MODESTUM EURASIA Journal of Mathematics, Science and Technology Education, 2024, 20(2), em2393
ISSN:1305-8223 (online)
OPEN ACCESS Research Paper https://doi.org/10.29333/ejmste/14151

User acceptance and adoption dynamics of ChatGPT in educational settings

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Received 10 November 2023 ▪ Accepted 04 January 2024

Abstract

Recent developments in natural language understanding have sparked a great amount of interest in the large language models such as ChatGPT that contain billions of parameters and are trained for thousands of hours on all the textual data of the internet. ChatGPT has received immense attention because it has widespread applications, which it is able to do out-of-the-box, with no prior training or fine-tuning. These models show emergent skill and can perform virtually any textual task and provide glimmers, or "sparks", of artificial general intelligence, in the form of a general problem solver as envisioned by Newell and Simon in the early days of artificial intelligence research. Researchers are now exploring the opportunities of ChatGPT in education. Yet, the factors influencing and driving users' acceptance of ChatGPT remains largely unexplored. This study investigates users' (n=138) acceptance of ChatGPT. We test a structural model developed using Unified Theory of Acceptance and Use of Technology model. The study reveals that performance expectancy is related to behavioral intention, which in turn is related to ChatGPT use. Findings are discussed within the context of mass adoption and the challenges and opportunities for teaching and learning. The findings provide empirical grounding to support understanding of technology acceptance decisions through the lens of students' use of ChatGPT and further document the influence of situational factors on technology acceptance more broadly. This research contributes to body of knowledge and facilitates future research on digital innovation acceptance and use.

Keywords: ChatGPT, large language models, artificial intelligence chatbots, technology acceptance, UTAUT

INTRODUCTION

The world is in the midst of a third information revolution as machines become intelligent after the advent of the personal computer, and the internet. Many commentators are concerned with questions of sentience and artificial general intelligence or the singularity. Yet the more pressing questions are how to integrate these new technologies into institutional and normative structures of practice that form the social order (Bourdieu, 1977). These new technologies that allow an individual to harness the power of the masses create an uneven playing field, where those that can use the technology well can be orders of magnitude more productive than those that cannot. Thus, the new "literacy" of computational thinking (Doleck et al., 2017b), which empowers individuals to use information technologies, becomes an inescapable skill to be successful in the world of today and a teaching imperative for educators everywhere.

Educators are experimenting with new innovations and finding ways to integrate it into their practice (Memarian & Doleck, 2023). Artificial intelligence (AI) technologies, such as large language models (LLMs), represent one of the most exciting innovations with the potential for transformative impact on processes and industries. Beyond simply providing canned and rigid experiences, these tools are able to interpret and interact with users, as such, rendering rich and complex forms of output and experiences. Indeed, LLMs (Ray, 2023) are being used for the whole spectrum of teaching and

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Contribution to the literature

- This study examines technology acceptance (TA) in the context of mass adoption and advances a situative perspective and shows how situational variables other than facilitating conditions inform TA decisions.
- The study offers further confirmation of the robustness of TA in the novel context of wholesale adoption of large language models.
- Our study shows the modulation of the relationships between the factors of Unified Theory of Acceptance and Use of Technology (UTAUT) in the novel context, that is, we find no significant relationship between Effort Expectancy (EE) and Behavioral Intentions (BI). In the face of a novel technology/interface, we posit a 'novelty effect' whereas the benefits of EE are not fully ascertained as the potential uses have not been fully developed.

instructional practice. Teachers are using it to build lessons, correct grammar, evaluate and give feedback (Memarian & Doleck, 2023). There are widespread reports that students use it for their own work too and there is much handwringing about the potential for cheating. Indeed, ghostwriters are hard-pressed to compete. Hence, teachers are keen to know student perceptions and the use of LLM technology like ChatGPT. LLMs challenge traditional activity by promising to automate important spheres of activity, namely those that operate through rote and repetition. Assuming that all students use ChatGPT in their work, teachers are forced to change up their lessons to ensure that the students do the learning.

