Examining the Impact of OpenAI's ChatGPT on PhD Student Achievement

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***Abstract*—Nowadays, Artificial Intelligence (AI) tools have revolutionized scientists' way of conducting research. Accordingly, the current study explores the role of OpenAI's ChatGPT on PhD students' achievement. For this purpose, a questionnaire was conducted among a sample of Moroccan PhD students in various scientific fields. The results achieved from structural equation modelling confirmed that perceived ease of use and perceived usefulness influence the degree of ChatGPT use and PhD students' satisfaction, thereby enhancing individual net benefits. These findings offer a number of useful insights for academic leaders and doctoral supervisors regarding how they might take steps to update practices in using artificial intelligence tools.**

***Keywords*—students, artificial intelligence, ChatGPT, satisfaction, net benefits**

I. Introduction

As a multidisciplinary field, Artificial Intelligence (AI) emerges from advancements in computer science that enable the performance of complex tasks requiring human-like intelligence, such as recognizing speech and visuals, processing natural language, and making decisions [1]. The use of Artificial Intelligence (AI) tools has significantly spread in the last few years and has deeply affected numerous aspects of our society, including healthcare [2], finance [3], manufacturing [4] and scientific research [5–9].

Building up research skills and carrying out empirical investigations are central components of PhD schooling. The PhD program also requires critical thinking skills and high-quality written work [10]. Therefore, PhD students are faced with challenging and complex tasks when conducting their studies, including data analysis, innovative idea generation, and drafting their outcomes. As such, the use of AI tools, such as ChatGPT, potentially addresses these challenges, by offering advanced support and guidance in various aspects of scientific research.

Since ChatGPT emerged, it became apparent that this tool will eventually yield massive implications for how researchers work [11]. Already, ChatGPT is equipped to assist scholars in drafting papers and abstracts, as part of literature reviews, summarizing data or information, offering suggestions for structure, references, and headlines, as part of linguistic revisions to make text more readable, or even generating a complete draft of a paper [12]. Furthermore, Chatbots could help save time, enhance efficiency, and lower the workload of scientists [13]. Besides, ChatGPT may perfectly support the researcher for scientific and academic writing in order to check grammar and syntax errors and to refine the language, especially for non-native speakers [14]. It should be noted that there have been articles published with the assistance of the ChatGPT tool and co-authored by this tool [15].

Despite the debate surrounding the usefulness of artificial intelligence tools in the research field, it is readily apparent that ChatGPT cannot fulfill the author's role [16], yet this tool offers multiple benefits for researchers. When exploring the benefits of using ChatGPT, Qasem [7] indicated that ChatGPT could serve as a valuable and advantageous tool when applied ethically in the realms of science and academia. Conversely, he underscored the adverse consequences of overusing ChatGPT, including an increased risk of plagiarism and the potential for researchers and students to become overly reliant on the technology, diminishing their self-sufficiency and motivation.

Notwithstanding the emergence of ChatGPT and other similar AI devices, there has been a lack of empirical studies focusing on how using these tools affects academic performance. Therefore, the current study explores the influence of ChatGPT use on PhD students' performance and examines factors that motivate their usage as well as their level of satisfaction with this tool. It is intended to provide key insights to university managers and PhD supervisors in order to help them in tailoring their practice of using AI tools based on PhD students' needs.

Understanding PhD students' reasons for using ChatGPT, as well as factors that influence their satisfaction levels, are essential for enhancing practices related to using these tools and maximizing the benefits they can offer. Accordingly, the objective of this paper is to bridge this knowledge gap by exploring these crucial aspects, by trying to address the following study questions: What motivates PhD students to use ChatGPT in their research work? How does using ChatGPT affect PhD students' performance in conducting their research?

The rest of this paper proceeds according to the following structure: first, the existing literature will be examined to establish the conceptual model. The study methodology will then be presented. Next, the outcomes achieved using structural equation modeling will be analyzed. Finally, the implications of these findings for university officials and thesis supervisors will be discussed, and we will conclude by

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highlighting the main limitations and prospects of this study.

II. Literature Review

In the current era of digitalization, AI technologies have become ubiquitous [17]. The concept of AI was initially introduced by John McCarthy in 1956, which originates from the fields of computing and engineering, has evolved into an interdisciplinary discipline that draws influence from cognitive science, philosophy, neuroscience, and economics [18]. Over time, the domain of AI has expanded significantly to encompass various areas.

According to Kaplan and Haenlein's definition [19], artificial intelligence refers to the ability of a technology to accurately analyze data from external sources, derive knowledge from it and exploit it to achieve specific goals and tasks through flexible adaptation. Consequently, AI refers to machines acquiring skills that were traditionally exclusive to humans, such as learning, reasoning, natural language processing, and problem solving.

