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Use of ChatGPT in academia: Academic integrity hangs in the balance

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ABSTRACT

In today's academic world, some academicians, researchers and students have begun employing Artificial Intelligence (AI) language models, e.g., ChatGPT, in completing a variety of academic tasks, including generating ideas, summarising literature, and essay writing. However, the use of ChatGPT in academic settings is a controversial issue, leading to a severe concern about academic integrity and AI-assisted cheating, while scholarly communities still lack clear principles on using such innovation in academia. Accordingly, this study aims to understand the motivations driving academics and researchers to use ChatGPT in their work, and specifically the role of academic integrity in making up adoption behavior. Based on 702 responses retrieved from users of ResearchGate and Academia.edu, we found that ChatGPT usage is positively shaped by time-saving feature, e-word of mouth, academic self-efficacy, academic self-esteem, and perceived stress. In contrast, peer influence and academic integrity had a negative effect on usage. Intriguingly, academic integrity-moderated interactions of time-saving, self-esteem and perceived stress on ChatGPT usage are found to be significantly positive. Therefore, we suggest that stakeholders, including academic institutions, publishers and AI language models' programmers, should work together to specify necessary guidelines for the ethical use of AI chatbots in academic work and research.

1. Introduction

As a variant of GPT-3 (Generative Pre-trained Transformer 3), ChatGPT is an extensive language model launched by Open Artificial Intelligence (OpenAI) in November 2022, has become one of the most crucial and unprecedented real-world AI platforms to date [1,2]. It specifically uses conversational chatbots to rapidly generate human-like texts with a unique capability to conduct a wide variety of language prompts, including question-answering, translation, summarisation, and text generation [3]. Surprisingly, the AI chatbot ChatGPT is likely the fastest-growing user application in internet history ever [4], with nearly 100 million users as of January 2023, and has roughly 1.8 billion website visitors per month currently [5,6]. Since its emergence, ChatGPT has been utilized for a wide range of purposes, including content generation, as it has been shown to be able to generate articles [7,8], stories [3] and other forms of realistic and coherent written content.

Despite its unprecedented success, ChatGPT is turning out to be a double-edged sword that has been making waves throughout the academic sphere [8,9]. One of the potential opportunities for such a revolutionary platform is to assist scientists and researchers in generating ideas and overcoming writer's block [3] and as a system to automate time-consuming and repetitive content production tasks [10]. However, there are critical challenges with using ChatGPT in academia: the possibility of plagiarism and academic dishonesty [11]; [8]. AI essay-writing platforms assist researchers and students in generating essays, articles, research, and assignments on their behalf, leading to a severe concern about academic integrity and AI-assisted cheating [3,8,12]. In response, some higher education institutions worldwide have banned access to ChatGPT or other AI tools on campuses [13] – while some are still reluctant to ban it [14] – over fears handing in unauthentic or potentially plagiarised content. On the other hand, technology experts are urging universities to train faculty, researchers, and students on how to use ChatGPT and AI platforms appropriately rather than ban them outright [15].

Since its release in late 2022, interest in ChatGPT has been incredibly high, especially among academicians [16]. The available data in Google Trends (GT) using "ChatGPT" as a search term for the "Job & Education"

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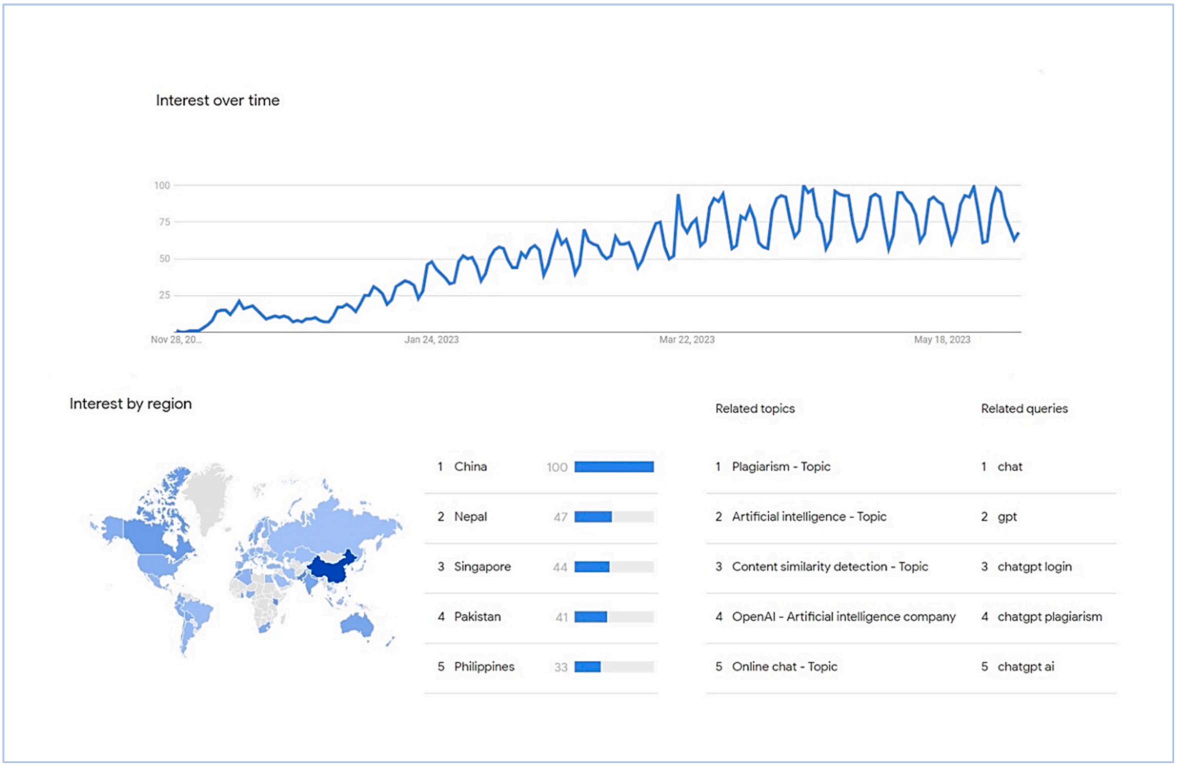

Fig. 1. GT on global search interest for ChatGPT, precisely "Job and Education" category for the period from late November 2022 (its release) until early June 2023 Note: Topics and queries are marked "breakout" by GT, showing a massive increase in interest and popularity.

category since its release contains interesting outcomes, as displayed in Fig. 1. Only a short time after public release, the popularity of ChatGPT soared, with search interest peaking on April 17, 2023. The term has been used worldwide, as GT aggregated search data from 71 different countries, indicating the unprecedented global demand and popularity for this AI tool. Most revealingly, the data shows that the term "plagiarism" was ranked as the top related search topic, followed by "AI"; meanwhile, "plagiarism" was also ranked among the top five related queries. Taken together, these outcomes shed light on the importance and timeliness of this research. There is a pressing need to provide a thorough understanding of factors driving researchers to use ChatGPT and the role of academic integrity in making up their motivations to adopt such an innovative tool.

