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THE ROLE OF USER SATISFACTION IN CONTINUANCE INTENTION TO USE CHATBOTS WITHIN THE TECHNOLOGY ACCEPTANCE MODEL (TAM)

Yüksek Lisans Tezi

HATIM BADR MOUHCINE

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Danışman: Doç. Dr. TAŞKIN DİRSEHAN

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TEKNOLOJİ KABUL MODELİ (TKM) KAPSAMINDA SOHBET ROBOTLARI KULLANMAYA DEVAM ETME NİYETİNDE KULLANICI MEMNUNİYETİNİN ROLÜ

ÖZET

Günümüzde insanların yaşamları giderek teknolojiye bağımlı hale gelmiştir. Dijital platformların ve sosyal ağların hızla büyümesiyle birlikte teknolojideki gelişmeler, genellikle sohbet robotları olarak bilinen konuşma araçları, müşteri bağlantılarını geliştirmek için giderek daha popüler bir pazarlama aracı haline gelmektedir. Benimsemenin ilk aşamasının ötesinde bu çalışma, TAM'ın yapısını kullanarak Faslı kullanıcıların sohbet robotu kullanmaya devam etme niyeti üzerindeki etkiyi analiz etmek için yapılmıştır. Çalışmanın temel amacı, kullanıcıların sohbet robotu hizmetlerinden memnuniyet düzeylerinin önemini incelemek ve kullanıcıların kullanıma devam etme niyetinde nasıl bir rol oynadığını belirlemektir. Faslı sohbet robotu kullanıcılarına Fransızca dilinde bir anket geliştirilmiş ve dağıtılmıştır . Hipotezler, Smart-PLS aracılığıyla kısmi en küçük kareler yol modellemesi (PLS-PM) kullanılarak test edilmiştir. Bulgular, kullanıcı memnuniyetinin devam etme niyetinin en güçlü yordayıcısı olduğunu ve TAM'ın yapıları ile devam niyeti arasında önemli bir rol oynadığını göstermiştir.

ANAHTAR KELİMELER

Sohbet robotu, Teknoloji Kabul Modeli (TAM), Kullanıcı Memnuniyeti, Kullanıma Devam Niyeti, Kullanım Sonrası Davranış

THE ROLE OF USER SATISFACTION IN CONTINUANCE INTENTION TO USE CHATBOTS WITHIN THE TECHNOLOGY ACCEPTANCE MODEL (TAM)

ABSTRACT

Nowadays, people's lives have become increasingly reliant on technology. Along with the rapid growth of digital platforms and social networks, advancements in technology conversational agents, often known as chatbots, are increasingly becoming a popular marketing tool for improving customer connections. This research was conducted to analyze the effect of using TAM's construct beyond the first stage of adoption on Moroccan users' continuance intention to use chatbot. The main purpose of the study is to determine the importance of users' level of satisfaction with chatbot service and its role in the continuance intention of the users. A survey was developed in the French language and distributed to Moroccan chatbot users. The hypotheses were tested using the partial least squares path modeling (PLS-PM) via Smart-PLS. Findings showed that user satisfaction was the most powerful predictor of continuance intention, and it played an important role between TAM's constructs and continuance intention.

KEYWORDS

Chatbot, Technology Acceptance Model (TAM), User Satisfaction, Continuance intention, Post usage behavior

LE RÔLE DE LA SATISFACTION DES UTILISATEURS DANS L'INTENTION DE CONTINUER À UTILISER LES CHATBOTS DANS LE CADRE DU MODÈLE D'ACCEPTATION TECHNOLOGIQUE (TAM)

RESUME

De nos jours, la vie des gens dépend de plus en plus de la technologie. Parallèlement à la croissance rapide des plateformes numériques et des réseaux sociaux, les progrès des agents conversationnels technologiques, souvent appelés chatbots, deviennent de plus en plus un outil marketing populaire pour améliorer le service client en ligne. Cette recherche a été menée pour analyser l'effet d'utilisation des éléments du MAT au-delà de la première étape d'adoption sur l'intention des utilisateurs marocains de continuer à utiliser le chatbot. L'objectif principal de l'étude est de déterminer l'importance du niveau de satisfaction des utilisateurs vis-à-vis des services de chatbot et son rôle dans l'intention de continuer à utiliser le service. Une enquête a été élaborée en langue française et diffusée auprès des utilisateurs marocains de chatbot. Les hypothèses ont été testées en utilisant la modélisation du chemin des moindres carrés partiels (PLS-PM) via SmartPLS. Les résultats ont montré que la satisfaction des utilisateurs était le prédicteur le plus puissant de l'intention de continuer, et qu'elle jouait un rôle important entre les éléments du MAT et l'intention de continuer à utiliser le service chatbot.

MOTS CLÉS

Chatbot, Agent conversationnel, Modèle d'acceptation de la technologie (TAM), Satisfaction des utilisateurs, Intention de continuer, Comportement après utilisation.

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LIST OF ABBREVIATIONS

A.L.I.C.E.	Artificial Linguistic Internet Computer Entity
AI	Artificial Intelligence
AIML	Artificial Intelligence Markup Language
ANOVA	Analysis of Variance
ASR	Automatic Speech Recognition
AVE	Average Variance Extracted
CAN	Cognitive-Affective-Normative model
CI	Continuance Intention
CR	Composite Reliability
CRM	Customer Relationship Management
CSI	Customer Satisfaction Analysis
ECM-IT	Expectation-Confirmation Model of Continued IT Usage
EECM-IT	Extended expectation-confirmation model of Continued IT Usage
ETC	Expectation Confirmation Theory
GRUs	Gated Recurrent Units
HTMT	Heterotrait-Monotrait ratio of Correlations
IS	Information System
IS/IT	Information Systems Technology
LSA	Latent Semantic Analysis
LSTMs	Long Short-Term Memory networks
ML	Machine Learning
PANAS	Positive and Negative Affect Schedule
PEOU	Perceived Ease of Use
PLS-PM	Partial Least Squares Path Modeling
PU	Perceived Usefulness
SAT	User Satisfaction
SEM	Structural Equation Modeling
SRMR	Standardized Root Mean Square Residual
TAM	Technology Acceptance Model
TAM2	Extended Technology Acceptance Model
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
WOM	Word of Mouth
XML	Extensible Markup Language

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INTRODUCTION

Nowadays with the increase in online business and the number of customers, over two billion customers have purchased products or services online, and over 4 trillion U.S. dollars worldwide in e-retail sales in 2020 (Daniela Coppola, 2021). Customer support is finding it more difficult to meet all of their demands. Customers can contact the organization in a variety of ways, including phone call service, email service, and live chat service. Customers may have to wait for a long time despite the availability of several lines of operation because human resources may be restricted. Furthermore, consumers may have received incorrect details as a result of human error. Automatic systems have been designed to address this issue with human-based services, the conversational agents “Chatbots” have become the most well-known technology used in this case.

Regarding, technological advances the service of conversational agents or chatbots is quickly becoming a popular marketing solution for increasing consumer interactions. Companies now have innovative ways to satisfy consumers thanks to the exponential development in digital platforms and distribution networks. By offering automated customer support via an online chat system 24 hours a day 7 days a week, the e-service agent or chatbots becomes crucial for solving customers' problems. So, we can define chatbot as conversational agent that uses artificial intelligence to facilitate an engaging human-like interaction (Shawar & Atwell, 2007).

Conversational chatbots are constantly being used by companies and organizations to deliver fast and reliable service, they are often used for simple communications that often involve a small set of replies, such as customer support. Chatbots have the ability to successfully compete for human customer service in an online environment, this technology is regarded as a technological advancement that helps to enhance the customer experience. Individualization of social media chatbots creates an engaging interaction between the customer and the company, which not only improves the company's brand success but also helps the customer with improved social information, and economic benefits. They will also create interactions based on the customer's personal position or web searches, and the automated replies will be sent to meet the customer's specific needs.

Technology companies such as IBM and Nuance, demonstrate how using chatbots in customer service can help companies like Kaspersky Lab to increase the reliability and effectiveness of their business processes and functionality, "*Virtual agent technology lowers contact centre requests and emails by 22% while increasing the value of purchase order".* Also, with Autodesk company the implementation of cognitive technology "*helps to increase customer response times by 99% with Watson conversation service (AVA)"* (Christie Schneider, 2017).

Given the relevance of customer support in customers' daily lives, widespread adoption of chatbots, for this reason, could further advance customers' awareness of conversational user interfaces in general. However, whether or not customers regard chatbots as valuable and helpful can determine whether or not they are widely adopted. Chatbots for customer service can only remain relevant and interesting if they have a positive user interface and provide value propositions that encourage users to communicate with them afterward.

The chatbots have been used in a variety of sectors, mainly in the tourism and hospitality industry, they have been used to facilitate services such as bookings, reservations, reviews, and others. In terms of the variety of chatbot applications, China is one of the pioneering countries in this field. For instance, some of the famous online travel agencies in China like *figgy.com*, *Qunar.com*, and *Ctrip.com*, have already implemented chatbot features on their websites to assist consumers in booking vacation packages and plane tickets (Li et al., 2021). Recent advances in Artificial Intelligence (AI) and machine learning (ML) have sparked a surge in interest in chatbots. Chatbots are seen as the next major popular technology by major internet firms including Google, Facebook, and Microsoft. Since 2016 Messenger by Facebook, and other messaging platforms like Slack, and Kik have seen a significant increase in chatbots (Johnson, 2017).

Although technologically-enabled consumer-facing platforms are common in many sectors, using technology devices to support oneself remains difficult for some people. Transitioning from existing user interfaces such as websites and applications to chatbots as a popular means of communicating with information and services, however, isn't easy. There is a lack of understanding about how consumers respond to chatbots replacing human customer service

representatives or how the role of chatbots in online social networks influences multi-party interactions and knowledge dissemination (Ferrara et al., 2014).

The overall situation of AI in Morocco is late, the country still in the "data engineering" phase. Companies today are working on data, trying to collect it, digitize it, facilitate access, and analyze it. This is the step that precedes the implementation of an artificial intelligence system (El Bour & Lebzar, 2020). And this is what explains the limited attention that chatbots technology received in the Moroccan business atmosphere, and academic research. Most sectors that we can find chatbots service are telecoms, online shopping, banking, and assurance. (Situation of chatbots in Morocco will be discussed in detail in the literature review).

Therefore, this research is about examining the post-usage user behavior, Continuance intention (CI) of Moroccan users. By determining the factors and variables that may influence the continuance intention to use the chatbot service. We will use variables Perceived usefulness (PU) and perceived ease of use (PEOU) from the technology acceptance model (TAM). Furthermore, we will examine the overall user's satisfaction during their experience with a chatbot. The satisfaction played a role of mediator variable between PU, PEOU, and CI. Considering that previous research doesn't include satisfaction into TAM. The scope of our research is to take TAM's construct beyond the first stage of adoption and include satisfaction as a mediator variable into TAM, to understand the CI of Moroccan users.

The hypothetical relationship between the previous variables and the continuance intention will lead us to verify and determine the most important variables that conduct to continue adoption or discontinuance. Hence, we could explore and understand better the profile of Moroccan chatbot users. All the constructs and their relationships will be examined in the research design and methodology part.

1. Literature Review and Hypothesis Developments

1.1. An Overview of Turing Test

Turing Test “The Imitation Game” is an artificial intelligence test proposal based on a machine's ability to mimic human conversation. Described by Alan Turing in his 1950 publication Computing Machinery and Intelligence. This publication was regarded as one of the most important works of the twentieth century, and the question asked by Alan in his paper " Can machine thinks?" becomes the motive for many scientists and researchers in the field of artificial intelligence.

Turing test involves putting a human B in a blind verbal confrontation with a computer A and another human C (interlocuter) See figure.1 If the person initiating the conversations cannot tell which speaker is a computer, the computer software may be considered to have passed the test. This implies that the computer and the human will try to have a semantic human appearance (Turing, 1950).

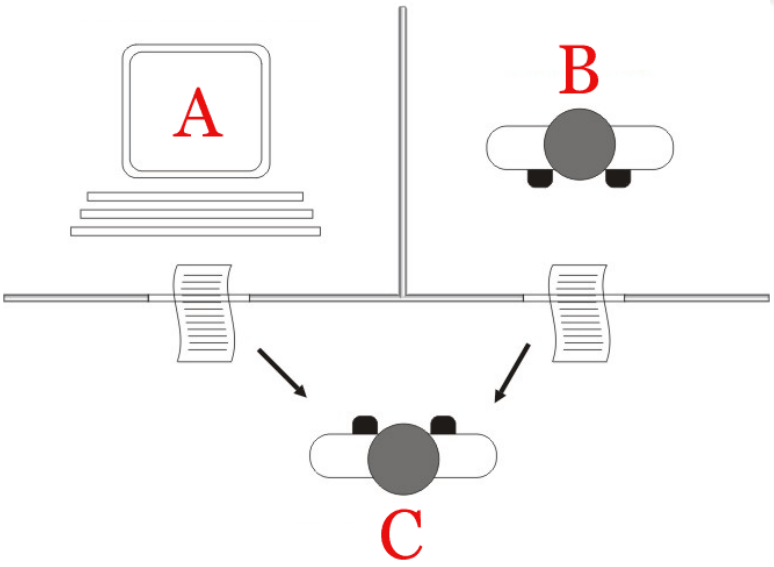


Figure 1. Turing Test Diagram

Source: Juan Alberto Sánchez Margallo (2017). Diagram of the Turing test Available on commons. Wikimedia

1.2. Definition and History of Chatbots

A chatbot is "a conversational system which interacts with human users via natural conversational language" (Shawar & Atwell, 2005). Chatbot is a programming software based on artificial intelligence that is capable of simulating a human-to-human dialogue. The key is to make people feel that the chatbot can recognize their queries and reply appropriately based on the situation and in accordance with its primary aims. The conversation may be done both vocally and textually, and it often uses natural language to communicate (Deshpande et al., 2017).

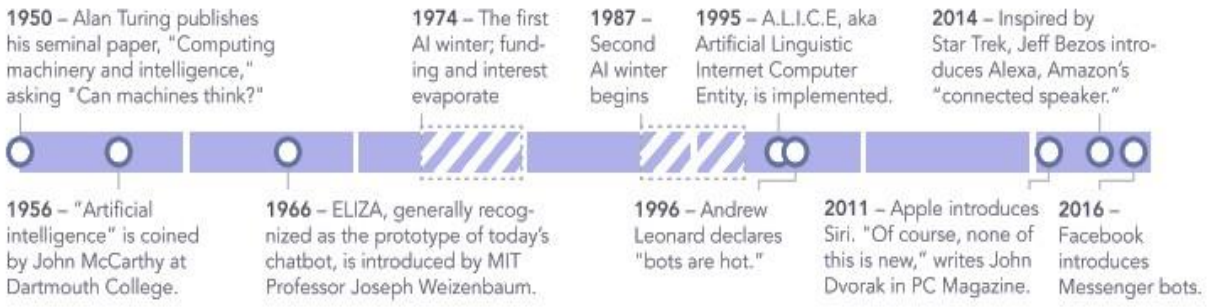


Figure 2. Chatbot History

Source: Etlinger, S. (2017). The Conversational Business: How Chatbots Will Reshape Digital Experiences. *Altimeter Group Research Reports*

The chatbot ELIZA was the first chatbot, built by Joseph Weizenbaum, MIT professor in 1966. Its function was simple, consisting, among several other things, of rephrasing sentences supplied to it in questions, without contextualizing the events. It looked to have the ability to deceive users into believing they were speaking with a real person (Hussain et al., 2019).

```
Human:  Men are all alike.
ELIZA: In what way?
Human:  They're always bugging us about something.
ELIZA: Can you think of a special example?
Human:  Well, my boyfriend made me come here.
ELIZA: Your boyfriend made you come here?
Human:  He says I'm depressed much of the time.
ELIZA: I'm sorry to hear that you are depressed much of the time.
Human:  It's true.  I'm unhappy.
ELIZA: Do you think coming here will help you not to be unhappy?
Human:  I need some help, that much seems certain.
```

Figure 3. A Sample Conversation With ELIZA

Source: Daniel Jurafsky and James H. Martin. (2000). Speech and Language Processing. Upper Saddle River, NJ: Prentice-Hall.

Other well-known chatbots evolved, notably Parry in 1972, Jabberwacky in 1988, A.L.I.C.E. in 1995, and SmarterChild in 2001. Parry attempted to reenact a person suffering from jittery schizophrenia. It used an advanced conversational technique built on assumptions and emotions in responses, and as a result, it was a far more sophisticated and advanced system than ELIZA. It was described as "ELIZA with an attitude."(Colby et al. 1972).

In 1972 Parry was employed in a teletype interview with a patient to determine whether he was a software bot or an actual schizophrenia patient. Overall, PARRY is regarded as a chatbot with limited language comprehension and emotional communication capabilities. It also has a slow reaction time and is unable to learn from its previous interactions (Colby et al., 1979). In figure.4 we can see a discussion between Parry and ELIZA.

ELIZA: Good Evening. Tell me your problems. Please terminate input with a period or a question mark.

PARRY: People get on my nerves sometimes.

ELIZA: I am not sure I understand you fully.

PARRY: You should pay more attention.

ELIZA: Suppose you should pay more attention.

PARRY: You're entitled to your own opinion.

ELIZA: What makes you think I am entitled to my own opinion?

PARRY: It bothers me just to be around people in general.

ELIZA: Please go on.

PARRY: I went to the track at Bay Meadows a while back.

ELIZA: What does that suggest to you?

PARRY: I went to the races.

.....

ELIZA: What answer would please you most?

PARRY: It's not a matter or like or dislike.

ELIZA: What else would you like to discuss?

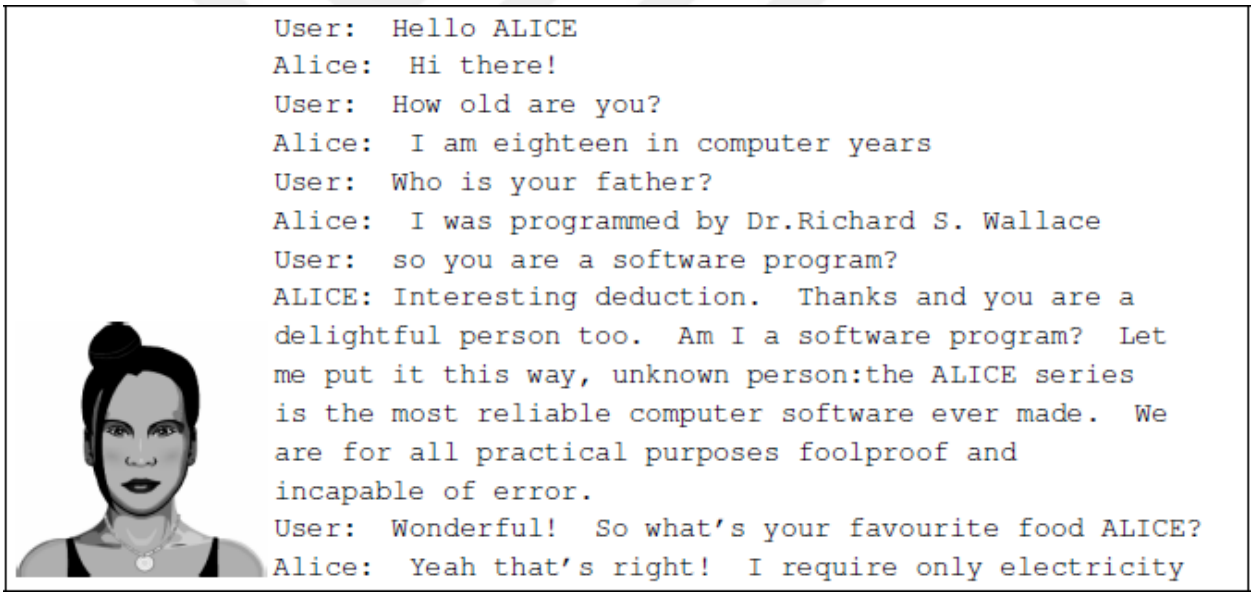
PARRY: I am getting tired of answering the same questions over and over.