Artificial Intelligence (AI) is gaining popularity among researchers as an essential tool for data analysis and literature reviews, due to its recognized potential and increasing prevalence in research [20]. AI use can significantly improve the accuracy and efficiency of the research process, by adding value in various stages of the research process, including research initiation and generating research questions, data collection, data analysis, and literature review by helping researchers quickly identify relevant papers and articles and analyze them [20].

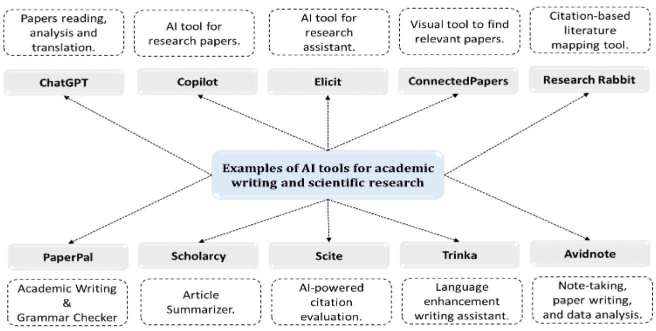

Fig. 1. Examples of AI tools used in academic writing and scientific research.

Golan *et al.* [21] have highlighted the benefits of using AI-based tools in academic writing. They concluded that these tools save time and enhance efficiency by identifying and correcting writing errors. They also aid in tasks like language translation, text summarization, and generating outlines for various written documents such as manuscripts, grant proposals, research protocols, and more. AI tools contribute to the improvement of papers and abstracts by providing specific suggestions, such as recommending relevant studies to include. They can quickly generate well-organized and visually appealing data outputs like figures and tables, suitable for manuscripts and presentations. Additionally, these tools can stimulate creativity in a specific field of interest and help identify gaps in the existing literature, which is especially useful for inexperienced trainees or young researchers [21]. These AI tools have the potential to be employed in scientific writing and research, providing better support and insights for PhD students. Today, there are a number of AI tools for scientific writing and research, such as ChatGPT [5, 22], ConnectedPapers [23], ResearchRabbit [24], Scholarcy, Elicit, Trinka, and Scite [25] (see in Fig. 1).

ChatGPT use may serve PhD students in several ways: information and knowledge retrieval, literature review and summarization, idea generation and brainstorming, writing assistance, feedback and proofreading, conceptual understanding and clarification, presentation and communication skills. Indeed, most of these aspects were discussed in earlier papers. By exploring the use of ChatGPT in scientific and academic research, Qasem [7] discussed the potential benefits of using AI language models, including their ability to simplify writing and to construct literature reviews in a short amount of time. However, they also acknowledge concerns about the ethical implications of using ChatGPT, such as plagiarism. To address these concerns, the authors suggest that there needs to be cooperation and integration between AI language models and academic platforms to curtail unethical actions. Overall, the authors conclude that while there are potential risks associated with using ChatGPT in research, they can be used effectively if researchers use them ethically and responsibly. Using ChatGPT responsibly and with considerations can bring benefits in scientific and academic settings. It has the potential to simplify tasks such as extracting insights and key findings, from scientific and academic fields aiding in literature review reports and saving time and effort in information retrieval and reporting procedures [7]. Salvagno *et al.* [26] have pointed out that while AI research assistants such as ChatGPT and elicit can be beneficial for summarizing academic articles and identified knowledge gaps, they are unable to deliver a critical review of differences between studies. Graf and Bernardi [27] discussed several potential benefits of using ChatGPT in neuroscience research, including the ability of this AI tool to help researchers identify research questions and hypotheses, design studies, analyze data (including writing code), write/edit documents, and correct grammar and syntax.

What makes ChatGPT so popular is its ability to generate text that sounds like it was written by a human. It can write essays about a range of topics and provide factual answers to questions. Additionally, it is freely accessible through a web portal created by the tool's developer, OpenAI. However, as the website states, "ChatGPT sometimes writes plausible-sounding but incorrect or nonsensical answers [16].

According to Dahmen *et al.* [28], ChatGPT can be used in medical research to analyze large amounts of data, including scientific articles, medical reports, and patient records. The AI bot uses natural language processing techniques to extract relevant information from the texts and present it in a structured format. However, the authors indicated that there are also potential risks and disadvantages associated with using ChatGPT in scientific writing. These include the possibility of generating plagiarized content due to lack of original authorship, inaccuracies or biases in the generated text due to limitations in the training data set or lack of understanding of nuances related to medical science(s) and language. Additionally, ChatGPT may overlook potentially important aspects of new research findings or limit researchers with a more generalized perspective rather than a quality-based assessment of the present data [28]. From previous studies, we can conclude that AI tools such as ChatGPT offer huge potential benefit in both academic and scientific writing, from research conception to outcomes publication.