Although there is a growing literature has begun to explore the potential role, implications, opportunities and threats of ChatGPT to academia and the higher education sphere [3,8,12,16–20], it is likely that no study to date has attempted to understand the motivations that drive academics and researchers to use ChatGPT in their work, and specifically the role of academic integrity in making up adoption behavior. Academic integrity has long been a concern in academia and higher education, and with the modern and pervasive technological revolution of AI chatbots, it has become more critical than ever [16]. Accordingly, the present study aims to bridge this gap by empirically examining the factors shaping ChatGPT usage among researchers worldwide and including academic integrity in the research model [21]. Social Cognitive Theory (SCT) provides a more holistic understanding of various personal, behavioral and environmental aspects that can stimulate the adoption behavior of new technologies [22], including ChatGPT usage in academic settings. Specifically, the attempt in this study seeks to answer the following questions: (1) How do time-saving feature, electronic word of mouth (e-WOM), peer influence, academic self-esteem, self-efficacy, and stress influence researchers' ChatGPT usage? (2) How does academic integrity moderate the relationships on ChatGPT's adoption model? Besides the research implications to the body of knowledge, the outcomes of this work offer profound implications for stakeholders in the academic community.

2. Literature review

2.1. Theoretical basis

SCT theory, recognized as one of the most potent theories of human behavior [21], underpins the present research. The central premise of SCT is that individuals' behavioral intentions are influenced not solely by their behaviors but also by personal, cognitive, and environmental aspects. According to Cooper and Lu (2016), the fundamental tenet of SCT posits that people's behavior is shaped by both their cognitive processes and external social environment situations [21]. advances the concept of triadic reciprocal determinism, which involves personal attributes like internal cognitive and affective states, as well as physical attributes, including external environmental components, all of which interact to shape overt behavior. Individuals' behaviors are driven by their perceptions, expectations, and beliefs. In other words, how people think and feel is related to their behavioral intention [21,22]. Furthermore, the theory proposes that a person's abilities, skills, and knowledge play a role in motivating them to undertake specific actions.

[21] further emphasizes that human behaviors are predicted by their environment, encompassing external determinants. Such an environment comprises both social and physical components. The physical environment encompasses natural and human-made elements within a person's surroundings. On the other hand, the social environment includes immediate physical surroundings, cultural contexts, and social relationships in which specific groups of individuals operate and interact, as [23] suggested. Indeed, it encompasses factors, such as social norms, community access, peer influence, values, and more [21]. Notably, the social environment is now recognized to include both real and virtual worlds [22].

The third facet of the SCT is behavior, which refers to how an

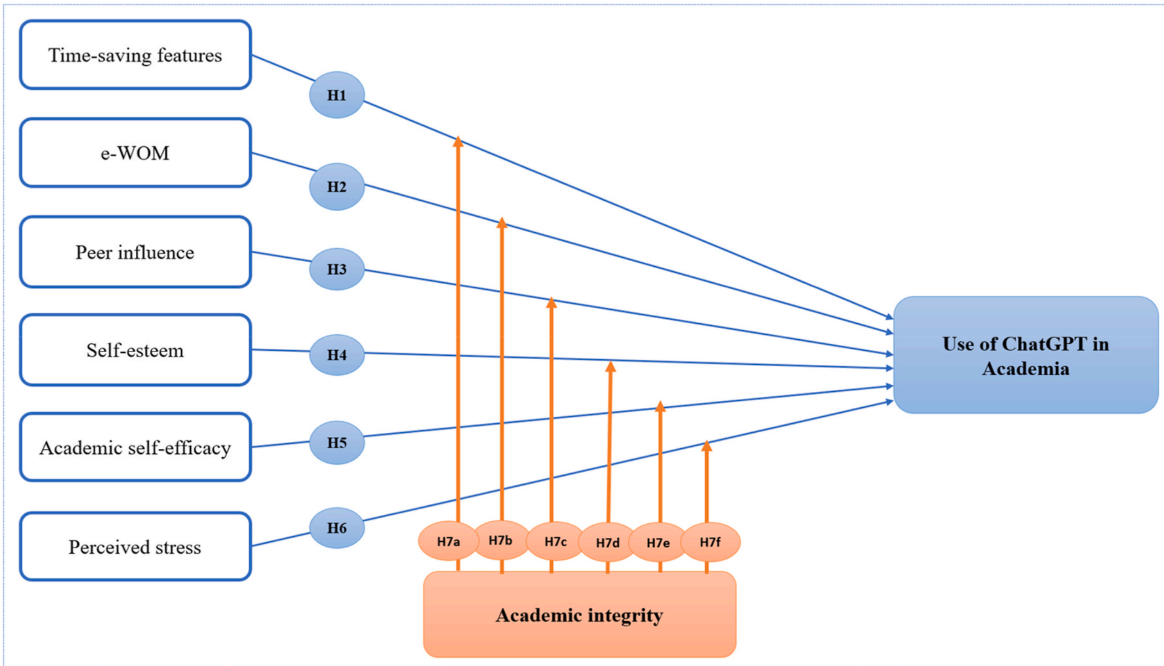

Fig. 2. Research model.

individual acts or reacts in specific situations or towards specific objects (Bandura, 1991). This concept also extends to how a person engages with technology and technological innovations (Ratten & Ratten, 2007; [22]. These three factors or components interplay with each other to forecast individuals' actions. Nevertheless, their predictive abilities are not uniform, and their effects on each other do not necessarily occur simultaneously [21]. The SCT framework has found application across various disciplines, likely due to its adaptable nature, as it is able to recognize human behaviors as dynamic and ever-changing (Kock, 2004). For instance, this has been extensively utilized in studies related to e-government system adoption [24], mobile learning [25], internet banking [22], telemedicine [26], e-tax systems [27]. However, the application of SCT in examining the adoption of AI platforms, including ChatGPT, within the academic context has been rarely attempted. As such, in the present study, we predict researchers' adoption of ChatGPT in their work and how their behavior can be shaped by a variety of behavioral, personal and environmental factors, such as eWOM, peer influence, time-saving features, self-esteem, academic self-efficacy, perceived stress and academic integrity (Fig. 2). Based on these essential aspects, SCT can provide a more holistic understanding of researchers' ChatGPT adoption behavior in academic settings [21,22,28,29].