In this study, we model students' acceptance of ChatGPT to understand the changing context of learning. Although the use of ChatGPT has exploded (Lee, 2023), it is important to explore the drivers of adoption to mitigate bad outcomes and support best practices in educational environments (Memarian & Doleck, 2023). Given the novelty and potentially disruptive nature of ChatGPT, it is crucial to understand how advances in AI-chatbots are likely to change education (Adeshola & Adepoju, 2023). An important step in this requires an understanding of what motivates students to use ChatGPT. Knowledge about the determinants of learners' acceptance and use of ChatGPT is scant. It is thus necessary to understand what drives or inhibits students' acceptance of ChatGPT. The knowledge of this process may enable educators to better understand the opportunities and challenges of LLMs in education.

LITERATURE REVIEW

Large Language Models & Education

Recent years have witnessed significant technological advancements. We are now seeing a new generation of technological tools that once appeared fantastical. Among a panoply of intelligent tools, ChatGPT–an AI agent that uses LLMs to perform high-level cognitive tasks–is one such innovation that has been transformed from vision to reality (van Dis et al., 2023). Released in Nov 2022, use of ChatGPT has experienced one of the fastest adoptions and its use is still increasing (Stringer & Wiggers, 2023). In fact, the release of ChatGPT has led to a wave of similar tools (e.g., Anthropic's Claude, Google Bard, and Meta's Llama).

ChatGPT is a language model trained to produce text (OpenAI, 2023; Ray, 2023). ChatGPT and LLMs are versatile and can be used for a variety of purposes, with uses seen across a large spectrum of industries. LLMs use a transformer architecture (Vaswani et al., 2017) trained to produce the next token provided with a context window over sequences of tokens with billions of parameters. Miraculously, LLMs can natively perform textual tasks without even having been taught them.

Given the rapid adoption of AI technologies, much attention has been paid to ChatGPT's practical and societal relevance. ChatGPT use has grown across a variety of application domains. ChatGPT has emerged as an undoubtedly popular tool in education (Michel-Villarreal et al., 2023). Indeed, the growing popularity of ChatGPT portends an important shift in the way that learners approach learning. Numerous benefits and opportunities of ChatGPT in education are documented in the literature (Kasneci et al., 2023). At the same time, many posit that such innovations are poised to upend normal activity and bring difficult challenges to teaching and learning (Memarian & Doleck, 2023; Dwivedi et al., 2023; van Dis et al., 2023). Practitioners, researchers, and academicians are increasingly interested in studying the use of ChatGPT in education (Kasneci et al., 2023).

Theoretical Framework

Technology acceptance analyzes the motivations for using technology (Davis, 1989; Teo et al., 2018, 2019). Technology acceptance refers to the willingness of individuals to adopt and use new technologies (Bazelais et al., 2018). It is a critical factor in the success of technology implementation. Indeed, this area of research has been the focus of both researchers and practitioners for many decades (Teo et al., 2019). There are several technology acceptance models that have been proffered to understand the process of technology adoption (Doleck et al., 2017a; Dwivedi et al., 2017): TRA, TAM, TPB, MPCU, IDT, and the Unified Theory of Acceptance and Use of Technology (UTAUT) model. These models offer several factors that are crucial in decision-making apropos acceptance of technology.

Among the gamut of frameworks available, UTAUT (Lemay et al., 2019) model continues to enjoy wide application in many fields, especially in teaching and learning (Dwivedi et al., 2017; Khechine et al., 2016). UTAUT is a model that aims to explain how and why people adopt and use new technologies (Khechine et al., 2016). UTAUT has been extensively validated in the literature and shows good robustness in its explanatory power across a range of situations. UTAUT model includes several key components that influence technology adoption and use: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). Most importantly, by including SI and FC, UTAUT is sensitive to the context of use and can help to elucidate the situational determinants that influence beyond the individual determinants of PE and EE.

According to Venkatesh et al. (2003), there are four key antecedent constructs that are associated with intentions and use:

(1) *PE:* "degree to which an individual believes that using the system will help him or her to attain gains in job performance" (p. 447).

(2) *EE:* "degree of ease associated with the use of the system" (p. 450).

(3) *SI:* "degree to which an individual perceives that important others believe he or she should use the new system" (p. 451).

(4) *FC:* "degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (p. 453).

In UTAUT model, PE, EE, & SI are direct antecedents of behavioral intentions, while FC is directly associated with use. Behavioral intention is considered to be a direct determinant of use (Ajzen & Fishbein, 1972). Considering the context of the study, the technology being studied, and the research question, the use of UTAUT for the current study is appropriate.

