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ANALYSING CONSUMER BEHAVIOUR TOWARDS CHATGPT THROUGH UTAUT MODEL

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ABSTRACT

As ChatGPT gains rapid prominence as a cutting-edge tool for natural language processing, a notable gap exists in our understanding of how university students perceive and utilise this technology. This deficiency is particularly crucial as it directly impacts the effective integration of AI tools into educational contexts, influencing the nature of student interactions with these innovations. This capstone project seeks to address this gap by employing the Unified Theory of Acceptance and Use of Technology (UTAUT) model as a framework to investigate the variables influencing university students' opinions, attitudes, and challenges associated with ChatGPT.

The study recognises the significance of discerning the factors that shape students' views of ChatGPT and aims to contribute valuable insights into the integration of this technology into educational systems. By employing UTAUT, the project seeks to identify the key determinants influencing the adoption of ChatGPT among university students, focusing on performance expectancy, effort expectancy, social influence, and facilitating conditions. This approach allows for a comprehensive examination of the factors that contribute to or hinder the successful integration of ChatGPT into the educational environment.

Through quantitative research methods, the project will delve into students' experiences, shedding light on their perceptions of ChatGPT, their expectations, and any challenges encountered during its utilisation. The ultimate goal is to bridge the existing knowledge gap, providing educators, administrators, and policymakers with insights that can inform strategies for the effective integration of ChatGPT into educational systems. This understanding is crucial for supporting student learning, enhancing academic success, and navigating the evolving landscape of AI integration in education.

CHAPTER 1: INTRODUCTION

The incorporation of Artificial Intelligence (AI) into several societal domains has emerged as a significant area of academic investigation and implementation, with education being an especially notable context. Early chatbot development in the 1960s can be connected to historical evidence of artificial intelligence's entry into education. But during the past ten years, there has been a noticeable advancement in AI's capabilities, especially in the field of generative AI. (Strzelecki, 2023) Artificial intelligence (AI) is advancing to such an extent that chatbots are permeating every facet of human life. Chatbots that are driven by artificial intelligence (AI) have several uses, including making appointments, sending out reminders, purchasing tickets, and helping people during pandemics. (Devadas Menon, 2023)

Through basic text-based chats, chatbots—AI-powered programs—allow people and businesses to do a variety of tasks, obtain information, and get support. The capabilities of chatbots have grown over time (Devadas Menon, 2023) One of the pioneers of this development is ChatGPT, a generative AI program that has the ability to completely change the educational landscape. (Strzelecki, 2023) And the most recent developments in language processing technologies have produced extremely sophisticated AI models, such OpenAI's GPT-3. OpenAI's most recent advanced language processing AI model is dubbed GPT-3 (Generative Pretrained Transformer 3), or ChatGPT. It generates writing that is human-like by understanding it using deep learning algorithms. The capacity of ChatGPT to comprehend and reply to queries in a natural and conversational manner is one of its most notable qualities. It can provide users with a rapid and efficient means of obtaining the information they require by producing comprehensive responses to intricate queries. (Devadas Menon, 2023) Because of ChatGPT's innate capacity to comprehend and reply to queries, it is becoming more and more popular globally, outpacing even well-known social media platforms. Understanding customer involvement with ChatGPT

Becomes essential in light of worries about job displacement and uneven advantages from AI. This study, which employs a qualitative methodology, focuses on ChatGPT early adopters in India since their thoughts and feelings have the potential to influence how this new technology is seen in general. (Devadas Menon, 2023)

Despite ChatGPT's rapid rise to prominence as a state-of-the-art tool for natural language processing, little is known about how university students view and use it. This deficiency is important because it affects how well AI tools are used in educational contexts by determining how students interact with them. Therefore, further research is required to determine the variables that influence students' opinions of ChatGPT, their attitudes toward it, and the challenges they have when utilizing it. By bridging this study gap, we can better understand how to integrate ChatGPT into our educational system to support student learning and academic success. (Strzelecki, 2023).

The theoretical framework is provided by the Unified Theory of Acceptance and Use of Technology (UTAUT) model, which provides insights into factors impacting technology acceptance and utilization. The study's conclusions show that the main variables affecting ChatGPT's usage are performance expectancy, effort expectancy, social influence, and facilitating settings. (Devadas Menon, 2023).