2.2. Time-saving feature

The value of time and its impact on individual behavior has been widely praised in behavioral economics [30,31]. In a time-sensitive modern society, time is a paramount intangible resource, the use of which can be exchanged for another resource, such as wealth or effort [32]. The literature consistently concluded that the timeliness of services has always been important in users' motivation to use technologies [33–35].

The time-saving feature of ChatGPT for data administering and assimilation into people's daily lives has made the timeliness element increasingly essential to accomplishing tasks, boosting productivity, and achieving goals [36]. In general, efficiency can be regarded as an advantage of using ChatGPT for users' experience. However, its effect on consumer behavior has been scarcely studied, particularly in the academic context. ChatGPT can be a fundamental means in academia [37]. The chatbot can save time by scheduling appointments, setting reminders, preparing lessons, and consultations, and recommending academic resources [36]. When academics perceive they can efficiently save time by using ChatGPT, they are more likely to use it to perform their job. Based on the relevant literature and the behavioral time theory [30], the following hypothesis was formed:

H1. Time-saving feature increases the use of ChatGPT in academia.

2.3. e-WOM

Word of Mouth (WOM) is an experimental method for disseminating information. WOM is communications between clients regarding a specific service/product or its provider without commercial control [38,39]. The advancement of digital platforms led to a novel form of communication, "e-WOM", the electronic version of traditional WOM. Essentially, e-WOM is defined as optimistic or adverse testimony made by existing or prospective customers about services, products, or their providers, made available to other institutions and individuals via cyberspace [40]. e-WOM has several unique characteristics, including greater scalability, diffusion speed, persistency, accessibility, measurability and quantifiability [41].

This phenomenon is relevant to marketers as e-WOM is weighed as a crucial factor shaping customer behavior towards technology uptake (Daugherty & Hoffman, 2014; [42]. A recent cross-cultural systematic literature review by Ref. [43] highlighted that e-WOM might influence a broad range of behavioral outcomes, including trust, attitude, risk perception, e-satisfaction, perceived usefulness and intention to use. Indeed, a prior study confirmed that the information shared among networking sites through e-WOM reflects the knowledge and experience of other users [44]. However, the literature has not refined the type of products; in terms of diagnosticity, the provision of tactile information within a mess community significantly impacts user evaluations. Such effects may vary depending on individuals' perceptions, needs, academic purposes, and the nature of systems like ChatGPT. However, this particular setting has rarely been examined. Thus, we attempt to fill this gap by exploring the potential linkage between e-WOM and ChatGPT usage in academia. Being regarded as the concrete evidence provided by web communities, a more reliable source to quantify the usefulness and benefits of ChatGPT, e-WOM communication among academics likely has a more significant impact to be integrated into their practices. Under such conditions, the following hypothesis is postulated:

H2. e-WOM increases the use of ChatGPT in academia.

2.4. Peer influence

The social psychology perspective emphasizes the importance of peer influence (also referred to as social influence) in determining behavior. The theory of conflict elaboration related to social influences is that an individual decision towards new product innovation is significantly determined by his/her peers and social groups [45–47]. [48] social influence theory, the elementary form of influence is "compliance", which occurs when individuals admit influence to make promising reactions from other people or groups; "internalisation", also known as social proof, arises when a person takes others' views as evidence of reality; "identification" happens when a person accepts beliefs to create or sustain relationships within society or groups of people. Therefore, such influences could be described as changes in attitude produced by extrinsic factors.

According to several well-established technology acceptance models like the TBP, TRA, UTAUT and TAM – peers' influence is a substance-determining factor of behavioral intention, which refers to the degree to which a person's acceptance of technology is pretentious by others' opinions [49]. Many technology-related studies asserted that users' behavior is significantly affected by individual inducements, preferences and expectations of others [50–52]. Nevertheless, this later conflicted with some studies that failed to report significant evidence [53–55]. The inconsistent inferences suggest that peer influence is context-dependent, which motivates the contextual examination included in this study. However, less consideration has been given to investigating the influence of peers in the context of ChatGPT usage. It could be inferred that ChatGPT is modern and trendy, posing weight to the idea that the peers' influence captures academics' use of ChatGPT.

H3. Peer influence increases the use of ChatGPT in academia.

2.5. Academic self-esteem

Core self-evaluation (CSE) by Ref. [56] and SCT (Bandur, 1989) are well-known personality trait theories reflecting individuals' fundamental beliefs about themselves. Self-esteem, also known as "self--concept or self-confidence", is the primary psychological dimension of these theories, creating optimistic self-belief [57]. This creates the necessary skills or possibilities for completing a task successfully and delivering a positive outcome. Self-esteem is a comprehensive construct focused on personality and feelings of self-worth [58]. The self-concept regarding one's character has been linked to various phenomena, such as performance, satisfaction, stress, success, and creativity [59]. Strong self-esteem is a favorable evaluation of self-worth [60]. Several studies suggested that people's self-esteem can boost their acceptance of systems [61–64]. For instance, in the context of e-learning acceptance, ensuring that an individual has a high self-concept to attain meaningful results [62].

Self-esteem has considerable implications for ChatGPT use in academia due to its association with reducing job anxiety, creating a positive attitude and optimistic self-belief of having a creative academic quality in accomplishing tasks related to research, teaching and assessment by automating tedious components of the task [36,37]. Within traditional education, the self-esteem construct has been extensively explored; however, implementing ChatGPT in academia as an innovative matter remains under research. Little is known about whether self-esteem motivates academics to use ChatGPT. Accordingly, the present work aims to fill this gap by investigating the association between self-esteem and using ChatGPT in academia. Against this backdrop, it can be grounded that academics with higher self-esteem evaluations are more sensitive to positive stimuli and tend to use ChatGPT. Thus, the following hypothesis can be formulated:

H4. Self-esteem increases the use of ChatGPT in academia.