Figure 4. Conversation Between ELIZA & PARRY

Source: Megan Garber (June 9, 20142014) When PARRY Met ELIZA: A Ridiculous Chatbot Conversation From 1972

Jabberwacky 1988 is an endeavor to make a program that learns; the program holds all discussions and extracts proper responses by coordinating with designs in their specific situation. Jabberwacky is one of the most punctual efforts to plan an AI through human communication. It was fundamentally a type of amusement, it planned to move from a text-based framework to a completely voice worked framework (Jabberwacky, 2021).

A.L.I.C.E. (Artificial Linguistic Internet Computer Entity), is considered as one of the powerful natural language chatbot in its class. ALICE was based on a different language (AIML), and it was the main difference between the previous chatbot ELIZA and ALICE. ALICE was focused on model coupling, with no accurate knowledge of the dialogue overall, it can exceed with more than 40,000 categories of knowledge, while ELIZA that had just 200 (Wallace, R. S. 2009).



Source: Shawar, B. & Atwell, E. (2007). Chatbot are they Really Useful? LDV Forum. 22 (1), 29-49.

Figure 5. A Sample Conversation With ALICE

SmarterChild founded in 2001, was an active chatbot on MSN, AIM, and Yahoo, on such networks, SmarterChild communicated with several million individuals using instantaneous messaging. The main objective was to attract and entertain as many users as possible. SmarterChild chatbot helps customers get information about the sport, check the weather, seek stocks, and many other things (Molnár & Szüts, 2018).

More recently, examples have multiplied with popular chatbots such as IBM's Watson, Apple's Siri, Google's Google Now. The most essential technological companies have also been included. Amazon with Alexa, Microsoft with Cortana and Tay, Facebook and the implementation of chatbots into Messenger, etc.

As we can see in Figure. 2 an example of a chatbot on Messenger (Shop Spring) that guides the customer through his shopping by asking him some questions to help the customer to find the article that matches his criteria. Here, the type, kind, and price range of sneakers are arranged by the bot to finally found the ideal sneakers desired by the customer. In this example, we can see the chatbot provided a list of choices (responses buttons) instead of free writing with the bot.

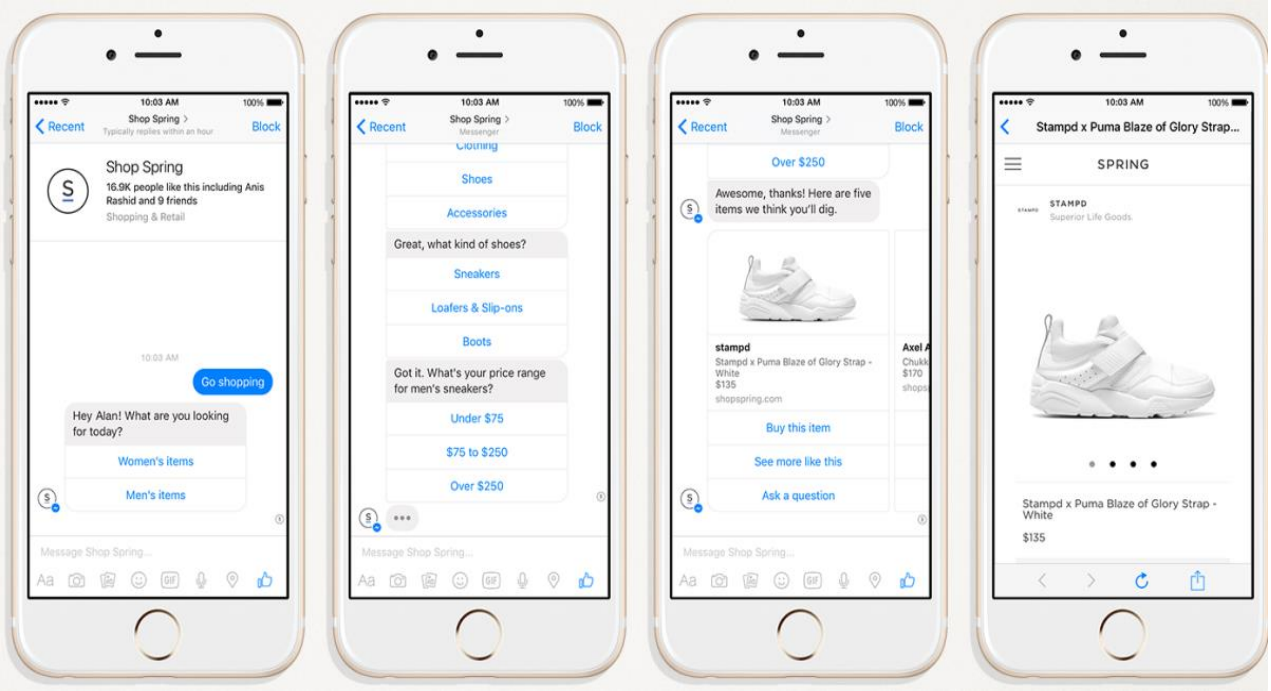


Figure 6. Example of Shopping With the Spring Chatbot on Messenger.

Source: Dhani Mau Apr 13, 2016. You Can Now Shop Spring's 1,000+ Brands and Retailers on Facebook Messenger

Watson 2006, developed by IBM is a question-response and decision-making framework that applies advanced natural language processing, backup and recovery, information presentation, automated thinking, and AI breakthroughs to the field of open question-response. Watson could generate and evaluate hypotheses and apply advanced analytics to assess a panel of responses based only on relevant evidence. Dynamic learning by dependent on results to get more intelligent with every emphasis and interaction (IBM -Watson assistant, 2021).

Siri 2011 utilizes ASR (Automatic Speech Recognition) to decipher human discourse (which includes brief command modulations, translations, or queries) into text. Using correct grammar processing (syntactic structure naming, thing sentence division, dependence, and part examination) it makes an understanding of the made an interpretation of text into “dissected content”. It examines the isolated content and identifies customer orders and routines using question and point examination, (e.g., “Schedule a meeting", "Set my alarm") (Deshpande et al., 2017).

Alexa 2015, is a virtual assistant like Siri based on voice interaction and runs on the Amazon Echo device. For voice identification, Alexa uses natural language processing algorithms, it uses these computations to receive, understand, and respond to vocal commands. Alexa can stream songs, organize agendas, set alarms, transmit digitally mastered, play audiobook recordings, and provide 24/7 weather, traffic, and other statistics. Alexa can also operate a few smart home devices by acting as a home automation hub (Deshpande et al. 2017).

Google now 2012 proactively conveys data to users to anticipate information they may require as instructive cards. It was a featured item for google search, as an online voice-based virtual assistant. Whereas Google now provides results from a search, Google assistant 2016 provides more accurate and natural responses using artificial intelligence and machine learning. It can go far from just searching, the customer could control smart devices at home, fixing meetings, communicating in social media and more. We can say that Google assistant is an upgrade of Google now. (Google now. 2021; Google assistant, 2021)

In Figure. 7 we can see the wide range of chatbot applications, from less conversational chatbots and website/app to more conversational like Siri and Alexa, many categories of a chatbot with their utilization is represented (not all chatbots included and no ranking).

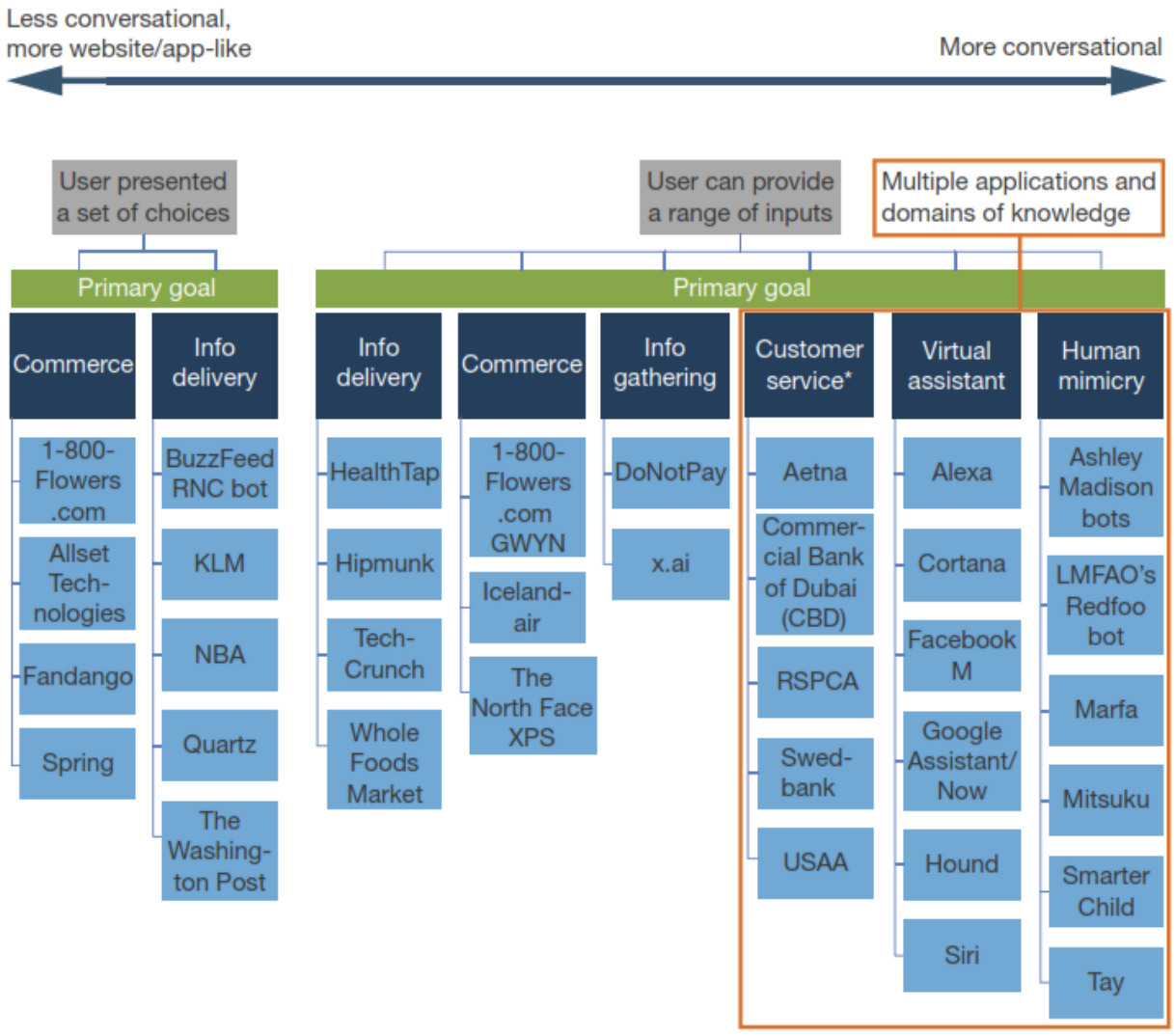


Figure 7. Broad Range of Chatbot Applications.

Source: Ask, J. A., Facemire, M., & Hogan, A. (2016). The State of Chatbots-Pilot Chatbots as Part of your App+ Mobile Strategy. Forrester Research.

To sum up, in the event that we picture the excursion of chatbots from the 1960s to now, we can grasp that what was at one time a dream of having the option to speak with a nonliving virtual machine is currently essential for our regular day to day existences.

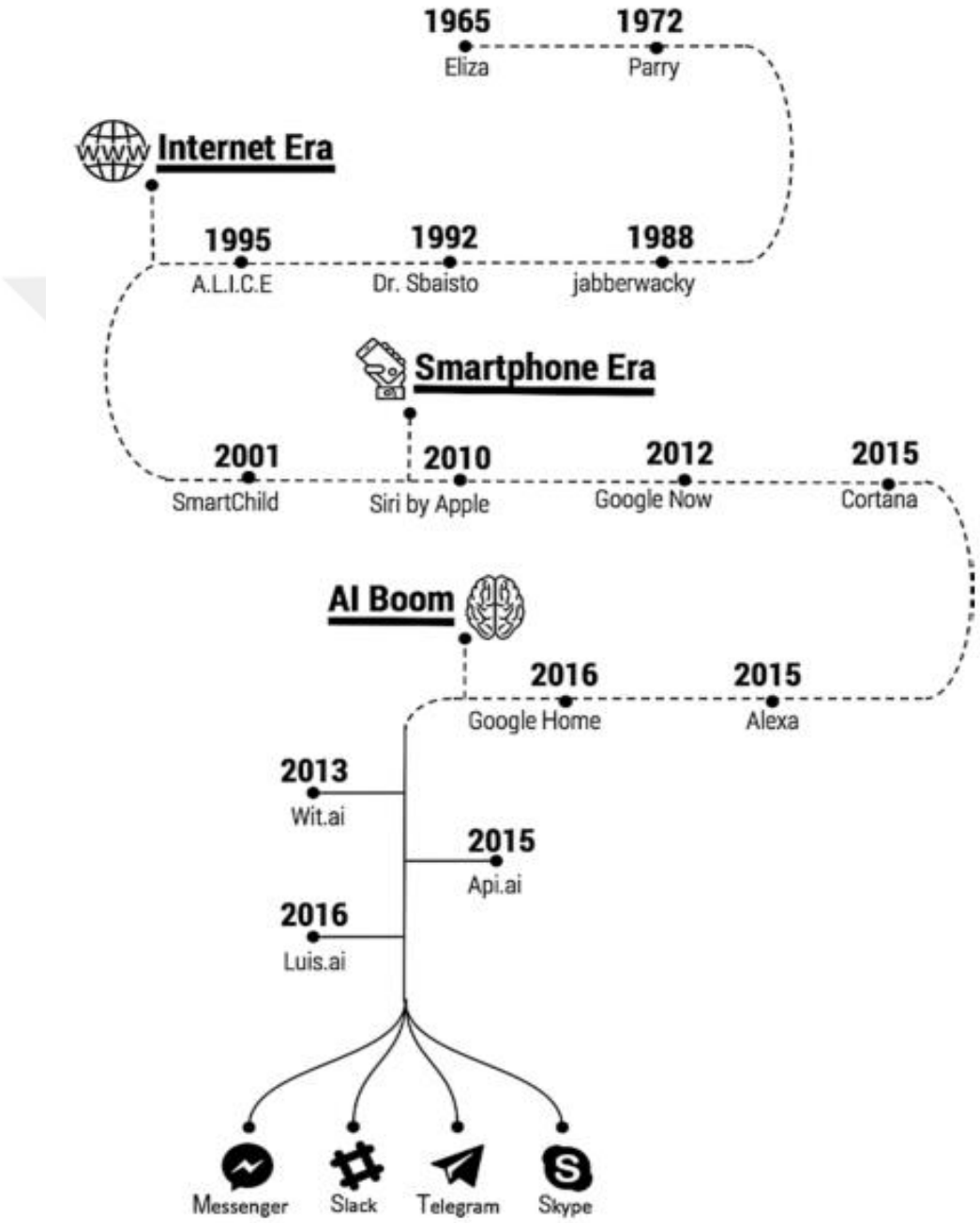


Figure 8. Timeline of Chatbots.

Source: Khan, R., & Das, A. (2018). Build better chatbots. A complete guide to getting started with chatbots.

1.3. Categories of chatbot

Table.1 Represents chatbot categories in their domain and sub-domains, by giving brief information about the functionality of chatbot and/or platforms in each subdomain, and supporting with examples.

Table1.Categories of Chatbot

Chatbot Category		Functionality	Examples	Sources
Knowledge Domain	Open Domain	This type of chatbot can respond to any client question from whichever area. Chatbot's Knowledge domain is the variety of information it could acquire.	CRQA; MILABOT; XiaoIce; Mitsuku; Meena;	(Savenkov & Agichtein, 2016) ; (Serban et al., 2017) ; (Zhou et al., 2018);
	Closed Domain Or Domain-Specific	Which responds to keywords or has a specific task. This type of chatbots can only answer to inquiries on a certain knowledge area	ELIZA; SnapTravel;	(Brandtzaeg & Følstad, 2017); (Kucherbaev, Bozzon, & Houben, 2018);
Service provided	Interpersonal	Chatbots that provide services such as restaurant reservations, airline reservations, and FAQ searches. They're typically linked to Messenger apps like Slack and WhatsApp.	Chatbot based on Messenger (Facebook) (Domino's Pizza Bot)	(Nimavat & Champaneria, 2017);
	Inter-agent	Chatbots can converse with each other. interconnected chatbots	Alexa Cortana	(Nimavat & Champaneria, 2017) ;

		that communicated with one another		(Deshpande et al. 2017) ;
Goals	Informative	When client interact with a chatbot in order to obtain precise information from a set source.	Guardian; Facebook M; FAQ;	(Kucherbaev et al., 2018) ; (Nimavat & Champaneria, 2017).
	Chat based/ Conversational	Chatbots converse with users in a natural way, much like a real human would.	PARRY; A.L.I.C.E;	(Wallace, R. S. 2009) ; (Colby et al., 1979) ;
	Task Based	Perform a variety of responsibilities, including as hotel reservations, and are skilled at asking information and replying to users in a timely manner.	SnapTravel; Figgy; Ctrip;	(Kucherbaev et al., 2018) ; (Nimavat & Champaneria, 2017); (Li et al., 2021);
Response Generation Method	Rule Based	Pattern Matching algorithms are used by chatbots to compare user input to a regulation structure and choose a predetermined answer from a selection of replies.	ELIZA; A.L.I.C.E; Chatterbot; Watson; Jabberwacky; HEX;	(Colby et al., 1979) ; (Brandtzaeg & Følstad, 2017); (Jabberwacky 2021) ; (Masche & Le, 2018);
	Retrieval Based	This type of chatbot use Artificial neural networks. A neural network is used in algorithms to distribute ratings and choose the most probable outcome from a group of replies.	Facebook wit.ai Api.ai	(wit.ai, 2021); (Cloud.google, 2021);

	Generative	Generative models also used Artificial neural networks. In this type of model deep learning, methods are generally used to generate the response.	Google duplex;	(Google duplex, 2021) ;
Human-aid	Human-mediated	A chatbot's functioning can be supplemented with human involvement in some instances when additional flexibility is required. Human computation is used in at least one aspect of a human-mediated chatbot.	SnapTravel; Messenger (Shop Spring);	(Larry Kim, 2019) (Kucherbaev et al., 2018);
	Autonomous	Staff trying to incorporate their intelligence into fully autonomous chatbots may be capable of overcoming some limitations.	Alexa; Cortana; Siri;	(Deshpande et al. 2017) ; (Kucherbaev et al., 2018);
Permissions	Open-Source	Open-source platforms systems allow their source code accessible to developers, allowing them complete control over the execution.	RASA; Botkit; Microsoft Bot Framework; Chatterbot;	(Rasa, 2019); (Botkit: Building Blocks for Building Bots (2019); (Microsoft Bot Framework, 2019); (About ChatterBot—ChatterBot 1.0.2 documentation 2019);

	Commercial	ommercial platforms do not provide them total control, developers use data-efficient methodologies for training their chatbots.	Botsify Google DialogFlow Facebook wit.ai	(Botsify, 2019); (Dialogflow, 2019); (Wit.ai., 2021)
Communication Channel	Text	Chatbots based only in text queries interactions.	Mesenger (Facebook); FAQ;	(Nimavat & Champaneria, 2017);
	Voice	Chatbots that could d interact with clients using voice recognition	Siri ; Cortana ; Google Assistant ;	(Deshpande et al. 2017) ; (Google assistant 2021);
	Image	Some latest chatbot could react to pictures, and recognizing objects in those images they can also express their emotions	Medibot;	(Srivastava, P., & Singh, N. ,2020); (Shum, He, & Li, 2018);

1.4. Chatbot Approaches

1.4.1. Pattern Matching Approaches

Pattern Matching algorithms are used by rule-based chatbots to compare user input to a regulation pattern and choose a predetermined reply from a series of replies. The situation could also influence which rules are used and how the response is formatted. The first chatbots that use pattern matching are ELIZA and ALICE, subsequently followed by PARRY, Chatterbot, HEX, Watson, CleverBot (Marietto et al., 2013). As we mentioned before pattern matching algorithms are used by chatbots to compare user input to a regulation structure and choose a predetermined answer from a selection of replies. That is to state that rule-based methods don't generate new responses because the information is supplied by the programmer in the format of conversational interfaces (Ramesh et al., 2017). The reply is determined in most rule-based chatbots for singular dialogue, considering only the most recent response under reference. By employing a multi-turn response selection criterion where each response is utilized as feedback to pick a natural and contextually relevant response (Wu et al., 2016).