III. Hypotheses and Research Model

After highlighting the various levels of impact that ChatGPT has on doctoral students, it becomes essential to examine how this tool influences the improvement of doctoral students' performance. In order to thoroughly explore the effects of ChatGPT on doctoral students' performance enhancement, it is necessary to question the manner in which this tool exerts its influence.

Perceived ease of use refers to an individual's subjective evaluation of the effort required to operate a specific device [29]. It reflects the extent to which a person perceives the use of a particular system as effortless or devoid of any significant effort.

Previous empirical studies have examined in depth how perceived ease of use affects different aspects of technology adoption. These studies have been consistent in supporting the direct effect of perceived ease of use on technology usefulness [30–33], as well as on user satisfaction [34, 35]. Hence, when individuals perceive a technology to be easy to use, the technology perceived usefulness will be highest and the user's level of satisfaction will be greatest. In other words, when a technology is perceived as effortless and user-friendly, it is more likely to be considered valuable and beneficial by users. Based on these outcomes, we can therefore hypothesize the following:

H_1: Perceived ease of use positively influences perceived usefulness.

H_2: Perceived ease of use positively influences ChatGPT use.

H_3: Perceived ease of use positively influences PhD student satisfaction.

Perceived usefulness captures a person's appreciation of the value of utilizing a specified technology such as AI tools. Earlier studies supported a positive effect of technology perceived usefulness on its use [36], as well as on end-user satisfaction [37, 38]. In particular, Al-Fraihat *et al.* [39] have confirmed the significant and direct influence of technology perceived usefulness on its use and user satisfaction. In other words, when users perceive that they benefit when using ChatGPT, they will use it more, leading to increased levels of their satisfaction. Consequently, we suppose the following assumptions:

H_4: Perceived usefulness positively influences ChatGPT use.

H_5: Perceived usefulness positively influences PhD student satisfaction.

ChatGPT can play a critical role in writing assistance, by helping students with writing assignments, including paraphrasing text, generating ideas and outlines, expanding on related concepts, and providing a structure framework for organizing ideas [40]. It is supported in prior literature that technology use has a direct impact on end-user satisfaction [34, 41, 42]. Hence, we suppose that:

H_6: ChatGPT use positively influences PhD student satisfaction.

Net benefits constitute the dependent variable of DeLone and McLean's model [41]. It relates to the extent to which technologies generate success for individuals, as well as for groups and organizations. Because the implementation of D&M model varies according to the context in which it is applied, this paper seeks to assess the impacts of AI tools on PhD students, focusing on individuals' perspective.

Previous empirical studies have demonstrated that net benefits are influenced directly by technology use and end user satisfaction [43, 44]. Past literature has suggested that high levels of user satisfaction with a given technology will positively influence the occurrence of net benefits related to using the technology in question [45, 46]. In other words, effective technology use coupled with high levels of end user satisfaction can lead to enhanced productivity performance, and increased overall benefits.

Researchers alike might be in a better position to use well-designed AI tools to enhance work efficiency for tasks such as manuscript proofreading and editing [47]. Benichou [48] reported that using ChatGPT can serve as a helpful device for researchers to enhance their ability to publish high-quality scientific papers. Based on the existing literature, we make the following assumptions:

H_7: ChatGPT use positively influences individual net benefits.

H_8: PhD student satisfaction positively influences individual net benefits.

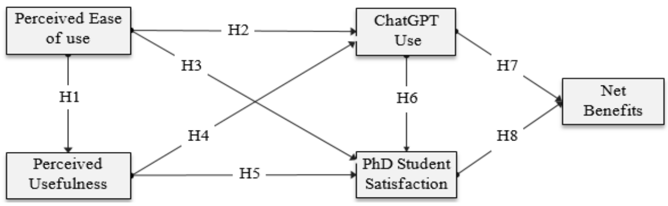

Fig. 2. Study model.

IV. Methods

A. Questionnaire Elaboration

The measurements used in this research were derived from existing literature and adjusted for the context of this study. ChatGPT perceived ease of use and perceived usefulness were successively measured using three and four items adapted from [29]. The use of this AI tool was assessed through three items chosen from the study of [41]. Regarding the construct of PhD student satisfaction, a three-item measurement scale was retained [49]. Lastly, net benefits were measured through five items [50, 51]. The study employed a research questionnaire based on a Likert scale of one (strong disagreement) to five (strong agreement). This process of items selection for each construct enabled the development of a two-part questionnaire (Table A1): the first part concerns the collection of data on the characteristics of the PhD students and the second part concerns the different concepts of the research (see in Fig. 3).