2.6. Academic self-efficacy

Self-efficacy is another concept from Bandur's (1989) SCT—it describes an individual confidence in his/her ability to do or learn specified tasks. In academia, it often refers to academic self-efficacy, defined as a person's confidence in achieving academic success and educational goals [65,66]. It relates to motivation, accomplishment, emotion, cognition, and self-regulation [65].

In the aftermath of ChatGPT's launch, educators have been immersed and alarmed; meanwhile, there are proponents and opponents of its use in academia. However, it is beneficial for academics to derive insights and make credentialed assessments about ChatGPT's significance in education (Jürgen-Rudolph et al., 2023) [67]. suggested that AI-powered platforms have tremendous potential for transformative changes in academic settings. Employing artificial intelligence in higher education could boost academic self-efficacy by giving academics access to a complex and powerful tool that enhances their capabilities [68]. Using ChatGPT in academia may similarly reduce teaching and learning workloads, gain insights into students' learning progress, and facilitate classroom innovation by streamlining grading, monitoring plagiarism, supervision, and feedback [69]. However, scarce empirical studies have investigated the effect of academic self-efficacy on using ChatGPT, which demands examination by this study. Based on the earlier arguments asserting that using ChatGPT will assist academics in mastering their skills and overcoming difficulties in work, it can be formally hypothesis that:

H5. Academic self-efficacy increases the use of ChatGPT in academia.

2.7. Perceived stress

Perceived stress refers to individuals' feelings or perceptions of tension or pressure he/she experiences over some time [70,71]. Perceived stress comes when a person must cope uncontrollably with persistent inconveniences, issues, or obstacles regarding crucial aspects of life or work. Previous studies have shown that stress has an adverse impact on mental health in the e-learning environment [72,73]. One of the significant stresses contributing to the rise in stress levels is the sudden and forced move to online education during COVID-19 [74]. Similarly, experiments reported a constructive relationship between optimistic perceptions of technology and mental well-being [75]; Zhuo et al., 2023), implying that the insight of ChatGPT as an unbiased tool is associated with perceived stress and positive user experience [76]. conducted a systematic review to evaluate the effectiveness of using chatbots. The findings were lacking and revealed weak evidence suggesting that chatbots can help manage depression, stress, distress, and acrophobia. However, using chatbots did not significantly affect subjective psychological well-being. Thus, the literature was inconclusive regarding the relationship between chatbots and anxiety severity, positive and negative effects. Based on the current discussion, ChatGPT has the potential to improve perceived stress, but further research is needed, given the lack of empirical evidence, particularly in academia [76].

H6. Perceived stress increases the use of ChatGPT in academia.

2.8. Academic integrity (moderator)

Integrity in education and academia requires a dedication to honesty, fairness, trust, responsibility and respect [77]. Academic integrity is the practice of researching and completing academic work with fairness and coherence [78,79]. Presently, academic usage of AI is a trending topic in education with numerous advantages, including academic engagement, collaboration, assessment, and accessibility. Yet, this technological arms-race has also raised concerns about academic honesty and plagiarism [3], which violate educational integrity principles [80].

For instance, academics may find it challenging to effectively assess the understanding of learners on materials when they use chatbot applications, as it may not accurately reflect their education level [3]. Similarly, using AI among academic staff brings more technologically innovative means of perpetrating academic dishonesty and violating the norms and standards of academic integrity, including research plagiarism, teaching practices and service misconduct [80]. The practical notion is that *"academic integrity hangs in the balance"* because using ChatGPT in academia is a double-edged sword_ It can either be used to save time, boost self-esteem, improve academic self-efficacy, and reduce stress, commit academic misconduct and plagiarism. Against this backdrop, it is argued that investigating the moderating role of academic integrity in using ChatGPT in academia is essential for developing meaningful insights. Although integrity is well reported in the literature and has been shown to exert a direct impact on academics' behavior [3,77,81]; hardly identify investigations explored its role as moderator to strengthen the association between various assumed constructs, especially in the context of using ChatGPT in academia. Accordingly, the following hypotheses are formulated:

H7. Academic integrity significantly predicts the use of ChatGPT in academia.

H7a. Academic integrity positively moderates the association between the time-saving feature and the use of ChatGPT in academia.

H7b. Academic integrity positively moderates the association between e-WOM and the use of ChatGPT in academia.

H7c. Academic integrity positively moderates the association between peer influence and the use of ChatGPT in academia.

H7d. Academic integrity positively moderates the association between self-esteem and using ChatGPT in academia.

H7e. Academic integrity positively moderates the association between academic self-efficacy and the use of ChatGPT in academia.

H7f. Academic integrity positively moderates the association between perceived stress and the use of ChatGPT in academia.

3. Research method

3.1. Research design, methodology, and data collection technique

In this study, quantitative research was adopted due to its suitability for examining causal models and relationships. It involved the controlled manipulation of a limited set of factors to address theory-driven research questions and hypotheses, ultimately aiming to provide a comprehensive overview of trends and associations [82]. To validate the ChatGPT usage model, the study adopted a cross-sectional research design with a web-based survey distributed to the global academic community. The internet survey tool is basically undertaken due to its effective features, such as responsiveness, cost-effectiveness and target population access [83,84], as well as the nature of the present research examining a technology-related issue [85]. The target sample in this research is academic researchers from all around the world, specifically users of ResearchGate (RG) and Academia.edu (Academia) sites with at least two research items available in their profiles. RG and Academia have become the two most popular academic social networking sites (ASNSs) in the world today [86,87]. RG and Academia have gained immense interest and popularity among researchers worldwide with a growing number of users. In 2021, the total number of users of RG and Academia reached 20 million and 170 million, respectively [88]; [89].

Table 1
Sample characteristics ($n = 702$).

Measure	Items	n	%
Gender	Male	424	60.4
	Female	278	39.6
Age	20–30 years	32	4.6
	31–40 years	341	48.6
	41–50 years	187	26.6
	51 years and above	142	20.2
Academic position	Postdoctoral Researcher/Fellow/Scholar	15	2.1
	Lecturer/Instructor	205	29.2
	Assistant Professor/Senior Lecturer	308	43.9
	Associate Professor	124	17.7
	Professor	50	7.1
Experience	1–5 years	177	25.2
	6–10 years	190	27.1
	11–15 years	203	28.9
	16 years and above	132	18.8

In terms of data collection technique, we sent over 6000 survey invitations with URL links to randomly selected users from RG and Academia, while a total of 702 useable responses were retrieved for analysis during the period from April 14 to May 15, 2023. The response rate of the survey was around 11.7%. This is not surprising as recent literature with online questionnaires about Academia.edu, RG, or Mendeley have obtained a similar response rate, ranging from 8% [86] to 10% [90]. Prior to carrying out the questionnaire distribution, we consulted 3 academicians and pilot-tested 20 researchers, and accordingly, a few revisions were made to attain the reliability and validity of the ChatGPT usage model. To mitigate the potential for social desirability bias in the research, a series of meticulous measures were put into practice, including ensuring the confidentiality of responses, conducting a comprehensive pilot test, and employing an online survey format [91]; [92].