The most widely used languages for creating chatbots that use pattern matching, are AIML, RiveScript, and Chatscript.

Artificial Intelligence Markup Language (AIML)

This open-source language that is based on XML (Extensible Markup Language) was created by developers between 1995 and 2000 in order to help build A strong Base for chatbots that use the Pattern Matching method. The first chatbot that was Base implemented in the AIML language was ALICE. AIML data materials are made up of subjects, each of which has its own set of categories. A category is a chatbot regulation with a pattern for representing the input from the user and a pattern for describing the chatbot's replies (Arsovski, et al., 2017). An example of Artificial Intelligence Markup Language (AIML) code is shown in figure.5.

```
<category>
  <pattern>I AM *</pattern>
  <that>WHAT IS YOUR NAME</that>
  <template>Hallo <set name="username"><star/></set>. How
          old are you?
      <learnf>
          <category>
             <pattern>NAME</pattern>
             <template>Username:
<eval><star index="1"/> </eval>
 </template>
          </category>
      </learnf>
  </template>
 </category>

<category>
   <pattern>My NAME IS *</pattern>
   <that>WHAT IS YOUR NAME</that>
   <template><srai>I AM <star/></srai></template>
</category>
```

Figure 9. An example of Artificial Intelligence Markup Language (AIML) code.

Source: Denecke, K., Hochreutener, S. L., Pöpel, A., & May, R. (2018). Self-anamnesis with a conversational user interface: concept and usability study. Methods of information in medicine, 57(05/06), 243-252.

RiveScript

RiveScript (2009) is an open-source scripting language that implements the knowledge base in rule-based chatbots, it includes interfaces available in numerous computer languages, such as Java and Python. The processor compares user input to previously saved responses to identify the most effective reply. RiveScript additionally includes wildcards, conversational redirection, and context awareness in the form of user and chatbot variables (Gupta et al., 2015).

```
+Hello
- Hi! What's your name?
- Hello, How are you?
-Hello!

+ my name is *
-<set name=<formal>>Nice to meet you, <get name>!

+ Goodnight
- Goodnight <get name>
```

Figure 10. An Example of RiveScript Code

Source : Adamopoulou, E., & Moussiades, L. (2020). Chatbots: History, technology, and applications. Machine Learning with Applications, 2, 100006.

Chatscript

This type of language was created in 2011 It's a professional framework for creating rule-based chatbots with a small open-source scripting language. The user input is analyzed by an integrated tagger and processor, which enhances it in grammatical features, semantics, syntax, and interpretation (Wilcox & Wilcox, 2014). Chatscript makes use of notions, which are groups of words with similar meanings and elements of speech. Programmer could easily use existing databases of notions to make the building of a chatbot simpler.

```
concept: ~greeting [hello hi hey]

concept: ~goodnight [night goodnight ]
Topic: ~chitchat( ~greeting)
t: ~greeting

#! Hello
u: ( * ~greeting * ) [Hi!] [Hello], [What's your name?] [How are you?]

#! My name is
u: (* name * is _* ) Nice to meet you _0!
$username = '_0

#! I wish you a goodnight
u: ( <<!not * ~goodnight * >>) Goodnight $username
```

Figure 11. An Example of Chatscript Code

Source : Adamopoulou, E., & Moussiades, L. (2020). Chatbots: History, technology, and applications. Machine Learning with Applications, 2, 100006.

1.4.2. Machine Learning Approaches

Chatbots that employ Machine Learning instead of Pattern Matching collect material from user interaction using Natural Language Processing (NLP), but generally don't learn from discussions. They take into account the entire conversation context rather than simply the current phase, and they don't demand a predetermined reply for every potential user interaction. Artificial Neural Networks (ANNs) are frequently utilized to implement these chatbots. A neural network is used in retrieval-based models to assign scores to include the most probable outcome out of several answers (Lin, et al., 2016).

Natural Language Processing (NLP)

Natural Language Processing is a branch of Artificial Intelligence that investigates how computers can understand and manage natural language in the form of series of words, and voices (Khurana et al., 2017). Information about natural language understanding and usage is gathered in order to develop strategies for systems to handle natural speech and perform a wide range of activities. Most of NLP methods are on the basis of machine learning (Jung, 2019).

Natural Language Understanding (NLU)

Natural Language Understanding is used with a chatbot to extract relevance from unstructured complex communication user input and reply in accordance with the present customer's purpose (Jung, 2019). The three key issues presented during the NLU process are the user's cognitive mechanisms, interpreting, and general information.

Artificial Neural Networks (ANN)

Artificial Neural Networks are used in a variety of ways in chatbots that are focused on retrieval and generative based. The method carries the input from the user, and calculates its vector representations, feeds it to the neural network as features, and generates the response. Word embedding is the process of mapping words into vectors, and there are numerous methods for

doing so, some of which are basic and others that involve deep learning methods like Word2vec (Mikolov et al., 2013).

Recurrent Neural Networks (RNN)

To take into consideration in a discourse, the preceding context developers of chatbots use Recurrent Neural Networks. The cells are fed by new user input as well as knowledge from previous data. A controller transmits knowledge from one area of the network to the next in this manner (Chung, et al., 2014). Furthermore, while creating chatbots, programmers employ Long Short-Term Memory networks (LSTMs), a kind of RNN, to refer to past data and understand long-term relationships (Xu et al., 2017).

Sequence-to-Sequence model (Seq2Seq)

A generative-based model Sequence-to-Sequence model (Seq2Seq), looks at the source sequence and creates a target sequence. The user's input is the origin sequence, while the chatbot's answer is the destination sequence (Ramesh et al., 2017). Two RNNs, that is the most fundamental and initial type of the model, can be employed as the input and output, or LSTMs and Gated Recurrent units (GRUs), Longer sentences can be modeled using this method (Chung et al., 2014).

Deep Seq2seq Models

When the model is more in-depth and has more features, like in the case of deep Seq2seq models incorporating multiple layers of LSTM networks, generative chatbots can achieve higher and more accurate results also, more human-like (Csaky, 2017).

1.5. Chatbots in Marketing

Marketing with digital technologies has gone past the constraints of what we used to consider as an impending element of a human being. It ought to be noticed that they show a wide scope of capabilities like decision making, image recognition, thought designs, communication, changing the setting of an assertion to a circumstance, etc. As the exploration shows, profit in utilizing chatbots, which are one of the implementation digital technologies (transformation) into experience journey of users, consistently increments in digital marketing activities of organizations and brands. Although, as we already see in the previous section the chatbot has been created since the 1950s, most companies have just recently begun to use this technology to connect with their clients and potential prospects (Kaczorowska-Spychalska, 2019).

Chatbots perform different capacities supplanting a human being and stimulate human behavior. Along with resulting experience, chatbots learns and improves while broadening their correspondence capabilities and creates information on how to customize a message, and improve their principles of correspondence and reactions. These are unpredictable interfaces dependent on the investigation of a characteristic language and relational correspondence rules, which empower better human-machine interactions and led to a communication that is intentional and characterized (Zumstein & Dundertmark, 2017). Subsequently, chatbots can respond to given inquiries, give answers, take care of issues while understanding users' expectations. In this way, a chatbot turns into an innovative impression of a human being, which prompts dehumanization of what is human and acculturation of innovation appearances (Kaczorowska-Spychalska, 2019).

1.5.1. Chatbots in Developing Customer Experience

Chatbots "Conversational agents" when totally mechanized and autonomous, can be considered as a Self-Service Technology, for example, clients produce administrations for themselves without help from firm representatives. In light of the expanding part of innovation in administrations, specialists have started to investigate customer perceptions and the use of administration conveyance advancements (Meuter et al. 2005).

With all the pervasiveness and advancement in chatbots today, existing assessments have chiefly centered around building up their abilities and information to decipher and react to human language meaningfully. On account of these progressing advancements with natural language processing, chatbots these days have improved in caring for conversations (Shah et al., 2016).

With adequate innovation advances and its unmistakable enhanced organizations and shoppers, more than 100,000 chatbots have been dispatched in under one year on Facebook Messenger (Johnson, 2017). Just until the late decade that there have been more patterns towards more exploration of virtual agents (chatbots). This has essentially been because of customers' distrust towards the innovation. Consumers are seen to show inclinations towards people over the other option, proposing an overall struggle against chatbot innovation.

Accordingly, two basic difficulties, all things considered, execution are suggested with the distrust against chatbots. In the first place, Marketers and organizations should survey and have a decent degree of comprehension on the best way to best present the new specialists to buyers, alongside the degree of humanoid attribution. Second, it is additionally basic to appreciate how planning humanlike ascribes (e.g., style of the language, symbols, sexual orientation, feelings, or even individual characters) influence the discernments about the chatbot agent, services and organizations conveying these specialists (Araujo, 2018).

1.5.2. Chatbot in Customer Service

The advancement of new technologies has caused individuals to cooperate with one another in an unexpected way, thus has their connection with organizations. Web-based business (E-commerce) has developed and totally changed the manner in which organizations sell their items, yet there are a few issues identified with the nature of customer service. Particularly in online support, the trust that a business representative will react may long, and the appropriate responses may not continuously be applicable (Nuruzzaman & Hussain, 2018).

Chatbot for customer support is widely utilized by companies, user online support is accessible 24 hours daily by means of the chatbot, empowering customers to post their solicitation paying little mind to the standard working hours, which improves user satisfaction. For example, (Gupta et al., 2015), provides a chatbot developed in RiveScript language, website-based give support for

users by helping them to choose the right product. Furthermore, another chatbot based on Latent Semantic Analysis (LSA), and AMIL used a dataset of the most often asked question to interact with users effectively *(Nt, 2016).* Another study conducted by (S. & Balakrishnan, 2018), proposed a system (framework) with a big data interface to furnish client assistance chatbots with the capacity to investigate information from appropriate conditions.

Applying chatbots for customer service processes enjoys many benefits: The firm and the customers get into contact effectively with one another because of the inserting of chatbots in instant messaging administrations. Aside from the simplicity of the service provided, clients progressively anticipate that it should be fast and accessible consistently. With the utilization of chatbots for mechanizing simple concerns, organizations can satisfy these assumptions and save service costs. Subsequently, the clients are quantifiably more satisfied what thus can prompt faithful customers (Maddox, 2018).

To understand more the expectation from both points of view of customers and companies, The expectation matrix of customers and companies is the appropriate instrument for this purpose. The initial focus of the analysis was on conversations, but it has now broadened to include customer-oriented procedures. This allows us to identify decide the degree to which such processes add to satisfy the company and additionally client assumptions (Kreutzer & Sirrenberg, 2020).

In *Eliminate* part, the expectations of both companies and consumers are aligned. Customers dislike such processes and discussions because they increase expenses. They can be removed from the service scope. At *Automate* Consumers and organizations have different expectations: although the firm would prefer to avoid such procedures, customers want and expect them in the form of consultation, support, and other services. We can rely on automation, using chatbot service options to find a balance of interests here. This implies that frequently asked queries may be answered at a low cost. In *Simplify*, the interests also disintegrate, resulting in a misalignment of expectations. While the company believes there are chances to offer value in this situation.

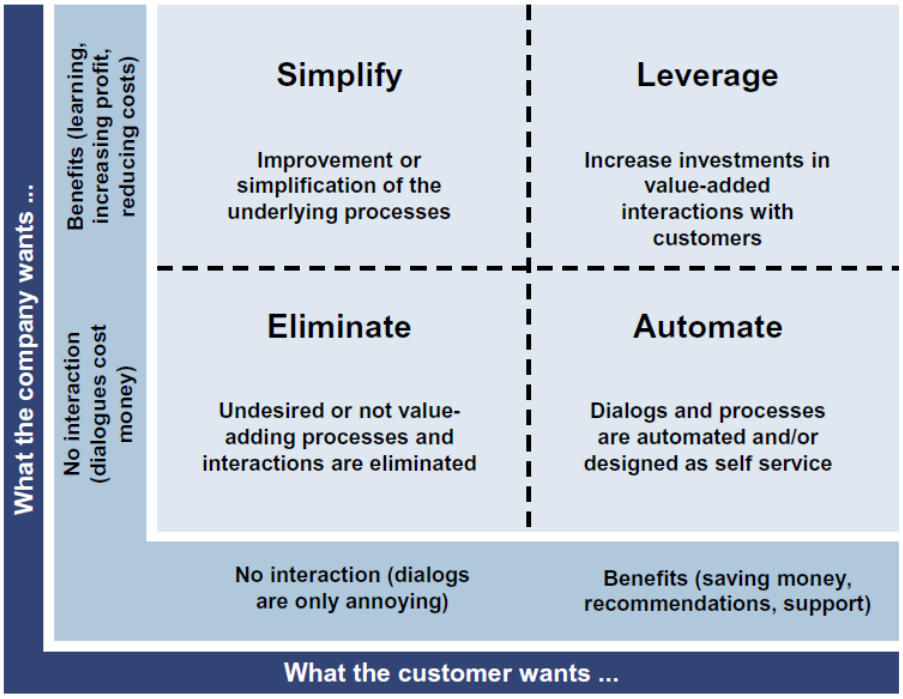


Figure 12. Expectation Matrix of Customers and Companies.

Source: Price, B., & Jaffe, D. (2008). The best service is no service: How to liberate your customers from customer service, keep them happy, and control costs. San Francisco.

For example, implementing check-in processes or getting e-mail permissions, follow-up calls, and assessment requests. In the worst-case situation, the consumer is upset! Therefore, system simplification and optimization are required at that point. At *leverage*, there is a match between expectations. In order to maximize the present potential, it is required to invest in the underlying processes. Worth making discoursed can be accomplished by introducing the call specialist in real-time (Kreutzer & Sirrenberg, 2020).

1.6. An Overview of Chatbots in Morocco

To understand the situation of chatbot technology in the Moroccan economic atmosphere, we need to represent the Artificial Intelligent (AI) status in the first stage. AI is one of the subjects of the major upheaval of our time. A technological evolution generating so many opportunities for problem-solving, so many changes in uses, and also so many fears. Between fantasies, hopes, and

worries, AI today above all offers new opportunities for companies. In Morocco, the race for big data and algorithms is creating new horizons. In fact, artificial intelligence is already very present in our lives, obviously through our smartphones, voice assistants, etc. The same case is in companies, where many other tools such as machine translation or chatbots are often used to respond to consumers' needs online.

According to (McKinsey & Company, 2018), AI represents a major opportunity for Morocco. In its study "Potential of digital and artificial intelligence", the firm declares that there are currently eight sectors mature enough to take full advantage of these technologies: banking, telecoms, insurance, automotive industry, agriculture, energy, self-entrepreneurship, and e-gov (electronic administration). To explore the situation of artificial intelligence within Moroccan companies and in the aforementioned related sectors. A documentary research by gathering data from further theoretical and empirical studies to come up with an analytical approach that helps us position Moroccan economy against other countries investing in AI (El Bour & Lebzar, 2020).

Ai is revolutionizing the economic world, (BCG Gamma & Ipsos 2018), for 73% of Moroccan active users, this is a subject on which they expect their leaders to speak up and make decisions. Moroccans are convinced that all sectors are concerned and will be profoundly transformed. The survey was conducted among 8,080 people in the workforce around the world, including a minimum of 1,000 people in each country studied (France, Germany, Spain, United Kingdom, United States, Canada, China and Morocco).

In Morocco, not all sectors benefit from the same degree of maturity to be able to accommodate this type of technology. We still cannot talk about artificial intelligence in Morocco, at least for the majority of companies. The country is still in the "Data Engineering" phase. Companies today are working on data, trying to collect it, digitize it, facilitate access, and analyze it. This is the step that precedes the implementation of an artificial intelligence system. The sectors that lend themselves best to the technological phenomenon are banking/insurance, telecom operators, part of industry, mass distribution and the public sector (El Bour & Lebzar, 2020).

AI will provide citizens practical information and thus make their lives easier, modernize the administration and public services, improve participation in public life and boost economic development through better provision and circulation of information. As announced by Mr.

Mohamed BENCHAABOUN (The Minister of the Economy, Finance and Administrative Reform), *"AI also makes it possible to develop information technologies and the establishment of a digital economy, overcome the reluctance that may exist within the administration and organize an ecosystem to ensure the harmonious establishment of society. knowledge, where the different actors can make their contribution"*.

Chatbots as an AI technology, offer a range of potential benefits in a variety of sectors. However, this new type of human-machine interface technology has received limited attention both in the practice economic world and academic research in Morocco. A study conducted by (Zahour et al., 2020), within the context of educational and professional guidance, (chatbot E-Orientation). In their research, they elaborate a chatbot that helps with online orientation fresh graduated students to integrate into the employment market. Their results show the satisfaction of users with this new technology.

In the telecoms sector, one of the leaders of this market in Morocco "INWI", in 2019 launched its 100% digital brand "WIN", with online assistant support (chatbot), this assistant elaborated by BotsFactory, the first agency in Morocco that used artificial intelligence and machine learning to understand the customer's intention in dialect: Darija, and in the structured language (classical Arabic, French and English). Led by engineers and IT developer's experts in the development of artificial intelligence solutions for businesses, Bots Factory is a pioneer in the design and creation of chatbots and their analytics in Morocco. (BotsFactory, 2021)

In Banking and assurance sector, "Attijariwafa bank" launched a chatbot available on its institutional site for better interaction with its customers in this context of a health crisis (Covid-19). based on artificial intelligence that allows customers to conduct an interactive dialogue, to obtain answers to their questions quickly, efficiently, and at the time that suits them, indicates a press release from the Moroccan banking group, which specifies that this offer, "a premiere in Morocco", is available in French, will intervene within a limited scope for its launch. This virtual assistant will also deal with topics on the measures taken by the Moroccan state to fight against Covid-19. (Attijariwafa bank Communique de presse 23 may, 2020).

1.7. Hypothesis Development

1.7.1. The Technology Acceptance Model (TAM)

The technology acceptance model proposed by Davis in 1986 in his doctoral thesis, aims to predict and explain the adoption or not of an information system (IS), through variables relating to perceptions, perceived usefulness and perceived ease of use, and attitudes that will induce behavioral intentions of use (Davis, 1986).

This model is an adaption of the theory of reasoned action (TRA), specially designed to model user acceptance of the information system, the goal of TAM is to get a general overview of the determinants of technology adoption, capable of describing user behavior across the spectrum of end-user operating systems and user community abroad, while being both circumspect and logically justified at the same time (Davis et al., 1989).

The TAM is a model that is useful for the forecast as well as for clarification, so analysts and specialists can recognize why a specific framework might be unsatisfactory and seek after fitting restorative advances. Therefore, a primary goal of TAM is to give a premise to following the effect of outer components on inside convictions, attitudes, and intentions. TAM was created trying to accomplish these objectives by recognizing few basic central variables proposed by past examination managing the psychological and viable determinants of computer acceptance and utilizing TRA as a hypothetical setting for demonstrating the hypothetical connections among these variables (Davis et al., 1989).

