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Factors Influencing Adoption Intention of AI Powered Chatbot for Public Transport Services within a Smart City

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ABSTRACT: Cities are growing in size in all parts of the world.This puts a burden on the public transport infrastructure and creates numerous issues such as overcrowding, delayed services, and commuter dissatisfaction. Government authorities in various countries including India are adopting smart city concepts to overcome these problems. Smart cities are characterized by their extensive use of emerging technologies for managing various citizen services. Accordingly, researchers of this paper studied the adoption intention of Artificial Intelligence (AI) powered Chabot by smart city citizens for delivering anytime, anywhere, and automated public transport information services. These services can include finding routes and schedules, buying tickets, registering complaints,or collecting feedback from commuters. The study employed an extended UTAUT model to measure the adoption intention. A primary survey is conducted using a structured questionnaire and the data is analyzed using the structural equation modeling technique.The findings from this study suggest that performance expectancy, effort expectancy, social influence, facilitating conditions, anthropomorphism, and trust directly affectthe adoption intention of the Chatbot. The proposed Chatbot solution in this study has social implications in terms of attracting more citizens to use public transport instead of their private vehicles thereby reducing congestion, travel delays, and climate pollution. The study also provides vital insights to public transport officials and policymakers while designing or upgrading public transport information systems in a developing country like India. This study makes a novel contribution to literature as it empirically validates the intention to use AI powered Chatbot for public transport in the context of a large developing country like India.

Keywords: Artificial Intelligence, Anthropomorphism, Chatbot, Public Transport Information System, Technology Adoption, UTAUT, Smart City.

I. INTRODUCTION

A commuter friendly and comprehensive online information system for city public transport is considered vital for residents as well as visiting travelers. A well designedpublic transport information system (PTIS) provides commuters the latest information such as routes, schedules, and fare for their intended journeys. This information assists citizens in their daily commute decisions and can further reduce the use of private vehicles, which often impact the surrounding environment adversely [1,2,3]. Lack of easy access, reliability, and uncertainty in waiting time resulting from a legacy PTIS keep many commuters away from using public transport [4]. With a growing urban population, expanding city limits and multiple transport options added every day, there is a need for a better PTIS that is easy to use and intelligent enough to understand the commuter's intent. An intelligent PTIS would then provide citizens with travel options that are optimal from time andcost perspectives [1].

However, the share of public transport usage is not very encouraging in India. As per government census data, only 18.1% of the working population uses public transport and remaining toopt fortheirvehicles or just prefer a walk to their workplace. With the Indian government launching smart cities missions, an intelligent and commuter friendly PTIS becomes even more important to achieve the goal of smart cities [5]. While there could be multiple reasons for the low usage of public transport, lack of timely assistance is one of the major reasons. The schedules are often displayed on boards at the bus or train stopswhich are not accessible from remote locations. Sometimes the schedules are also postedon a web portal but that requires computer literacy [6]. Many times, the sites have pdf-based timetables which make cross-referencing annoying [7]. Most often, there are no easy ways to receive changes to transport routesunless one speaksto transport department personnel. In multi-mode travel that involves hailing a bus and a train, it is more difficult to plan travel considering the above-mentioned challenges. Moreover, unforeseen transport breakdowns can not only cause financial loss to transport departments but may also result in commuter dissatisfaction [8]. Hence, a good PTIS is desirable to handle communication related to disruption in services.

With widespread smartphone adoption and popularity of chat based mobile applications such as WhatsApp and Facebook messenger, a conversational chat application, known as Chatbot, can be envisioned for public transport information and inquiry purpose. Emerging technology, such as Artificial Intelligence (AI), with its natural language processing capabilities, has the potential to realize such a Chatbot application. The Chatbot possess abilities to understand natural language queries and respond in a human-like manner. As per Harvard study, such Chatbots would reduce the workload on understaffed government departments and help improve customer satisfaction by being available 24x7 to answerthe most commonly asked questions [9]. There is an increase in the number of Chatbots deployed using Facebook messengerwith one studyestimating approximately 34000 such conversational agents serving various customer needs [10]. They are helping organizations increase revenue by providing automated, interactive, and personalized communication. Chatbots also reduce costs through salary savings of customer service representatives [11]. Therefore, the authors of this research paper believe that AI-powered Chatbot provides a novel solution approach to solve the commuter's public transport information challenges.