Table 1. Hypotheses

Hypothesis	Path
H1	PE→BI
H2	EE→BI
H3	SI→BI
H4	FC→US
H5	BI→US
H6	PE→BI, moderated by age
H7	EE→BI, moderated by age
H8	SI→BI, moderated by age
H9	FC→US, moderated by age
H10	PE→BI, moderated by gender
H11	EE→BI, moderated by gender
H12	SI→BI, moderated by gender

PURPOSE OF STUDY

For educators to better support students' use of new innovations, such as generative AI tools, educators themselves must be aware of the nature of students' acceptance and use of such new digital innovations.

The aim of the present study is to answer the following overarching research question:

What are the determinants underlying ChatGPT use among college students?

RESEARCH MODEL

In alignment with the aim and research question posed in the current study, we enumerated hypotheses in alignment with the original UTAUT model, which are presented in **Table 1** and **Figure 1** (Venkatesh et al., 2003).

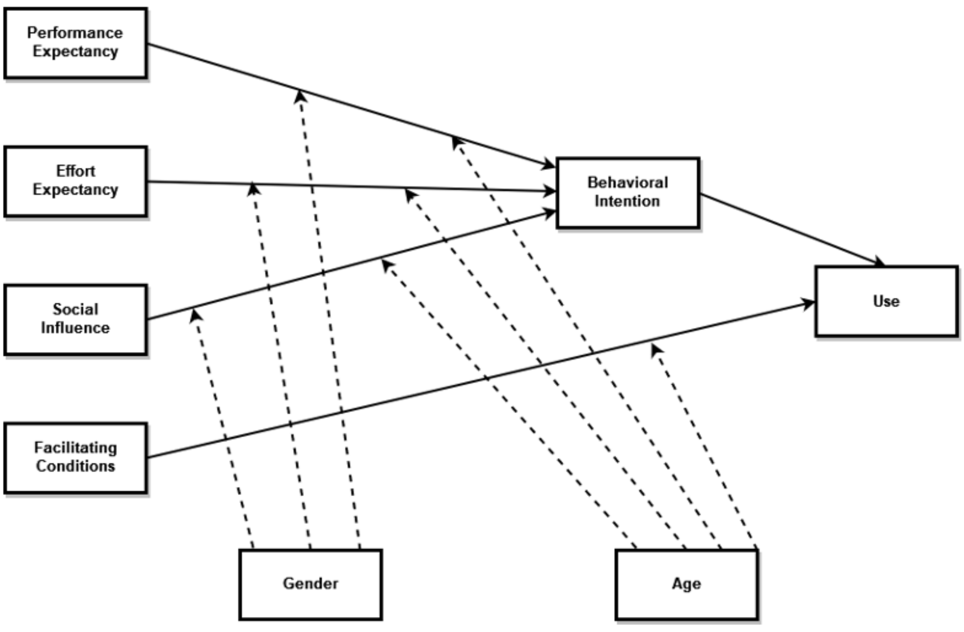

Figure 1. UTAUT model (Venkatesh et al., 2003)

Table 2. Model fit statistics

Measure	Values	Recommended criterion (acceptable if)
Average path coefficient	0.143, p=0.021	p<0.05
Average R-squared	0.432, p<0.001	p<0.05
Average adjusted R-squared	0.408, p<0.001	p<0.05
Average block VIF	1.725	≤5.0
Average full collinearity VIF	1.876	≤5.0
Simpson's paradox ratio	0.750	≥0.7
R-squared contribution ratio	0.966	≥0.9
Statistical suppression ratio	1	≥0.7
Nonlinear bivariate causality direction ratio	1	≥0.7

METHOD

Procedure

Participants, who voluntarily agreed to participate in the research, were sampled from an English CEGEP in Canada (CEGEP, for a review, see Bazelais et al., 2016). Participants completed the questionnaire online. To ensure anonymity, students did not identify themselves. Additionally, no incentives and/or compensation was offered for participation.

Participants

Participants (n=188) responded. Of the responses, n=50 participants indicated that they had not used ChatGPT. The final sample (n=138) included 65 females and 73 males, with an average age of 18.19 years (standard deviation=0.95).

Materials

Existing scales from the literature (Maruping et al., 2016) were adapted to fit the purpose of the study. Participants responded to statements (on a seven-point scale) related to the following study measures:

- PE: e.g., "I find ChatGPT useful in learning."
- EE: e.g., "I find my interaction with ChatGPT clear and understandable."
- SI e.g., "People who are important to me think I should use ChatGPT."
- FC e.g., "I have control over using ChatGPT."
- BI: e.g., "I intend to use ChatGPT in the future."
- US: e.g., "I use ChatGPT quite often."