3.2. Measurements and analysis tool

In this research, the online survey comprising 47 measurement items to evaluate eight constructs, namely time-saving features, e-WOM (electronic word-of-mouth), peer influence, self-esteem, perceived stress, self-efficacy, academic integrity, and the use of ChatGPT in academia. All measurement items were derived from previously validated scales and carefully rephrased to align with the specific context of ChatGPT usage in academic settings. The measurement of time-saving features was based on five items adapted from Ref. [31]; while the assessment of e-WOM involved the adaptation of five items from Ref. [39]. Peer influence was evaluated using four questions adapted from Ref. [46]; and well-established Rosenberg's self-esteem scale [57] were adapted to measure self-esteem. We assessed academic self-efficacy by using four items adapted from Ref. [66]; while perceived stress was evaluated through six items adapted from Ref. [71]. The measurement of academic integrity drew upon seventeen items adapted from Ref. [79]; and the assessment of the use of ChatGPT in academia employed five items adapted from Refs. [28,29].

Participants' perceptions in the study were assessed using a five-point Likert-type scale, wherein the scale ranged from one, indicating "strongly disagree," to five, indicating "strongly agree". The current study utilized partial least squares structural equation modeling (PLS-SEM), a robust method for examining intricate interrelationships among latent constructs [93]. PLS-SEM is a variance-based modeling approach that has gained popularity in the fields of management and social sciences due to its capacity to handle small sample sizes, non-normal data distributions, and complex relationships among latent constructs [94]. Unlike covariance-based SEM (CB-SEM), PLS-SEM is particularly suitable for studies that aim to predict outcomes rather than establish causal relationships among constructs [93].

Table 2
Measurement model results.

Construct	Item	Loading	Cronbach's α	CR	AVE
Time-saving feature (TSF)	TSF1	0.723	0.857	0.895	0.631
	TSF2	0.801			
	TSF3	0.739			
	TSF4	0.826			
	TSF5	0.875			
Electronic word-of-mouth (e-WOM)	EWOM1	0.807	0.837	0.891	0.672
	EWOM2	0.876			
	EWOM4	0.844			
	EWOM5	0.748			
Peer influence (PI)	PI1	0.945	0.919	0.897	0.688
	PI2	0.905			
	PI3	0.711			
	PI4	0.732			
Self-esteem (SE)	SE1	0.894	0.888	0.918	0.693
	SE2	0.804			
	SE3	0.887			
	SE4	0.839			
	SE5	0.728			
Academic self-efficacy (ASE)	ASE1	0.927	0.754	0.848	0.653
	ASE2	0.691			
	ASE3	0.789			
Perceived stress (PS)	PS1	0.762	0.817	0.864	0.562
	PS2	0.762			
	PS3	0.828			
	PS4	0.655			
	PS6	0.730			
Academic integrity (AI)	AI1	0.913	0.955	0.956	0.735
	AI3	0.902			
	AI5	0.920			
	AI7	0.706			
	AI9	0.964			
	AI10	0.669			
	AI11	0.765			
	AI12	0.964			
Use of ChatGPT in academia (ChatGPT)	ChatGPT1	0.896	0.887	0.917	0.691
	ChatGPT2	0.853			
	ChatGPT3	0.899			
	ChatGPT4	0.852			
	ChatGPT5	0.627			

4. Data analysis and findings

4.1. Sample profile

The questionnaire revealed a noteworthy gender disparity among the respondents, with more than half of (60.4%) of respondents being male, whereas (39.6%) identifying as female. The demographic information displayed in Table 1 also shows that 48.6% of respondents fell within the 31-40-year-old age group, while 26.6% of them were in the 41-50-year-old age bracket. With regard to the academic position, the sample comprised 43.9% Assistant Professors/Senior Lecturers, 29.2% Lecturers/Instructors, and 17.7% were Associate Professors. Additionally, 28.9% of respondents stated that they have 11–15 years of academic experience, while 27.1% had 6–10 years of academic experience.

4.2. Common method bias

As an essential analysis, we assess common method bias (CMB) to ensure the validity of research results, as it may threaten validity. Hence, the current study utilized Harman's single-factor analysis to determine whether a single construct can account for a significant share of variance in the model. The analysis results indicated that the largest single construct explains 25.44% of the variance. This value is lower than the recommended maximum limit of 50% suggested by Ref. [95]. Consequently, it can be concluded that there were no validity concerns associated with CMB in the model. Furthermore, the research performed a comprehensive examination of collinearity by conducting a test of full collinearity to determine if the variance inflation factor (VIF) values surpassed the maximum threshold of 3.3. The results showed that the VIF values ranged from 1.09 to 1.80, indicating that the presence of CMB did not threaten the study's validity.

4.3. Measurement model

The evaluation of the reflective model in this research encompassed an assessment of the reliability and validity of the variables. Setting standards for internal consistency, discriminant validity, convergent validity, and reliability is crucial. According to Ref. [94]; a factor loading greater than 0.70 is considered acceptable for establishing reliability and validity, while [96] suggests a threshold of 0.4. However [94], propose that items with loadings between 0.40 and 0.70 may be considered for removal only if their exclusion would improve composite reliability. In this study, eight items (e-WOM3, SE6, ASE4, PS6, AI2, AI4, AI6, and AI8) needed to be removed from the initial set of 47 survey items. Convergent validity was supported by the average variance extracted (AVE) values, which exceeded the recommended threshold of 0.50, as suggested by Ref. [94]. Table 2 presents Cronbach's α values for all latent constructs, surpassing the required threshold of 0.70, indicating strong internal consistency of the measures. Additionally, the composite reliability (CR) values for each latent variable exceeded 0.70, affirming the reliability of the latent constructs. Ensuring the reliability and validity of the variables is essential to prevent errors in the research results and draw accurate conclusions.