The current Chatbot literature is heavily inclined towards technical aspects of the solution and there are relatively very few studies conductedin the domain of social science. A comprehensive and focused academic study is required to understand the factors that potentially impact Chatbots' public adoption. Additionally, there are no prior studies that researched Chatbot's application in the context of city public transport in a large developing country like India. Hence, this paper contributes to Chatbot and PTIS literature by examining the following research problem: *What factors impact the adoption intention of Chatbot in public transport information services?*

II. LITERATURE REVIEW

A. Public Transport Information System (PTIS)

Extant literature is available in the PTIS domain. Information availabilityhas emerged as the most important satisfaction parameter amongst the Japanese railway commuter's survey [12]. Similarly, few other public transport related studies indicate that travelers' satisfaction is mainly dependent on the accuracy of PTIS [13, 14]. One study observes that the satisfaction of metro commuters in Greece is affected by the quality of the information provided by the PTIS [15].

Another research study suggests providing the high quality, accurate, and latest information to commuters is required to shift them from private transport mode to public transport mode [16].This is confirmed bya study in Dublin that shows 42% of commuters do not use public transport largely due to a lack of information [17]. An interactive web based PTIS is recommended within a smart metro city such as Hong Kong where commuters need to select the right option from more than ten available transport modes [1]. Few researchers also find that local train commuters prefer a mobile based PTIS [9] and propose the use of internet-of-things for intelligent, real-time PTIS within smart cities [18]. A recent study highlights that the transport department can playfully engage with commuters using a crowdsourcing approach for improving transport services data accessibility [19]. In summary, theliterature suggests that improving information quality and accessibility can lead to an increase in commuters' satisfaction concerning their public transport usage.

B. AI Powered Chatbot

The use of natural language processing information systems has been a long studied area for researchers. Over the last decade, the field of dialogue based system or Chatbot has evolved rapidly after the advancement in both GPU hardware and NLP algorithms. The Chatbot is not operated by human operators but, takes spoken language or text as input from users, processes it based on trained models, and responds to users from the available knowledge base. With smartphone emergence, Chatbot assistants in form of Apple Siri, Google Assistant, and Amazon Alexa have become accessible to common people for use cases such as answering questions, log complaints and translate information [9]. A study exploreda spoken dialogue based system for automating some parts of the public transport information system in the Netherlands [20].

Another study proposes the use of Chatbot for buying train tickets, finding the schedule, and getting real-time contextual information about long distance travel. Chatbot acts as a new touchpoint between the organization and users reducing servicing costs, performing personalized marketing, and providing 24x7 contact support [11]. Patent analysis of Chatbot shows that there is an increasing thrust towards employing Chatbot as a virtual assistant that infers user intentions [21]. However, incorrect identification of user intention can reduce the human-like characteristic of Chatbot [22]. One recent study explored the use of Chatbot as a shopping assistant and found that trust influences adoption intention [23]. Brania is another type of Chatbot that is modeled after the human brain to instruct a computer while MurdochBot suggests TV programs based on the likes of the user [24].

C. Technology Adoption Models

Researchers have studied the determinants of technology adoption behavior extensively [25]. The rapid innovations in information technology have significantly attracted researchers to study factors behind adoption intention and actual usage of technology led solutions [26]. The seminal work from Fishbein & Ajzen in the form of the theory of reasoned actions was introduced first [27]. Ajzen then came up with the theory of planned behavior [28]. These theories formed the base to measure the adoption intention of technology solutions. Drawing on these theories, Davis proposed a simple technology acceptance model [29] which was further evolved to Unified Theory of Acceptance and Use of Technology (UTAUT) theory proposed by Venkatesh et al. The UTAUT theory posits that technology adoption is dependent on perceived efforts, usefulness, conditions and social encouragement [30]. The Chatbot solution is expected to aid commuters with faster and accurate information as per local communication norms facilitated by respective public transport departments [31, 32]. Hence, the authors of this paper have chosen UTAUT as the base theory for the research study.