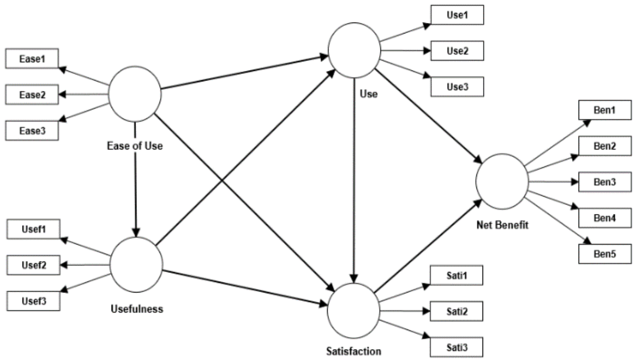

Fig. 3. Constructs and measurement scales.

B. Sample and Survey Participants

PhD students from Moroccan higher education institutions with previous experience using ChatGPT were chosen for inclusion in this study through a convenience sampling approach. Prior to collecting data, a preliminary test of the questionnaire was carried out, by engaging two faculty members and two PhD students in order to check the questionnaire for clarity. Furthermore, a screening query, “Have you ever used ChatGPT to help you with your research?” was included to assess the participant’s eligibility. Only people answered “yes” were permitted to proceed with the questionnaire. The questionnaire for this research was administered online using Google Forms. The link to the questionnaire was emailed to PhD students. Data were acquired during the period spanning from January 26th to March 28th, 2023. Over the course of a two-month interval, a total of 80 eligible responses were gathered from Moroccan PhD students.

The collected data was gathered from more female PhD students (66.25%) than male (33.75%) respondents, most of whom belonging to the 24–27 age group (43.75%) and 28–31 (20%). The majority of participants in the study are single (63.75%), followed by married individuals (35.00%), with a smaller proportion being divorced (1.25%). Most of the participants are enrolled within three years of enrollment in the doctoral program (1st year = 28.75%; 2nd year = 27.50%; 3rd year =15%).

The dominant research areas are business, management, and accounting, as well as economics, econometrics, and finance (both at 38.75%). Physics, chemistry, and material sciences have a smaller representation (10.00%), followed by arts, humanities, and social sciences (7.50%). In addition, Ibn Zohr University has the largest number of participants (37.50%), followed by Abdelmalek Essaadi (15.00%) and Mohamed V-Rabat (10.00%), among others (Table 1).

C. Dataset Analysis Method

The dataset was analyzed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique [52, 53], with the SmartPLS4 software. SmartPLS offers a graphical user interface for creating structural equation models. It utilizes a contemporary Java-based programming environment as its foundation. The analysis involved evaluating two distinct models: the outer and the inner model. The verification of the measurement models included assessing reliability and convergent validity. Afterwards, the inner model was assessed using metrics such as the coefficient of determination, the effect size, the goodness of fit and the predictive relevance.

Table 1. Profile of the study participants

Variable	Category	Frequency	Percent
Gender	Female	53	66.25%
	Male	27	33.75%
Age	24-27	35	43.75%
	28-31	16	20.00%
	32-35	13	16.25%
	Less than 24 years old	2	2.50%
	More than 35 years old	14	17.50%
Marital status	Divorced	1	1.25%
	Married	28	35.00%
	Single	51	63.75%
Year of enrollment PhD program	1st year	23	28.75%
	2nd year	22	27.50%
	3rd year	12	15.00%
	4th year	10	12.50%
	5th year	8	10.00%
	6th year	5	6.25%
Research area	Business, Management and Accounting	31	38.75%
	Economics, Econometrics and Finance	31	38.75%
	Physics. chemistry and material sciences	8	10.00%
	Arts. Humanities and social sciences	6	7.50%
	Biochemistry. Genetics and Molecular Biology	2	2.50%
	Mathematics and Computer Science	1	1.25%
	Agricultural and Biological Sciences	1	1.25%
University	Ibn Zohr	30	37.50%
	Abdelmalek Essaadi	12	15.00%
	Mohammed V	8	10.00%
	Hassan I	6	7.50%
	Mohammed I	5	6.25%
	Sidi Mohammed Ben Abdellah	5	6.25%
	Cadi Ayyad	5	6.25%
	Hassan II	4	5.00%
	Ibn Tofail	3	3.75%
	Chouaib Doukkali	1	1.25%
	Moulay Smail	1	1.25%

V. RESULTS

A. Outer Model Validation

Table 2 depicts the results for checking reliability and validity of the measurement models. All loading values are considered appropriate, as the values of the 17 items are above 0.7, indicating a good reliability [54]. The Average Variance Extracted (AVE) values were all above 0.5, varying between 0.659 and 0.845. Additionally, the values of Cronbach’s alpha and composite reliability (CR) for all latent constructs were above 0.7, ranging from 0.814 to 0.942, confirming a good level of reliability and convergent validity of the measurement models.

