A BEHAVIOURAL STUDY ON THE IMPACT OF ARTIFICIAL INTELLIGENCE ON CUSTOMER SERVICES RETENTION IN TELECOM INDUSTRY

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Abstract: *Customer services are always found special for the companies to improve their business perspectives and earlier management can't reach to the customer in that way. Now through Artificial Intelligence, they can reach out to the customer's perception what in turn improved the organizational efficiency but the major gap was found in, was majority of users gets frustrated with it. Although with AI some experiences are pleasant and unforgettable as used by hotels and airlines but AI allows only limited amount of customized communication hence its results into service dissatisfaction, hence their performance may have negative influences on them. Hence, the present study aims to find the impact of AI on the customer services retention in telecom industry.*
The data was collected from 400 mobile phone users to assess the impact of AI on their commitment (retention) with the telecom company. PLS-SEM, through SMART PLS software, has been done to assess the theoretical model of the study and the results were analyzed in this chapter. The results of the structural model have shown that both experiences of hedonic and recognition has a significant impact on customer commitment. Thus, we can say that AI-enable services of telecom brands should increase the customer experience in terms of hedonic and recognition to retain their customers. The findings have some important practical implications for marketing managers in the telecom industry.

Keywords: *Customer Retention, Artificial Intelligence, Customer Experience, Customer Recognition*

INTRODUCTION

Digital advertising and artificial intelligence (AI) have had a significant impact on the whole economic landscape in recent decades. AI is already a part of our lives, whether we realise it or not. AI is also expected to play a significant role in marketing and advertising. It can be used to forecast user behavior and recommend new goods accordingly. It can also easily evaluate massive amounts of data; something that was previously impossible to do manually. It can also assess how customers view a brand and their overall feelings toward a new brand or product.

AI is used in conjunction with automated marketing chores to uncover the data required to create extraordinary experiences for both prospects and customers. AI has a wide variety of applications in business. According to Syam and Sharma (2018), experts believe that the upcoming years will be a glimpse of the fourth industrial revolution, which will be fueled by digitization, information technology, machine learning, and artificial intelligence, and will result in the gradual transfer of human decision-making to machines.

Winning clients is only a tiny part of the battle for any advanced or internet firm. It is also about attracting and retaining clients in order to make long-term progress. Artificial Intelligence (AI) is an intriguing topic in marketing right now. According to Teradata's research, 80 per cent of businesses report that their organization is currently utilizing some form of AI. Throughout 2017 and 2018, AI has had a constant impact on many ventures, changing how firms finish particular cycles. Regardless, research has shown that its most significant impact has been on the shopper. Aside from providing a consistent omnichannel experience and improving personalization, AI gives up many new possibilities. AI can improve the overall consumer experience by using the intensity of information far faster and more effectively than people could.

Relationship marketing has emerged as a critical strategic tool for businesses in the face of rapidly changing customer needs and preferences. The importance of relationships and the need to build networks of relationships is highlighted by the rapid changes in almost every business type. Mobile commerce is now essential in all aspects of life, including education, health, business, and entertainment. Mobile phones are described as “those telephones that are fully portable and not attached to a base unit operating on dedicated mobile phone networks, where revenue is generated by all voice and data transmissions originating from such mobile phones” (“Mintel Report, 1998, cited in Turnbull and Leek, 2000, p.148”).

The wireless communication sector is not excluded from this phenomenon, being one of the fastest-growing service segments in telecommunications (Kim and Yoon, 2004), and has both “high customer turnover and high customer acquisition cost” (Bolton, 1998, p.52). The recent increase in competition in the wireless telecommunications sector emphasises the significance of retaining current customers (Seo et al., 2008).

Despite using various relationship marketing strategies to retain existing customers (Grönroos, 1995; Ravald and Grönroos, 1997; Ranaweera and Prabhu, 2003), many mobile phone companies are losing existing customers at rates exceeding 30%. Also, according to Andic (2006), the UK's major mobile network operators, Orange, T-Mobile, O2 and Vodafone, lose over a third of their youth subscribers to competitors. Despite their efforts to understand the causes of the loss, many managers are unable to address this fact directly (Reichheld, 1996). Loss of current and prospective customers means a loss of sales and profits, and ultimately, business failure (“Reichheld and Sasser, 1990; Reichheld and Kenny, 1990”). A lost customer means a potential loss of cash flow (Alshurideh, 2014b). Many wireless telecommunications and relationship marketing studies show that most businesses, particularly mobile service providers, continue to lose customers at an alarming rate. Many aspects of this paper have emphasised the significance of studying CR. Some of the factors cited include changes in consumer purchasing patterns, more demanding and sophisticated customers, shifting business themes, and the rapid pace of innovation (“Alshurideh, 2009; Alshurideh, 2014a: Alshurideh et al., 2014; Altamony et al., 2012”). Accordingly, this study of CR has focused on the mobile-phone sector, as about 50% of mobile-phone contracts are renewed (Dalen et al., 2006).

LITERATURE REVIEW

Artificial intelligence (AI) systems are a collection of software and hardware components that may be used to continuously assess and analyze data in order to characterize environmental elements and make judgments and take actions (European Commission, 2018). Prior research has concentrated on the benefits of using AI in online settings but has neglected to examine how consumers accept AI in online shopping. According to utility theory, this new technology enables consumers to discover and select the best product alternatives while lowering the cost and duration of the search.

According to existing research, technological advancements in apps such as Artificial Intelligence (AI), Augmented Reality (AR), and Virtual Reality (VR) provide highly personalised experiences that influence consumer preferences and behaviours (Huang and Rust 2017; Pantano and Pizzi 2020). In today's competitive consumer market, it is critical for all service companies to maintain a high level of customer retention, and this topic will receive a lot of attention over the next few years (Appiah-Adu, 1999). This is because businesses regard consumers as a true asset, and the vast majority of them are experiencing significant losses in their consumer base (Swanson and Hsu, 2009). Because of the significant expansion, change, and increase in competition that has occurred in the mobile phone market on both a global and domestic scale, CR has emerged as a critical phenomenon in this industry. Despite using a variety of relationship marketing strategies (Gronroos, 1995; Ravald and Gronroos, 1996; Ranaweera and Prabhu, 2003), a sizable number of mobile phone companies are losing their current customer bases at rates greater than thirty per cent (Gronroos, 1995; Ravald and Gronroos, 1996; Ranaweera and Prabhu, 2003).