III. HYPOTHESIS DEVELOPMENT

Many theories in technology adoption area have been developed. These theories use several determinants such as user perception and attitude, effort to learn, and social context affecting technology adoption and acceptance with moderating factors such as age, gender, and experience. Adoption is typically measured before introducing the technology and acceptance is typically measured after system usage.UTAUT has been used by many researchers in the past to identify important and distinguishable factors affecting technology adoption intention in the societal contexts [33]. According to this theory, adoption intention (AINT) of technology solutions or services is influenced by performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC).

Public transport is being used by everyone from students to working and retired population including males and females voluntarily in India; hence the control variables such as experience, age, gender, and voluntary use are not considered in this research study. Additionally, Chatbot differs from other technology solutions in a way that Chatbot user interaction is similar to that of human-to-human interaction. Hence, researchers of this paper believe that the effect of anthropomorphism (ATH) [34,35] and trust (TST) [36] on AINT should also be studied along with UTAUT factors due to their natural importance in human conversations. Fig. 1 represents the conceptual model for this research.

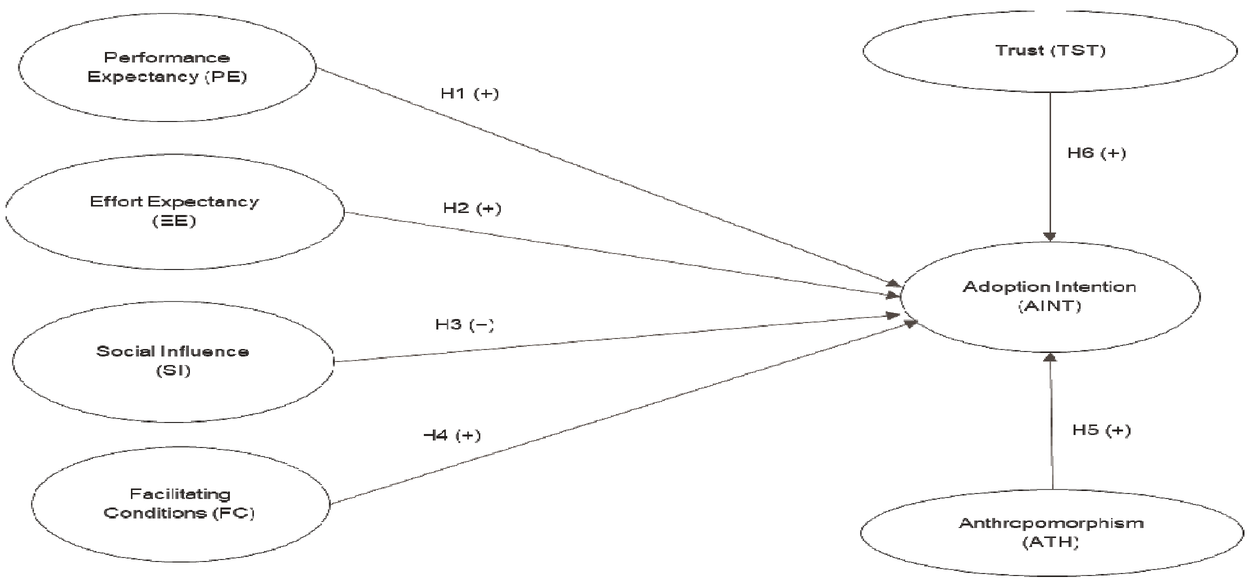

Fig. 1. Conceptual Model.

The conceptual model consists of the following six hypotheses.

Relationship between PE and AINT: PE is a measure of expected benefits technologybrings to the user while performing the task [30]. Prior research demonstrated that PE affects the adoption intention of novel technology solutions [37, 38]. Chatbots are expected to aid users to perform their information exchange tasks more effectively. Several past studies have shown PE positively affects AINT [39, 40]. Hence following hypothesis is formed.

H1: PE positively affects AINT of the Chatbot for public transport services.

Relationship between EE and AINT: EE is a measure of ease of using the technology solution by the users [30]. EE can explain AINT of technology solution since users dislike complex or difficult to use solutions. Various other technology solutions such as internet and smart phone based applications have found wide usage due to their ease of use [41, 42]. Prior studies have shown that EE shares a positive relationship with AINT [37,38,39,43]. This leads to the following hypothesis.