The discriminant validity results based on Fornell-Larcker and heterotrait-monotrait ratio of correlations (HTMT) criteria are displayed in Table 3. The PLS analysis revealed that the square roots of the Average Variance Extracted (AVE) for each construct were greater than the highest quadratic correlation between that construct and any other latent construct, confirming discriminant validity. Furthermore, applying the HTMT ratio (see in Fig. 4), it was observed that the largest HTMT value of 0.808 was comfortably below the recommended threshold of 0.85, as advised by [54, 55].

Table 2. Outer loadings, construct reliability and convergent validity

Construct	Items	FC	alpha	Composite reliability		AVE
				rho_a	rho_c	
Perceived Ease of Use	Ease1	0.925	0.908	0.910	0.942	0.845
	Ease2	0.932				
	Ease3	0.901				
Perceived Usefulness	Usef1	0.860	0.889	0.894	0.931	0.819
	Usef2	0.948				
	Usef3	0.906				
ChatGPT Use	Use1	0.845	0.814	0.848	0.889	0.729
	Use2	0.920				
	Use3	0.791				
PhD Students Satisfaction	Sati1	0.875	0.874	0.877	0.922	0.799
	Sati2	0.903				
	Sati3	0.903				
Net Benefits	Ben1	0.799	0.870	0.875	0.906	0.659
	Ben2	0.818				
	Ben3	0.759				
	Ben4	0.869				
	Ben5	0.808				

Table 3. Discriminant validity assessment using Fornell-Larcker and HTMT criteria

Criterion	Construct	1	2	3	4	5
Fornell-Larcker criterion	Ben (1)	0.811*				
	Ease (2)	0.523	0.919*			
	Sati (3)	0.703	0.669	0.894*		
	Use (4)	0.592	0.520	0.650	0.854*	
	Usef (5)	0.638	0.654	0.715	0.629	0.905*
Heterotrait-monotrait ratio	Ben (1)					
	Ease (2)	0.595				
	Sati (3)	0.800	0.747			
	Use (4)	0.686	0.588	0.753		
	Usef (5)	0.723	0.725	0.808	0.719	

* Square root of AVE

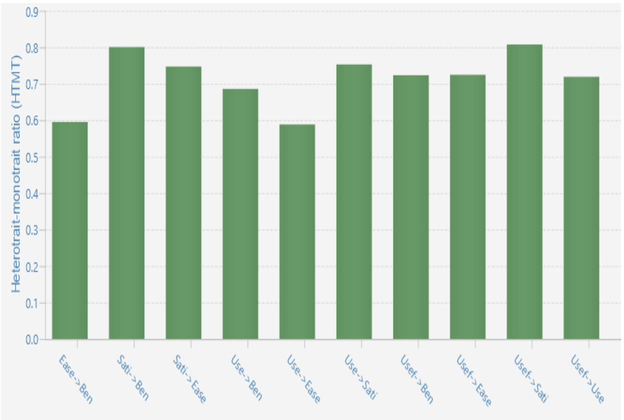

Fig. 4. HTMT values.

Discriminant validity was also assessed based on the items cross loading, which indicated that the loading values of the elements of the constructs were higher than the loading of any other construct as shown in Table 4.

Table 5 provides insights into the model fit of the saturated model and the estimated model. The results demonstrate favorable fit indices for both models, with the standardized Root Mean Square Residual (SRMR) values below the recommended threshold of 0.1, indicating a close alignment between the observed and predicted covariance matrices. Although the estimated model exhibits slightly higher d_ULS and Chi-square values compared to the saturated model, both models still demonstrate acceptable levels of fit. Furthermore, the d_G values signify a strong overall fit. The Normed Fit Index (NFI) values, above the threshold of 0.7, indicate a satisfactory fit when compared to the null model. These results collectively demonstrate the robustness and reliability of the estimated model, reinforcing its validity in capturing the underlying relationships within the data.

Table 4. Discriminant validity—Cross loadings

Item	BEN	EASE	SAT	USE	USEF
Ben1	0.799	0.399	0.614	0.427	0.508
Ben2	0.818	0.331	0.543	0.399	0.440
Ben3	0.759	0.601	0.509	0.390	0.570
Ben4	0.869	0.467	0.536	0.537	0.522
Ben5	0.808	0.353	0.628	0.613	0.545
Ease1	0.501	0.925	0.581	0.506	0.570
Ease2	0.538	0.932	0.650	0.439	0.663
Ease3	0.401	0.901	0.611	0.493	0.567
Sati1	0.612	0.587	0.875	0.523	0.598
Sati2	0.620	0.660	0.903	0.656	0.726
Sati3	0.652	0.540	0.903	0.556	0.585
Use1	0.476	0.261	0.468	0.845	0.376
Use2	0.581	0.529	0.667	0.920	0.652
Use3	0.443	0.502	0.497	0.791	0.539
Usef1	0.520	0.517	0.614	0.530	0.860
Usef2	0.600	0.583	0.687	0.623	0.948
Usef3	0.607	0.669	0.639	0.551	0.906

Fig. 5 depicts the PLS model following the convergent and discriminant validity assessment for the five measurement models.

