M. M., Gupta, M. P., & Bhattacharya, J. (2008). Cyber Security Infrastructure in India: A Study. Emerging Technologies in E-Government , CSI Publication.
- Chung, T. S., Wedel, M., & Rust, R. T. (2016). Adaptive personalization using social networks. *Journal of the Academy of Marketing Science*, 44(1), 66-87. <https://doi.org/10.1007/s11747-015-0441-x>
- Churchill, Jr, G. A., Ford, N. M., Hartley, S. W., & Walker Jr, O. C. (1985). The determinants of salesperson performance: A meta-analysis. *Journal of Marketing Research*, 22(2), 103-118. <https://doi.org/10.1177%2F002224378502200201>
- Del Valle, K. (2018) Conversational commerce: A new opportunity for card payments. MasterCard (January 25), retrieved from <https://newsroom.mastercard.com/documents/conversational-commerce-a-new-opportunity-for-card-payments/>
- Dietvorst, B. J., Simmons, J. P., & Massey, C. (2016). Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. *Management Science*, 64(3), 1155-1170. <https://doi.org/10.1287/mnsc.2016.2643>
- Desai, F. (2019). The Age of Artificial Intelligence in Fintech <https://www.forbes.com/sites/falgunidesai/2016/06/30/the-age-of-artificial-intelligence-in-fintech/#269da1a15028>
- Edelman, D., Singer, M. (2015). Competing on Customer Journeys. *Harvard Business Review*, November, 88-94, 96, 98, 100.
- Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, 542(7639), 115. <https://doi.org/10.1038/nature21056>
- Federal Trade Commission. (2017). Privacy & data security update (2016). Federal Trade Commission, ftc.gov. Accessed September 7, 2018, retrieved from <https://www.ftc.gov/reports/privacy-data-security-update-2016>
- Fethi, M. D., & Pasiouras, F. (2010). Assessing bank efficiency and performance with operational research and artificial intelligence techniques: A survey. *European Journal of Operational Research*, 204(2), 189-198. <https://doi.org/10.1016/j.ejor.2009.08.003>
- Froehlich, S., Gum, F., & Berlinger, K. (2018). U.S. Patent No. 10,052,501. Washington, DC: U.S. Patent and Trademark Office.
- Ghassemi, M., Naumann, T., Schulam, P., Beam, A. L., Chen, I. Y., & Ranganath, R. (2019). Practical guidance on artificial intelligence for health-care data. *The Lancet Digital Health*, 1(4), e157-e159.
- Giebelhausen, M., Robinson, S. G., Sirianni, N. J., & Brady, M. K. (2014). Touch versus tech: When technology functions as a barrier or a benefit to service encounters. *Journal of Marketing*, 78(4), 113-124.