Whang, Ren, and Lu (2018) explored the use of AI in telecommunication and led research entitled Key technologies of AI in customer service systems, Telecommunication Science they believed they artificial intelligence systems have some factors like very high efficiency and low expense when it is compared to traditional customer service operated by a human in the area of customer service in the business field. Client satisfaction, according to Ra'ed (2012), has a positive impact on long-term customer retention. Further, Ra'ed (2012) found that there is a direct correlation between customer pleasure and the length of the supplier-customer relationship, that mobile services provided by call centres have an impact on customer satisfaction and retention.

Customer engagement is a sort of co-creation between service providers and their consumers that has been identified as a marketing approach to increase customer purchase and loyalty (Brodie et al., 2011; Hoyer et al., 2010; Nambisan and Nambisan, 2008). Because the amount of involvement with a service organisation and its linked enterprises has financial ramifications for the organisation as well as for clients, this notion has gained widespread acceptance in marketing literature (Doorn et al., 2010). Customer engagement has been conceptualised in a variety of ways due to the fact that it is a relatively new idea. As a result, there is variability in both the drivers and the results of the literature. In accordance with the relevant literature, customer engagement is defined as the sum of a customer's behavioural, cognitive, and emotional involvement with a company (Hollebeek, 2011b; Prentice et al., 2018, 2019b). They also examined consumer engagement from the viewpoints of emotive, cognitive, and psychological factors. Customer identification, which indicates their perceived oneness with or belongingness to the brand or organisation; attention, which indicates their attention, focus, and connection with the brand or organisation; enthusiasm, which indicates customers' exuberance and interest; absorption, which indicates customers' pleasant state of mind; and interaction, which indicates customers' participation with the brand or organisation were included in this assessment. Each dimension has its own set of antecedents and consequences (Hollebeek, 2011a).

From the literature, the major gap found that their lacking behaviour in handling consumer experiences, what in turn affect the management of the company. Through a literature, it was found that the customer retention is affected by customer satisfaction if product purchased by customers and perform well as per their desires then their satisfaction will improve and hence, their perspectives will change. Hence, it was also, found that the consumer perspectives were not matching with the support given the company management. Customer services are always found special for the companies to improve their business perspectives and earlier management can't reach to the customer in that way. Now through Artificial Intelligence, they can reach out to the customer's perception what in turn improved the organizational efficiency but the major gap was found in, was majority of users gets frustrated with it. Although with AI some experiences are pleasant and unforgettable as used by hotels and airlines but AI allows only limited amount of customized communication hence its results into service dissatisfaction, hence their performance may have negative influences on them. Hence, the present study aims to find the impact of AI on the customer services retention in telecom industry.

THEORETICAL MODEL

Variables for this research are as follows:

1. Customer Commitment towards telecom brands
2. Customer experience with AI-enabled telecom services – Hedonic and Recognition
3. AI-enable telecom service components – responsiveness, reliability, empathy, assurance, convenience, and personalisation.
4. Perceived Threat in using AI-enable telecom services

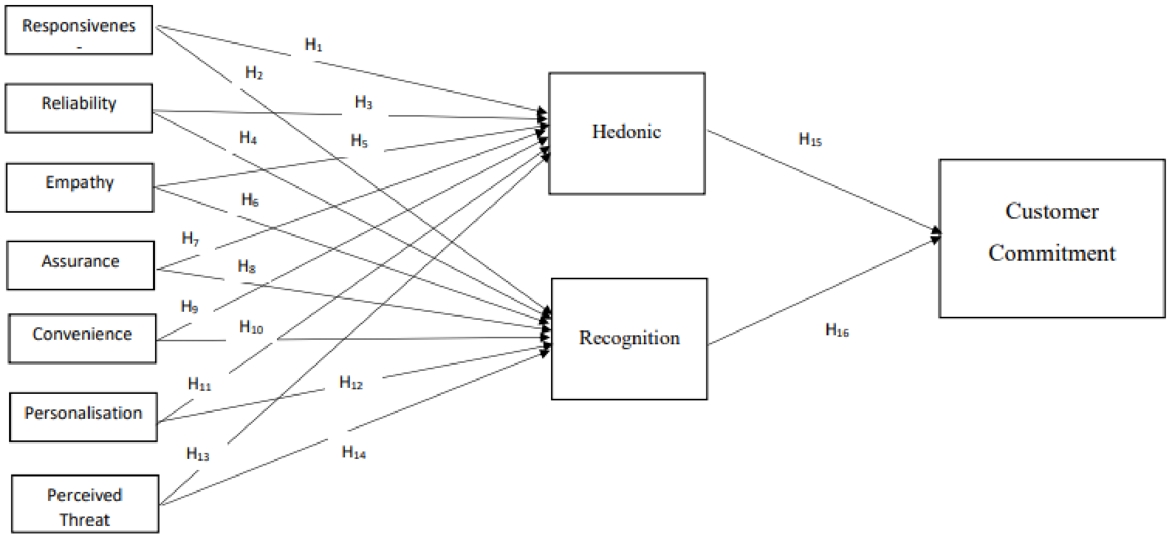


Figure 1: Theoretical Model of the Study

Hypotheses of the Study

H_1 - Responsiveness of AI-enabled telecom services has a significant impact on the hedonic customer experience

H_2 - Responsiveness of AI-enabled telecom services has a significant impact on the customer experience of recognition

H_3 - Reliability of AI-enabled telecom services has a significant impact on the hedonic customer experience

H_4 - Reliability of AI-enabled telecom services has a significant impact on the customer experience of recognition

H_5 - Empathy of AI-enabled telecom services has a significant impact on the hedonic customer experience

H_6 - Empathy of AI-enabled telecom services has a significant impact on the customer experience of recognition

