

Exploring Academics Intentions to Incorporate ChatGPT into Their Teaching Practices

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Abstract

This paper sets to investigate the factors that affect UK academics attitudes towards incorporating Chat GPT in their teaching practices. To do so, the Technology Acceptance Model (TAM) and its extension the Unified Theory of Acceptance and Use of Technology (UTAUT) are employed, using a quantitative web-based survey questionnaire by collecting data from the University of Liverpool Management School (ULMS) in UK. The findings show that the original TAM variables of perceived ease of use and perceived usefulness, and the perceived self-efficacy (from the UTAUT) are positively affecting UK academics attitudes toward Chat GPT. Hence, the original TAM is still suitable for use, even for new disruptive technologies such as Chat GPT. To date, this is the only study that empirically explores the factors that influence academics to use Chat GPT within the UK Higher Education context.

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Introduction

"Chat GPT passes exams from Law and Business Schools" (CNN Business, 2023)

Artificial intelligence (AI) represents a paradigm shift in technology, which could fundamentally alter how humans interact with machines because it empowers computers to imitate human intelligence and judgments (e.g. Javaid et al.,2023). Chat GPT is a notable AI language model that combines artificial intelligence (AI) with Machine learning (ML) to generate human like responses to user queries (Ray, 2023). Chat GPT is versatile across several real-world applications (OpenAI, 2024), including coding, daily guidance, poetry creation, mathematical computations, statistical analyses, and book writing (Karakose, 2023). Since its launch in 2022, Chat GPT has been considered an unprecedented technological revolution and has generated a vivid discussion around its benefits and drawbacks (Saif et al., 2023).

In the Higher Education sector, Chat GPT has been introduced as a powerful tool that can be used by educators and students to create educational content and aid in learning and assessment. This tool can generate high-quality written text including among others, credible student essays, module syllabus, lecture materials, case studies, basic research papers, and systematic literature reviews, (e.g. Marchandot et al., 2023). Chat GPT can also be used as a diversified teaching tool to enhance students' learning experience by creating an interactive classroom, offer personalised educational content and further explain complex concepts (Igbal et al., 2023; Mollick & Mollick, 2022). Balanced against these advantages and opportunities, scholars have also identified challenges related to the use of Chat GPT in Higher Education. A key argument is that the use of Chat GPT by students to complete assignments may lead to academic dishonesty, cheating behaviours, and plagiarism (Alser & Waisberg, 2023; Ratten & Jones, 2023; Ray, 2023). Moreover, the extensive use of Chat GPT can result in students losing their ability to think critically, explore and verify content (Iqbal et al., 2023; Willems, 2023). Another key limitation levelled against Chat GPT is the argument that it produces 'bad knowledge' because it does not utilise reflexivity in generating its responses, (Lindebaum & Fleming, 2023) and that it is blind to the personal, social, and cultural conditions and circumstances that are inhabited by humans (Ratten & Jones, 2023).

Since its launch, researchers have extensively investigated the potential benefits and drawbacks of incorporating Chat GPT in Higher Education. However, less research exists on the factors that affect the adoption of Chat GPT in the Higher Education sector. Some studies have started to investigate the factors affecting students' willingness to use Chat GPT in their learning, but we currently have little evidence on academics' attitudes towards using Chat GPT in their teaching practices. Moreover, although UK is among the highest performing European and Western countries in Education (Gov.uk, 2023, December 15), majority of the current research on the factors influencing students' willingness to use Chat GPT has been conducted in countries outside the UK such as Indonesia (e.g. Tiwari et al., 2023); Oman; (e.g. Habibi et al., 2023) ; Hong Kong (e.g. Yilmaz et al., 2023) and Kazakhstan (e.g. Lai et al., 2023). To the best of our knowledge, only two studies have investigated academic's intentions to adopt Chat GPT in their teaching, and none of these studies have been conducted within the UK Higher Education context (Iqbal et al., 2023 and Bin-Nashwan et al., 2023).

Considering the above, this study sets the following research objectives; 1) explore the level of acceptance of the UK academic community towards Chat GPT, 2) identify the factors that affect UK academics intentions to incorporate Chat GPT in their teaching practices and 3) assess if the TAM model is still a relevant model that explains new technology acceptance. To this end, this study makes the following contributions; (1) it contributes to the novel debate on the adoption of Chat GPT in Higher Education (2) it investigates the phenomenon from the academics' perspective, (3) collects its data from the University of Liverpool Management School, a UK Russel Group University, (4) investigates the extent of which the Technology Acceptance Model

(TAM) and its extensions are still able to explain the adoption of disruptive technologies such as Chat GPT.