The evaluation of the measurement model includes an important

Table 3
Discriminant validity.

Fornell-Larcker criterion		1	2	3	4	5	6	7	8
1	TSF	0.795							
2	e-WOM	0.477	0.820						
3	PI	−0.120	0.282	0.830					
4	SE	0.232	0.152	−0.075	0.833				
5	ASE	0.095	0.171	0.105	0.083	0.808			
6	PS	0.335	0.121	−0.300	0.131	−0.335	0.750		
7	AI	0.212	0.155	0.145	0.063	−0.243	0.083	0.857	
8	ChatGPT	0.414	0.281	−0.332	0.205	0.189	0.322	−0.254	0.831
HTMT 0.85 criterion		1	2	3	4	5	6	7	8
1	TSF								
2	e-WOM	0.613							
3	PI	0.228	0.393						
4	SE	0.276	0.174	0.092					
5	ASE	0.254	0.265	0.305	0.206				
6	PS	0.382	0.235	0.286	0.246	0.43			
7	AI	0.279	0.289	0.113	0.078	0.253	0.231		
8	ChatGPT	0.429	0.307	0.193	0.233	0.198	0.326	0.199	

Table 4
Structural model results.

Hypotheses	Path	β	Std error	t-value	p-value	Supported?
H1	TSF - > ChatGPT	0.233	0.039	5.918	0.000	Yes
H2	e-WOM - > ChatGPT	0.233	0.042	5.539	0.000	Yes
H3	PI - > ChatGPT	−0.279	0.152	1.835	0.033	No
H4	SE - > ChatGPT	0.075	0.033	2.263	0.012	Yes
H5	ASE - > ChatGPT	0.146	0.052	2.837	0.002	Yes
H6	PS - > ChatGPT	0.195	0.028	6.835	0.000	Yes
H7	AI - > ChatGPT	−0.284	0.036	7.886	0.000	Yes
H7a	TSF*AI - > ChatGPT	−0.173	0.045	3.882	0.000	No
H7b	e-WOM*AI - > ChatGPT	−0.039	0.057	0.683	0.247	No
H7c	PI*AI - > ChatGPT	−0.333	0.129	2.577	0.005	No
H7d	SE*AI - > ChatGPT	0.206	0.055	3.732	0.000	Yes
H7e	ASE*AI - > ChatGPT	0.050	0.044	1.147	0.126	No
H7f	PS*AI - > ChatGPT	0.150	0.069	2.188	0.014	Yes

component referred to as discriminant validity, which was measured using the approach recommended by Ref. [97]. The findings, as shown in Table 3, present that the square roots of AVE for the latent constructs were greater than the inter-construct correlation coefficients. These results provide evidence of discriminant validity, demonstrating that each latent variable measures a distinct construct that is not excessively correlated with other constructs. Besides, the heterotrait-monotrait (HTMT) ratio was used to measure the discriminant validity, quantifying the correlation between two items of the same construct. The analysis shows that all construct ratios were below the conservative threshold of 0.85 [98], indicating that the constructs were sufficiently different from each other. Statistical tests were conducted to evaluate the validity and reliability of the measurement model. These outcomes confirmed that the measurement scales employed for the factors of interest were both valid and reliable, allowing for the structural model's testing.

4.4. Structural model

A structural model evaluation is done to assess how the exogenous constructs influence the endogenous construct. The evaluation involves examining collinearity amongst constructs, determining the significance of the hypothesized relationships, measuring the explained variance (R^2), evaluating the model's predictive relevance (Q^2), and determining the effect size (f^2) [99]. A bootstrapping approach was used to measure the significance of the hypothesized relationships, drawing 5000 samples. The statistical findings of the analysis indicated that all the path relationships were significant, with a bootstrap critical t-value above ±1.65 (one-tailed test).

The analysis outcomes indicate strong positive associations between several constructs and the use of ChatGPT in academia. Specifically, Time-saving feature, e-WOM, self-esteem, self-efficacy, and stress are positively linked to the Use of ChatGPT in academia ($\beta = 0.233$, $p = 0.000$), ($\beta = 0.233$, $p = 0.000$), ($\beta = 0.075$, $p = 0.012$), ($\beta = 0.146$, $p = 0.002$), and ($\beta = 0.195$, $p = 0.000$), respectively. However, peer