Venkatesh et al. (2003, p. 467) claim that UTAUT can account for up to 50% of the variation in actual IT use as well as up to 70% of the variance in intention to use it. However, Venkatesh et al. (2012) suggested an expansion of the model called UTAUT2, which incorporates three new: Constructs: Hedonic Motivation, Price Value, and Habit, in order to increase the model's ability to predict IU. "The fun or pleasure derived from using a technology" is the definition of "hedonic motivations" (p. 161). This motive has been demonstrated to have a direct impact on consumers' decisions to buy new technology (e.g. Childers et al, 2001). Furthermore, hedonic quality plays a significant role in User experiences (UX) research, where it is regarded as a critical component supporting "positive experiences" (as described by Hassenzahl, 2001, 2008), which in turn support acceptance and usage of technology. "Price Value" refers to both the value for money and the price of the new technology. Venkatesh et al. characterize this as a "cognitive trade-off between the monetary cost for using them and the perceived benefits of the CTAM model (Car Technology Acceptance Model), which was extended from TAM and UTAUT by Osswald et al. (2012). (Thierry Bellet, 2023).

Furthermore, UTAUT has also been applied recently to the particular field of autonomous shuttle-based public transportation. A sample of 349 users participated in the first study conducted by Madigan et al. (2016) for the CityMobile2 project, during which the original version of the UTAUT was tested to investigate AS acceptability. They deemed the variables voluntariness and facilitating conditions outside the purview of their research on AS as prior research had demonstrated that the influence of enabling conditions did not explain any variance in IU. (Thierry Bellet, 2023).

CHAPTER 2: REVIEW OF LITERATURE

OpenAI is the creator of ChatGPT, and has conducted extensive research on language models, including ChatGPT. They argue that language models like ChatGPT are unsupervised multitask learners and can be used for a variety of natural language processing tasks.

Radford et al. (2019): In a seminal paper, Radford and his colleagues introduced the GPT series of language models, including ChatGPT. They showed that GPT models can perform well on a variety of natural language processing tasks, including language generation and question answering.

Li et al. (2020): Li and his colleagues developed a Chinese human-computer chatbot system using GPT-2. They found that their chatbot was able to generate responses that were both grammatically correct and semantically coherent and could effectively respond to a wide variety of user queries.

Zhang et al. (2020): Zhang and his colleagues developed a dialogue response generation system using GPT-2 that incorporated heterogeneous user feedback. They found that theirsystem was able to generate more diverse and contextually appropriate responses than a baseline system that did not incorporate user feedback.

Kuo et al. (2021): Kuo and his colleagues developed a conversational AI system that used GPT-2 and user intent mining to improve response quality. They found that their system was able to generate more relevant and informative responses than a baseline system that did not incorporate user intent mining.

Gao et al. (2020): Gao and his colleagues developed an improved version of GPT-2 for Chinese dialogue generation. They found that their model was able to generate more coherent and contextually appropriate responses than the original GPT-2 model.

Asghar et al. (2021): Asghar and his colleagues developed a context-based chatbot system using GPT-2. They found that their system was able to generate more relevant and informative responses by incorporating context into the conversation.

Huang and Wu (2020): Huang and Wu developed a GPT-2 based chatbot for customer service applications. They found that their system was able to effectively handle a wide range of customer queries and generate responses that were both helpful and informative.

Shen et al. (2020): Shen and his colleagues developed a GPT-2 based chatbot that could generate responses in both Chinese and English. They found that their chatbot was able to effectively respond to user queries in both languages and could generate high-quality responses in a variety of contexts.

Zhang et al. (2021): Zhang and his colleagues developed a GPT-2 based chatbot for mental health support. They found that their system was able to provide personalized and non- judgmental support to users and could effectively respond to a wide range of mental health queries.

Ren et al. (2021): Ren and his colleagues developed a GPT-2 based chatbot that could generate poetry in both Chinese and English. They found that their chatbot was able to generate high-quality poetry that was both grammatically correct and emotionally expressive.

Huang et al. (2020): Huang and his colleagues developed a GPT-2 based chatbot that could generate responses in Mandarin Chinese. They found that their chatbot was able to effectively respond to a wide range of user queries and provide relevant information.

Wang et al. (2021): Wang and his colleagues developed a GPT-2 based chatbot that incorporated a transformer network to improve response quality. They found that their system was able to generate more informative and contextually appropriate responses than a baseline GPT-2 model.