ANALYSIS & RESULTS

The proposed research model (see **Figure 1**) was tested using a multivariate statistical technique called partial least squares structural equation modeling (PLS-SEM; Guenther et al., 2023). PLS-SEM is an alternative to the commonly known covariance-based structural equation modeling (CB-SEM) and is often used in research studies when the data is non-normal and/or the sample size is small.

For the statistical analysis, PLS-SEM was conducted in a two-step process using the WarpPLS software (Guenther et al., 2023; Kock, 2022a): first we assessed the measurement model and then we evaluated the structural model.

Measurement Model

Prior to model validation and hypothesis testing, we conducted the assessment of the measurement model by following the measurement model evaluation guidelines suggested in the literature (Guenther et al., 2023; Henseler et al., 2016; Kock, 2022b). The data fit the model well (Kock, 2022b) as demonstrated in **Table 2**.

The evaluation of the measurement model involved checking the loadings, composite reliability (CR), average variance extracted (AVE), and discriminated validity. **Table 3** illustrates the measurement scale characteristics. Item reliability was demonstrated as loadings were greater than 0.70 (loading values below the threshold value of 0.70 were dropped). The convergent validity of the constructs was confirmed as all AVE values were greater than 0.50. CR coefficients of the measures also exceeded the threshold value of 0.70, indicating sufficient internal consistency reliability.

Table 3. Measurement scale characteristics

Construct	Items	Loadings	CR coefficients	AVE
PE	PE1	0.893	0.954	0.720
	PE2	0.874		
	PE3	0.818		
	PE4	0.806		
EE	EE1	0.805	0.897	0.685
	EE2	0.825		
	EE3	0.839		
	EE4	0.842		
SI	SI1	0.787	0.878	0.643
	SI2	0.799		
	SI3	0.836		
	SI4	0.836		
FC	FC2	0.940	0.938	0.883
	FC3	0.940		
BI	BI1	0.977	0.985	0.955
	BI2	0.972		
	BI3	0.983		
US	US1	0.954	0.953	0.910
	US2	0.954		

Table 4. Discriminant validity test

	PE	EE	SI	FC	BI	US
PE	**0.849**	0.518	0.560	0.372	0.700	0.683
EE	0.518	**0.828**	0.397	0.457	0.447	0.443
SI	0.560	0.397	**0.802**	0.281	0.439	0.506
FC	0.372	0.457	0.281	**0.940**	0.380	0.290
BI	0.700	0.447	0.439	0.380	**0.977**	0.555
US	0.683	0.443	0.506	0.290	0.555	**0.954**

Note. Square roots of AVEs shown on diagonal

Discriminant validity was also assessed by using the Fornell-Larcker criterion (Fornell & Larcker, 1981). In **Table 4**, we find that the indicators are consistent with Fornell-Larcker criterion (Fornell & Larcker, 1981), which specifies that the diagonal values should be greater than the off-diagonal numbers in the corresponding rows and columns. This exercise indicates that there are no issues concerning the discriminant validity.

Structural Model

We first tested to see whether the model has any collinearity issues using variance inflation factor (VIF) values. There was no indication of multicollinearity issues as VIF values were below five. In addition, the predictive relevance of the proposed model was reinforced as Q^2 coefficient values were greater than zero (Kock, 2022b).

The hypotheses were examined using the results of the structural model. **Table 4** summarizes the results of the structural model assessment: path coefficients (β, path significance (p-value), and effect sizes (f^2). f^2 values of 0.35, 0.15, and 0.02 indicate large, medium, and small effect sizes, respectively (Cohen, 1988).

As seen in **Table 5**, only two hypotheses were supported. We know highlight the key takeaways from the assessment of the structural model:

- PE is related to BI.
- Links between EE, SI and BI are not supported.
- Link between FC and US is not supported.
- BI is related to US.
- No support for the moderating role of age for the four links (PE→BI; EE→BI; SI→BI; FC→US).
- No support for the moderating role of gender for the three links (PE→BI; EE→BI; SI→BI).
- 51.7% of the variance in BI explained.
- 34.7% of the variance in US explained.