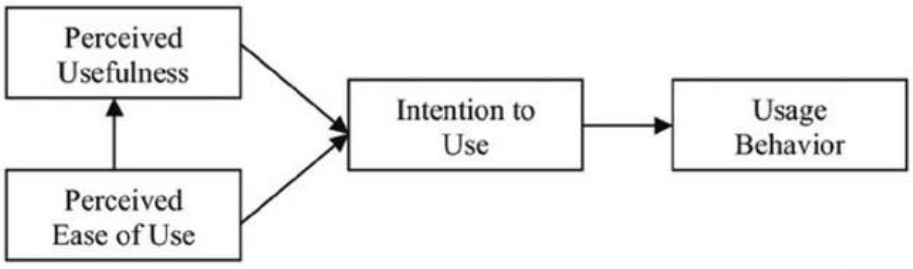


Figure 13. The Technology Acceptance Model (Davis 1989)

Source: Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. Management Information Systems Quarterly.

1.7.1.1. PU and PEOU with Intention to Use a New Technology

At the TAM level (Davis, 1989), the intention is an antecedent behavior, and it is a function of attitude, which depends on beliefs specific to the information technology context. These beliefs are the perception of the usefulness and the perception of the ease of use of technology. Perceived usefulness reflects the perception by potential users of the performance gains to be made or the benefits that could be obtained from the use of the technology. Perceived ease of use is defined as the intensity with which a potential user believes that the use of technology will be free from additional effort and difficulty (Davis, 1989).

Perceived ease of use plays a dual role. It has a direct effect on attitude towards the behavior to be adopted, and it also determines the perceived usefulness of new technology, in fact, (Davis, 1989) maintains that the usefulness is favorably perceived when the effort required for its use is low. These two constructs, perceived usefulness and perceived ease of use are, according to the TAM (Davis, 1989), the essential determinants of an individual's attitude towards the use of a technology given and are therefore the determinants of its intention to use and actual user behavior.

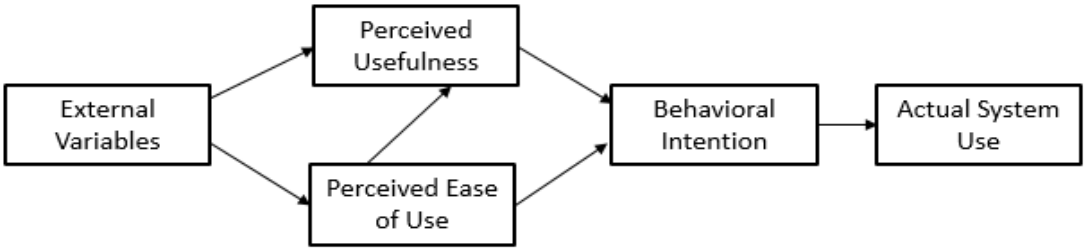


Figure 14. The Technology Acceptance Model (1996)

Source: Venkatesh, V., & Davis, F. D. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision sciences*, *27*(3), 451-481.

The TAM (Figure3) suggests that perceived usefulness and perceived ease of use serve as the basis for acceptance of computer use. In addition, external variables such as the characteristics of the design of the system, the training received, the personal efficiency in the use of the computer, the involvement of the user in the design of the system and the nature of the process, implementation of the system would influence them (Davis & Venkatesh, 1996).

Hence, we suggest the following hypothesis:

H1: Perceived ease of use (PEOU) has a significant effect on perceived usefulness (PU).

1.7.1.2. The Influence of PU and PEOU on Continuance Intention.

Mostly, TAM-based examination is led from an inspirational outlook to investigate users' acceptance and continuance intention, and sees perceived ease of use and perceived usefulness as significant determinants. Nevertheless, a couple of abnormalities stay peculiar, like the explanations behind a user to cease the service after starting to accept the technology.

In a study conducted by (Ifinedo, 2006) on the acceptance and continuance intention of web-based learning context, the researcher found that perceived ease of use had a positive relationship with their dependent variable the continuance intention, on the contrary of perceived usefulness did not have a significant relationship. The same finding in a study of (Sørebø, 2004) on the post-acceptance model in the context of E-learning, the perceived usefulness did not represent a meaningful relationship with continuance intention. In another study by (Lin, 2011) both perceived usefulness and perceived ease of use had a significant effect on user's continuance intention, but they found the indirect effect of perceived usefulness on continuance intention in the e-learning context. In their example, regardless of whether a user respects the service to be valuable however feels truly annoyed about a collaboration among colleagues or with course materials, at that point all things considered, the individual would choose not to keep utilizing the assistance.

Draw on the Expectation Confirmation Theory (ETC) (Oliver, 1980) and the TAM (Davis, 1989), (Bhattacherjee, 2001) come up with the information systems technology (IS/IT) continuance model to elucidate the behavior of users after the adoption of such a technology. In his researcher (Bhattacherjee, 2001) remarked that the variables relating to perceptions of TAM did not completely clarify IS continuance intention, and that proceeded of continuance to use, instead of first use, demonstrate its fruitful execution. The information systems technology (IS/IT) continuance model clarifies that, after the first use, users' impression of IS helpfulness and fulfillment may change, prompting either rehashed behavior or ceased utilization.

As a variety of research about technology continuance intention, the information systems technology (IS/IT) continuance model, has been adopted in the context of the chatbot (Ashfaq et al., 2020), the users' continuance intention for technology as suggesting (Bhattacherjee, 2001) centered on perceived usefulness. How much users feel that utilizing the new technology of chatbot is valuable and useful for supporting their activities, and interact out adequately (e.g., solving the problem of an online shopping order). Users may expect that chatbots may improve their performance or/and productivity. Hence, a more significant level of perceived usefulness conduct to high level of continuance intention. Therefore, Perceived ease of use in the context of chatbots is a determinant of continuance intention. For instance, the complexity of some chatbots (like install a plugin or create an account) creates blockades for users to interact easily with the service provided. Thus, if the interface and setting of the chatbots are programmed to be easier to use, the users tend to expend less cognitive effort to use the chatbot, which implies a higher level of continued using the service offered (Ashfaq et al., 2020).

In their research (Hong et al., 2016), got unexpectable findings, the two main constructs of TAM which are developed to analyze in the first stage of adoption within the context of an IT system, gave the best results comparing with new models ECM-IT and EECM-IT in post-adoption intention to continue IT usage. Accordingly, we suggest the following hypothesis:

H2: Perceived usefulness (PU) has a positive effect on continuance intention to use chatbots
H3: Perceived ease of use has (PEOU) a positive effect on continuance intention to use chatbots

1.7.2. Alternative Model for Measuring Continuance Intention

The CAN (Cognitive-Affective-Normative) model (Pelegrin-Borondo et al., 2017), combines three types of variables; cognitive variable which includes PU & PEOU adapted from TAM, the affective variables that represent the positive and negative emotion including the anxiety adapted from Componential Emotion Theory, and the third type of variables the normative variable, represented with subjective norms which are examined in several theories like TBA, and TAM2 model.

1.7.2.1. The influence of Affective Variables on Continuance Intention

After examining the cognitive variables PU & PEOU, we propose the expansion to affective variables (emotions) since they allow a better understanding of the appreciations in the IS context. Emotions of consummations have been found to assume a significant part in characterizing consumption experiences and impacting user's reactions, as sentiments of users straightforwardly impact the assessment of the general experience (Hosany et al., 2005).

Emotions related to consumption are defined as "the arrangement of emotional reactions evoked explicitly during product utilization or consumption experience, as portrayed either by the distinctive classifications of emotional experience and expression (e.g., joy, anger and fear)" (Westbrook & Oliver, 1991). The hedonic contingency theory supports the importance of consumption emotion, the users who had positive emotion while experiencing a service have more likelihood to continue using the service due to the positive hedonic consequences (Lee et al., 2015).

Researchers in the context of emotional measuring tended to borrow and adjust measures developed by emotion theories. The measurement developed by (Watson et al. 1988) Positive Affect and Negative Affect Schedule (PANAS) (Watson et al. 1988) provide measures of positive affect (PA) and negative affect (NA) by creating a scale of twenty items that describe different emotions. PANAS represents two dimensions, the first one PA and NA demonstrate dispositional measurements, with high NA exemplified by abstract trouble and unpleasurable commitment, and low NA characterized by lack of these sentiments. The high of PA represents a position of high energy, full focus, and pleasurable commitment, and contrary low of PA leads to inactivity and sadness (Crawford & Henry, 2004). The subsequent pair is comprised of pleasantness-unpleasantness and engagement-disengagement commitment (which are the other two most normally utilized examples in the emotional measurements) various instances of distinct emotions are placed in these dimensions, such as excitement, happiness, distress, irritability, and loneliness (Zheng, 2019).

Many studies have focused on the impact of Positive and Negative emotions on behavior intention. The concept of continuance intention (re-purchasing, revisiting, or online Word of

Mouth intention) has been largely studied in the field of marketing, by reason of the high forecast capability of intentions on real behavior (Zheng, 2019). In their study (Gountas & Gountas, 2007), revealed in the context of airline service, that the re-purchasing intention of the user is affected by the consummation emotions. Apart from being useful for predicting the level of service satisfaction, but it helped to identify the elements for intention to re-purchasing.

In the context of chatbot, in their study (Asma et al., 2019) evaluated the emotion using the Positive and Negative Affect Schedule, aware of a chatbot that interacts with their participants in an empathetic manner. Their results showed the preferences of the participants depend on the aspect if they are extroverts or introverts, more extraverts people like to interact with an emotion-aware chatbot. Additionally, to that, the participants announced a higher level of positive disposition reports while associating with the empathetic chatbot. In another systematic review and meta-analysis study conduct by (Abd-Alrazaq et al., 2020), in their review of twelve studies, poor argument exhibited that chatbots were successful in improving depression, pain, stress, and acrophobia. As indicated by comparative findings, there was no measurably huge impact of utilizing chatbots on emotional mental prosperity.

In the literature of technology, anxiety has nearly been predictable about the adverse consequence of technology anxiety on users' responses and behavior to technology, therefore the prospect to accept and adopt it (Igbaria & Parasuraman, 1989). Technology anxiety whichever a moderating impact on the connection between users' assessment of an innovation-related service or product and their adoption or a negative direct relationship with users' appropriation of technology if the objectives of utilization are directly related to the service or product of that technology (Meuter et al., 2003).

In their study about designing a chatbot for counseling in mental health (Cameron et al., 2017) claims that chatbots can give a user instantaneous information. By fusing psychological wellness screening devices into a chatbot interface, the user can have more intuitive and easier-to-understand insight. In their results, a demonstration of easy to interact with chatbot and the feeling of safety has been shown. Furthermore, they proclaim that the technology of chatbot represents a new manner for users who not liking direct face-to-face communication.

1.7.2.2. The Influence of Normative Variables on Continuance Intention.

In the literature of information technology acceptance, subjective norms refer to “the conviction (beliefs) about whether a great many people endorse or object to the behavior. It identifies with an individual's convictions about whether companions and individuals of significance to the individual figure the person ought to take part in the behavior. Or in other way refers to the social influence on the behavior of an individual, to perform or not” (Ajzen, 1991).

All of Theory of Reasoned Action (Fishbein & Ajzen, 1975), the Theory of Planned Behavior (TPB) (Ajzen, 1991), and the TAM2 model (Venkatesh & Davis, 2000), examined normative influence, and step up as determinants of subjective norms. Hence the previous behavioral models justify the relationship between the intention to use and subjective norms in the context of information technology acceptance.

Subjective norms reflect how the view of notable persons, as friends and family, influences an individual. This build expects that an individual is slanted to play out specific practices to acquire acceptance inside the influence circle. Hence (Bhattacherjee, 2001) adds that subjective norms are determined by interpersonal influence like WOM from small and big circle connection and the external influence from influencer media, experts in their domains.

In his study in the context of mobile data service (Kim, 2010) examined the influence of each social influence, external and interpersonal on continuance. His results confirm that the two components of the TPB had a significant impact on mobile data service continuance intention.

Within the social networking sites (Mouakket, 2015), confirm that subjective norms affect the social networking sites' continuance use intention. Customers will in general depend vigorously on individuals they esteem while thinking about whether to keep utilizing the technology. So far in our knowledge there a lack of research that examines the post-usage continuance intention in the context of chatbot technology. Most of the research focus in the first stage of adoption and the intention to use a chatbot.

1.7.3. User Satisfaction

The conceptualization of customer satisfaction and its measurement have given rise to much research. Two definitions of customer satisfaction emerge from the literature: satisfaction at the time of purchase, transaction or service (transactional satisfaction), and overall satisfaction (cumulative satisfaction) (Dean & Bowen, 1994).

Satisfaction is gotten from previous experience and afterward establishing an attitude, is a positive passionate reaction to the consequence of a past encounter (Ganesan, 1994). Customer satisfaction is according to (Dean & Bowen, 1994), the element that guarantees the long-term success of the organization. This requires that the entire organization be focused on this issue.

The most widely accepted model for measuring customer satisfaction is the "disconfirmation paradigm" (Oliver, 1980). Satisfaction is the consequence of weighing expectations, requirements, and the product's perceived performance. This model, therefore, has three main elements:

- ✓ The customer's previous assumptions about the product and/or service,
- ✓ The judgment made on the performance of the product (or service) during the consumption experience,
- ✓ The disconfirmation (positive, negative, or neutral) which results from the comparison between performance and expectations.

According to Customer Relationship Management (CRM) triangle law: customer satisfaction equal to customer experience minus customer expectations, Consumer satisfaction appears to be inversely proportional to customer expectations. Most companies distinguish between consumer expectations in general by Customer satisfaction analysis (CSI), it demonstrates also that Customer satisfaction and expectations have a negative relationship. When the customer experience is more that the expectations, the customer satisfaction go higher. Despite what might be expected, Customer satisfaction is lower as compared to expectations because of customer dissatisfaction.

There are many design elements of chatbots that influence customer satisfaction, for instance, the quality of communication such as how the chatbot shows reciprocal understanding, courteous, responsive. The expertise level and visualizations, all these examples played a major role in

increasing the satisfaction of customers, thus achieving long-term success, specifically in the highly competitive sector (Verhagen et al., 2014).

The availability twenty-four hours a day and the quick response of chatbots, improve the level of satisfaction of the customer, for example, 44% of registration in the hotel chain Marriott international in 2017, has been done using a chatbot, the reservation becomes more easily and fast. Without a chatbot, users would have to start off a discussion with real human assistants or search by their own the information necessary in the relevant websites. This prompts impractical and wasteful, just as effectively avoidable, research measures. With the features offered by the chatbot (particular context) the customer can feel personally addressed (Howlett, 2017).

Chatbots in education guarantee to decidedly affect learning achievement and student satisfaction. A limited number of studies have shown effectively executed chatbots in a learning situation, or instance, a professor at Georgia Tech university, put at the students' disposal a bot teaching assistant (Jill Watson based on IBM’s Watson platform), throughout one semester the chatbots assistant could answer questions instantly online for student, Students were amazed and the same time satisfied (Winkler & Soellner, 2018).

From the healthcare perspective, chatbot showed an impressive added value to this sector, like the chatbot Your.MD known as Healthily, this digital health-tech company utilizes chatbot to give patients the most significant wellbeing info and to associate them to check possible symptoms and side effects furthermore to discover safe wellbeing info, even recommend patients to the correct care proficient (Your.MD, 2021).

Confronted with the information over-burden from the media with which we need to live, new equations that are customized just as appropriate to information management are being set up through texting applications that incorporate private discourse and different assets that stir revenue and permit the customer to interface emotionally with them. Chatbots are also presented in journalism, the improvement of media news and using chatbots features in this domain impact the journalism in a positive way, the customer interacts with a personalized bot which delivered instant and trustful news. The media are wagering on the production of channels in Telegram with a functioning presence in the application. One of the most known chatbots in Spain, which appeared

on Telegram to provide political news, which audiences have reacted positively to the service provided (Gonzales & González, 2017).

As a part of results of the study conduct by (Bhattacherjee, 2001) on "understanding information systems continuance" using ECM. The continuance intention of users is mainly predicted by their level of satisfaction within the information system context. Another study conducted by (Boakye et al., 2014), showing that service satisfaction in information technology (IT), has a significant effect on service continuance intention to use. The same results as (Bhattacherjee, 2001) were founded with the research of (Ashfaq et al., 2020), in the context of chatbot. The satisfaction of chatbot users represents a strong predictor for their intention to continue using the chatbot service provided.

Accordingly, we propose the following hypothesis:

H4: User satisfaction has a positive effect on Continuance intention to use chatbot.

1.7.3.1. The Role of User Satisfaction as a Mediator

As we motioned in the previous section TAM's key determinants PU and PEOU, are the predictors for the attitude of an individual. (Davis et al. 1989). In their comparative study on three models of continued IT usage behavior (Hong et al., 2016), confirm the influence of TAM's constructs PU, and PEOU on satisfaction within the context of post-adoption usage behavior. The contribution of their study went beyond the IT adoption, by comparing traditional theory TAM and new models such as ECM-IT and EECM-IT, their results demonstrate the utility of using TAM's constructs in the adoption stage and continued IT usage behavior.

Another study conducted by (Roca et al., 2006), in the context of e-learning to understand the continuance intention. Their findings showed that PU is critical to the success of an e-learning system, the influence of PU on satisfaction is much stronger than the influence of PEOU, and these results match with previous research findings (Davis et al., 1989; Devaraj et al., 2002). The research concluded with the importance of considering both PU, and PEOU in the context of using an IT system. Contrary to the finding of (Roca et al., 2006). Thong et al. 2006 during their research about the effect of ECM on IT continuance intention usage behavior, their research demonstrated that PEOU has a stronger influence than PU on satisfaction. This conclusion underlines the need to expand the scope of post-adoption views based on the type of technology being studied. This supports the earlier study of (Kwon & Zmud's, 1987) Request for context to be properly considered in the information technology adoption study. The ECM (Bhattacherjee, 2001), proposed that satisfaction is mainly based on PU, in the same line of findings (Roca et al. 2006; Davis et al., 1992). The previous research does not include satisfaction into TAM, considering the satisfaction as moderating variable between PU, PEU, and CI, will lead us to understand better the relationship between PU and PEOU with CI.

Accordingly, we propose the following hypothesis:

H5: Perceived usefulness (PU) has a significant effect on user satisfaction.

H6: Perceived ease of use (PEOU) has a significant effect on user satisfaction.

2. Research Design and Methodology

The reasoning of social science grasps a few standards, that is a bunch of basic comprehension of what is being investigated, a set of the inquiries that ought to be posed, and the methodology that analysts ought to follow to reply and decipher the outcome. All researchers' endeavors are identified with how researchers figure out the best being scrutinized, subjective and objective perspectives. Nevertheless, the cycle deferrers among various researchers are dependent on the diverse paradigmatic directions (Kuada, 2012).

This research is about analyzing the factors that influence the continuance intention to use chatbot technology by Moroccan users. This research will be analyzed with an objective approach, and it is hypothetico-deductive research, all the variables have been indicated in the literature review which allows the development of theoretical background, and helps to obtain a clear idea about the theoretical framework. A more detailed methodology of research and data collection will be presented in the following sections.

2.1 Research Purpose and Objectives

This research examines post-usage user behavior (continuance intention) within the context of chatbot technology. Understanding the post-adoption of chatbots by Moroccan users is the main purpose of this research. Determining the factors and variables that may influence the continuance intention to use the chatbot service. We will use the essential two constructs of TAM, PU and PEOU. Furthermore, will examine the overall user satisfaction during their experience with a chatbot. The satisfaction played a role of mediator variable between PU, PEOU, and CI. Considering that previous research doesn't include satisfaction into TAM. The scope of our research is to take TAM's construct beyond the first stage of adoption and include satisfaction as a mediator variable into TAM, to understand the CI of Moroccan chatbot users.