H_7 - Assurance of AI-enabled telecom services has a significant impact on the hedonic customer experience

H_8 - Assurance of AI-enabled telecom services has a significant impact on the customer experience of recognition

H_9 - Convenience of AI-enabled telecom services has a significant impact on the hedonic customer experience

H_{10} - Convenience of AI-enabled telecom services has a significant impact on the customer experience of recognition

H_{11} - Personalisation of AI-enabled telecom services has a significant impact on the hedonic customer experience

H_{12} - Personalisation of AI-enabled telecom services has a significant impact on the customer experience of recognition

H_{13} - Perceived Threat of AI-enabled telecom services has a significant impact on the hedonic customer experience

H_{14} - Perceived Threat of AI-enabled telecom services has a significant impact on the customer experience of recognition

H_{15} - Hedonic customer experience of AI-enable telecom services has a significant impact on customer commitment

H_{16} – Customer experience of recognition from AI-enable telecom services has a significant impact on customer commitment

METHODOLOGY

The data for research was collected from 400 customers as sample has been selected who were using mobile and asking for several services. The customers will be selected randomly from market of Delhi-NCR. A questionnaire was also prepared, containing different questions that will help conclude. These samples were selected based on a random sampling technique. PLS SEM analysis has been done using the SMART-PLS software.

RESULT AND ANALYSIS

The data was collected from 400 mobile phone users to assess the impact of AI on their commitment (retention) with the telecom company. PLS-SEM, through SMART PLS software, has been done to assess the theoretical model of the study and the results were analyzed in this chapter.

Demographic Profile of the Respondents

It can be inferred from Table 1 that Reliance (31.75%) and Airtel (30.25) are the two major mobile network providers used by the respondents. The majority of the respondents are using their network for more than two years but less than five years (31.25%). 48.5% of the respondents are male and 51.5% are female. Nearly 56% of the respondents are less than 40 years of age.

Table 1: Demographic Profile of the Respondents

	Category	N	n	%
Primary network Partner	Reliance	400	127	31.75
	Airtel	400	121	30.24
	Vodafone	400	66	16.5
	BSNL	400	71	17.75
	Other	400	15	3.75
Time using current network	For last 1 year	400	92	23
	1 to less than 2 years	400	124	31
	2 to less than 5 years	400	125	31.25
	More than 5 years	400	59	14.75
Gender	Male	400	194	48.5
	Female	400	206	51.5
Age	Less than 20 Year	400	102	25.5
	20 to 40 Years	400	123	30.75
	40 to 60 Years	400	98	24.5
	Greater than 60 years	400	77	19.25

PLS-SEM RESULTS

Assessment of the Measurement Model

Hair et al. (2019) guidelines on how to report PLS-SEM results have been followed for measurement model assessment. In this study, the individual indicator variables are reflective in nature. ***Hair et al. (2019)*** state that "assessment of reflective measurement models comprises of measuring the internal reliability, internal consistency, convergent validity, and discriminant validity."

Internal reliability is ensured by looking into the indicator loadings, which are shown in Table 2.

Table 2: Indicator Loadings

Construct	Item	Loadings
Responsiveness	RS01	0.822
	RS02	0.908
	RS03	0.88
Reliability	RL01	0.779
	RL02	0.879
	RL03	0.813
	RL04	0.884
Empathy	E01	0.901
	E02	0.903
	E03	0.888
	E04	0.884
Assurance	A01	0.872
	A02	0.916
	A03	0.894
	A04	0.914
Convenience	C01	0.897
	C02	0.933
	C03	0.918
Personalisation	P01	0.893
	P02	0.872
Perceived Threat	PT01	0.721
	PT02	0.833
	PT03	0.773
Hedonic	HE01	0.861
	HE02	0.91
	HE03	0.895
	HE04	0.893
	HE05	0.791
Recognition	RE01	0.858
	RE02	0.883
	RE03	0.872
	RE04	0.888
	RE05	0.862

Customer Commitment	CC01	0.804
	CC02	0.927
	CC03	0.933
	CC04	0.93

Saari et al. (2021) postulate that "indicator loadings explain the amount of variance shared between the individual variables and the construct associated with them." Indicator loadings ensure the indicator reliability of reflective measurement models. It can be seen in Table 2 that all the indicator loadings of our measurement models are more than the recommended critical value of 0.708 ***(Hair et al., 2019)***. The crucial value of 0.708 denotes that the corresponding construct adequately provides item dependability by explaining more than 50% of the variation of the related indicator. Thus, we can say that our model has satisfactory indicator reliability.

After ensuring indicator reliability, the next step is to assess internal consistency and convergent validity. The internal consistency of reflective constructs is evaluated using the composite reliability and ρA, while the convergent validity of reflective constructs is evaluated using AVE (Average Variance Extracted). The compositie reliability, ρA and AVE of our assessment model are shown in Table 3. It has been inferred from Table 3 that both the composite reliabilty and ρA lies in between the recommended thresholds of 0.70 and 0.95. and all the AVE values surpass the recommended threshold value of 0.5. Thus, we can say that our reflective assessment model has a satisfactory level of internal consistency as well as convergent validity.

Table 3: Reliability and Validity

Constructs	ρA	Composite Reliability	Average Variance Extracted
Responsiveness	0.849	0.904	0.758
Reliability	0.866	0.905	0.706
Empathy	0.917	0.941	0.8
Assurance	0.928	0.944	0.809
Convenience	0.912	0.94	0.839
Personalisation	0.72	0.876	0.779
Perceived Threat	0.765	0.82	0.604
Hedonic	0.92	0.94	0.759
Recognition	0.926	0.941	0.761
Customer Commitment	0.929	0.945	0.81

The final step in the assessment of the reflective measurement model is to ensure discriminant validity, which explains the extent to which each construct is empirically separate from the other constructs. ***Saari et. al (2021)*** state that "HTMT (Heterotrait-monotrait) ratio is used to assess the discriminant validity of the model." The HTMT values are shown in Table 4.