DISCUSSION

LLMs show emergent skill and can perform virtually any textual task and provide glimmers, or "sparks", of artificial general intelligence (Microsoft Research, 2023), in the form of a general problem solver as envisioned by Newell and Simon (1972) in the early days of AI research. Imagine a tool that understands and can complete virtually any task.

Clearly, these LLMs are incredibly useful, and the ease-of-use is quite democratizing. Yet it remains the case that computational thinking is a set of competences that are unequally distributed through the population (Doleck et al., 2017b). Findings on computational thinking suggest that those with the requisite competencies have a significant competitive advantage. As people have adopted LLMs into their daily workflows, it is becoming apparent that having a creative problem-solving mindset and some programming ability allows one to make much more powerful use of the technology. With some basic coding, one can use an LLM as an agent, which interacts with other applications to complete tasks and automate complex workflows, and not simply as a fancy autocomplete. As with literacy and numeracy, using AI effectively will be increasingly necessary to compete in the new information economy.

In our study, we found that only PE was predictive of BI. That PE is a determinant should not come as a surprise since the promise of ChatGPT is to boost productivity. Surprisingly, EE and FC were not. In the context of mass adoption, we should be surprised that neither would be determinant. Perhaps the barriers are low enough not to register. More likely, the technology is too new and the promises too nebulous for individuals to make informed opinions of the actual effort and

Table 5. Hypothesis testing

Hypothesis	Path	Path coefficient (β)	p-value	Effect size (f^2)	Result
H1	PE→BI	0.618	<0.001	0.439	Supported
H2	EE→BI	0.070	0.201	0.032	Not supported
H3	SI→BI	0.056	0.255	0.028	Not supported
H4	FC→US	0.055	0.257	0.017	Not supported
H5	BI→US	0.564	<0.001	0.335	Supported
H6	PE→BI, moderated by age	-0.069	0.205	0.016	Not supported
H7	EE→BI, moderated by age	-0.088	0.148	0.017	Not supported
H8	SI→BI, moderated by age	0.078	0.176	0.019	Not supported
H9	FC→US, moderated by age	0.028	0.372	0.005	Not supported
H10	PE→BI, moderated by gender	0.021	0.400	0.008	Not supported
H11	EE→BI, moderated by gender	-0.001	0.495	0.000	Not supported
H12	SI→BI, moderated by gender	-0.064	0.224	0.011	Not supported

resources (conditions) required to make successful use of the new technology.

These findings tell us precious little about the situation of use, that is, when technology becomes imperative in a culture. Findings clearly demonstrate that students are adopting ChatGPT en masse. We must study efforts to support and develop the new literacy of computational thinking and ensure that all students have the same opportunities. We need interventionist studies that show how instruction can foster proper and effective use of LLMs for learning and teaching.

Implications

One consequence of the emergence of LLM is that the professions and disciplines that are especially text heavy are those with the most "disruptive" capacity. The professional horizon may be radically changed when a practice like law and medicine can be largely automated, how will these professions be affected? What will be the context of adoption when your job is transformed, and you are forced to learn to use ChatGPT or another A.I. to stay competitive.

Limitations & Future Directions

This is a single exploratory study considering only a small sample of college students from Northeastern North America. Their perspectives may not be representative of the whole. Future studies should explore the adoption of LLMs within and across groups and how to encourage and cultivate the new skills of computational thinking required to facilitate adoption and to establish new teaching approaches that teach how to incorporate AI into education responsibly and effectively. As a correlational study, no causal conclusions should be drawn from the findings. Given our findings, a research direction involves examining qualitative data to provide additional context to understanding acceptance behaviors.

CONCLUDING REMARKS

The rapid rate of adoption, faster than any other internet technology, with 100 million users in three months (Reuters, 2023), portends some seismic changes in the workplace and society. Those that can make good use of the new technology have a competitive advantage and new innovations are coming every day. As with each previous information revolution, it will transform our social activities, education no less. Educators will have to make necessary adjustments in their instruction to remain relevant. And prepare students for the new information economy, where computational thinking competence is vital.

Author contributions: All authors have sufficiently contributed to the study and agreed with the results and conclusions.

Funding: No funding source is reported for this study.

Ethical statement: The authors stated that the study was approved by the John Abbott College Research Ethics Board (Certificate number: JACREB202303). Written informed consents were obtained from the participants.

Declaration of interest: No conflict of interest is declared by authors.

Data sharing statement: Data supporting the findings and conclusions are available upon request from the corresponding author.

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