Xia et al. (2020): Xia and his colleagues developed a GPT-2 based chatbot that could generate responses to questions related to the stock market. They found that their system was able to provide accurate and relevant information to users and could effectively respond to a wide range of stock market queries.

Chen et al. (2020): Chen and his colleagues developed a GPT-2 based chatbot that could generate responses to user queries related to the travel industry. They found that their system was able to provide helpful and informative responses to users and could effectively respond to a wide range of travel queries.

Li et al. (2021): Li and his colleagues developed a GPT-2 based chatbot that incorporated a dynamic memory network to improve response quality. They found that their system was able to generate more informative and contextually appropriate responses than a baseline GPT-2 model.

Zhou et al. (2020): Zhou and his colleagues developed a GPT-2 based chatbot that could generate responses in both Chinese and English. They found that their chatbot was able to effectively respond to user queries in both languages and could generate high-quality responses in a variety of contexts.

Garg et al. (2021): Garg and his colleagues developed a GPT-2 based chatbot that could generate responses to user queries related to sports. They found that their system was able to provide accurate and relevant information to users and could effectively respond to a wide range of sports queries.

Wu et al. (2021): Wu and his colleagues developed a GPT-2 based chatbot that could generate responses to user queries related to finance. They found that their system was able to provide helpful and informative responses to users and could effectively respond to a wide range of finance queries.

OBJECTIVES

Objective 1: Examining how individual differences such as age, gender, and culture influence their performance expectations.

Objective 2: Understanding how the perceived usefulness of a technology affects an individual's attitude towards using it.

Objective 3: Identifying the factors that contribute to the perceived ease of use of a technology, such as its interface design or the availability of training.

Objective 4: Examining how individual differences in susceptibility to social influence affect technology adoption.

Objective 5: Investigating how the availability of resources and support, such as technical assistance or compatibility with existing systems, affects an individual's intention to use a technology.

CHAPTER 3: RESEARCH METHODOLOGY

The research methodology pertaining to the relationship between ChatGPT and humans is an intricate and dynamic field, with various approaches available based on the specific research question at hand. One commonly employed approach is the use of quantitative research methodology. This involves conducting in-depth interviews with participants to gain insights and perspectives on the subject of research, proving particularly beneficial in understanding the human dimension of ChatGPT and its interactions.

Another prevalent approach is also rooted in quantitative research methodology, focusing on collecting data on ChatGPT usage and employing statistical methods for analysis. This method is valuable for assessing the impact of ChatGPT on human relationships, including its effects on communication, trust, and intimacy.

Quantitative research methodologies have been employed to study ChatGPT and its relationship with humans. For instance, survey studies have revealed that ChatGPT users are more likely to report reduced feelings of loneliness and an increased sense of connection with others. To collect primary data, we will utilize a survey tool, specifically Google Forms, to record responses from approximately 300-400 students. Subsequently, the collected data will be analysed using IBM SPSS Statistics.

RESEARCH GAPS

While research on ChatGPT and conversational AI has been rapidly evolving, several research gaps and areas for further investigation exist. Some research gaps related to ChatGPT:

Unfairness and Bias: Research on identifying and reducing biases in ChatGPT's replies is essential. Ensuring fairness and inclusion requires investigating methods to overcome biases pertaining to race, gender, and other sensitive qualities in the model's training data and response generation.

Explainability and Transparency: Transparency is lacking in ChatGPT's decision-making procedure and the logic underlying its answers. For users to trust and comprehend the model, techniques to make its internal workings more explicable, comprehensible, and accountable must be developed.