HTMT is the mean correlation value of items across constructs in relation to the geometric mean of average correlations for items measuring the same construct. When HTMT values are high, discriminant validity is said to be low. It can be seen from Table 4. that all the HTMT values of our reflective measurement model are significantly lower than the conservative threshold limit of 0.85. Thus, it can be said that the discriminant validity of our model is satisfactorily established.

Table 4: HTMT Ratio of Correlations

	Assurance	Convenience	Customer Commitment	Empathy	Hedonic	Perceived Threat	Personalisation	Recognition	Reliability
Convenience	0.607								
Customer Commitment	0.433	0.463							
Empathy	0.498	0.69	0.436						
Hedonic	0.357	0.505	0.383	0.459					
Perceived Threat	0.202	0.291	0.766	0.282	0.257				
Personalisation	0.378	0.483	0.412	0.522	0.466	0.261			
Recognition	0.348	0.362	0.403	0.385	0.499	0.231	0.427		
Reliability	0.433	0.504	0.311	0.556	0.449	0.177	0.615	0.356	
Responsiveness	0.565	0.571	0.533	0.438	0.595	0.401	0.383	0.458	0.35

Assessment of the Structural Model

The guidelines of ***Hair et al. (2019)*** has been followed for structural model assessment of the study. According to ***Hair et al. (2019)***, "assessment of the structural model involves three important things viz., checking the collinearity issues, checking the relevance and significance of path coefficients and checking the models' explanatory and predictive power." The results of our structural model were shown in Table 5, and the significance of the path coefficients with relevant hypothesis has been separately shown in Figure 2.

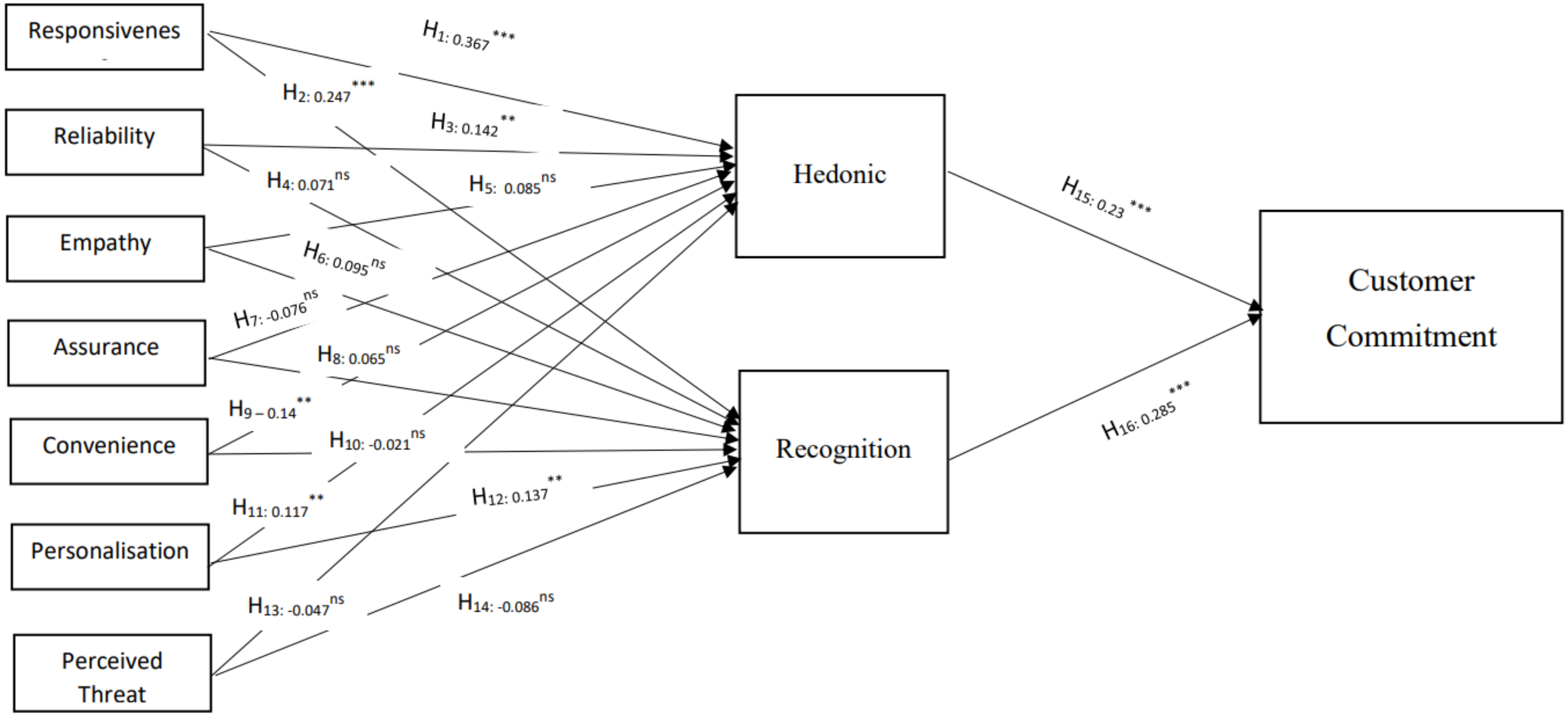
In model, collinearity issues has been checked using the Variance Inflation Factor (VIF). It can be seen from Table 5 that the VIF values are lower that 3. The largest inner VIF value of our model construct is 2.145 ***(Hair et al., 2019)***. Thus, we can say that "collinearity is not at a critical level in the inner model and will not affect the regression results." In the next step, the path coefficients' significance and size has been assessed.

With respect to control variables, age has significant impact on six predictors, namely reliability (β = -0.166), empathy (β = -0.182), convenience (β = -0.184), personalisation (β = -0.133), Hedonic experience (β = -0.165), and on the experience of recognition (β = -0.253); gender has a significant impact on five predictors, namely reliability (β = 0.279), empathy (β = 0.253), convenience (β = 0.226), personalisation (β = 0.319), and recognition (β = 019); and period of use has significant impact on five predictors namely reliability (β = 0.205), empathy (β = 0.165), convenience (β = 0.185), personalisation (β = 0.114), and perceived threat (β = -0.155), and also on the endogenous construct, customer commitment (β = 0.117). Control variables such as age and gender doesn't have any significant impact on the endogenous construct of the model.