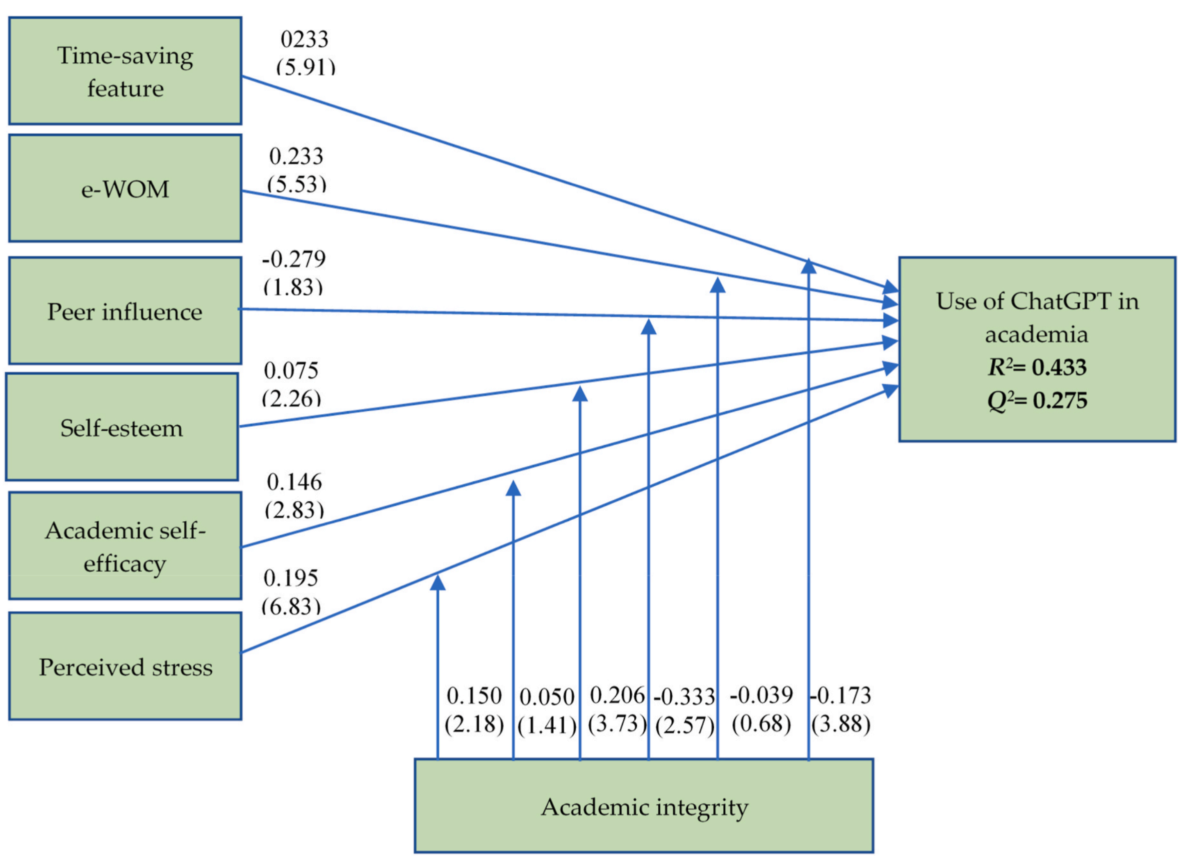

Fig. 3. PLS results for structural model assessment.
Notes: Values in brackets refer to t-statistics; values without brackets refer to standardized beta.

influence is found to have a negative relationship with the Use of ChatGPT in academia ($\beta = -0.279$, $p = 0.033$). Further, academic integrity significantly and negatively relates to ChatGPT usage ($\beta = -0.284$, $p = 0.000$). Accordingly, these findings support hypotheses H1, H2, H4, H5, H6 and H7, while not H3.

Regarding the interaction relationships, Table 4 presents the results. The interaction effects of time-saving feature × academic integrity, self-esteem × academic integrity, and perceived stress × academic integrity on using ChatGPT in academia are significantly positive. However, the moderating effect of academic integrity on peer influence and usage is significantly negative. Interactions of e-WOM × academic integrity, and self-efficacy × academic integrity have no effect. Hence, this supports hypotheses H7d, and H7f, while H7a, H7b, H7c, and H7e are not supported.

Looking at the model's explanatory power, the coefficient of determination (R^2) for the endogenous variable, ChatGPT use in academia, exceeds the recommended threshold value of 0.02. The R^2 value indicates that the model has a high degree of predictive accuracy, and the variables included in the study collectively explain 43.3% of the variance in the use of ChatGPT in academia (Fig. 3). To assess the model fit, the study employed the blindfolding procedure in PLS-SEM, which yielded a Q^2 value greater than zero (0.275) for the endogenous variable. This indicates the predictive relevance of the model. The structural assessment results are presented in Table 4.

5. Discussion and conclusions

5.1. Discussion

ChatGPT has become a hot topic in the academic community as a language model driven by AI, offering a wide variety of profound benefits, including academic content generation, accessibility, collaboration, and assessment. Nevertheless, this technological arms-race is raising concerns about academic honesty and plagiarism, facilitating the violation of ethical principles of the academic setting. In this research, an attempt has been made to pinpoint the motivations that drive academicians to use ChatGPT in their academic work, stressing the role of academic integrity in shaping their behavior to uptake such an innovation.

This work is a theoretically informed study that developed and validated a comprehensive adoption model highlighting ChatGPT usage behavior among researchers by applying the SLT theory. The outcomes of the empirical analysis indicated that the time-saving feature in relation to ChatGPT exerts a significant positive influence on academicians' behavior toward the use of ChatGPT. This implies that the time-saving feature of ChatGPT for integration and information processing into researchers' academic work has made the timeliness element increasingly essential to promptly generate content, accomplish tasks, boost productivity, and achieve goals [36]. We also found that e-WOM has a positive impact on ChatGPT usage in academia. That is, being regarded as the tactile information provided by web communities a more reliable source to quantify the usefulness and benefits of ChatGPT, e-WOM communication among academics likely has a more significant impact to be integrated into their practices. This result corresponds with prior studies but from different contexts (Daugherty & Hoffman, 2014; [42]. Unexpectedly, the results demonstrate that social influence negatively affected academicians' behavior toward using ChatGPT. This indicates that academics' peers, such as researchers, scholars and colleagues, negatively influence their decisions to use ChatGPT in the academic setting. This interesting outcome is likely traced to the fact that the use of ChatGPT raises security, ethical and legal concerns related to transparency, bias, misuse, privacy and copyright. A few research, but in different settings, has affirmed the conclusion of the negative influence of social norms on behavioral decisions [100].

The analysis also shows that academicians' behavioral intention to use ChatGPT was positively influenced by academic self-esteem. It implies that academic self-esteem has considerable implications for ChatGPT use in academia due to its association with reducing job anxiety, creating a positive attitude and optimistic self-belief of having a creative academic quality in accomplishing tasks related to research, teaching and assessment by automating tedious components of the task [36,37]. Likewise, academic self-efficacy – an academician's confidence in achieving academic success and performance goals – had a positive influence on ChatGPT usage in academic work. Employing AI chatbot ChatGPT in academia and higher education could boost academic self-efficacy by giving academics access to a complex and powerful tool that enhances their capabilities and reduces research, teaching and learning workloads (Jürgen-Rudolph et al., 2023). Perceived stress also plays a significant role in fostering people's ChatGPT adoption in academia. ChatGPT is described as a helpful tool for academics who struggle with time management, task accomplishment, workload and productivity. By providing prompt and accurate content, the use of ChatGPT can potentially manage depression, stress, distress, anxiety, and acrophobia in relation to academic capabilities.