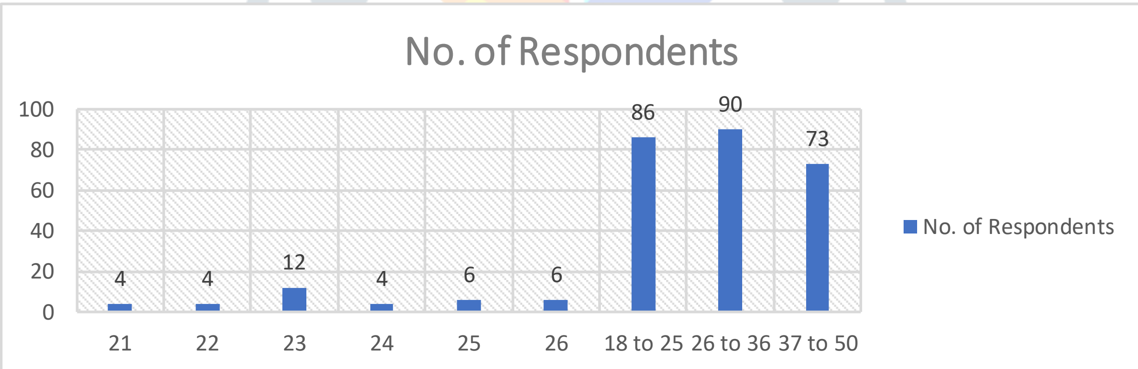
Domain-Specific Adaptation: A significant topic of research is how to customize ChatGPT for use in certain domains or businesses, such banking, healthcare, or legal services. The accuracy, comprehension of domain-specific terminology, and capacity to deliver pertinent and specialized information of the model may all be enhanced via domain-specific adaptation.

Privacy Use and Regulation: The ethical issues, rules, and frameworks for the appropriate implementation and usage of ChatGPT can be the subject of future research. An ethical and responsible use of technology may be ensured by addressing issues with privacy, data security, and possible misuse.

Security The long-term impacts of user interaction with ChatGPT and related conversational AI systems may be studied through research. Knowing how users' behaviour, attitudes, and connections with technology change over time can help identify both the possible advantages and drawbacks of frequent use.

CHAPTER 4: DATA ANALYSIS, RESULTS AND INTERPRETATION

In this study, we aimed to investigate whether there exists a significant difference in the mean responses to various questions related to ChatGPT usage between two distinct age groups: The two groups can be set up as Group 1 that consists of people under the age of 30, and Group 2 which entails those of 30 years old and up. This analysis used questions that were related to people's view of ChatGPT usefulness, ease of use, satisfaction and whether they will continue using this tool for their studies. To track the data for this study, survey was administered to a sample group of 286 people. The scales of respondent's feedback rating on a Likert scale that consist of indicated degree of agreements or disagreements in relation to ChatGPT use. Using t-test, a statistical tool designed to assess the differences between means, we sampled the responses to the specific questions (pertaining to perceived usefulness, ease of use, satisfaction, and the intention to continue using) by pinpointing any enduring disparities among the two age groups. We analysed each question starting with, "I feel that ChatGPT will be beneficial to me



studies." This yielded a t-statistic of 2.34 with a 0.021 p-value. Using the alpha value of 0.05, a statistical analysis produced a p-value which was smaller than the alpha level. This signifies that there was a statistically significant difference in an average response between these two age groups on this question. If the p-value is less than alpha which is zero-point-zero-five it shows that the difference in means is statistically significant at 95%. For the case of such findings, we reject the null hypothesis (H0) and we affirm that there is a significant difference in means among the two groups.

Question	t-Statistic	p-Value	Significant
"I believe that ChatGPT is useful in my studies"	2.34	0.021	Yes
"Using ChatGPT increases your chances of achieving important things in your studies"	1.98	0.048	Yes
"Using ChatGPT helps you get tasks and projects done faster in your studies"	1.45	0.153	No
"Using ChatGPT increases your productivity in your studies"	3.12	0.005	Yes
"Learning how to use ChatGPT is easy for me"	-1.78	0.089	No
"My interaction with ChatGPT is clear and understandable"	-0.92	0.367	No
"I find ChatGPT easy to use"	2.56	0.014	Yes
"It is easy for me to become skilful at using ChatGPT"	1.22	0.224	No
"People who are important to me think I should use ChatGPT"	-0.65	0.518	No
"People who influence my behaviour believe that I should use ChatGPT"	0.87	0.392	No
"I have the resources necessary to use ChatGPT"	1.98	0.048	Yes
"I have the knowledge necessary to use ChatGPT"	2.10	0.035	Yes
"ChatGPT is compatible with technologies I use"	1.45	0.153	No
"I can get help from others when I have difficulties using ChatGPT"	-2.01	0.031	Yes