Figure 2 illustrates the size and significance of path coefficients between the endogenous and exogenous constructs. It can be seen from figure 4.1 that responsiveness (β = 0.367), reliability (β = 0.142), personalisation (β = 0.117) and convenience (β = 0.14) has a significant positive correlation with the hedonic customer experience; responsiveness (β = 0.247), and personalisation (β = 0.137) are the only two exogneous constructs which has a significant positive correlation with the customer experience of recognition. The exogenous constructs assurance, empathy and perceived threat doesn't have any siginificant impact on both hedonic and recognition. Both the experiences of hedonic (β = 0.23) and recognition (β = 0.285) has a significant positive correlation with endogenous construct, i.e, the customer commitment.

A look into the R^2 values in Table 5 shows that responsiveness, reliability, personlaisation and heconic are the important predictor constructs in explaining the hedonic customer experience (R^2 = 0.418); responsiveness and personlisation are the important predictor constructs in explaining the customer experience of recognition (R^2 = 0.311); and both the experiences of hedonic and recognition are important predict constructs in explaining customer commitment (R^2 = 0.198). Thus, customer experience of hedonic and recognition will explains nearly 20% of the variance in customer commitment (retention). It could be noted that responsivenss (f^2 = 0.151) has the largest f^2 effect size among the predictor constructs, followed by recognition (f^2 = 0.075) and hedonic (f^2 = 0.051).

Figure 2: Structural Model Results



Note: *Control Variables - age, gender, and period of use.*
**** = p<0.01; ** = p<0.05; ns = Not Significant.*

Table 5: Structural Model Results

Outcome	R Sq.	Predictor	Direct Paths & Hypotheses	β	CI	Significance?	f^2	VIF
Responsiveness	0.008	CV	Age -> Responsiveness	-0.068	[-0.201; 0.063]	No	0.003	1.476
		CV	Gender -> Responsiveness	0.092	[-0.038; 0.218]	No	0.006	1.361
		CV	Period of Use -> Responsiveness	0.03	[-0.096; 0.151]	No	0.001	1.22
Reliability	0.109	CV	Age -> Reliability	-0.166	[-0.27; -0.064]	Yes	0.021	1.476
		CV	Gender -> Reliability	0.279	[0.181; 0.380]	Yes	0.064	1.361
		CV	Period of Use -> Reliability	0.205	[0.106; 0.301]	Yes	0.039	1.22
Empathy	0.08	CV	Age -> Empathy	-0.182	[-0.290; -0.077]	Yes	0.024	1.476
		CV	Gender -> Empathy	0.253	[0.144; 0.358]	Yes	0.051	1.361
		CV	Period of Use -> Empathy	0.165	[0.055; 0.271]	Yes	0.024	1.22
Assurance	0.017	CV	Age -> Assurance	-0.116	[-0.24; 0.009]	No	0.009	1.476
		CV	Gender -> Assurance	0.117	[-0.004; 0.236]	No	0.01	1.361
		CV	Period of Use -> Assurance	0.067	[-0.041; 0.172]	No	0.004	1.22

Convenience	0.076	CV	Age -> Convenience	-0.184	[-0.293; -0.071]	Yes	0.025	1.476
		CV	Gender -> Convenience	0.226	[0.117; 0.331]	Yes	0.041	1.361
		CV	Period of Use -> Convenience	0.185	[0.072; 0.292]	Yes	0.03	1.22
Personalisation	0.077	CV	Age -> Personalisationn	-0.133	[-0.255; -0.013]	Yes	0.011	1.476
		CV	Gender -> Personalisation	0.319	[0.206; 0.433]	Yes	0.063	1.361
		CV	Period of Use -> Personalisation	0.114	[0.003; 0.225]	Yes	0.009	1.22
Perceived Threat	0.038	CV	Age -> Perceived Threat	-0.064	[-0.207; 0.077]	No	0.003	1.476
		CV	Gender -> Perceived Threat	-0.01	[-0.123; 0.107]	No	0	1.361
		CV	Period of Use -> Perceived Threat	-0.155	[-0.263; -0.045]	Yes	0.02	1.22
Hedonic	0.418	RS	Responsiveness -> Hedonic	0.367	[0.254; 0.478]	Yes	0.151	1.544
		RL	Reliability -> Hedonic	0.142	[0.037; 0.257]	Yes	0.016	1.643
		P	Personalisation -> Hedonic	0.117	[0.021; 0.213]	Yes	0.028	1.5
		C	Convenience -> Hedonic	0.14	[0.024; 0.252]	Yes	0.015	2.145
		A	Assurance -> Hedonic	-0.076	[-0.182; 0.027]	No	0.007	1.679

		E	Empathy -> Hedonic	0.085	[-0.039; 0.209]	No	0.006	1.924
		PT	Perceived Threat -> Hedonic	-0.047	[-0.132; 0.032]	No	0.003	1.178
		CV	Age -> Hedonic	-0.165	[-0.253; -0.071]	Yes	0.031	1.547
		CV	Gender -> Hedonic	0.094	[-0.001; 0.183]	No	0.01	1.509
		CV	Period of Use -> Hedonic	-0.028	[-0.110; 0.056]	No	0.001	1.178
Recognition	0.311	RS	Responsiveness -> Recognition	0.247	[0.125; 0.372]	Yes	0.058	1.544
		P	Personalisation -> Recognition	0.137	[0.016; 0.254]	Yes	0.03	1.5
		A	Assurance -> Recognition	0.065	[-0.068; 0.195]	No	0.003	1.679
		C	Convenience -> Recognition	-0.021	[-0.178; 0.142]	No	0	2.145
		E	Empathy -> Recognition	0.095	[-0.050; 0.231]	No	0.006	1.924
		PT	Perceived Threat -> Recognition	-0.086	[-0.182; 0.01]	No	0.008	1.178
		RL	Reliability -> Recognition	0.071	[-0.038; 0.193]	No	0.003	1.643
		CV	Age -> Recognition	-0.253	[-0.354; -0.149]	Yes	0.061	1.547
		CV	Gender -> Recognition	0.19	[0.096; 0.285]	Yes	0.035	1.509