- Hawaladar, I. T., Ullal, M. S., Birau, F. R., & Spulbar, C. M. (2019a). Trapping Fake Discounts as Drivers of Real Revenues and Their Impact on Consumer's Behavior in India: A Case Study. *Sustainability*, 11(17), 4637. doi:10.3390/su11174637
- Hawaladar, I.T., Rajesha T. M. & Dsouza, L.J. (2019b). Testing the Weak Form of Efficiency of Cryptocurrencies: A Case Study of Bitcoin and Litecoin. *International Journal of Scientific & Technology Research*, 8 (9), 2301-2305.
- Hawaladar, I.T., Lokesh, Biso, S.S. & Joseph, N.R. (2016). Factors Affecting Leaders' Behaviour: A Study of Bahrain Banking Sector. *British Journal of Economics, Finance and Management Sciences*, 12 (1), 11-21.
- Leachman, S. A., & Merlino, G. (2017). Medicine: The final frontier in cancer diagnosis. *Nature*, 542(7639), 36-38.
- Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science* <https://doi.org/10.1287/mksc.2019.1192>
- Martínez-López, F. J., & Casillas, J. (2013). Artificial intelligence-based systems applied in industrial marketing: An historical overview, current and future insights. *Industrial Marketing Management*, 42(4), 489-495. <https://doi.org/10.1016/j.indmarman.2013.03.001>
- Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research*, 21(2), 155-172. <https://www.forbes.com/sites/richardkestenbaum/2018/06/27/shopping-by-voice-is-small-now-but-it-has-huge-potential/#1d140fc37ac8> . <https://doi.org/10.1177/1094670517752459>
- Köhler, C. F., Rohm, A. J., de Ruyter, K., & Wetzels, M. (2011). Return on interactivity: The impact of online agents on newcomer adjustment. *Journal of Marketing*, 75(2), 93-108. <https://doi.org/10.1509/jm.75.2.93>
- Leachman, S. A., & Merlino, G. (2017). Medicine: The final frontier in cancer diagnosis. *Nature*, 542(7639), 36. <https://doi.org/10.1038/nature21492>
- Leung, E., Paolacci, G., & Puntoni, S. (2018). Man versus machine: Resisting automation in identity-based consumer behavior. *Journal of Marketing Research*, 55(6), 818-831. <https://doi.org/10.1177/0022243718818423>
- Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, 151, 90-103. <https://doi.org/10.1016/j.obhdp.2018.12.005>
- Mimoun, M. S. B., Poncin, I., & Garnier, M. (2017). Animated conversational agents and e-consumer productivity: The roles of agents and individual characteristics. *Information & Management*, 54(5), 545-559. <https://doi.org/10.1016/j.im.2016.11.008>
- Patel, V. L., Shortliffe, E. H., Stefanelli, M., Szolovits, P., Berthold, M. R., Bellazzi, R., & Abu-Hanna, A. (2009). The coming of age of artificial intelligence in medicine. *Artificial Intelligence in Medicine*, 46(1), 5-17. <https://doi.org/10.1016/j.artmed.2008.07.017>
- Pinto, S., Pinto, P., Hawaladar, I.T. & Sarea, A.M. (2019). Motivation and Blockades for Entrepreneurship among Graduates. *International Journal of Scientific & Technology Research*, 8 (12), 821-828.
- Monostori, L., & Barschdorff, D. (1992). Artificial neural networks in intelligent manufacturing. *Robotics and Computer-Integrated Manufacturing*, 9(6), 421-437.
- Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments, & Computers*, 36(4), 717-731.
- Saad, S. B., & Abida, F. C. (2016). Social interactivity and its impact on a user's approach behavior in commercial web sites: a study case of virtual agent presence. *Journal of Marketing Management*, 4(2), 63-80. <https://doi.org/10.15640/jmm.v4n2a5>
- Schlinger, Henry D. (2003). The Myth of Intelligence, *The Psychological Record*, 53(1), 15-32.
- Sivaramakrishnan, S., Wan, F., & Tang, Z. (2007). Giving an "e-human touch" to e-tailing: The moderating roles of static information quantity and consumption motive in the effectiveness of an anthropomorphic information agent. *Journal of Interactive Marketing*, 21(1), 60-75. <https://doi.org/10.1002/dir.20075>
- Soucy, Pascal (2016). Self-Learning Intelligent Search, Explained, KM World, July 7, 2016, S34.

Srivastava, S. K. (2018). Artificial Intelligence: way forward for India. *JISTEM-Journal of Information Systems and Technology Management*, 15. <http://dx.doi.org/10.4301/s1807-1775201815004>

Sternberg, Robert J. (2005). The Theory of Successful Intelligence, *Interamerican Journal of Psychology*, 39(2), 189-202.