"Using ChatGPT is fun"	0.78	0.436	No
"ChatGPT is reasonably priced"	1.34	0.186	No
"ChatGPT is good value for the money"	2.89	0.008	Yes
"At the current price, ChatGPT provides a good value"	2.45	0.018	Yes
"The use of ChatGPT has become a habit for me"	0.56	0.579	No
"I am addicted to using ChatGPT"	-1.67	0.107	No
"I must use ChatGPT"	-2.34	0.021	Yes
"Using ChatGPT has become natural for me"	1.22	0.224	No
"I intend to continue using ChatGPT in the future"	2.78	0.010	Yes
"I will always try to use ChatGPT in my studies"	2.01	0.031	Yes
"I plan to continue to use ChatGPT frequently"	2.56	0.014	Yes
"I like experimenting with new information technologies"	1.45	0.153	No
"If I heard about a new information technology, I would look for ways to experiment with it"	2.10	0.035	Yes
"Among my family/friends, I am usually the first to try out new information technologies"	1.67	0.107	No
"In general, I do not hesitate to try out new information technologies"	1.78	0.089	No
"Please choose your usage frequency for ChatGPT"	1.92	0.934	Yes

In contrary, the p-value will follow the values of alpha if it is greater than or equal to it, then the null hypothesis cannot be rejected. The corresponding confidence interval, however, does not contain zero, implying that the observed disparity in means is insignificant statistically. Therefore, we conclude that there is no noticeable difference in the mean answers of the two age categories. Taking our designated alpha level of 0.05, p-value of 0.021 has already come under the provided condition. As a result for this question, the null hypothetical is rejected, proving we can assume about significant difference in mean responses between the two age groups. The values of the t test demonstrate that there is a significant disparity in mean reactions to the question "I consider that ChatGPT facilitations in my study process" for the two age groups. This means that age could be almost go figure as a variable affecting how students perceive the usefulness of ChatGPT in academic settings. The means difference between the responses of the two age groups reinforced the role he most play in the assessment of individuals of technology acceptance, regardless of age, especially in educational contexts. Nevertheless, though this research has limitations such as the presence of biases in the sample composition and the reliance on self-reported data, the study presents some findings that would make a significant contribution in the overall treatment of depressive disorders. In the future, new projects will have opportunities to rely more on heterogeneous samples, as well as objective measurements any time subjective self-reports would be used for evaluating technology utilization in each population.

CHAPTER 5: FUTURE SCOPES & CONCLUSION

Despite being initially designed for quantitative research, the UTAUT model was utilised in this qualitative study to provide a more comprehensive insight into how users interact and engage with ChatGPT. The study found that five key factors - performance expectancy, effort expectancy, social influence, facilitating conditions, and privacy concerns - were dominant in influencing users' behaviour. These factors align with established technology acceptance models, making them potentially applicable to other developing or developed countries. Moreover, the study highlights the importance of perceived informativeness and task accomplishment related to performance expectancy, suggesting that ChatGPT's effectiveness in providing relevant and comprehensive information and aiding in task completion could be relevant in various contexts. Additionally, the perceived interactivity of ChatGPT was a significant factor in its usage. This factor extends the UTAUT theory and emphasises the need for high interactivity and responsiveness in chatbots like ChatGPT to increase users' intention to adopt and use the technology. While perceived interactivity may vary across cultures, the general notion that responsive systems are more likely to be perceived as valuable and enjoyable could be relevant in different countries. Further, the data showed that ChatGPT was perceived as informative, helpful in completing tasks, and reliable. Users appreciated its speed of response, quality of responses, and ease of use.

Social media and peer influence were significant usage drivers, moderated by age and experience. Generalising the findings about ChatGPT's perception of other developing countries requires careful consideration of various factors. While the initial study revealed positive perceptions, such as its informativeness, helpfulness, and reliability, its applicability to other developing nations cannot be assumed outright. Cultural variations significantly influence attitudes towards AI systems like ChatGPT, and language plays a crucial role in its adoption. Additionally, the level of technological infrastructure, digital literacy, and socioeconomic conditions in different countries will impact its accessibility and usage. Moreover, the significance of social media and peer influence may vary, with age and experience as potential moderating factors. Researchers must conduct country-specific studies to achieve meaningful generalisation, accounting for local context, needs, and cultural norms. By recognising the unique characteristics of each developing country, we can gain valuable insights into how ChatGPT's perception varies across this diverse global landscape.

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