		CV	Period of Use -> Recognition	-0.007	[-0.123; 0.110]	No	0	1.311
Customer Commitment	0.198	HE	Hedonic -> Customer Commitment	0.23	[0.113; 0.347]	Yes	0.051	1.299
		RE	Recognition -> Customer Commitment	0.285	[0.161; 0.409]	Yes	0.075	1.342
		CV	Age -> Customer Commitment	0.016	[-0.112; 0.151]	No	0	1.606
		CV	Gender -> Customer Commitment	-0.082	[-0.204; 0.041]	No	0.006	1.482
		CV	Period of Use -> Customer Commitment	0.117	[0.012; 0.218]	Yes	0.014	1.226

CI = “95% bootstrap two-tailed confidence interval”, CV = “Control Variable”, RS = “Responsiveness”, RL = “Reliability”, PT = “Perceived Threat”, P = “Personalisation”, A = “Assurance”, C = “Convenience”, E = “Empathy”, HE = “Hedonic”, RE = “Recognition”.

Importance-Performance Map Analysis (IMPA)

In order to identify the impact and performance of the constructs with respect to the endogenous construct, importance-performance map analysis (IMPA) has been conducted with customer commitment as the target construct, and the results are shown in Table 6 and Figure 3. ***Saari et al. (2021)*** state that "the results of IMPA demonstrate for which exogenous construct the total effects are important by explaining the variance of the endogenous construct."

It has been inferred from Table 6, and Figure 3 that recognition (0.296), and responsiveness (0.147) have the largest total effects and are important in explaining the impact of AI components on customer retention (performance recognition – 46.751; and performance responsiveness – 47.114). Hedonic (0.228) has an above-average total effect, but they score low in performance (performance hedonic – 45.08). Perceived Threat has a smaller total effect (-0.06)) but realizes above-average performance (51.835). Assurance (0.001), Convenience (0.023), Empathy (0.04), Personalisation (0.062), and Reliability (0.05) have a very small total effect and also score low in performance (performance assurance – 45.966; performance convenience – 46.036; performance empathy – 46.233; performance personalisation – 45.785; and performance reliability – 42.705).

If 1 unit of performance of Recognition increases from 46.752 to 47.752, then Customer Commitment will increase from 46.749 to 47.045. This is the highest increase in the performance of our target variance, that is, Customer Commitment. Thus it can be said that the customer experience of recognition plays a very significant role in the retention of customers in the Indian mobile market.

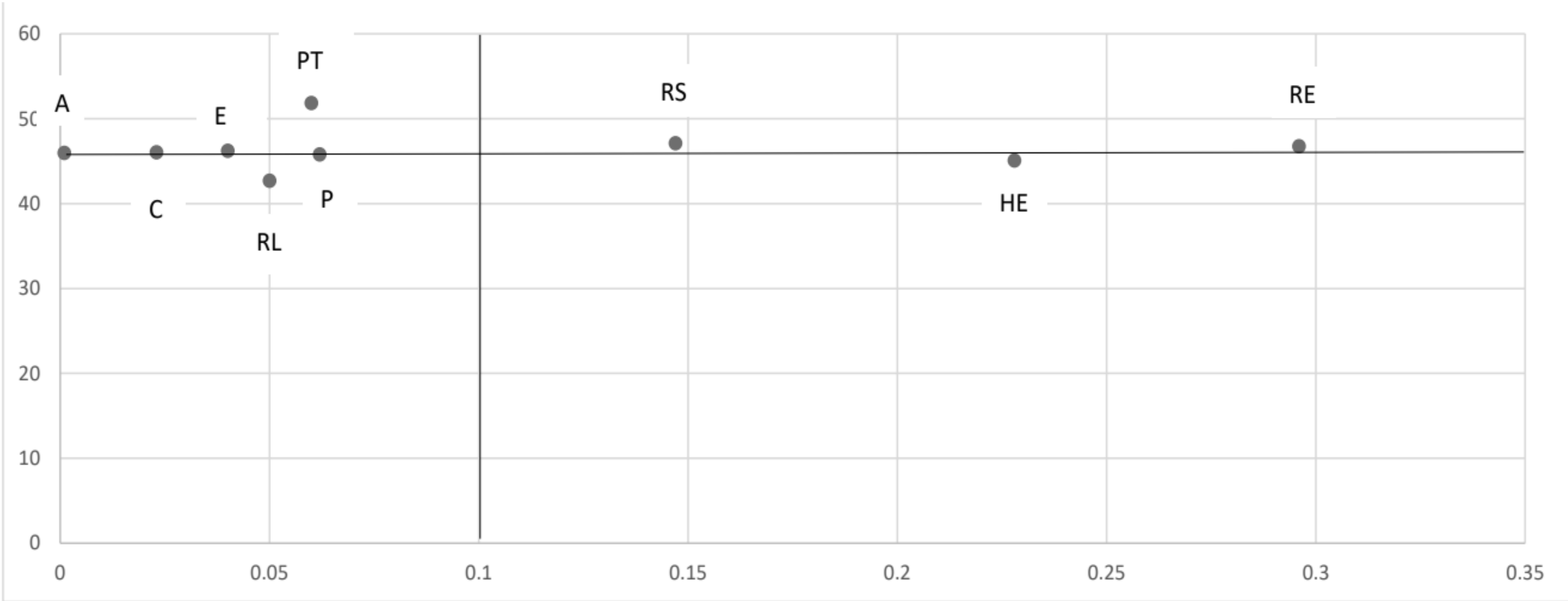
Table 6: Importance-Performance Map Analysis

	Unstandardized Total Effect (With Sign)	Unstandardized Total Effect (Without Sign)	Performance	LV Performance
Assurance	0.001	0.001	45.966	-
Convenience	0.023	0.023	46.036	-
Empathy	0.04	0.04	46.233	-
Hedonic	0.228	0.228	45.08	-
Perceived Threat	-0.06	0.06	51.835	-
Personalisation	0.062	0.062	45.785	-
Recognition	0.296	0.296	46.751	-
Reliability	0.05	0.05	42.705	-
Responsiveness	0.147	0.147	47.114	-
Customer Commitment	-	-	-	46.389
Average	-	0.1	46.39	

Source: *Primary Data*

Note: PLS-SEM analysis is done using SMART PLS software.