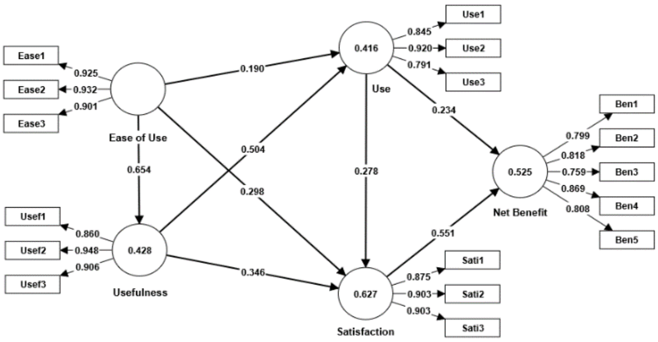

Fig. 5. Outer model assessment results.

Table 5. Model fit

Criterion	Saturated model	Estimated model
SRMR	0.083	0.086
d_ULS	1.056	1.140
d_G	0.649	0.659
Chi-square	285.587	287.733
NFI	0.750	0.748

B. Structural Model Validation

The inner model evaluation included verifying coefficient of determination, the effect size, the predictive relevance, and goodness of fit of the model. The R^2 scores for each of the four endogenous constructs (see Table 6), i.e., Perceived Usefulness (USEF), ChatGPT use (USE), PhD student satisfaction (SAT), and Individual Net Benefits (BEN), were respectively 0.428, 0.416, 0.627, and 0.525, indicating a moderate level of determination [56].

Table 6. The coefficient of determination (R^2)

Construct	R^2	R^2 adjusted	Remarks
USEF	0.428	0.420	Moderate
USE	0.416	0.401	Moderate
SAT	0.627	0.612	Moderate
BEN	0.525	0.513	Moderate

The effect size values of exogenous latent constructs on endogenous latent variables are displayed in Table 7.

Table 7. Effect size (f^2)

Construct			f^2	Remarks
Exogenous		Endogenous		
EASE	→	USEF	0.747	Large effect
EASE	→	USE	0.035	Small effect
EASE	→	SAT	0.132	Small effect
USEF	→	USE	0.249	Medium effect
USEF	→	SAT	0.147	Small effect
USE	→	SAT	0.121	Small effect
USE	→	BEN	0.067	Small effect
SAT	→	BEN	0.369	Large effect

The endogenous latent constructs, which included USEF, USE, SAT, and BEN, have a predictive relevance (Q2) of 0.344, 0.265, 0.487, and 0.331, respectively, showing a good predictive relevance (Table 8).

Table 8. Construct cross-validated redundancy (Q^2)

Construct	Q^2	Predictive relevance
BEN	0.331	Yes
SAT	0.487	Yes
USE	0.265	Yes
USEF	0.344	Yes

The model Goodness-of-Fit (GoF) serves as a comprehensive gauge for evaluating the overall appropriateness of model fit. In this study, the calculated GoF value was found to be 0.62 (Table 9), showing a high adequacy level of the PLS model.

Table 9. The goodness-of-fit of the model

Construct	R^2	AVE	GoF calculation	Meanings
EASE	-	0.845		
USEF	0.428	0.819		
USE	0.416	0.729	$\text{GoF} = \sqrt{\overline{R^2} \times \overline{AVE}}$ $= 0.619889579$	Large GoF
SAT	0.627	0.799		
BEN	0.525	0.659		

The hypotheses testing according to the PLS-SEM approach under the SmartPLS4 software validated all hypotheses, except for the second hypothesis related to the influence of perceived ease of use on ChatGPT perceived usefulness (t = 1.733, p = 0.083), which were non-significant and were rejected (Table 10).