H2: EE positively affects AINT of the Chatbot for public transport services.

Relationship between SI and AINT: SI measures the user's belief of technology solution being used by his or her friends, family, or other members of social circles [30]. In the past, SI has explained AINT for various technology based solutions such as smartphone applications [41], online payments [44], and internet games [45]. Chatbots are a type of smartphone applications. In line with prior studies, SI is considered to have a positive influence on AINT of a Chatbot as well [37, 38, 39, 46]. Thus, the study proposes the following hypothesis.

H3: SI positively affects AINT of the Chatbot for public transport services.

Relationship between FC and AINT: FC is the user's perception that there is sufficient infrastructure available for the usage of the technology solution [30]. Past studies have shown that FC affects AINT considerably. It is important to note that India is a developing country and setting up novel technology solutions such as Chatbot for the general public requires vast infrastructure and budgets. Several past researchers found that FC affects AINT positively [37,38,39,47]. Hence following hypothesis is formed.

H4: FC positively affects AINT of the Chatbot for public transport services.

Relationship between ATH and AINT: People tend to evaluate both functional use and human like characters of Chatbot like technology solutions. In the past, researchers have studied Chatbot technology in the field of Human Robot Interaction and that makes natural conversational elements important [39]. Research studies by [48,49] found that people consider social robots as human-like entities with properties such as emotions and mental abilities. The more these robots are made realistic in their behavior and appearance, people tend to perceive them as more intelligent. ATH feature makes these social robots appear more genuine and can lead to an increase in human-robot interactions [22,35,50,51]. Hence, Chatbot AINT also needs to be evaluated from the ATH point of view. This leads to the following hypothesis.

H5: ATH positively affects AINT of the Chatbot for public transport services.

Relationship between TST and AINT: The researchers observed that TST plays a critical role in the wider adoption of any new technology intervention [52]. The reason for TST being studied by many similar past studies [53,54,55] is the risk being taken by the user to depend on new technology for accomplishing the goals. Studies by [36] have shown than TST plays an important role in human decision making while adopting automated technology solutions. Trust can be measured by various factors but, most of the technology researchers have measured it using reliability, functionality, and helpfulness parameters [56]. Past studies have demonstrated the role of TST in technology acceptance in various contexts as well [26]. Thus, the study proposes the following hypothesis.

H6: TST positively affects AINT of the Chatbot for public transport services.

IV. RESEARCH METHODOLOGY

A. Measures

The conceptual model combined the UTAUT theory with anthropomorphism and trust factors. The study employed a quantitative method by sharing an online survey with public transport commuters to gather the necessary research data.

B. Research Instrument

Similar to prior studies that measured adoption intention using the UTAUT model, this study was also conducted using the survey questionnaire as a research instrument [39]. The individual parameters of the survey questionnaire were based on a fivepoint Likert scale and the scale's validity is established based on recommendations from [57]. The questions were formulated to gather the respondents' perception of Chatbots' functional use in day-to-day public transport information query needs. A simulated AI based Chatbot as shown in Fig. 2 was presented to respondents before collecting the survey feedback to familiarize them with this emerging technology solution. Several public transport related queries were simulated into the Chatbot application.

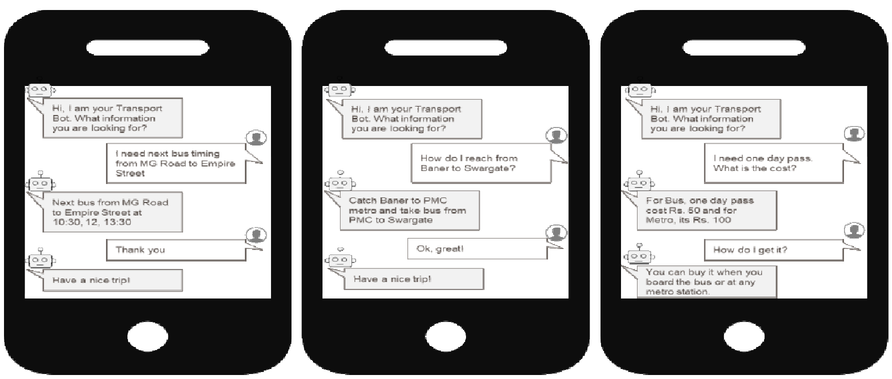

Fig. 2. Illustrative public transport Chatbot application.