Figure 3: Importance-Performance Map Analysis



Note: *RS = "Responsiveness", RL = "Reliability", PT = "Perceived Threat", P = "Personalisation", A = "Assurance", C = "Convenience", E = "Empathy", HE = "Hedonic", RE = "Recognition".*

DISCUSSION

The results of the structural model have shown that both experiences of hedonic and recognition has a significant impact on customer commitment. Thus, we can say that AI-enable services of telecom brands should increase the customer experience in terms of hedonic and recognition to retain their customers. This finding is in line with the study of Keiningham et al. (2017) which states that “understanding the relationship between customer experience and customer commitment is critical to achieving what Peter Drucker described as the goal of every business – to create a customer”. Further, Roy, Gruner & Guo (2019) postulates, “customer experience positively affects customer commitment, which in turn positively affects customer engagement behaviors”.

The study finds that responsiveness, reliability, convenience and personalisation have a significant impact on hedonic customer experience. Selcuk (2016) found that “partner responsiveness predicts hedonic well-being”. Paushneh & Parraga (2017) found that reliability plays a significant role in customer’s experience, satisfaction and willingness to buy. Wong (2021) states that positioning the service strategy as convenient is essential to give a hedonic experience to consumers. Bagdare (2015) states that personalization is essential to create an emotional bond with the customers.

The results of the structural model further showed that responsiveness and personalisation are the only two constructs which have a significant impact on customer recognition. This finding is in line with the study of Baaddullah et al. (2022) which found that “the statistical results of the study largely supported the role of personalisation and responsiveness in shaping the virtual flow experience with chatbots, which in turn has a significant impact on both communication quality and satisfaction”.

The importance-performance map analysis (IMPA) has shown that recognition and responsiveness have the largest total effects on customer commitment and hence, they are important in explaining the impact of AI components on customer commitment (retention). If 1 unit of performance of Recognition increases from 46.752 to 47.752, then Customer Commitment will increase from 46.749 to 47.045. This is the highest increase in the performance of our target variance, that is, Customer Commitment. Thus it can be said that the customer experience of recognition plays a very significant role in the retention of customers in the Indian mobile market. This is in line with the findings of Khan et al. (2020) which state that “customer recognition has a positive impact on both customer’s affective/calculate commitment, and also on customer commitment on brand loyalty. These findings have important practical implications for marketing managers in the telecom industry. In order to increase customer commitment, they have to focus on AI-based customer experience (particularly on customer recognition) and also should give more focus on the responsiveness component of the AI.

CONCLUSION

From the study, it can be concluded that a customer-journey analytics solution tracks each customer’s movements across its ecosystem in the telecom industry. The service builds maps of each travel and timestamps visitor interactions. Comcast swiftly resolves experience issues by utilizing AI to collect data and pinpoint where journeys fail, such as with its mobile application. Businesses are integrating numerous AI, Martech, and back-office technologies with standard application programming interfaces to generate and utilize personalized data more effectively. New digital media enable users to interact with companies in novel ways. The optimal strategy for challenger brands is to establish a data and technology road map with precise, customer-driven use cases and granular requirements in the telecom industry. The Telecom industry must define, for instance, which client data pieces must be used in real-time to fuel app recommendations, or which systems must communicate with one another after a booking is completed to promote relevant add-on services. Then, it must unite the business and technology teams to create the foundation while focused on delivering value iteratively.

The more advanced AI becomes, the more individualized marketing will become. Using machine learning and pattern recognition, marketers can build more effective advertisements and target user needs. With the ability to deliver precise solutions based on a huge array of data, virtual assistants will become the norm and transform customer service systems. Improving self-service is one of the most effective methods to promote consumer engagement and agent efficiency. It supports the self-service system. Self-service also allows your agents to spend more time with consumers requiring special attention instead of frequently answering simple questions. With AI and cognitive search, you can provide these individualized customer experiences while relieving the strain on your support employees. For instance, the content performance in your self-service community influences the content ranking agents to see in the CRM. The content agents use to settle situations is pushed to the top of search results within your customer community. This closes the loop between self-service and assistance, allowing you to give your consumers frictionless experiences. At each point of the user life cycle, AI-powered solutions may assist businesses in persuading customers to take action.

REFERENCES

[1] Alshurideh, M. (2014a), “The Factors Predicting Students' Satisfaction with Universities' Healthcare Clinics' Services: A Case-Study from the Jordanian Higher Education Sector”. Dirasat: Administrative Sciences. 41(2), 451-464.

[2] Alshurideh, M. (2014b), “A Qualitative Analysis of Customer Repeat Purchase Behaviour in the UK Mobile Phone Market”. Journal of Management Research 6(1), 109-125.

[3] Alshurideh, M., Shaltoni, A-M., &Hijawi, D. (2014), “Marketing Communications Role in Shaping Consumer Awareness of Cause-Related Marketing Campaigns”. International Journal of Marketing Studies. 6(2), 163- 168

[4] Altamony, H., Masa’deh, R., Alshurideh, M., &Obeidat, B. (2012), “Information systems for competitive advantage: Implementation of an organisational strategic management process”. Proceedings of the 18th IBIMA conference on Innovation and Sustainable Economics Competitive advantage: From Development to World Economies. International Business Information Management Association.

[5] Andic, S. (2006), “Mobile operators must tune into youth market”. New Media Age, 7-7.

[6] Appiah-Adu, K. (1999). "Marketing Effectiveness and Customer Retention in the Service Sector." The Service Industries Journal 19(3): pp: 26 - 41.