Table 10. Mean, STDEV, T values, p values

Association				β	t statistics	p values	Accepted
H_1	Ease of use	→	Usefulness	0.654	8.888	0.000	Yes
H_2	Ease of use	→	Use	0.190	1.733	0.083	No
H_3	Ease of use	→	Satisfaction	0.298	2.830	0.005	Yes
H_4	Usefulness	→	Use	0.504	4.866	0.000	Yes
H_5	Usefulness	→	Satisfaction	0.346	3.188	0.001	Yes
H_6	Use	→	Satisfaction	0.278	3.355	0.001	Yes
H_7	Use	→	Net Benefits	0.234	2.010	0.044	Yes
H_8	Satisfaction	→	Net Benefits	0.551	5.049	0.000	Yes

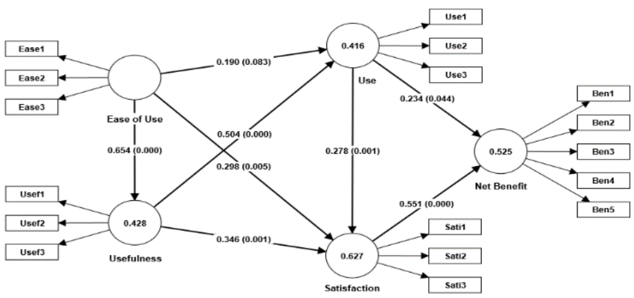

Fig. 6. Results of hypothesis testing.

The outcomes confirmed that the perceived ease of use significantly and positively affects ChatGPT's perceived usefulness (H_1 β= 0.654, t = 8.888, p = 0.000), and PhD students' satisfaction (H_3 β= 0.298, t = 2.830, p = 0.005). In addition, the positive effect of ChatGPT's perceived usefulness on ChatGPT use (β= 0.504, t = 4.866, p = 0.000), and PhD student satisfaction (β= 0.346, t = 3.188, p = 0.001) were both shown to be positive and significant, leading to the acceptance of H_4 and H_5. Likewise, the study revealed a direct and significant association between ChatGPT use and PhD students' satisfaction (β = 0.278, t = 3.355, p = 0.001), providing support for the acceptance of hypothesis H6. Finally, the outcomes showed that ChatGPT use (β = 0.243, t = 2.010, p = 0.044) and PhD student satisfaction (β = 0.551, t = 5.049, p = 0.000) significantly and directly affect individual net benefits, thereby confirming H_7 and H_8 (see in Fig. 6).

VI. Discussions

The current study represents the first empirical investigation designed to examine how AI tools like ChatGPT might shape PhD students' research practices. The findings confirmed that perceived ease of use positively influences on ChatGPT's perceived usefulness and PhD students' satisfaction. Put another way, when PhD students perceive ChatGPT as easy to navigate and interact with, they are more likely to find it valuable and be satisfied with its performance. These findings are consistent with prior empirical investigations, which have indicated that the perceived usefulness [31–33] and overall satisfaction are influenced by ChatGPT's ease of use [34, 35, 57]

In contrast to what previous literature has confirmed [29, 57, 58], the results of our study disproved that perceived ease of use influences ChatGPT's perceived usefulness.

The findings have supported the direct and positive effect of ChatGPT's perceived usefulness on ChatGPT use and PhD students' satisfaction. These outcomes are in keeping with earlier studies, which concluded that the perception of technology usefulness plays a role in explaining technology use [36], and end-user satisfaction [37, 38]. Based upon an empirical study designed to evaluate the success of e-learning systems among students, Al-Fraihat *et al.* [39] have empirically confirmed that perceived usefulness positively and directly influences on technology use and user satisfaction.

As in previous work [34, 41, 42, 50, 59], our results confirmed the positive influence of ChatGPT use on PhD student satisfaction. By acting as a virtual mentor, ChatGPT can help PhD students by replying to their questions, providing conceptual clarification and suggestions linked to ongoing research, so the more the PhD student uses this tool, the more their level of satisfaction increases.

In line with prior literature, the results showed that ChatGPT use and PhD students' satisfaction significantly and directly affect individual net benefits. As confirmed by Al-Fraihat *et al.* [39], the higher the technology's use and user satisfaction, the more significant are the benefits.

A. Implications for Theory

The current study provides a deeper understanding on the way AI devices such as ChatGPT influence PhD students' outcomes in their research work, by looking at factors that facilitate the use of this tool, as well as PhD students' satisfaction. This empirical study, specifically, corroborated the favorable influence of ChatGPT's ease of use on both its perceived usefulness and the satisfaction of PhD students. Likewise, the perceived usefulness was identified as an important determinant of ChatGPT use and PhD students' satisfaction. Lastly, both ChatGPT use and PhD students' satisfaction directly lead to enhance individual net benefits.

Regarding the theoretical implications, this research brings a certain body of knowledge to light on factors that foster the use of AI tools and the satisfaction of doctoral students. As such, the main theoretical implication of this paper lies in contextualizing the Information Systems Success Model (ISSM) variables in order to assess the success of AI tools, rarely studied in previous literature.

Based on DeLone *et al.*'s [41] model, the present study offers a unique scientific insight into how AI tools (ChatGPT) shape PhD students' work. Furthermore, this study offers a significant and pertinent new contribution for the literature by expanding [41] model by adding Technology Acceptance Model (TAM) derived variables, such as perceived usefulness and ease of use.