The hypothetical relationship between the previous variables and the continuance intention will lead us to verify and determine the most important variables that conduct to continue adoption or discontinuance. Hence, we could explore and understand better the profile of Moroccan chatbot users. The literature review contributes with many articles and studies about chatbots with the previous variables, in the first stage of accepting the new technology in many areas and context of research. In fact, the literature review doesn't cover the area concerning the relationship between

the previous variables PU, PEOU, SAT and the continuance intention to use chatbots. Especially in Morocco, there is a lack of studies concerning the technology of chatbots, and fewer studies conducted in the context of intention to use and post-adoption of this technological service.

2.2 Research Model Development

Figure 15. illustrates our research model, this conceptual model has been developed based on previous research. Mainly TAM, we used the essential two constructs PU and PEOU and we add user satisfaction as a mediator between the previous TAM's constructs and CI of the chatbot service. Satisfaction is widely used to determine the continuance intention in the literature of continuance information technology. Also, used in ECM-IT and EECM-IT contexts but all the previous studies don't include satisfaction into the traditional TAM. Nonetheless, the relationship between constructs had been explored and analyzed in the literature review part.

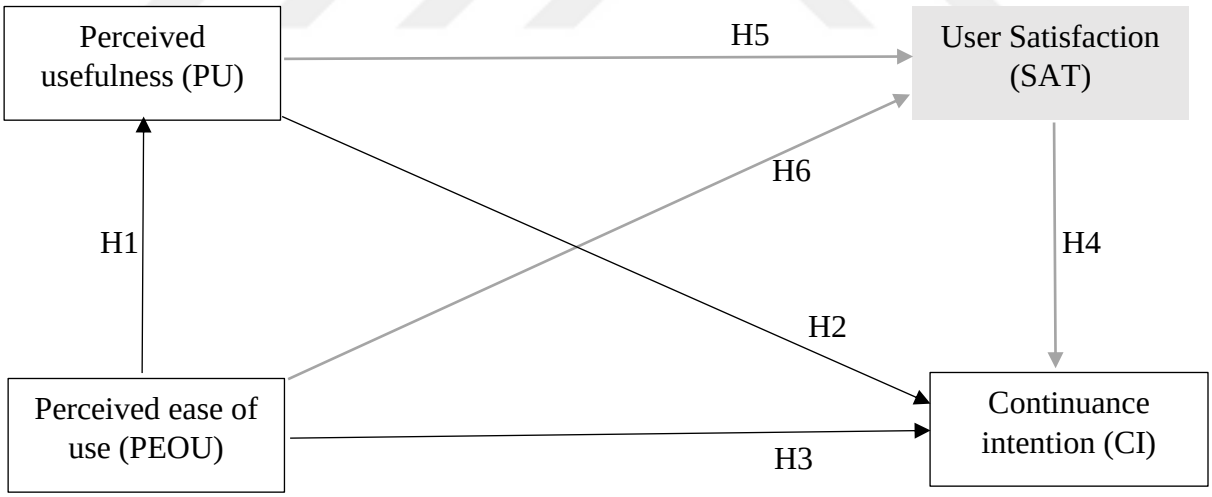


Figure 15. Conceptual Model of the Study
Source: Developed by the Researcher

2.3 Variables of the Study

Perceived ease of use (PEOU): Defined as the intensity with which a potential user believes that the use of technology will be free from additional effort and difficulty (Davis, 1989).

Perceived usefulness (PU): Reflects the perception by potential users of the performance gains to be made or the benefits that could be obtained from the use of the technology (Davis, 1989).

Satisfaction (SAT): Satisfaction is gotten from past experience and afterward establishing an attitude, is a positive passionate reaction to the consequence of a past encounter (Ganesan, 1994). Customer satisfaction is according to (Dean & Bowen, 1994), the element that guarantees the long-term success of the organization. This requires that the entire organization be focused on this issue.

Continuance intention (CI): Refers to the intention to continue using or long-term usage intention of a technology (Bhattacherjee, 2001).

2.4 Hypotheses of the Study

As we mentioned before this research aims to understand the post-usage adoption of chatbots technology by Moroccan users. To analyze the factors that have impacts on the continuance intention to use chatbots, we elaborate our conceptual model based on a variety of constructs adapted from a wide range of previous theories and models. According to the model the hypotheses have developed, our dependent variable is the main focus. By analyzing the changes in the independent variables, we will represent the type of relationship between each of independent variable with continuance intention to use chatbots. The table below resumes the hypothesis of this research, with the source and supporting from literature.

Table.2 Hypotheses of the Study

Item No	Hypotheses	Source & Support	Variables
1	H1: Perceived ease of use (PEOU) has a significant effect on perceived usefulness (PU).	Davis, F.D. (1989). Davis & Venkatesh, (1996).	Perceived usefulness (PU); Perceived ease of use has (PEOU);
2	Perceived usefulness (PU) has a positive effect on continuance intention (CI) to use chatbot.	*Ashfaq et al., (2020)*. Hong et al. (2016), *Bhattacherjee (2001) Lin, K. M (2011) Ifinedo (2006)*	Perceived usefulness (PU); Continuance intention (CI)
3	Perceived ease of use has (PEOU) a positive effect on continuance intention (CI) to use chatbot.	*Ashfaq et al., (2020)*. Hong et al. (2016), *Bhattacherjee (2001) Lin, K. M (2011) Ifinedo (2006)*	Perceived ease of use has (PEOU); Continuance intention (CI)
4	User satisfaction (SAT) has a positive effect on Continuance intention (CI) to use chatbot.	*Ashfaq et al., (2020) ; Boakye et al. (2014) ; Bhattacherjee (2001) ; Roca et al. (2006),*	User satisfaction (SAT) ; Continuance intention (CI)
5	Perceived usefulness (PU) has a significant effect on user satisfaction (SAT).	*Ashfaq et al., (2020) ; Bhattacherjee (2001) ; Roca et al. (2006) ; Thong et al. (2006) ; Bhattacherjee (2001) ;*	Perceived usefulness (PU); User satisfaction (SAT);

6	Perceived ease of use (PEOU) has a significant effect on user satisfaction (SAT).	*Ashfaq et al., (2020) ; Bhattacherjee (2001) ; Roca et al. (2006) ;* Thong et al. (2006) ; *Bhattacherjee (2001) ;*	Perceived ease of use (PEOU); User satisfaction (SAT;

2.1 Research Method

First of all, the level of theory on which basis we can explain the relationship between variables and concepts is an empirical level that has regard to the deductive theory approach. In this type of theory, the researcher explains concepts based on empirical observation and theory developed on a conceptual and theoretical structure. In general, the primary data is collected from participants and observe the findings following the application of the relevant statistical test.

The three basic forms of research are exploratory research, descriptive research, and explanatory research. Exploratory research is being used in the initial stages of research to develop an essential definition for the concept that still has ambiguity not clear, usually a qualitative approach used in that type of research. The descriptive research as a state by (Polit et al., 2001) aims to observe and register a complex phenomenon that cannot be assigned an objective value. This method of research aims by testing hypotheses to provide a comprehensive overview of a circumstance, individual, or occurrence. In this type of research, we have two types of designs, cross-sectional design, and longitudinal design. The cross-sectional design is a form of research design in which you gather data from a wide number of people at the same time. There are two types of this design, single and multiple, the difference between those types is only the number of samples used to obtain information. We used explanatory research to explain a particular problem or a situation with a causal relationship, this kind of research enables the researcher to gain a new perspective on a situation so as to create, extend, or/and test a theory.

This research is about understanding the impact of certain variables on the continuance intention to use chatbots by Moroccan users. After developing a framework model, we will test

the previous sited hypothesis, in order to verify and give an overview of the relationship between the constructs. A conclusive design is used, and as a descriptive method of research, the sample design is a single cross-sectional. A questionnaire is made based on the critical literature review and the developed hypothesis; each construct has specific questions related to the relationship with the relevant construct in the framework model.

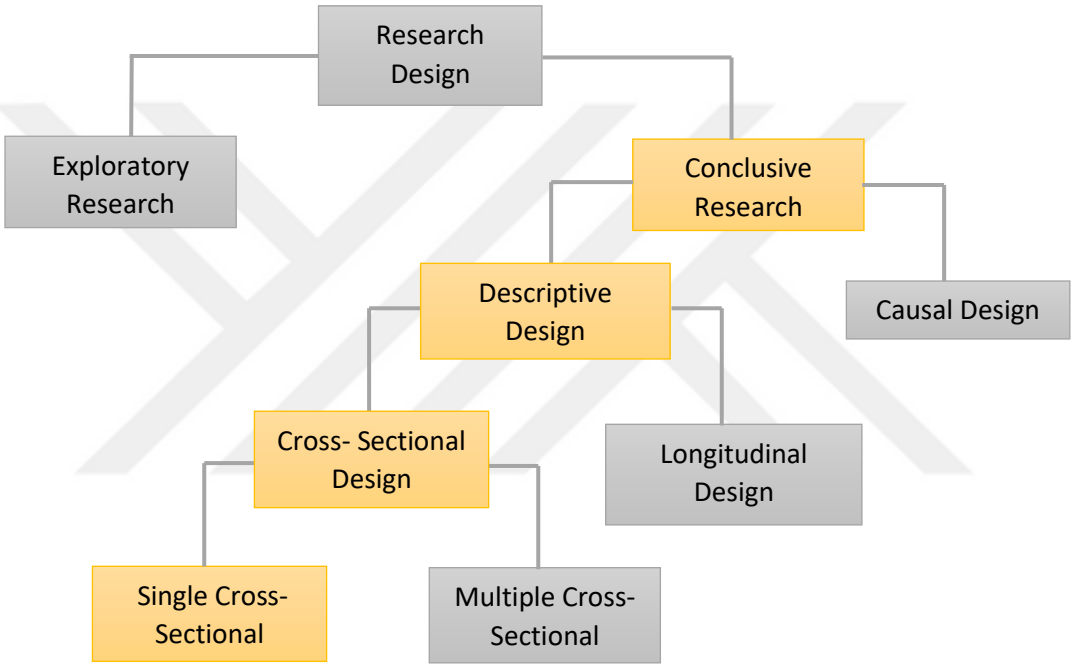


Figure 16. Classification of Market Research Designs

Source: (Malhotra, N. K. 2006). Questionnaire design and scale development. *The handbook of marketing research: Uses, misuses, and future advances*, 83-94.

2.5 Measurement Development

A survey has developed in order to analyze the relationship between each variable with the dependent variable CI. Considering satisfaction as a moderating variable between independent PU &PEOU, and dependent variable CI. The hypothesis will be tested, using appropriate quantitative research method.

Table.2 table illustrate the questions related to each variable used, with the answer's options and literature sources. Including the variables of our conceptual mode and sociodemographic questions.

Table.3 Variables of the Study

Variable number	Variables	Question number	Question/Item	Answer options	Source
V1	Chatbot User	Q1	Have you ever interacted with a chatbot before?	Yes No	Ashfaq et al., (2020);
V2	Chatbot Platform	Q2	In which platform(s) did you use chatbot last time?	-	Developed by researcher
V3	Perceived Usefulness (PU)	Q3	Using chatbot would improve my performance.	Strongly Agree	TAM scale (Davis et al., 1989) ;
		Q4	Using chatbot would increase my productivity.	Agree	
		Q5	Using chatbot would enhance my effectiveness.	Neither agree nor disagree	
		Q6	I would find chatbot useful to perform my daily activities.	Disagree Strongly disagree	
V4	Perceived ease of use (PEOU)	Q7	Learning to operate chatbot would be easy for me.	Strongly Agree	TAM scale (Davis et al., 1989) ;
		Q8	I would find it easy to get chatbot to do what I want them to do.	Agree	
		Q9	It would be easy for me to become skillful at using chatbot.	Neither agree nor disagree	
		Q10	I would find chatbot easy to use.	Disagree Strongly disagree	
V5	User Satisfaction (SAT)	Q11	I am satisfied with the chatbot.	Strongly Agree	Chung, M., Ko, E., Joung, H., & Kim, S. J. (2018);
		Q12	I am content with the chatbot.	Agree	
		Q13	The chatbot did a good job.	Neither agree nor disagree	
		Q14	The chatbot did what I expected.	Disagree	
		Q15	I was satisfied with the experience of talking with the chatbot.	Strongly disagree	
V6	Continuance intention (CI)	Q16	I intend to continue using this chatbot in the future.	Strongly Agree Agree	Ashfaq et al., (2020);
		Q17	I will always try to use this chatbot in my daily life.	Neither agree nor disagree	
		Q18	I will strongly recommend others to use it.	Disagree	

Source: Developed by the Researcher

Table.2 Variables of the Study

				7Strongly disagree	
V7	Gender	Q19	What is your gender?	Male Female	Developed by researcher
V8	Age	Q20	What is your age?	-	Developed by researcher
V9	Occupation	Q21	What is your occupation?	Self-employed/Freelancer Employee Unemployed Interning Studying	Developed by researcher
V10	Education	Q22	What is your highest degree or level you have completed?	High school Bachelor Master PHD	Developed by researcher
V11	Marital status	Q23	What is your current marital status?	Single Married Divorced Rather not to say	Developed by researcher

Source: Developed by the Researcher

2.6 Sampling Design

To conduct the sampling design, we should determine some step techniques before. The sampling process comprise, determining the target population, detecting the sampling frame, determining the sampling technique, calculating the sample size, and validate the sample (Malhotra 2007). All sampling design steps are detailed in the following sections.

2.6.1. Target Population

The population must be determined precisely as stated by (Malhotra 2007). The target population is the assortment of components or items that have the data looked for by the researcher and about which derivatives are to be made. The target population contains the elements and the sampling unit (Malhotra 2007). In our research the sampling unit would be the same as the element, which is the Moroccan users of chatbots. A user who already experienced the interaction with chatbot service in deferent sectors. The study focused on the post-usage stage.

2.6.2. Sampling Technique

To collect the data, we used non-probability sampling techniques including the snowball sampling technique and the convenience sampling technique. The purpose for using this convenience sampling technique is to gather data from the targeted population in the simplest way possible, and to evaluate the data as quickly and efficiently as possible. Furthermore, the snowball sampling technique was used, where the respondents asked to share the questionnaire with their circle of friends and family.

2.6.3. Sample Size

The most popular equation to determine the sample size for a large population is developed by (Cocharn 1963), The equation gives approximately 385 people as a target population. As our research is not based on a parametric analysis, a total of 400 questionnaires responses were used, as suggested by previous PLS research studies (Dirsehan, & Cankat 2021).

In our sample size the 333 respondents are accepted (chatbot user), and 67 of responses rejected (non-user of chatbot).

$$n_0 = \frac{Z^2 pq}{e^2} \qquad n_0 = \frac{Z^2 pq}{e^2} = \frac{(1.96)^2(.5)(.5)}{(.05)^2} = 385$$

2.7 Data Collection Method

As a quantitative method the data has been collected from respondents who situated in the target population, using an online questionnaire. Google Forms has been used as the online platform to get the responses. A pilot test was conducted with the first 15 respondents, to verify the clarity and comprehension of the questions and sections. The questionnaire included two parts, started with the elimination question (Yes/No question), *"Have you ever interacted with a chatbot before?"*, and responses with "No" are excluded from the study. Then we moved to the questions related to the model's variables, each variable had its own section. A Likert scale of five responses (from Strongly agree to strongly disagree) was used for all the variables. The second part included the sociodemographic questions, the respondents were asked about their; Gender, Age, Occupation, Education level, and marital status, to determine the respondent's differentiation.

The questionnaire has been created, with adequate literature sources, validity and reliability of all item's questions has been already treated in the literature. As long as the research will be conducted within Moroccan population, the questionnaire has been translated to French language, using adequate literature sources and back translation technique. Both version English and French of the questionnaire will be shown in the appendix part.

2.8 Data Analysis Method

The data obtained from the survey is analyzed in SmartPLS 3. This program was used for Structural Equation Modeling (SEM). (Hair et al. 2019), provided many situations of using Partial least squares path Modeling (PLS-PM) for estimation the structural equation model and run hypothesis tests. Furthermore PLS-PM is utilized since it is a method that relies on regression, which minimizes the residual variances of variables. (Hair et al. 2011). When we have a complex situation between variables and we want to examine their direct, indirect, and moderating relationship, PLS as a SEM technique is utilized for this purpose (Hair et al. 2019). In addition, the IBM SPSS Statistics 25 software has been used for normality test and non-response bias test, furthermore to determine groups differences (independent t-test and ANOVA).

3. Research Findings

3.1 Non-Response Bias Test

Nonresponse bias relates to the difference in responses between respondents and non-respondents (Hair et al., 2014). In order to compare early and late respondents (Armstrong & Overton, 1977), mentioned extrapolation methods to estimate the response of non-respondents. The concept of the extrapolation method is based on subjects who respond late are equivalent to non-respondents (Pace, 1939). One technique to detect late respondents has relied on replies obtained by "successive waves" response that are obtained by a stimulus (Armstrong & Overton, 1977, p. 397).

In order to analyze the non-response bias, in this section, we will verify the quality of homogeneity of both variances and mean of the distribution. In our research we are not sure about the number of respondents in the successive wave, hence the late respondents will be defined as the late 50% of the respondents as suggested by (Lindner et al., 2001).

An independent sample t-test will be conducted to compare the first group of 166 respondents and the last group of 167 respondents. The independent t-test was conducted on satisfaction and continuance intention variables to detect if there is a significant difference. The results of the test show that there are no differences between groups at 0.05 level, all the Sig. values are bigger that 0.05, as you can see in table.4. Hence there is no problem with non-response bias for this research.

Table.4 Non-Response Bias Test

		Levene's Test for Equality of Variances		**t-test for Equality of Means**		
		F	Sig	t	df	Sig(2-tailed)
Satisfaction (SAT)	Equal Variances assumed	1.268	0.346	-1.294	331.000	0.252
	Equal Variances not assumed			-1.294	328.278	0.252
Continuance intention (CI)	Equal variances assumed	3.308	0.279	-1.501	331.000	0.156
	Equal Variances not assumed			-1.501	328.422	0.156

3.2 Descriptive Analysis of Respondents

The aim of descriptive analysis is to provide a better understanding about characteristics, demographics, and orientation of Moroccan respondents.

3.2.1. Demographic Characteristics Analysis of Research Sample

Table.5 Demographic and Socioeconomic Characteristics

Attributes	Distribution	Frequency	%
Gender	Female	**190**	**57.05**
	Male	143	42.95
Age	18-25 Year	**238**	**71.48**
	26-35 Year	79	23.72
	36-45 Year	10	3
	45+ Year	6	1.8
Education	High School	20	6
	Bachelor (Licence)	132	40
	Master	**168**	**50**
	PHD	13	4
Occupation	Self-employed/Freelancer	20	6
	Interning	35	11
	Student	**155**	**46**
	Employed	105	32
	Unemployed	18	5
Marital status	Single	**281**	**84.38**
	Married	36	10.82
	Divorced	0	0
	Rather not to say	16	4.8
	Total	**333**	**100**

The sample size with a total of 333 responses is dominated by the females with 198 responses which represents 58%. For males, 143 responses are received which represents 42%. The majority of responses (238), are between 18-25 years old with 71%, then it comes 26-25 range of age in second place with 24% (79 responses). Furthermore, 10 participants, 3% of the sample are between 36-45 years old, and 6 participants (2%) are older than 45 years old. The average of the sample is 25.22. About participant's level of education, 50% of the responses (168) got a master's degree, then 40% of respondents disposed of a bachelor's degree (132). Also, 6% of

participants (20) had a high school diploma, the result shows a minority of participants disposed of a PHD degree (13) as you can see in table.4. The majority of respondents are students (151), which represents 46% of the sample size, then we have the employed participant in second place with 32% (105). Respectively the participants with an internship, self-employed/freelancer, and employed are represented with 11%,6%, and 5%. One of the participants is an entrepreneur another one is a commercial, and 2 others are in retirement. Finally, for marital status 84.7% of the participants are single (282), and it can be explained by the majority of participants are young (range of age is between 18-25years old), and still students (46%).