C. Sampling and data collection

Initially, the survey was exposed to five subject matter experts from the public transport domain to validate the data collection instrument. Post validation, a pilot test was conducted amongst 25 respondents by distributing the survey. After the pilot test, the questionnaire was then shared with larger samples for the main data collection. Partial least squares-structural equation modeling (PLS-SEM) method was employed to examine collected data. PLS-SEM methodology also does not suffer from the small sample size.

The researchers have used the common rule often the number of survey questions to ascertain the sample size [58]. Hence, the minimum sample size should be more than 200 for this research paper. Table 1 shows the constructs operationalized for this study. The questionnaire was distributed amongst citizens in and around the upcoming Pune smart city and a total of 463 valid survey responses were collected. The measurement reliability was tested using outer item loading and composite reliability. The constructs' Average Variance Extracted (AVE) was examined for a convergent validity test. The constructs' internal consistency was investigated based on Cronbach's alpha.

Table 1: Operationalization of model constructs.

Construct	Type	Measure	References
Performance Expectancy	Reflective	PE1: I believe using a Chatbot for public transport will be useful for me. PE2: I believe Chatbot for public transport will be accurate. PE3: I believe Chatbot for public transport will be quicker.	[37,38,39]
Effort Expectancy	Reflective	EE1: My interaction with a Chatbot for public transport will need to be unambiguous. EE2: A Chatbot for public transport should be free from mental effort. EE3: A Chatbot for public transport will need to be easy.	[39,41,42]
Social Influence	Reflective	SI1: My friends think that using a Chatbot for public transport will be a good idea. SI2: My friends think that I should use a Chatbot for public transport. SI3: My friends think that I should try-outChatbot for public transport.	[38,45,46]
Facilitating Conditions	Reflective	FC1: I have the necessary resources for using a Chatbot for public transport. FC2: I have the necessary skills to use a Chatbot for public transport.	[38,39,47]
Anthropomorphism	Reflective	ATH1: I believe interactions with a Chatbot for public transport will be similar to interaction with the human operator. ATH2: I believe interactions with a Chatbot for public transport will be natural. ATH3: I believe interactions with a Chatbot for public transport will be interactive.	[35,50,51,59]
Trust	Reflective	TST1 - I will use a Chatbot for public transport if it is trustworthy. TST2 – I will use a Chatbot for public transport if it is reliable. TST3 - I will use a Chatbot for public transport if it is dependable.	[26,54,56,60]
Adoption Intention	Reflective	AINT1: I intend to use a Chatbot for public transport. AINT2: Compared to the manual current way, I will use a Chatbot for public transport. AINT3: I will recommend others to use a Chatbot for public transport.	[37,38,39,40,42,46]

D. Response and method bias

When some of the respondents do not respond to the survey, it may result in non-response bias due to the absence of data [61]. This kind of bias can prevent the results of the study to be generalized for the researcher [62]. Therefore, it is necessary to treat non-response bias during research data processing [63]. The authors of this research study took appropriate steps to make sure results are not affected by non-response bias. The data set separation technique was employed to tackle non-response bias by using the wave analysis from early and late respondents. The authors performed a t-test analysis to compare response data sets obtained in the early and late phases of data collection for testing non-response bias [64]. It was observed that there was an insignificant difference ($p=0.63$) between the initial and last set of respondents. The researchers also deployed a single factor Harman test to verify common method bias that may occur during the survey-based data collection mechanism [65]. The analysis shows that no factor crossed the 50 percent variance limit and thus is free from common method bias. This further enhances the reliability of data collected for the study.

E. PLS-SEM

PLS-SEM path modeling technique is employed for a second order construct analysis of the research study. Gudergan *et al.* suggested using the PLS-SEM technique for conceptual model validation and examining the relationship between observed and latent variables [66]. PLS-SEM modeling is also applied in the past by various researchers to test established theoretical assumptions [67,68] as it provides more flexibility in terms of construct modeling [69]. SmartPLS application was utilized for performing the PLS-SEM technique [70].