[7] Baabdullah, A.M., Alalwan, A.A., Algharabat, R.S., Metri, B. and Rana, N.P., 2022. Virtual agents and flow experience: An empirical examination of AI-powered chatbots. *Technological Forecasting and Social Change*, *181*, p.121772.

[8] Bagdare, S., 2015. Emotional determinants of retail customer experience. *International Journal of Marketing & Business Communication*, *4*(2), pp.9-16.

[9] Bolton, R. N. (1998). "A Dynamic Model of the Duration of the Customer's Relationship with a Continuous Service Provider: The Role of Satisfaction." Marketing Science 17(1), 45-65.

[10] Brodie, R. J., Hollebeek, L. D., Jurić, B., & Ilić, A. (2011). Customer engagement: Conceptual domain, fundamental propositions, and implications for research. Journal of Service Research, 14(3), 252–271. https://doi.org/10.1177/1094670511411703

[11] Dalen, D. M., E. R. Moen, et al. (2006), "Contract renewal and incentives in public procurement." International Journal of Industrial Organization 24(2), 269-285.

[12] European Commission, (2018). *A definition of AI: Main Capabilities and Disciplines. Definition developed for the purpose of the AI HLEG's deliverables*. [online] Available at: <https://ec.europa.eu/digital-single-market/en/news/definition-artificial-intelligence-main-capabilities-and-scientific-disciplines>

[13] Grönroos, C. (1995), "Relationship Marketing: The Strategy Continuum." Journal of the Academy of Marketing Science 23(4), 252-254.

[14] man-computer interaction, 1-16.

[15] Hair, J.F., Risher, J.J., Sarstedt, M. and Ringle, C.M., 2019. When to use and how to report the results of PLS-SEM. *European business review*.

[16] Hollebeek, L., 2011b. Exploring customer brand engagement: definition and themes. J. Strat. Market. 19 (7), 555–573.
[17] Hollebeek, L.D., 2011a. Demystifying customer brand engagement: exploring the loyalty nexus. J. Market. Manag. 27 (7–8), 785–807. https://doi.org/10.1080/0267257X.2010.500132.
[18] Huang, M. H., & Rust, R. T. (2017). Technology-driven service strategy. Journal of the Academy of Marketing Science, 45(6), 906–924.
[19] Keiningham, T., Ball, J., Benoit, S., Bruce, H.L., Buoye, A., Dzenkovska, J., Nasr, L., Ou, Y.C. and Zaki, M., 2017. The interplay of customer experience and commitment. *Journal of Services Marketing*, *31*(2), pp.148-160.
[20] Kim, H.-S. & C.-H. Yoon (2004). "Determinants of subscriber churn and customer loyalty in the Korean mobile telephony market". Telecommunications Policy 28(9-10), 751-765
[21] Pantano, E., & Pizzi, G. (2020). Forecasting artifcial intelligence on online customer assistance: Evidence from chatbot patents analysis. Journal of Retailing and Consumer Services, 55, 102096.
[22] Poushneh, A. and Vasquez-Parraga, A.Z., 2017. Discernible impact of augmented reality on retail customer's experience, satisfaction and willingness to buy. *Journal of Retailing and Consumer Services*, *34*, pp.229-234.
[23] Prentice, C., and Nguyen, M., (2020). Engaging and retaining customers with AI and employee service. Journal of Retailing and Consumer Services, 56(), 102186-. doi:10.1016/j.jretconser.2020.102186
[24] Prentice, C., Wang, X., Loureiro, S.M.C., (2019b). The influence of brand experience and service quality on customer engagement. J. Retailing Consum. Serv. 50, 50–59. https://doi.org/10.1016/j.jretconser.2019.04.020.
[25] Ranaweera, C. & J. Prabhu (2003), "The influence of satisfaction, trust and switching barriers on customer retention in a continuous purchasing setting." International Journal of Service Industry Management 14(4), 374-395.
[26] Ravald, A. and C. Grönroos (1996). "The value concept and relationship marketing." European Journal of Marketing 30(2): pp: 19-30
[27] Reichheld, F. & E. Sasser (1990), "Zero defections: Quality comes to services." Harvard Business Review 68(5), 105-111.
[28] Reichheld, F. F. & D. W. Kenny (1990), "The hidden advantages of customer retention." Journal of Retail Banking XII (4), 19-23.
[29] Reichheld, F. F. (1996), "Learning from Customer Defections." Harvard Business Review 74 (2): 56-67.
[30] Roy, S.K., Gruner, R.L. and Guo, J., 2022. Exploring customer experience, commitment, and engagement behaviours. *Journal of Strategic Marketing*, *30*(1), pp.45-68.
[31] Saari, U.A., Damberg, S., Frömbling, L. and Ringle, C.M., 2021. Sustainable consumption behavior of Europeans: The influence of environmental knowledge and risk perception on environmental concern and behavioral intention. *Ecological Economics*, *189*, p.107155.
[32] Selcuk, E., Gunaydin, G., Ong, A.D. and Almeida, D.M., 2016. Does partner responsiveness predict hedonic and eudaimonic well-being? A 10-year longitudinal study. *Journal of Marriage and Family*, *78*(2), pp.311-325.
[33] Seo, D., C. Ranganathan, et al. (2008), "Two-level model of customer retention in the US mobile telecommunications service market." Telecommunications Policy 32(3-4), 182-196.
[34] Swanson, S. R. and M. K. Hsu (2009). "Critical incidents in tourism: failure, recovery, customer switching, and word-of-mouth behaviors." Journal of Travel & Tourism Marketing 26(2): pp: 180-194.
[35] Syam, N., & Sharma, A. (2018). Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice. Industrial Marketing Management, 135-146.

[36] Turnbull, P. W., S. Leek, et al. (2000), "Customer Confusion: The Mobile Phone Market." Journal of Marketing Management 16(1-3), 143-163.
[37] Wong, A., 2021. Consumer perceptions of service convenience in hedonic and utilitarian retail settings in China. *Journal of International Consumer Marketing*, *33*(4), pp.452-470.

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