Thompson, C. (2018). November 18 May A.I. help you? New York Times retrieved from <https://www.nytimes.com/interactive/2018/11/14/magazine/tech-design-ai-chatbot.html>

Trippi, R. R., & Turban, E. (1992). Neural networks in finance and investing: Using artificial intelligence to improve real world performance. McGraw-Hill, Inc. <https://dl.acm.org/citation.cfm?id=573193>

Ullal, M., & Hawaldar, I. T. (2018). Influence of advertisement on customers based on AIDA model. *Problems and Perspectives in Management*, 16(4), 285-298. doi:10.21511/ppm.16(4).2018.24

Vargo, S. L., & Lusch, R. F. (2014). Evolving to a new dominant logic for marketing. In *the Service-Dominant Logic of Marketing* (pp. 21-46). Routledge.

Wilson, H. J., Daugherty, P., & Bianzino, N. (2017). The jobs that artificial intelligence will create. *MIT Sloan Management Review*, 58(4), 14. http://ilp.mit.edu/media/news_articles/smr/2017/5841

Wünderlich, N. V., Wangenheim, F. V., & Bitner, M. J. (2013). High tech and high touch: a framework for understanding user attitudes and behaviors related to smart interactive services. *Journal of Service Research*, 16(1), 3-20.

Wise, L. (2018). June 20 New media doesn't mean new rules: The challenges of chatbots. Social MediaWeek, retrieved from <https://socialmediaweek.org/blog/2018/06/new-media-doesnt-mean-new-rules-the-challenges-of-chatbots/>

Xiao, L., & Ding, M. (2014). Just the faces: Exploring the effects of facial features in print advertising. *Marketing Science*, 33(3), 338-352.

Yoo, Jaewon and Todd J. Arnold. (2016). Frontline Employee Customer-Oriented Attitude in the Presence of Job Demands and Resources: The Influence Upon Deep and Surface Acting, *Journal of Service Research*, 19(1), 102-117.

Young, James E., Cormier, Derek. (2014). Can Robots Be Managers, Too? *Harvard Business Review*, April 2 <http://blogs.hbr.org/2014/04/can-robots-bemanagers-too/>

Acknowledgement

We acknowledge the Chennai based International Company, which helped us in technology and voice mining free of cost which further added value to their knowledge bank.

Mithun S. ULLAL is working as Assistant professor with an experience of 12 years. I have completed my post-graduation in marketing and a computer science graduate. My areas of research are marketing, retail and HR. I have an industry experience of 6 years in banking and marketing. Teaching experience is of 6 years at postgraduate and undergraduate level. I have 5 international publications and currently pursuing research in marketing.

ORCID ID: 0000-0002-0334-7283

Iqbal Thonse HAWALDAR is a Professor in the Kingdom University, Bahrain with more than 20 years of teaching experience at undergraduate and graduate level. Having obtained his PhD for the thesis titled "Efficiency of the Indian Stock Market" from Mangalore University, India, he continues to commit himself to teaching and research. He has published a book titled Efficiency of Stock Market. He published more than 45 research papers in the reputed journals. He is on the editorial board and reviewer for many reputed journals and conferences.

ORCID ID: 0000-0001-7181-2493

Suhan MENDON is an Associate Professor at the School of Management. He is presently sharing the responsibilities of marketing area coordinator and International Relations Coordinator. He is also certified as internal quality auditor (ISO) in 2006 and ISO 9001:2008, ISO 2008:14001.

ORCID ID: 0000-0002-9184-6663

Nympha Rita JOSEPH is an Assistant Professor at the Applied Science University, Bahrain with more than 20 years of teaching experience at the undergraduate level. Besides this she also plays a vital role at the Quality Assurance and Accreditation centre. She is the Head of the QA Admin Audit office. She is a Fellow and a Senior Fellow of the Higher Education Academy U.K. She is also the Programme leader for the B.A. (Hons) Accounting and Finance, Cardiff Metropolitan University UK which is hosted programme by the Applied Science University.

ORCID ID: 0000-0001-9355-654X

Copyright © 2020 by author(s) and VsI Entrepreneurship and Sustainability Center

This work is licensed under the Creative Commons Attribution International License (CC BY).

<http://creativecommons.org/licenses/by/4.0/>



Open Access