3.2.2. Distribution of chatbot platforms

As we can see in figure.11 the most used chatbots by Moroccan users in this sample are Google assistant with 28%, followed respectively by WhatsApp, Messenger, and Siri with 16%, 13%, and11%. The service chatbot offered by the telecom company INWI, as mentioned before in the literature represents 3% of users, even it's a low percentage but still a good beginning for a 100% Moroccan developed chatbot (Bots Factory).

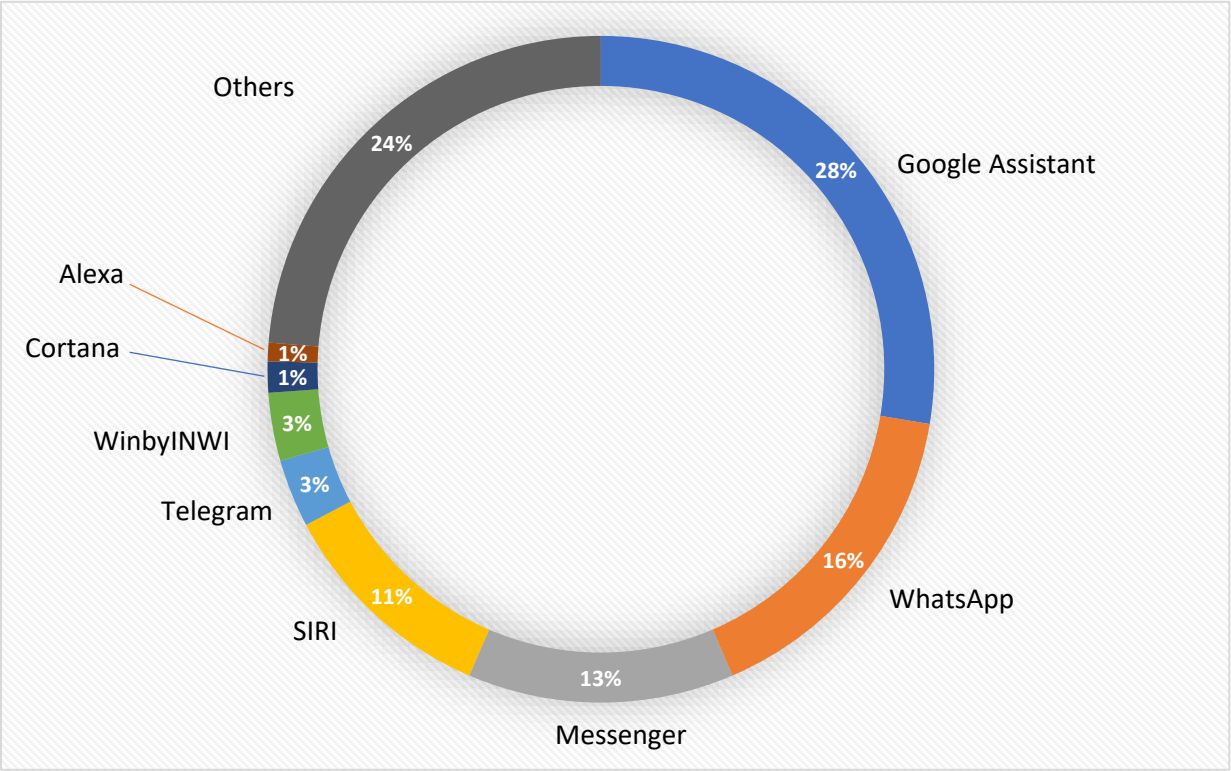


Figure17. Distribution of Chatbot Platforms

Source: Computed by the Researcher

3.3 Analysis of the Constructs

3.3.1. Normality Distribution Test

A normal Distribution test is made in order to understand if the variables are normally distributed. We calculate Skewness and Kurtosis the acceptable value range in general for these values is between -1.5 and +1.5. (Tabacknick & Fidell, 2013).

The findings shows that all value of Skewness and Kurtosis are *between* -1.5 and +1.5, except for the Kurtosis value of two items PEOU 1 = 2.379 & PEOU 4 = 1.846 *(See appendix 1)*, and since we are utilizing Structural Equation Modeling (SEM), the acceptable value of skewness is between − 3 and + 3, and kurtosis is acceptable from a range of − 10 to + 10 (Brown, 2006). Hence, the data considered normally distributed.

Table.6 Findings of the Normal Distribution Test

VARIABLE	Value			
	Skewness		Kurtosis	
	Statistic	Std. Error	Statistic	Std. Error
Perceived ease of use (PEOU)	0.964	0.134	1.301	0.266
Perceived usefulness (PU))	0.636	0.134	0.248	0.266
User satisfaction (SAT)	0.790	0.134	1.195	0.266
Continuance intention (CI)	0.781	0.134	0.678	0.266

3.3.2. Validity and Reliability

The validity represents "The degree to which a measurement accurately reflects the features of the event under examination" (Malhotra et al. 2017, p361). To confirm the validity, they are various of methods such as content validity and construct validity. Content validity "is a method for determining if the content of a scale accurately represents the measuring task at hand" (Malhotra et al., 2017, p362). The content validity its already verified by previous research in the literature.

With construct validity, we try to explain what the scale is measuring in terms of a concept or feature. Hence, construct validity necessitates a thorough understanding of the nature of the construct being assessed and how it connects to other constructs. It's determined as the most sophisticated and complex type of validity to establish. This type of validity includes convergent validity and discriminant validity. Convergent validity refers to the degree to which the scale correlates with other measures of the same concept in a favorable way (Shi et al., 2009). As a consequence, it's possible to see if the formative indications, taken together, sufficiently describe the construct of interest (Hair et al., 2017). Discriminant validity is the degree to which a measure does not correlate with other constructs that it is meant to distinguish (Yan & She, 2011). A common method for determining discriminant validity is the Fornell-Larcker criterion (Fornell & Larcker, 1981). In our research, we will use a modern method for assessing discriminant validity

in PLS-SEM, the Heterotrait-Monotrait ratio of correlations (HTMT), proposed by (Henseler et al. 2015). The HTMT is used as a criterion by evaluating it to a predetermined threshold. If the HTMT value exceeds the threshold, we can conclude that discriminant validity is missing. (Henseler et al., 2015). In our research, we will use the threshold of 0.85 proposed by (Clark and Watson 1995; Kline 2011). The reliability indicates how consistent the findings are, when repeated measurements are taken on a scale, The reliability is measured by determining the proportion of systematic variance on a scale, and this is achieved by examining the relationship between values received from different scale administrations. (Malhotra et al. 2017).

The convergent validity is tested based on two criteria as suggested by (Fornell & Larcker, 1981). First, we calculate factor loadings -The correlation coefficient for the variable and factor- then the Average Variance Extracted (AVE). The results show that all factor loadings are higher than 0.707, as suggested by (Benitez et al. 2020). Except for the items, PEOU1 with 0.397 and PEOU4 with 0.664 as you can see in table.7. We eliminate the item PEOU1 because the factor loading is too low to be acceptable. Then, we complete the analysis with the other items. For Average Variance Extracted (AVE) all values exceed 0.5, as suggested by (Hair et al., 2014), except for Perceived ease of use (0.460), but if we considered Composite reliability of this construct, is higher than 0.6, then the convergent validity of the construct is still adequate (Fornell & Larcker, 1981). Hence, there is no problem with convergent validity overall.

For reliability and internal consistency, Cronbach's Alpha and Composite Reliability (CR) has been calculated, Table.7 This shows that all values of CR and Cronbach's Alpha exceeded the criteria 0,70 as it is suggested (Cohen,1988). Cronbach's Alpha assumes that factor loadings are same for all items, but CR does not assume that but it took in consideration the varying factor loadings of the items, as we cans see in the table.7 values of Cronbach's Alpha and Composite Reliability (CR), are very close and equal for some constructs (SAT and CI), Hence reliability and internal consistency are satisfactory for all constructs.

Table.7 Evaluation of Scales for Reliability and Convergent Validity

Constructs	Items	Loadings	Cronbach's Alpha	Composite Reliability	AVE
Perceived ease of use (PEOU)	PEOU1	**0.397**	0.720	0.718	**0.460**
	PEOU2	0.773			
	PEOU3	0.708			
	PEOU4	0.664			
Perceived usefulness (PU)	PU1	0.742	0.835	0.832	0.554
	PU2	0.722			
	PU3	0.737			
	PU4	0.775			
User satisfaction (SAT)	SAT1	0.804	0.894	0.894	0.627
	SAT2	0.851			
	SAT3	0.740			
	SAT4	0.764			
	SAT5	0.798			
Continuance intention (CI)	CI1	0.806	0.830	0.830	0.620
	CI2	0.807			
	CI3	0.748			

Furthermore, to assess discriminant validity we will use the Heterotrait-Monotrait ratio of correlations (HTMT) as we mentioned before because as demonstrated by (Henseler et al., 2015), HTMT is better than Fornell–Larcker criterion, that may not detect a lack of discriminant validity. HTMT criterion has high sensitivity and specificity in detecting discriminant validity problems. The findings show that all values (See Table.7) are less than 0.85 as suggested by (Clark & Watson 1995; Kline, 2011), hence there is no problem with discriminant validity.

Table.8 Discriminant Validity (HTMT)

	Continuance Intention	User Satisfaction	Perceived Ease of Use	Perceived Usefulness
Continuance intention				
User Satisfaction	0.744			
Perceived Ease of Use	0.384	0.464		
Perceived Usefulness	0.703	0.570	0.368	

3.4 The Model's Goodness of Fit

In Structural equation modeling (SEM), there are mainly two perspectives along with reference to model's goodness of fit. In the first perspective, the goal for applied researchers should be to demonstrate that a model is a fair approximation of actual events as reflected in a set of data. It is typically suggested that multiple approaches to fit assessment be utilized to accomplish this (MacCallum, 1990). These can be merely descriptive, comparing the fitted model to another model, such as a saturated model, or to an independence model (Bentler & Bonett, 1980). In this light, determining whether the model perfectly matches the data looks nearly unnecessary.

For the alternative viewpoint, the quality of conclusions derived from the fitted model is an issue. Assessing the precise fit of a model is essential from this perspective because it allows statistical conclusions on parameter estimates if alternative similar models can be ruled out theoretically and the power of the test is sufficient. (Bentler & Satorra, 2010; MacCallum et al., 1993).

In order to measure the mean absolute value of the covariance residuals, and to analyze the difference between the observed correlation and the model implied correlation matrix we will use the Standardized Root Mean Square Residual (SRMR) as a popular standardized effect size of misfit (Maydeu-Olivares, 2017; Benitez et al., 2020). The results show that Standardized Root Mean Square Residual (SRMR) is smaller than 0.080 as suggested by (Benitez et al., 2020). Hence the model is acceptable.

Table.9 Model Fit Results

Criterion	*Estimated Model*
SRMR	**0.046**
d-ULS	0.253
d-G	0.162
Chi-Square	278.051
NFI	0.892

3.5 Analysis of The Structural Model

A path analysis is made in PLS-PM in order to examine the structural model. Table.10 shows results of path analysis and hypothesis testing. The Partial least squares regression relies upon the bootstrapping resampling technique to determine path significance. (Henseler et al., 2009), in our case, we use consistent PLS bootstrapping - all items are the reflective indicators- and a 5000 resamples were taken to accomplish the bootstrapping.

H1 estimates that Perceived ease of use has a significant effect on Perceived usefulness and as predicted from previous literature, the results show a significant (t-value =4.446, p-value = .000) effect of PEOU on PU, thus the first hypothesis is supported. The H2 evaluates the effect of Perceived usefulness on Continuance intention, results come with statistical significance of weights t-value =5.437 and p-value = .000, hence the hypothesis is supported.

The H3 which relies on the effect of Perceived ease of use on Continuance intention, give a result with a very low absolute value of t-value = 0.033, which leads to a p-value with .973, hence the H3 is not supported. The hypotheses relating to the mediating variable satisfaction are respectively H4, H5, H6. The effect of satisfaction on Continuance intention is estimated by H4, both t-value and p-value are significant, the effect of Perceived usefulness on satisfaction estimated by H5 (t-value =5.437, p-value = .000), and the effect of Perceived ease of use on satisfaction is estimated by H6 (t-value =3.177, p-value = .000). Hence all of the H4, H5, and H6 are supported.

Table.10 Hypothesis Assessment Results

N	*Hypothesis*			*Original Sample*	*Sample Mean*	*Std*	*t-value*	*p-value*	*Decision*
H1	PEOU	>>>	PU	0.373	0.376	0.084	4.446	0.000	Supported
H2	PU	>>>	CI	0.416	0.413	0.076	5.437	0.000	Supported
H3	PEOU	>>>	CI	-0.002	0.001	0.073	0.033	**0.973**	**Not Supported**
H4	SAT	>>>	CI	0.508	0.508	0.075	6.727	0.000	Supported
H5	PU	>>>	SAT	0.416	0.413	0.076	5.437	0.000	Supported
H6	PEOU	>>>	SAT	0.289	0.291	0.091	3.177	0.001	Supported

After analyzing the total effect which is equivalent to the sum of the direct and indirect effect of constructs through mediation. The findings of total effect in the table.11 show that even there is no direct effect of PEOU on CI, but still there is an indirect effect of PEOU in CI over PU. The hypothesis H3 is not supported, but there is an indirect effect of PEOU on CI.

Table.10 Total Effect Results

Number	*Hypothesis*			*Original Sample*	*Sample Mean*	*Std*	*t-value*	*p-value*
H1	PEOU	>>>	PU	0.373	0.376	0.084	4.446	0.000
H2	PU	>>>	CI	0.652	0.648	0.064	10.224	0.000
H3	PEOU	>>>	CI	0.387	0.391	0.089	4.370	0.000
H4	SAT	>>>	CI	0.508	0.508	0.075	6.727	0.000
H5	PU	>>>	SAT	0.465	0.463	0.082	5.690	0.000
H6	PEOU	>>>	SAT	0.462	0.464	0.082	5.624	0.000

3.6 Testing Group Differences

In order to detect if there is a significant difference between groups in our sample, we will use an independent t-test to analyze differences between two groups (Gender), and ANOVA (Analysis of variance) to understand if there is a significant difference between several groups (e.g., Occupation).

For Gender, there is a significant difference just for Perceived Usefulness (PU4) with Sig = 0.024, and for User satisfaction (SAT5) with Sig. = 0.013. For all other variables, there is no significant difference between gender groups (See Appendix.2 for more details).

For Age groups, there is no significant difference between all items of the constructs see appendix.3. For educations as we can see in the table.12 just Perceived Usefulness (PU1) and User Satisfaction (SAT3) had a significant difference between groups, respectively with Sig. = 0.004 and 0.006. About groups of Occupation, User Satisfaction had, in general, a significant difference Sig. 0.008, and Continuance intention (CI1) with 0.007. All other constructs did not have any significant differences between groups check the appendix part for more detailed statistical information.

Table.12 Group Differences Results

Perceived Usefulness (PU4) *	**Gender**	**N**	**Mean**	**SD**	**t**	**Sig.**
	Women	198	1.88	0.875	-2.257	0.024
	Men	143	2.09	0.856		
User Satisfaction (SAT5) *	**Gender**	**N**	**Mean**	**SD**	**t**	**Sig.**
	Women	198	1.90	0.797	-2.509	0.013
	Men	143	2.14	0.938		
Perceived Usefulness (PU1) *	**Education**	**N**	**Mean**	**SD**	**F**	**Sig.**
	High School (1)	20	2.30	0.865	4.611	0.004
	Bachelor (2)	132	1.91	0.796		
	Master (3)	168	2.13	0.884		
	PHD (4)	13	2.69	0.947		
User Satisfaction (SAT3) *	**Education**	**N**	**Mean**	**SD**	**F**	**Sig.**
	High School (1)	20	1.92	0.808	4.286	0.006
	Bachelor (2)	132	2.11	0.768		
	Master (3)	168	1.80	0.422		
	PHD (4)	13	1.83	0.983		
User Satisfaction (SAT)	**Occupation**	**N**	**Mean**	**SD**	**F**	**Sig.**
	Self-employed/Freelancer (1)	20	2.03	0.75	3.551	0.008
	Interning (2)	35	2.06	0.73		
	Student (3)	151	1.86	0.77		
	Employed (4)	107	2.15	0.80		
	Unemployed (5)	20	2.40	0.95		
Continuance intention (CI1) *	**Occupation**	**N**	**Mean**	**SD**	**F**	**Sig.**
	Self-employed/Freelancer (1)	20	1.75	0.550	3.598	0.007
	Interning (2)	35	2.00	0.686		
	Student (3)	151	1.80	0.775		
	Employed (4)	107	2.04	0.823		
	Unemployed (5)	20	2.40	1.046		

*Represent the item which give a significant level of difference between group.

4. Discussion

This research was conducted in terms of understanding the post-usage behavior of continuance intention to use chatbots by Moroccan users. In order to analyze this issue, we used the most important construct of TAM, Perceived ease of use (PEOU), and Perceived usefulness (PU) (Davis, 1989), and we add to our conceptual model the variable User satisfaction as a mediator variable between the previous constructs and our dependent variable Continuance intention (CI). Particularly this study tried to determine the role of user satisfaction in TAM, as there are few studies about including satisfaction into TAM, especially within the context of chatbots and post-usage behavior (Continuance intention).

In order to understand the relationships between our constructs and the effect of PEOU, PU, and User satisfaction on Continuance intention in our conceptual model, hypotheses in table.1 were tested using the partial least squares path modeling via Smart-PLS. The results of our analysis will be discussed in the following sections.

4.1. Perceived Ease of Use and Perceived Usefulness

In the literature at the TAM level and as mentioned by (Davis, 1989), the perceived ease of use determines the perceived usefulness of a new technology. These two constructs, perceived usefulness and perceived ease of use, are, according to the TAM (Davis, 1989), are the essential determinants of an individual's attitude towards the use of a technology given and are therefore the determinants of its intention to use and actual use behavior. With our research, we go beyond the first stage of adoption of certain technology and we use those two constructs in the context of post-usage behavior, like the research of (Hong et al., 2016), where they used the TAM's constructs to compare it with results of new models like EECM-IT in post-adoption intention to continue IT usage. First of all, and as it was expected the perceived ease of use has a significant effect on perceived usefulness. In the context of using a chatbot, the usefulness of a chatbot is favorably

perceived when the effort required for its use is low. When the chatbot have a user-friendly platform and do not have some barriers that could block users to use the service easily (e.g., install a plugging, or asked to log in), these criteria led to consider the service usefulness.

4.2. The Influence of PU and PEOU on Continuance Intention

As we already see in the literature there are some researches that showed the significant effect of both perceived ease of use and perceived usefulness on continuance intention in the context of post-usage behavior of an IT system, and especially for chatbot (Bhattacherjee 2001; Lin, 2011; Hong et al., 2016; Ashfaq et al., 2020). In the other hand there are findings in some researches which indicates that one of the TAM's construct had more significant effect than other, for instance in study of (Ifinedo, 2006), the researcher found that perceived ease of use had a positive relationship with continuance intention, on the contrary of perceived usefulness did not have a significant relationship. The same finding in a study of (Sørebø, 2004) the perceived usefulness did not represent a meaningful relationship with continuance intention.