V. RESULTS

The researchers reached out to public transport commuters for this study. Table 2 contains the demographic profile of the research participants.

A. Measurement model

The hypotheses testing for the conceptual model is based on the measurement of multi-item reflective constructs. As per Hair et al., the convergent validity of model constructs is tested using Average Variance

Table 2: Table of Demographics.

Demographic	Characteristics	Frequency	(%)
Gender	Male	268	58%
	Female	195	42%
Age	21-30	156	34%
	31-40	104	22%
	41-50	111	24%
	Above 50	92	20%
Type of mobile phone	Basic phone	97	21%
	Smartphone	366	79%
Frequency of public transport usage	Daily	223	48%
	Weekly twice	117	25%
	Weekly once	39	8%
	Ad-hoc	84	18%

Extracted (AVE) [71] is observed to be more than the lower threshold value of 0.5 for every model construct. Composite Reliability (CR) for constructs was calculated for reflective measurement. The high values of CR indicate internal consistency. As per Nunnally, the reliability of constructs is established by examining that Cronbach's alpha value of constructs to be greater than 0.7 [72] as shown in Table 3.

Fornell-Larcker criterion was employed to test the discriminant validity of model constructs. Off-diagonal values are calculated (Table 4) to verify discriminant validity and the correlation between the constructs. AVE is compared with the construct's inter-correlation to find out discriminant validity. For each construct, the variance with other constructs is lesser than the square root of AVE of that construct. This confirms the research constructs have discriminant validity between them [73].

Table 3: Construct Measurement Validity.

Construct	Average Variance Extracted (AVE)	CompositeReliability (CR)	Cronbach's Alpha
PE	0.749	0.898	0.831
EE	0.663	0.853	0.742
SI	0.804	0.925	0.878
FC	0.870	0.930	0.853
ATH	0.659	0.850	0.731
TST	0.768	0.908	0.847
AINT	0.667	0.854	0.740

Table 4: Discriminant Validity of Measurement Constructs (Fornell–Larcker criteria).

Construct	PE	EE	SI	FC	ATH	TST	AINT
PE	*0.865*						
EE	0.615	*0.814*					
SI	0.667	0.806	*0.897*				
FC	0.608	0.788	0.769	*0.933*			
ATH	0.856	0.610	0.643	0.568	*0.812*		
TST	0.844	0.615	0.641	0.589	0.811	*0.876*	
AINT	0.858	0.804	0.860	0.843	0.781	0.819	*0.817*

B. Structural model

PLS-SEM path analysis method is used for structural model relationship assessment. The path coefficients, standard errors and t-statistics for significance testing are shown in Table 5.

H1 tested PE influence on AINT of the Chatbot. The analysis of the data finds that PE significantly affects AINT. Hence, the H1 is supported and conforms to prior research [37, 38,39, 40] which implies that commuters perceive that AI powered Chatbot would improve the performance of information retrieval tasks related to public transport and would further lead to Chatbot adoption.

Table 5: Hypothesis testing results and structural relationships.

Hypotheses	Path	Path coefficient	Standard error	*t* Statistics	Decision
H1	PE → AINT	0.530	0.099	5.344***	Supported
H2	EE → AINT	0.162	0.058	2.182**	Supported
H3	SI → AINT	0.212	0.057	3.726***	Supported
H4	FC → AINT	0.225	0.067	3.342***	Supported
H5	ATH → AINT	0.189	0.041	4.586***	Supported
H6	TST → AINT	0.164	0.042	3.923***	Supported
Note: Two-tailed t-test values > ***t-values 2.58 (sig. level = 1%); **1.96 (sig. level = 5%); and *t-values 1.65 (sig. level = 10%) as given by Hair *et al.* [59]					

H2 tested the effect of EE on AINT of the Chatbot. The results of the study indicate that EE significantly affects AINT and conforms to prior research [41, 42, 43]. Hence, the H2 is accepted indicating commuters believe that Chatbot would be an easy to use application for online public transport information inquiry and thus leading to its adoption in the future.