The study of AI tools' use in education has been extensively explored in the literature [60–62]; yet, studying ChatGPT's impact on PhD students' productivity remained unexplored. As such, this paper provides empirical proof of previous research, focusing on the assessment of the impact of a new technology.

B. Implications for HEIs Policy-Makers and PhD Students

The results of this study show that the use of ChatGPT and user satisfaction together lead to better individual net benefits, particularly in terms of improvement of research quality, simplification of research tasks and enhancement of scientific productivity and PhD students' performance in research tasks. The AI tools use in scientific writing include increased efficiency, improved accuracy, and the ability to generate new ideas. However, researchers must use these tools with extreme care. Additionally, over-reliance on these language bots can limit intellectual growth and confidence, especially for PhD students who are writing their first manuscripts [63]. Despite the positive influence of AI tools on enhancing user performance, PhD students should consider ChatGPT as a supplementary device that can help them achieve high quality scientific articles more quickly, rather than as a substitute for human work. As researchers have reported that ChatGPT does not withstand the literature review because it gives too many fake papers [64], PhD students are advised to use this tool vigilantly in reviewing the literature. To ensure ethical and accurate use of these tools, researchers should be aware of their limitations and potential biases. They should also carefully review and edit the output generated by AI language bots to ensure that it accurately reflects their intended meaning [63].

VII. Conclusions

The study findings showed that the integration of AI tools, such as ChatGPT, could significantly improve the PhD student's research output. As a result, it is advised that leaders within Moroccan higher education, including key figures from the Moroccan Ministry of Higher Education, Scientific Research and Innovation, as well as university councils, collaborate to incorporate AI tool-related courses into doctoral programs. This initiative aims to promote optimal utilization of AI tools in research endeavors through the dissemination of best practices. Additionally, it is strongly recommended that administrators of higher education institutions and PhD supervisors play an active role in cultivating awareness of scientific integrity. They should encourage PhD students to approach the use of AI tools with mindfulness, emphasizing the importance of cautious and thoughtful application in their research pursuits.

Although the present study provides useful theoretical and practical insights, there are a number of potential limitations, which could provide a valuable avenue for future research. First, the study sample was drawn from a limited number of Moroccan PhD students; as such, the results may not be able to be generalized to all PhD students. It is therefore possible to increase the sample size through the inclusion of a significant sample of PhD students, in order to establish if the outcomes could be generalized. The second limitation concerns using only a quantitative approach. Therefore, future research should consider applying a mixed approach that blends qualitative and quantitative methods to examine the effects of AI tools on PhD students' research output. Considering the fast-paced advances in AI tools and their applications in scientific research, exploring their potential influence on PhD students' productivity by using a longitudinal perspective could also be examined in future studies. Finally, the role of institutional support in enhancing PhD students' use of AI tools should be explored.

Appendix

Table A1. Questionnaire items

Variable	Code	Items	Source
Perceived ease of use	Ease1	I find ChatGPT easy to use.	[29]
	Ease2	My interaction with ChatGPT is clear and understandable.	
	Ease3	I find it easy to get ChatGPT to do what I want it to do.	
Perceived Usefulness	Usef1	Using ChatGPT will improve my learning.	[29]
	Usef2	Using ChatGPT will enhance my effectiveness.	
	Usef3	I find ChatGPT a useful tool in my learning.	

	Usef4	Using ChatGPT will save my time.	
ChatGPT Use	Use1	I use ChatGPT on daily basis	[41]
	Use2	I use ChatGPT frequently	
	Use3	I visit ChatGPT often	
Student Satisfaction	Sati1	I am pleased enough with ChatGPT	[49]
	Sati2	ChatGPT satisfies my educational needs	
	Sati3	I am satisfied with performance of ChatGPT	
Net Benefits	Ben1	ChatGPT increases my scientific productivity (paper, conference)	[50, 51]
	Ben2	I have learnt much through ChatGPT	
	Ben3	ChatGPT enhances task performance	
	Ben4	ChatGPT simplifies research tasks	
	Ben5	ChatGPT helps to improve the research quality	

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Conceptualization, O.B., H.B., J.E., M.A. and R.S.; methodology, O.B. and J.E.; software, O.B., H.B., J.E., M.A. and R.S.; formal analysis, O.B., H.B., J.E. and M.A.; investigation, O.B., H.B., J.E., M.A. and R.S.; resources, O.B., H.B. and J.E. data curation, H.B., J.E., M.A. and R.S.; writing—original draft preparation, O.B., H.B., M.A. and R.S.; writing—review and editing, O.B. and J.E.; supervision, O.B., M.A. and R.S.; project administration, O.B. All authors have read and agreed to the published version of the manuscript.

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