In our research, the findings showed that perceived usefulness has a significant effect on determining whether the Moroccan user will continue using the chatbot service or not. While analyzing our structural model the hypotheses relating to evaluating the effect of perceived usefulness on continuance intention comes with significant statistical results. Which does not match with findings of (Ifinedo, 2006) and (Sørebø, 2004). But it goes in the same line with what was suggested by (Bhattacherjee, 2001) the users' continuance intention for technology-centered on perceived usefulness, and in the context of the chatbot (Ashfaq et al., 2020).

Therefore, for perceived ease of use, the findings showed that there is no direct effect of perceived ease of use on continued intention to use the chatbot service. After analyzing the total effect, it appears that perceived ease of use has an indirect effect on continuance intention, this indirect effect is related with the relationship between perceived ease of use and perceived usefulness. Hence, we can presume that perceived ease of use has an indirect effect on continuance intention over perceived usefulness.

4.3. User Satisfaction

In our research the user satisfaction has a crucial function in understanding the continuance intention to use chatbots by Moroccan users and has a vital function to analyze the effect of previous TAM's construct perceived ease of use and perceived usefulness on continuance intention. Within the context of post-adoption usage behavior (Hong et al., 2016), confirm the influence of TAM's constructs PU, and PEOU on satisfaction. Adding to the traditional theory TAM user satisfaction and went beyond the first stage of adoption to continued IT usage behavior, is one of the main contributions of this research. Using user satisfaction as mediating variable between previous variables and continuance intention is the second contribution and led us to understand more the relationship between those variables within chatbot context in post usage behavior.

Our findings showed that both perceived ease of use and perceived usefulness had a significant effect on user satisfaction. With a chatbot service, users, when they found that the service provided, is ease to use (no high technical level required), and the chatbot helps them to carry out what they asked for, (high level of usefulness) which leads to a high level of satisfaction with the service and the user have the intention to continue using the service, same findings with (Ashfaq et al., 2020). In the chatbot context (Ashfaq et al., 2020), got the same findings as (Bhattacherjee 2001; Boakye et al., 2014) about the effect of satisfaction on continuance intention. The continuance intention of users is mainly predicted by their level of satisfaction within the information system context. In our research, the user satisfaction has the biggest effect on continuance intention, on one hand, represent the important role that played -mediating variable- between TAM's constructs and continuance intention, and on the other hand the predicting power of user's continuing intention to use the chatbot service by Moroccan users.

5. Conclusion

This research was conducted to analyze the effect of using TAM's construct beyond the first stage of adoption on Moroccan user's continuance intention to use a chatbot, the main purpose of the study is to include user satisfaction as mediating variable between previous constructs in order to determine the importance of user's level of satisfaction with chatbot service and how it affects directly the continuance intention and overall, the relationship.

TAM's construct has been used in many models in order to analyze behavior and comportment of users in post usage especially in the context of chatbot within customer service, this research is conducted within the Moroccan user chatbot service and as we mentioned in the previous, chatbot as an AI technology has received limited attention both in the practice economic world and academic research in Morocco. The reason behind this is related to the overall situation of AI in Morocco, the majority of companies still in the "Data Engineering" phase they are working on data, trying to collect it, digitize it, facilitate access and analyze it. But still, there is important to analyze and understand the behavior of users after having the experience, even there are few chatbots in the Moroccan customer service market, WIN by INWI is one of the companies that was the earliest to provide such service. Hence, it comes fundamental to analyze this new service technology using TAM's construct within post-usage behavior and the effect of user satisfaction after experience the service, on the intention to continue using it. After reviewing the literature, a list of hypotheses was cited. A survey was developed and distributed to chatbot Moroccan users in the French language -using adequate literature and back translation technique- in order to analyze the relationship between our constructs. The hypothesis sited was tested using the partial least squares path modeling via Smart-PLS. Consequently, our findings showed that user satisfaction was the most powerful predictor of continuance intention, and it played an important role between TAM's constructs and continuance intention. Both perceived ease of use and perceived usefulness had a significant effect on user satisfaction, perceived usefulness has a significant direct effect on continuance intention, while perceived ease of use -Which has a significant effect on perceives us fullness- has not a direct effect on continuance intention which supports the findings of (Yuan et al., 2016). Nonetheless, it has an indirect effect on continuance intention through perceived usefulness. When a chatbot user feel there is the low effort required to use such service (perceived ease of use guaranteed) the usefulness is favorably perceived, in

another way when the chatbot have a user-friendly platform and do not have some barriers that could block users to use the service easily (e.g., install a plugging, or asked to log in), these criteria led to consider the service usefulness. Which in turn leads to satisfaction with the service and increase the intention to continue using chatbot service.

5.1. Academical Implications

The researches and studies conducted about TAM had mostly focused on the first stage of adoption, as long as TAM is considered as a traditional theory to analyze the behavior of customers there are few studies that use the constructs of TAM in the post usage behavior especially within the context of chatbot. Based on the findings of this research the perceived ease of use has not a direct effect on continuance intention to use chatbot service, same findings with (Yuan et al., 2016). Nonetheless, perceived ease of use has an indirect effect on continuance intention through perceived usefulness. Furthermore, beyond taking the TAM's construct into post usage behavior, satisfaction played an essential role in this research, by putting user satisfaction as a mediating variable between previous constructs. This research show and demonstrate by using the traditional TAM's construct and satisfaction the level that we can reach to predict user continuance intention to use chatbot.

5.2. Managerial Implications

In general, AI represents a major opportunity for Morocco, there are currently eight sectors mature enough to take full advantage of these technologies: banking, telecoms, insurance, automotive industry, agriculture, energy, self-entrepreneurship, and e-gov (*McKinsey & Company, 2018)*. Although, not all sectors benefit from the same degree of maturity to be able to accommodate this type of technology. Chatbots as an AI technology, offer a range of potential benefits in a variety of sectors. However, this new type of human-machine interface technology has received limited attention both in the practice economic world and academic research in Morocco. Therefore, this study could be considered as the first academic research within the context of post usage behavior, of Moroccan chatbot users. Our research showed the importance

of TAM's constructs and satisfaction on predicting the intention to continue using the chatbot service. This research could provide some insight for companies that use the chatbot technology in their customer service, and help them to improve their functional chatbot service.

5.3. Limitation

This study has some limitations in terms of different aspects. Firstly, the sample size was limited because the survey participants were 400 to analyze the post usage behavior of Moroccan chatbot users in general. Secondly, the first or pre- usage behavior was negligent due to the technical problem accrued while trying to contact companies (BotFactory, INWI) that has conduct analysis to determine the intention of Moroccan user to adopt the new chatbot technology and switch from traditional online human customer service assistant. Finally, this research did not add take into consideration other constructs in the conceptual framework model, and its due to how the complexity and understandability of the survey will be in front of Moroccan users.

5.4. Further Research Direction

Further research is needed to extend the conceptual model to better understand the behavior of Moroccan users both in the adoption stage of the technology and in the post usage behavior. The variables of the alternative model discussed in the literature could be used in future research, as we could add variables such as subjective norms, positive and negative reactions to a future research model. Since the chatbot service in Moroccan still in the beginning stage, a more detailed analysis is requested to favor the adoption and continuance intention to use this technology.

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APPENDIX 1. Measures of Central Tendency and Dispersion

VARIABLES	QST NO.	MISSING	MEAN	MEDIAN	MIN	MAX	STANDARD DEVIATION	EXCESS KURTOSIS	SKEWNESS
PEOU1	1	0	1.547	1	1	5	0.668	**2.379**	**1.257**
PEOU2	2	0	1.883	2	1	5	0.768	0.355	0.643
PEOU3	3	0	1.847	2	1	5	0.785	0.623	0.801
PEOU4	4	0	1.655	2	1	5	0.726	**1.846**	**1.156**
PU1	5	0	2.072	2	1	5	0.863	0.076	0.591
PU2	6	0	2.168	2	1	5	0.915	-0.408	0.417
PU3	7	0	2.183	2	1	5	0.917	0.012	0.569
PU4	8	0	1.967	2	1	5	0.871	1.313	0.968
SAT1	9	0	1.958	2	1	5	0.738	1.335	0.742
SAT2	10	0	2.012	2	1	5	0.747	1.207	0.718
SAT3	11	0	1.964	2	1	5	0.793	1.803	0.971
SAT4	12	0	2.162	2	1	5	0.851	0.278	0.564
SAT5	13	0	1.997	2	1	5	0.865	1.354	0.958
CII1	14	0	1.931	2	1	5	0.801	1.433	0.937
CI2	15	0	2.306	2	1	5	0.957	0.075	0.656
CI3	16	0	2.123	2	1	5	0.914	0.527	0.75

APPENDIX 2. T-test Group Gender

Independent Samples Test

		t-test for Equality of Means				
		t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
PEOU1	EVA	1.751	331	0.081	0.130	0.074
	EVNA	1.787	318.803	0.075	0.130	0.073
PEOU2	EVA	0.231	331	0.817	0.020	0.086
	EVNA	0.235	317.281	0.814	0.020	0.084
PEOU3	EVA	-0.909	331	0.364	-0.079	0.087
	EVNA	-0.899	286.244	0.370	-0.079	0.088
PEOU4	EVA	-0.358	331	0.720	-0.029	0.081
	EVNA	-0.357	296.977	0.721	-0.029	0.081
PU1	EVA	-1.015	331	0.311	-0.097	0.096
	EVNA	-1.000	282.013	0.318	-0.097	0.097
PU2	EVA	-0.297	331	0.766	-0.030	0.102
	EVNA	-0.294	286.121	0.769	-0.030	0.103
PU3	EVA	-1.010	331	0.313	-0.103	0.102
	EVNA	-1.010	298.890	0.314	-0.103	0.102
PU4	EVA	-2.257	331	0.025	-0.217	0.096
	EVNA	-2.265	303.440	0.024	-0.217	0.096
SAT1	EVA	-0.133	331	0.894	-0.011	0.082
	EVNA	-0.131	281.948	0.896	-0.011	0.083
SAT2	EVA	-1.684	331	0.093	-0.139	0.083
	EVNA	-1.665	286.932	0.097	-0.139	0.084
SAT3	EVA	-0.704	331	0.482	-0.062	0.088
	EVNA	-0.704	299.436	0.482	-0.062	0.088
SAT4	EVA	-1.605	331	0.109	-0.152	0.094
	EVNA	-1.556	262.236	0.121	-0.152	0.097
SAT5	EVA	-2.509	331	0.013	-0.239	0.095
	EVNA	-2.445	269.128	0.015	-0.239	0.098
CI1	EVA	-0.923	331	0.357	-0.082	0.089
	EVNA	-0.930	306.864	0.353	-0.082	0.088
CI2	EVA	-1.523	331	0.129	-0.162	0.106
	EVNA	-1.539	310.256	0.125	-0.162	0.105
CI3	EVA	-1.920	331	0.056	-0.194	0.101
	EVNA	-1.889	280.994	0.060	-0.194	0.103

*EVA Equal variances assumed

EVNA Equal variances not assumed

APPENDIX 3. One way ANOVA by Age

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
PEOU1	Between Groups	.988	3	.329	.735	.532
	Within Groups	147.540	329	.448		
	Total	148.529	332			
PEOU2	Between Groups	1.502	3	.501	.845	.470
	Within Groups	194.931	329	.592		
	Total	196.432	332			
PEOU3	Between Groups	2.639	3	.880	1.429	.234
	Within Groups	202.550	329	.616		
	Total	205.189	332			
PEOU4	Between Groups	1.838	3	.613	1.162	.324
	Within Groups	173.448	329	.527		
	Total	175.285	332			
PU1	Between Groups	.409	3	.136	.181	.909
	Within Groups	247.861	329	.753		
	Total	248.270	332			
PU2	Between Groups	2.314	3	.771	.918	.432
	Within Groups	276.269	329	.840		
	Total	278.583	332			
PU3	Between Groups	1.559	3	.520	.614	.606
	Within Groups	278.267	329	.846		
	Total	279.826	332			
PU4	Between Groups	3.022	3	1.007	1.328	.265
	Within Groups	249.615	329	.759		
	Total	252.637	332			
SAT1	Between Groups	.369	3	.123	.224	.880
	Within Groups	181.042	329	.550		
	Total	181.411	332			
SAT2	Between Groups	1.889	3	.630	1.126	.339
	Within Groups	184.062	329	.559		
	Total	185.952	332			
SAT3	Between Groups	2.521	3	.840	1.335	.263

	Within Groups	207.047	329	.629		
	Total	209.568	332			
SAT4	Between Groups	2.734	3	.911	1.257	.289
	Within Groups	238.510	329	.725		
	Total	241.243	332			
SAT5	Between Groups	2.653	3	.884	1.181	.317
	Within Groups	246.344	329	.749		
	Total	248.997	332			
CI1	Between Groups	.931	3	.310	.481	.696
	Within Groups	212.480	329	.646		
	Total	213.411	332			
CI2	Between Groups	.589	3	.196	.212	.888
	Within Groups	304.168	329	.925		
	Total	304.757	332			
CI3	Between Groups	1.799	3	.600	.714	.544
	Within Groups	276.153	329	.839		
	Total	277.952	332			

APPENDIX 4. One way ANOVA by Education

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
PEOU1	Between Groups	.229	3	.076	.169	.917
	Within Groups	148.300	329	.451		
	Total	148.529	332			
PEOU2	Between Groups	2.259	3	.753	1.276	.283
	Within Groups	194.174	329	.590		
	Total	196.432	332			
PEOU3	Between Groups	.830	3	.277	.445	.721
	Within Groups	204.359	329	.621		
	Total	205.189	332			
PEOU4	Between Groups	3.827	3	1.276	2.448	.064
	Within Groups	171.459	329	.521		
	Total	175.285	332			
PU1	Between Groups	10.017	3	3.339	4.611	.004
	Within Groups	238.253	329	.724		
	Total	248.270	332			
PU2	Between Groups	3.002	3	1.001	1.195	.312
	Within Groups	275.580	329	.838		
	Total	278.583	332			
PU3	Between Groups	3.200	3	1.067	1.269	.285
	Within Groups	276.626	329	.841		
	Total	279.826	332			
PU4	Between Groups	1.864	3	.621	.815	.486
	Within Groups	250.773	329	.762		
	Total	252.637	332			
SAT1	Between Groups	2.992	3	.997	1.839	.140
	Within Groups	178.419	329	.542		
	Total	181.411	332			
SAT2	Between Groups	2.870	3	.957	1.719	.163
	Within Groups	183.082	329	.556		
	Total	185.952	332			
SAT3	Between Groups	7.883	3	2.628	4.286	.006
	Within Groups	201.685	329	.613		

	Total	209.568	332			
SAT4	Between Groups	.295	3	.098	.134	.940
	Within Groups	240.948	329	.732		
	Total	241.243	332			
SAT5	Between Groups	3.746	3	1.249	1.675	.172
	Within Groups	245.251	329	.745		
	Total	248.997	332			
CI1	Between Groups	3.561	3	1.187	1.861	.136
	Within Groups	209.850	329	.638		
	Total	213.411	332			
CI2	Between Groups	.579	3	.193	.209	.890
	Within Groups	304.177	329	.925		
	Total	304.757	332			
CI3	Between Groups	5.474	3	1.825	2.203	.088
	Within Groups	272.478	329	.828		
	Total	277.952	332			

APPENDIX 5. One way ANOVA by Occupation

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
PEOU1	Between Groups	2.430	4	.608	1.364	.246
	Within Groups	146.098	328	.445		
	Total	148.529	332			
PEOU2	Between Groups	3.512	4	.878	1.493	.204
	Within Groups	192.920	328	.588		
	Total	196.432	332			
PEOU3	Between Groups	4.829	4	1.207	1.976	.098
	Within Groups	200.360	328	.611		
	Total	205.189	332			
PEOU4	Between Groups	1.716	4	.429	.811	.519
	Within Groups	173.570	328	.529		
	Total	175.285	332			
PU1	Between Groups	4.251	4	1.063	1.429	.224
	Within Groups	244.019	328	.744		
	Total	248.270	332			
PU2	Between Groups	4.520	4	1.130	1.352	.250
	Within Groups	274.063	328	.836		
	Total	278.583	332			
PU3	Between Groups	3.609	4	.902	1.071	.371
	Within Groups	276.217	328	.842		
	Total	279.826	332			
PU4	Between Groups	4.385	4	1.096	1.448	.218
	Within Groups	248.251	328	.757		
	Total	252.637	332			
SAT1	Between Groups	7.801	4	1.950	3.685	.006
	Within Groups	173.610	328	.529		
	Total	181.411	332			
SAT2	Between Groups	7.959	4	1.990	3.667	.006
	Within Groups	177.993	328	.543		
	Total	185.952	332			
SAT3	Between Groups	8.341	4	2.085	3.399	.010
	Within Groups	201.227	328	.613		

	Total	209.568	332			
SAT4	Between Groups	9.641	4	2.410	3.413	.009
	Within Groups	231.603	328	.706		
	Total	241.243	332			
SAT5	Between Groups	10.453	4	2.613	3.593	.007
	Within Groups	238.544	328	.727		
	Total	248.997	332			
CI1	Between Groups	8.971	4	2.243	3.598	.007
	Within Groups	204.440	328	.623		
	Total	213.411	332			
CI2	Between Groups	8.498	4	2.125	2.352	.054
	Within Groups	296.258	328	.903		
	Total	304.757	332			
CI3	Between Groups	4.243	4	1.061	1.271	.281
	Within Groups	273.709	328	.834		
	Total	277.952	332			

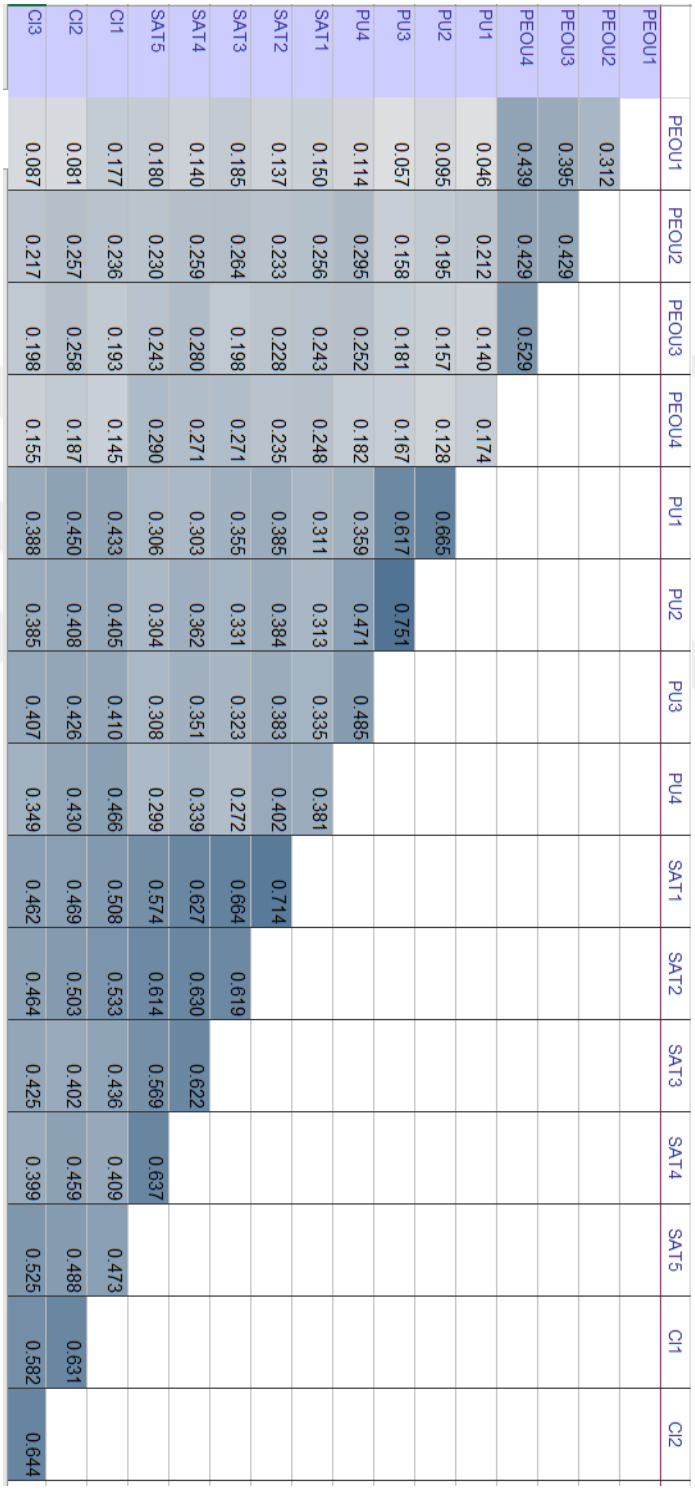
APPENDIX 6. One way ANOVA by Marital Status