H3 tested the impact of SI on the AINT of the Chatbot. The analysis shows that SI strongly impacts AINT suggesting that as more fellow passengers start using the Chatbot, there would be a corresponding increase in its adoption. Thus H3 is supported and conforms to prior research [44, 45, 46] which also found that users tend to adopt a novel technology when their social circle also adopts it.

H4 tested FC influence on the AINT of the Chatbot. The analysis indicates that FC significantly influences AINT of the Chatbot. Hence H4 is supported and conforms to prior research [37, 38, 39, 47] implying commuters believe that they will have enough resources such as the internet, smartphones at their disposal to adopt a Chatbot solution for public transport inquiries.

H5 tested the effect of ATH on AINT of the Chatbot. The results of the study find that ATH has a significant effect on AINT. Hence, H5 is accepted and conforms to prior research [22, 35, 50, 51]. The result shows that anthropomorphism or human-like conversation features are important to the adoption of the Chatbot system for public transport commuters.

Finally, H6 tested the TST impact on the AINT of the Chatbot. The analysis suggests that TST significantly impacts AINT implying that the commuters intend to use a Chatbot enabled system if Chatbot responses are reliable and useful thereby gaining the trust of end users. Hence, H6 is accepted and conforms to prior research [26,36,55,56].

As shown in Fig. 3, the overall findings from the extended UTAUT model indicate that AI powered Chatbot with ATH and TST features is a suitable self-service technology tool for anytime, anywhere, and automated public transport information services in India and justifies the unique contribution of this paper.

VI. DISCUSSION

The research found that PE explains future AINT of the Chatbot. This is in line with previous research studies [37, 38, 39, 40] where users expect a Chatbot to answer their frequently asked queries, get status of their past requests, and raise any complaints. Users will get accustomed to using Chatbot only when they can perform these tasks with adequate success. As the performance of the Chatbot meets user needs, there would be higher adoption of the Chatbots. This entails the public transport department to design Chatbot services according to the commuter needs such as providing transport routes, schedules, and real-time status on-demand.

The study also found that EE affects the AINT of the Chatbot similar to prior studies [41, 42, 43]. Hence, a public transport Chatbot that has a simple user interface and understands users' needs is perceived to be easy and leads to higher adoption intention. Typically, the Chatbot is going to be a simple mobile application or a widget on the website of the public transport department. Since most of the users are familiar with mobile applications and websites, the learning curve for a Chatbot is expected to be flat.

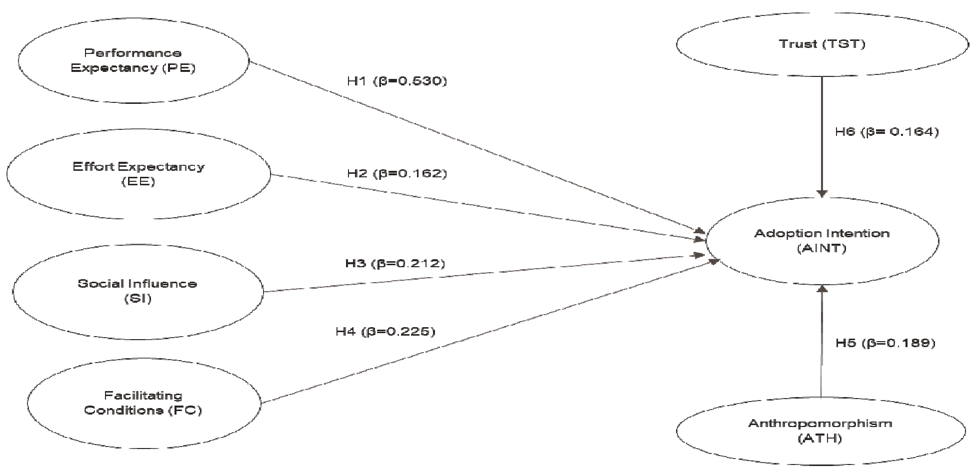

Fig. 3. PLS-SEM Model Results.