Intriguingly, some meaningful outcomes were also extracted from the moderating effect of academic integrity in the ChatGPT usage model. Initially, the direct effect of academic integrity on academicians' adoption of ChatGPT was significantly negative. This implies that the higher the academic integrity among academicians, the lower their usage of ChatGPT in their work. Some academicians may claim that adopting ChatGPT is as unethical as ordinary plagiarism and academic dishonesty, which will likely cause catastrophic issues for the academic community. Due to the significant role of academic integrity, specifically in the era of AI platforms, we tested the moderating effect of academic integrity on the relationships between ChatGPT usage and its determinants. The analysis demonstrates that academic integrity-moderated interaction of time-saving feature on ChatGPT usage was significantly negative, in contrast to the previously hypothesized positive relationship. This shows that the higher the perceived academic integrity in relation to ChatGPT in academia, the lower the academics believe that using ChatGPT can be beneficial in saving their time, but not to the detriment of the principles of research ethics. The research also suggests that the association between self-esteem and academicians' ChatGPT usage is contingent on the level of their academic integrity. This means that academicians perceive that their integrity regarding ChatGPT usage could enhance self-esteem, thus fostering their adoption of such an innovative tool in academic settings. Furthermore, academic integrity strengthens the positive relationship between perceived stress and ChatGPT usage behavior. Academicians with high levels of academic integrity could strongly use ChatGPT in their academic work as a potentially effective way to relieve anxiety and stress associated with feeling overwhelmed by the workload. However, contrary to what has been hypothesized, the existence of academic integrity strengthened the negative association between social influence and ChatGPT usage behavior. This implies that the stronger the influence of academic peers (e.g., researchers or scholars and colleagues) with high levels of academic integrity, the lower their usage behavior of ChatGPT.

5.2. Theoretical implications

This attempt provides invaluable insights into the adoption of AI-powered chatbots, such as ChatGPT, within the academic sphere. It empirically explores a relatively new discipline, enriching the existing literature by considering various significant factors that shape the adoption behavior of such an innovative tool. Furthermore, it sheds light on the crucial aspect of academic integrity in AI adoption among researchers. These findings establish a robust groundwork for future studies in this domain, emerging several profound implications that can advance the AI adoption literature.

First, given the sensitive timing of this research topic and the existing theoretical gaps in the literature, which highlight the scarcity of research on ChatGPT adoption in academic settings, this study is likely

Table 5
Relevant policies for AI platforms adoption in academia.

- Stakeholders, such as higher education institutions, publishing companies, sponsors and other entities associated with academic and research ethics, should initiate sensitisation programs to build sufficient guidelines for AI chatbots usage (e.g., ChatGPT) in academic and research settings in particular. Simply banning the use of AI-driven chatbots in academia is a practical impossibility and would not overcome issues raised; thus, stakeholders should consider legal ways to embed them into the academic process.
- Since the use of AI chatbots ChatGPT has become a reality and inevitable in the realm of academic researchers and students; this research suggests that any academic content, including research for academic purposes, is to be examined and validated. Although academic staff and researchers strive for self-esteem and efficacy through achieving ideal performance indicators, it is necessary to familiarize them with ChatGPT limitations, e.g., having limited updated knowledge, generating incorrect or falsified information, and relying on biased data.
- As a further reassurance to ensure the protection of research ethics, it is of utmost importance to ethically use all AI-generated content platforms. As such, there should be cooperation and integration between AI language model programmers, academic institutions, publishers and any other relevant stakeholders to work together to curtail the spread of unethical behaviors, including academic dishonesty, plagiarism and fake citations, to protect researchers' rights.
- Stakeholders, such as AI language model programmers, academic institutions, publishers and any other relevant stakeholders, are also advised to concert efforts in making AI chatbots ChatGPT or upcoming update releases safe with the ability to detect unethical actions.
- To ensure academic integrity, some scholars have suggested including the AI language model as a co-author in AI-generated scientific papers [8,101]. However, this is likely to result in similar content but in different papers without any acknowledgment or citation, which can be known as self-plagiarism. It is crucial that publishers, editors, sponsors, as well as academic institutions clearly specify research ethics for authorship in terms of allowing or not allowing adding these tools as co-authors in case a researcher plans to involve AI language models in writing.

the first empirical investigation of OpenAI applications among academic researchers. Secondly, drawn on social cognitive aspects, the study enriches the literature by examining ChatGPT usage among academicians from all over the globe using the most popular ASNSs (RG and Academia). Thirdly, the model is built on various crucial determinants that could drive academic community adoption of ChatGPT, which have yet to be empirically tested in AI adoption, including time-saving feature, e-WOM, peer influence, academic self-esteem, academic self-efficacy and perceived stress. Accordingly, this developed and validated model has the potential to serve as a launching point for future studies in the discipline of AI applications, providing an opportunity to gain deeper insights into this innovative technology. In addition, we provide significant and timely evidence on academic integrity in relation to ChatGPT in academic settings. Academic integrity demonstrated significant moderating effects on the ChatGPT usage model in academia.

5.3. Practical implications

As scholarly communities still lack clear principles and instructions on using AI applications in academic work, significant and timely empirical evidence has emerged from this study that can inform policies and practices in academic settings and higher education. First, the results shed light on the drivers that fuel academicians' usage of ChatGPT. Academic researchers could be overwhelmed by heavy workloads, and thus, they perceive that using ChatGPT can help effectively with time, anxiety, and stress management, as well as to attain their academic self-esteem – academicians' confidence about their ability (who they are and what they can do). On the other hand, there is a severe issue raised regarding academic integrity and credibility in using AI-generated content platforms. Based on the analysis, we argue that the higher the academic integrity among academicians, the lower their usage of ChatGPT in their work. As such, some preliminary and relevant policies could be suggested in Table 5.

5.4. Limitations and directions for future studies

Despite the profound contributions of this study to theory and policy, some limitations are to be highlighted. RG and Academia were chosen in this study as the most popular ASNSs; however, they may not represent all other ASNSs users. Future research may look into other vital ASNSs like LinkedIn, Mendeley and Google Scholar. Moreover, the study solely relied on the SLT theory to explain the behavior of academicians in using ChatGPT in academic settings. By framing this research as a preliminary investigation, future studies may extend this theoretical framework to include other relevant technology usage theories, such as UTAUT and TAM, that can capture the nuances of this significant topic. Researchers may also expand the target population to include students and academic staff to understand better their motivations for shaping AI language models' adoption. Further, other crucial factors, such as academic performance, competence, and personal best goals, in the ChatGPT era will likely warrant investigation by future studies. Since this study mainly employs quantitative cross-sectional research, it is recommended to conduct future quantitative research to explore the finer-grained aspects and delve deeper into the perspectives of ChatGPT adoption behavior.

Author statement

Saeed Awadh Bin-Nashwan: Conceptualization, Methodology, Software, Data curation, Writing- Original draft preparation, Writing - Review & Editing, Project administration. **Mouad Sadallah:** Writing- Original draft preparation, Conceptualization, Software, Formal analysis. **Mohamed Bouteraa:** Writing- Original draft preparation, Visualization, Investigation, Writing - Review & Editing.

Data availability

Data will be made available on request.

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