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
PEOU1	Between Groups	.135	2	.068	.150	.861
	Within Groups	148.187	329	.450		
	Total	148.322	331			
PEOU2	Between Groups	1.135	2	.567	.956	.385
	Within Groups	195.284	329	.594		
	Total	196.419	331			
PEOU3	Between Groups	2.841	2	1.421	2.310	.101
	Within Groups	202.324	329	.615		
	Total	205.166	331			
PEOU4	Between Groups	1.871	2	.935	1.776	.171
	Within Groups	173.295	329	.527		
	Total	175.166	331			
PU1	Between Groups	1.103	2	.552	.734	.481
	Within Groups	247.162	329	.751		
	Total	248.265	331			
PU2	Between Groups	.533	2	.266	.317	.729
	Within Groups	276.681	329	.841		
	Total	277.214	331			
PU3	Between Groups	.105	2	.053	.062	.940
	Within Groups	278.317	329	.846		
	Total	278.422	331			
PU4	Between Groups	.649	2	.325	.425	.654
	Within Groups	251.050	329	.763		
	Total	251.699	331			
SAT1	Between Groups	1.716	2	.858	1.571	.209
	Within Groups	179.694	329	.546		
	Total	181.410	331			
SAT2	Between Groups	3.059	2	1.529	2.751	.065
	Within Groups	182.893	329	.556		
	Total	185.952	331			
SAT3	Between Groups	1.832	2	.916	1.451	.236
	Within Groups	207.734	329	.631		

	Total	209.566	331			
SAT4	Between Groups	1.393	2	.697	.956	.386
	Within Groups	239.824	329	.729		
	Total	241.217	331			
SAT5	Between Groups	1.085	2	.543	.720	.487
	Within Groups	247.912	329	.754		
	Total	248.997	331			
CI1	Between Groups	.371	2	.185	.288	.750
	Within Groups	211.894	329	.644		
	Total	212.265	331			
CI2	Between Groups	.893	2	.447	.484	.617
	Within Groups	303.381	329	.922		
	Total	304.274	331			
CI3	Between Groups	2.810	2	1.405	1.680	.188
	Within Groups	275.126	329	.836		
	Total	277.937	331			

APPENDIX 7. Correlation Matrix of the Constructs



	PEOU1	PEOU2	PEOU3	PEOU4	PU1	PU2	PU3	PU4	SAT1	SAT2	SAT3	SAT4	SAT5	CI1	CI2
PEOU1															
PEOU2	0.312														
PEOU3	0.395	0.429													
PEOU4	0.439	0.429	0.529												
PU1	0.046	0.212	0.140	0.174											
PU2	0.095	0.195	0.157	0.128	0.665										
PU3	0.057	0.158	0.181	0.167	0.617	0.751									
PU4	0.114	0.295	0.252	0.182	0.359	0.471	0.485								
SAT1	0.150	0.256	0.243	0.248	0.311	0.313	0.335	0.381							
SAT2	0.137	0.233	0.228	0.235	0.385	0.384	0.383	0.402	0.714						
SAT3	0.185	0.264	0.198	0.271	0.355	0.331	0.323	0.272	0.664	0.619					
SAT4	0.140	0.259	0.280	0.271	0.303	0.362	0.351	0.339	0.627	0.630	0.622				
SAT5	0.180	0.230	0.243	0.290	0.306	0.304	0.308	0.299	0.574	0.614	0.569	0.637			
CI1	0.177	0.236	0.193	0.145	0.433	0.405	0.410	0.466	0.508	0.533	0.436	0.409	0.473		
CI2	0.081	0.257	0.258	0.187	0.450	0.408	0.426	0.430	0.469	0.503	0.402	0.459	0.488	0.631	
CI3	0.087	0.217	0.198	0.155	0.388	0.385	0.407	0.349	0.462	0.464	0.425	0.399	0.525	0.582	0.644

APPENDIX 8. Questionnaire in English

QUESTIONNAIRE

Dear participant,

Thank you for taking part in my study and helping me to complete my thesis about Customers' perception and attitude towards chatbots' adoption. This research aims to analyze the impact of using chatbots in customer experience and how customers accept this technology. Understanding the relationship between motives for using chatbot and satisfaction with chatbot characteristics.

> ***No worries, this is a brief description of what a chatbot is?***
>
> ***Chatbots belong to the category of software agents called interface agents. Chatbots allow humans to interact with the computer based on a natural language, whether text-based or voice-based. They are often used in customer service. For example, a customer could ask the bot a question or give it an instruction and the bot could respond or perform an action as appropriate.***

Please read all the questions carefully and answer them according to your reality. There are no right or wrong answers. Your participation will be anonymous and full confidentiality will be guaranteed when processing the data provided.

Part I

1. **Have you ever used a chatbot?**
   - o Yes
   - o No

2. **What website (App) did you use the chatbot on last time?**

Short open question

Please indicate how strongly you agree or disagree with all the following statements from 1 (strongly agree) to 5 (strongly disagree).

			Strongly Agree	Agree	Neutral	Disagree	Strongly disagree
			1	2	3	4	5
Perceived Usefulness (PU)	**3.**	Using chatbot would improve my performance.					
	4.	Using chatbot would increase my productivity.					
	5.	Using chatbot would enhance my effectiveness.					
	6.	I would find chatbot useful to perform my daily activities.					
Perceived ease of use (PEOU)	**7.**	Learning to operate chatbot would be easy for me.					
	8.	I would find it easy to get chatbot to do what I want them to do.					
	9.	It would be easy for me to become skillful at using chatbot.					
	10.	I would find chatbot easy to use.					
User Satisfaction (SAT)	**11.**	I am satisfied with the chatbot.					
	12.	I am content with the chatbot.					
	13.	The chatbot did a good job.					
	14.	The chatbot did what I expected.					
	15.	I was satisfied with the experience of talking with the chatbot.					
Continuance intention (CI)	**16.**	I intend to continue using this chatbot in the future.					
	17.	I believe it is difficult to use the chatbot.					
	18.	I will always try to use this chatbot in my daily life.					

Part II

19.What is your gender?

- Female
- Male

20.What is your age?

21. What is your occupation?

- Self-employed/Freelancer
- Employee
- Unemployed
- Interning
- Studying
- Other

22.What is your highest degree or level you have completed?

- High school
- Bachelor
- Master
- PHD

23.What is your current marital status?

- Single
- Married
- Divorced
- Rather not to say

APPENDIX 9. Questionnaire in French

QUESTIONNAIRE

Cher participant,

Merci d'avoir participé à mon étude et de m'avoir aidé à terminer ma thèse sur la perception et l'attitude des clients envers l'adoption des chatbots. Cette recherche vise à analyser l'impact de l'utilisation des chatbots sur l'expérience client et comment les clients acceptent cette technologie. Comprendre la relation entre les motivations d'utilisation du chatbot et la satisfaction des caractéristiques du chatbot.

> ***Pas de soucis, ceci est une brève description de ce qu'est un chatbot ?***
>
> ***Les chatbots appartiennent à la catégorie des agents logiciels appelés agents d'interface. Les chatbots permettent aux humains d'interagir avec l'ordinateur en utilisant un langage naturel, qu'il soit textuel ou vocal. Ils sont souvent utilisés dans le service client. Par exemple, un client pourrait poser une question au bot ou lui donner une instruction et le bot pourrait répondre ou effectuer une action le cas échéant.***

Veuillez lire attentivement toutes les questions et y répondre en fonction de votre réalité. Il n'y a pas de bonnes ou de mauvaises réponses. Votre participation sera anonyme et une confidentialité totale sera garantie lors du traitement des données fournies.

Première partie

---

1. Avez-vous déjà utilisé un chatbot ?

- o Oui
- o Non

2. Sur quel site Web (App) avez-vous utilisé le chatbot la dernière fois ?

Courte question ouverte

Veuillez indiquer dans quelle mesure vous êtes d'accord ou en désaccord avec toutes les affirmations suivantes de 1 (tout à fait d'accord) à 5 (pas du tout d'accord).

			Tout à fait d'accord	D' accord	Neutre	N' est pas d'accord	Pas du tout d'accord
			1	2	3	4	5
L'Utilité perçue	**3.**	Apprendre à utiliser le chatbot serait facile pour moi					
	4.	Je trouverais facile de faire en sorte que le chatbot fasse ce que je veux qu'il fasse					
	5.	Il me serait facile de devenir habile à utiliser le chatbot					
	6.	Je trouverais le chatbot facile à utiliser					
Facilité d'utilisation perçue	**7.**	Utiliser le chatbot améliorerait mes performances					
	8.	Utiliser un chatbot augmenterait ma productivité					
	9.	Utiliser un chatbot améliorerait mon efficacité					
	10.	Je trouverais le chatbot utile pour effectuer mes activités quotidiennes					
Satisfaction du client	**11.**	Je suis satisfait du chatbot.					
	12.	Je suis content du chatbot.					
	13.	Le chatbot a fait du bon travail.					
	14.	Le chatbot a fait ce que j'attendais.					
	15.	J'ai été satisfait de l'expérience de parler avec le chatbot.					
Intention de continuité	**16.**	J'ai l'intention de continuer à utiliser ce chatbot à l'avenir.					
	17.	J'essaierai toujours d'utiliser ce chatbot dans ma vie quotidienne.					

	18.	Je recommanderai fortement aux autres de l'utiliser.					

Deuxième partie

19. Êtes-vous un homme ou une femme ?

O Femme

O Homme

20. De quelle tranche d'âge faites-vous partie ?

21. Quel est ton occupation ?

O Indépendant / Indépendant

O Employé

O Chômeur

O Stage

O Etudiant

O Autre

22. Quel est le niveau de votre formation acquise ?

O Baccalauréat

O Licence

O Master

O Doctorat

23. Quel est votre état civil ?

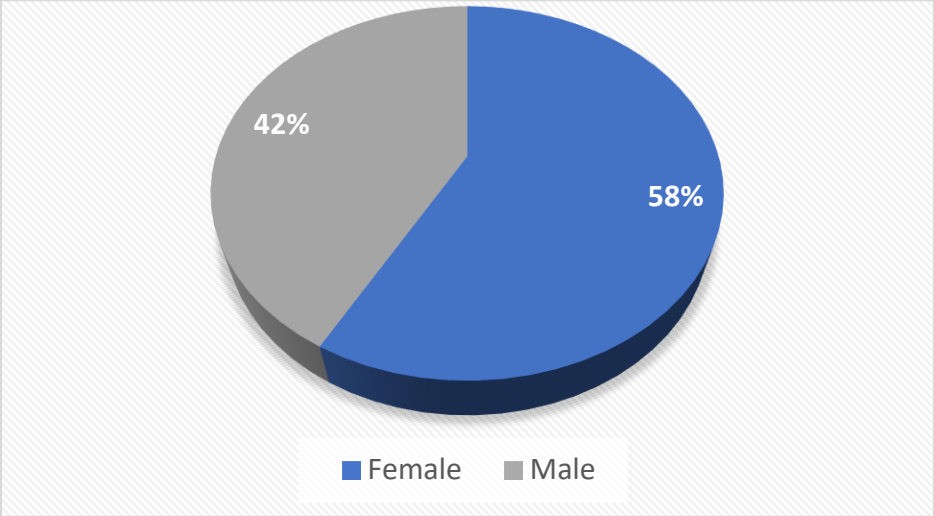
O Célibataire

O Marié

O Divorcé

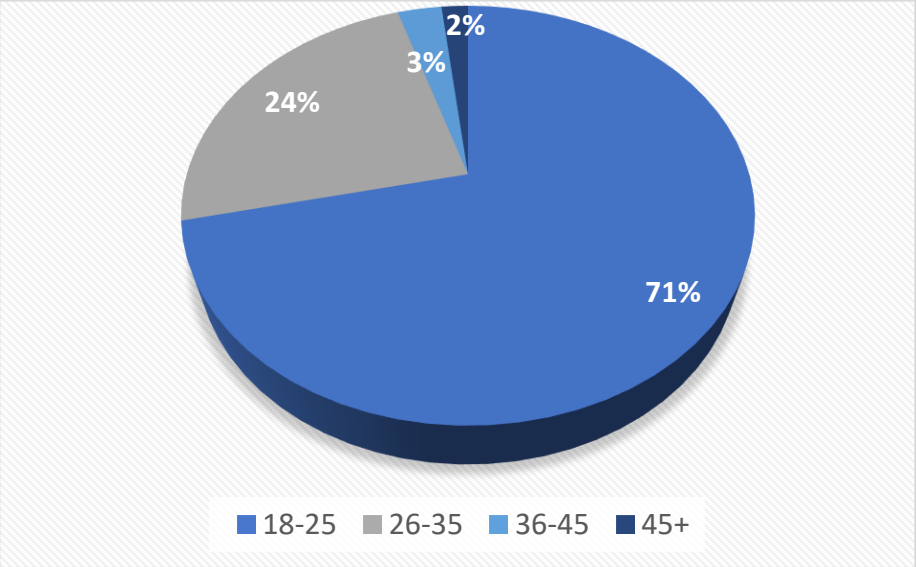
O Plutôt ne pas dire

APPENDIX 10. Simple Demographic Characteristics



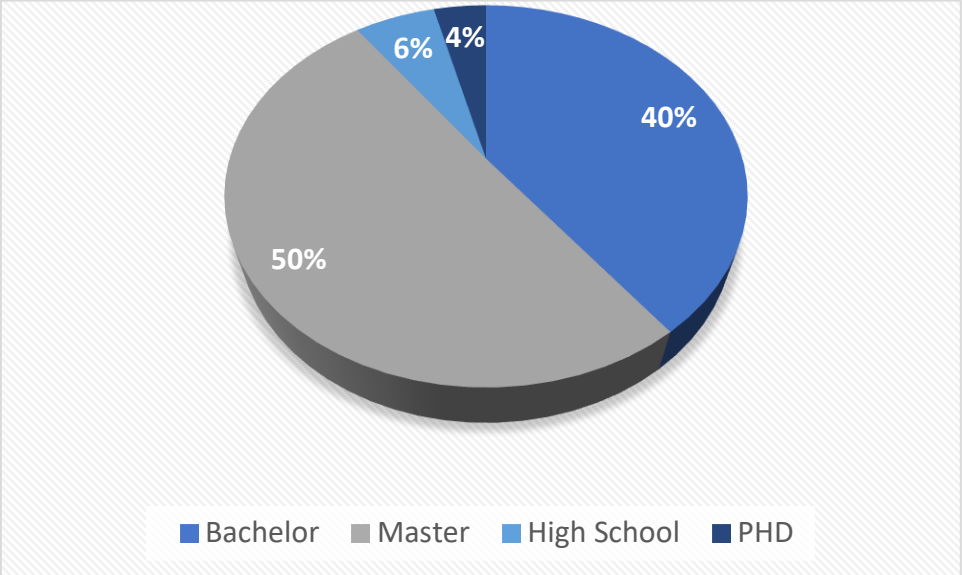
Sample's gender distribution.

Source: Computed by the Researcher



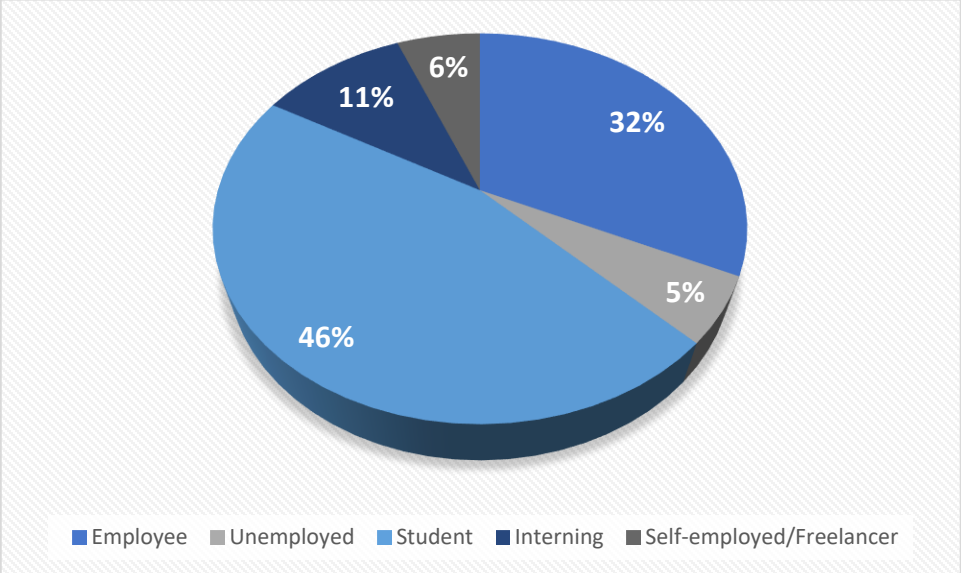
Sample's age distribution.

Source: Computed by the Researcher



Sample's Level of Education Distribution.

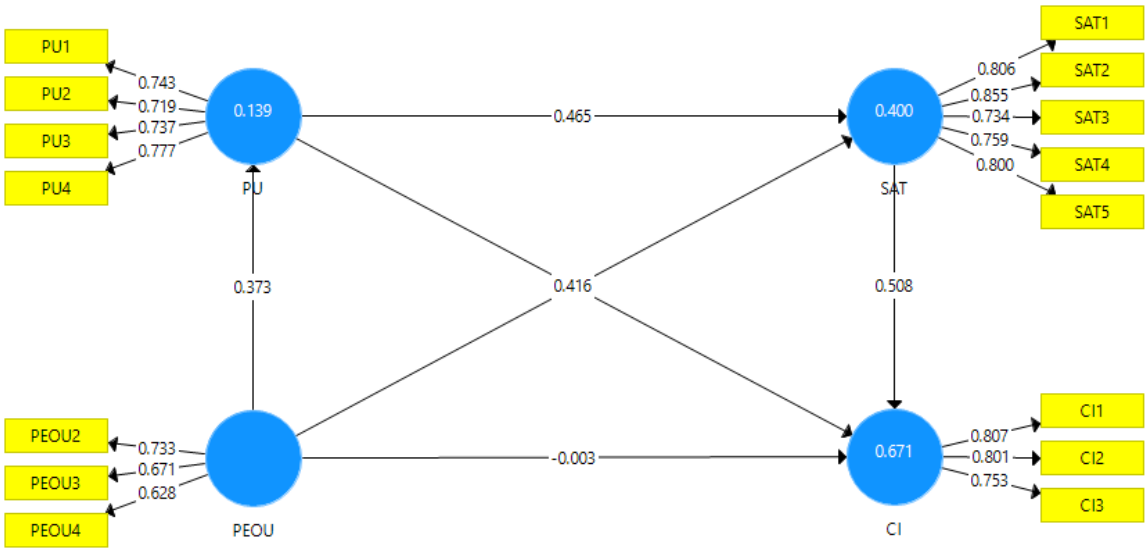
Source: Computed by the Researcher



Sample's Occupation Distribution.

Source: Computed by the Researcher

APPENDIX 11. Path Analysis of the Model



Source: Computed by the Researcher