The results of the study show that SI has a positive influence on the AINT of the Chatbot. This is in line with previous research studies [44, 45, 46] that demonstrated users intend to adopt novel technology solutions when their friends and influencers post positive reviews about the new application. It is also commonly observed that many smartphone applications such as WhatsApp, Facebook, etc. became popular only when SI positively affected AINT. Daily commuters of public transport generally know their fellow commuters. Therefore, SI can play a very vital role in the future AINT of Chatbot.

Users also perceive that FC will positively affect AINT of the Chatbot which conforms to prior studies [37, 38, 39, 47]. Mobile phones are part of FC and present with the commuters when they board the public transport system. The other condition for a Chatbot to work is to have an internet connection on these mobile phones. There is a very high penetration of internet enabled mobile phones in the urban areas of India. Thus, FC in the form of internet enabled mobile phones will lead to higher AINT of the Chatbot to obtain relevant information anytime, anywhere.

Other than the above UTAUT factors, this research study found ATH has a positive influence on AINT of the Chatbot. While users perceive that a Chatbot based system will be useful, it needs to have anthropomorphic or human-like qualities such as context-awareness, intelligence, interactive, and responsiveness. The ATH features of Chatbot also make it easy for users who are not technology savvy to adopt the technology solution and get quick responses to their queries. This is in line with previous Chatbot studies [22, 35, 50, 51].

As with any online services, commuters intend to use the Chatbot system only if it is trustworthy, reliable, and dependable. The results confirm that TST positively influences AINT of a Chatbot which is in accordance with past studies on the internet or smartphone based technology solutions [26, 36, 55, 56]. Particularly, public transport users are time constrained which necessitates the Chatbot to provide real-time, trustworthy, and accurate information to commuter's queries.

VII. IMPLICATIONS

The study has both theoretical and managerial implications. From a theoretical point of view, the research confirms that the UTAUT model is useful in explaining the adoption intention of the technology solution. This conforms to prior research studies that deployed UTAUT models. While UTAUT factors are important, this study adds to existing self-service technology literature by uniquely extending the UTAUT model with constructs such as anthropomorphism and trust. The study underscores the importance of anthropomorphism features while developing Chatbotlike technology solutions which is in line with prior research. As per previous research studies, trust remains an important determinant that provides additional explanatory power to the technology adoption conceptual model.

From a managerial point of view, public transport officials will be able to serve commuters'growing needs without necessarily adding more human staff. The Chatbot system can run in a continuous manner which may help in reducing or altogether removing human staff in the night shift.Economically, this would reduce the overall cost to government departments. With Chatbot, commuters can log their requests at any time of the day and can track it to closure. This would ensure the accountability of respective department personnel. Additionally, connecting the vehicle GPSwith theChatbot will provide immense benefits in terms of communicating real-time transport status to commuters. Due to its human-like conversation ability, citizens with minimal computer skills will be able to better query and accordingly plan their transport dependent tasks. Chatbot enabled PTIS can answer commuters' frequently asked questions. Hence, the Chatbot would also reduce the burden of queries on department staff. With increased and easy access to information, there is a possibility of more citizens using public transport.

VIII. CONCLUSION AND FUTURE SCOPE

The results of the study indicate that commuters intend to use a Chatbot for public transport within a smart citywhen there is a conducive infrastructure, social acceptance, ease of use, and meets performance.The Chatbot would help enormously commuters since a large part of the working population in India is dependent on an accurate schedule and quality of public transport services. Anthropomorphism or human-like chat feature makesthe conversation with Chatbot more natural rather than a traditional fixed format interaction.The reliability of Chatbot responses makes them more trustworthy. Compared to previous studies, which mainly exploredweb-based PTIS adoption, this study uniquely highlights an emerging technology led AI powered Chabot solutionto overcome many issues of current PTIS and potentially improve commuter's satisfaction.

Although this research study found that the Chatbot system would be a useful addition to PTIS, it has several limitations that create avenues for researchers for further studies. The data was only collected from public transport commuters of the Pune metropolitan region in India. Generalizing the results of the study for other geographies requires careful considerations. The research only studied the adoption intention of AI powered Chatbot for public transport. However, other constructs such as ActualUsage and Customer Satisfaction may be investigated in future studies.

Conflict of Interest. No.

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