This study uses the Technology Acceptance Model (TAM) (Davis, 1989) and its extension the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) to identify the factors that influence University of Liverpool Management School academics' attitude towards Chat GPT usage. TAM model posits that individual's intention to use a new technology depends on the perceived ease of use and perceived usefulness of the new technology (Davis, 1989). The UTAUT model, suggests that on top of the TAM key premises, external factors such as 1) social influence 2) facilitating conditions, 3) attitude towards usage, and 4) perceived selfefficacy (Venkatesh et al., 2003) can also affect an individual's willingness to adopt a new technology. To investigate the effect of the aforementioned factors, we employ a web-based survey questionnaire of 31 Likert-scale questions. We draw our sample from academics employed in the University of Liverpool Management School (ULMS) of all ranks and across different departments. Through correlation analysis, we find evidence that perceived ease of use, perceived usefulness and perceived self-efficacy positively influence ULMS academics' attitude towards incorporating Chat GPT in their teaching practices. We also find evidence that perceived self-efficacy positively influences ULMS academics' perceived ease of use towards Chat GPT. Our findings suggest that the TAM model is still a representative model to use in the context of new technology adoption, with the key determinants of perceived ease of use and perceived usefulness, being powerful predictors of the intention of individuals to adopt a new technology (in this context Chat GPT). On the contrary, from the external variables put forward by the UTAUT model, only the perceived self-efficacy seems to play an important role.

Literature Review

Chat GPT in Higher Education sector

Chat GPT's remarkable possibilities of use in the Higher Education sector, has led to an abundance of academic research on the topic, with majority of the research focusing on conceptually identifying the benefits and drawbacks of incorporating Chat GPT in the Higher Education sector. Specifically, Lo (2023) reviewed 50 academic papers on the effect of Chat GPT in the Education sector and found that, Chat GPT can assist educators in the development of learning materials and assessment design, and can support students in exam/assignment preparation, instant feedback, and simple explanation of complex concepts. However, he also found evidence that Chat GPT can interfere with academic integrity (plagiarism) and can generate biased and incorrect information. Along the same lines, Baidoo- Anu and Ansah (2023) in their literature review, identified that Chat GPT can act as personalised tutor to students and resolve knowledge questions quickly. Baidoo-Anu and Owusu Ansah (2023) also found that Chat GPT can promote interactive learning and in-class collaborations and adaptive learning for students and help educators to adapt their teaching methods based on students' progress and needs. On the downside, Chat GPT lacks contextual understanding, which can lead to inappropriate/incorrect responses, it is prone to biases and mistakes, and lacks creativity and originality. Similarly, in their systematic literature review, Elbanna and Armstrong (2023), found evidence that Chat GPT can offer personalised learning, assist in learning and content development and boost educators and students' productivity. However, its breadth is particularly limited when it comes to generating responses that can affect the society and the well-being of individuals as its moral code and ethical principles reflects the data it is trained on. Additional literature reviews by Montenegro-Rueda et al. (2023), Karthikeyan (2023) and Gill et al. (2024) identify very similar benefits and drawbacks of Chat GPT in the education sector.

It is worth noting two review papers that used social media data and news articles to investigate the effect of Chat GPT in the Education sector. Sullivan and colleagues (2023) examined 100 news articles on how Chat GPT is disrupting higher education, in Australia, New Zealand, United

States, and United Kingdom. Their data revealed mixed public discussion with the majority focusing on how Chat GPT can destroy academic integrity and only a small proportion emphasising the need to embrace Chat GPT and incorporate it into the teaching and assessment. On the contrary, Adeshola and Adepoju (2023), collected and analysed 3870 tweets on the effect of Chat GPT in the Education sector and found that majority of people have a favourable and positive attitude towards the usage of Chat GPT in Education.

From the review of extant literature above, it is evident that a clear-cut conclusion on whether Chat GPT should be incorporated in the Universities' teaching practices, cannot be drawn. Acknowledging this existing tension, this paper takes the debate to UK Higher Education academics and empirically investigates their willingness and intention to incorporate Chat GPT in their teaching practices. Drawing insights from the existing research on technology acceptance, the study employs the Technology Acceptance Model (TAM) (Davis, 1989) and its extension the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al.,2003) to conceptualise the phenomenon.

Technology Acceptance Model

To investigate academic's acceptance and willingness to use innovative technologies, existing research has utilised the Technology Acceptance Model (TAM), Theory of Planned Behaviour (TPB), Unified Theory of Acceptance and Use of Technology (UTAUT) and value adoption model (VAM) (Sohn & Kwon, 2020). However, the Technology Acceptance Model (TAM) (Davis, 1989; Davis et al., 1989), is the most widely used model in explaining the behaviour of users in relation to a new technology adoption (Lee et al., 2003; Sohn & Kwon, 2020).

TAM is based on Ajzen and Fishbein's (1980) Theory of Reasoned Action (TRA). According to TRA, an individual's intention to perform a behaviour is a function of his/her attitude toward the function as well as behaviour and social norms. Building on TRA, TAM initially put forward perceived usefulness, and perceived ease of use as two fundamental determinants that help to answer the question '*what causes people to either accept or reject information technology*'? (Davis, 1989p.320). TAM posits that technology acceptance is a three-stage process wherein external factors or system design features trigger cognitive responses from users i.e. perceived ease of use and perceived usefulness, which in turn generates an effective response, i.e. attitude toward using (AT) or behavioural intention (BI), which influences actual use of the technology (AUT) (Davis et al., 1989; Wojciechowski & Cellary, 2013).

Figure 1



Original TAM model (Davis et. al., 1989, p.985)

Perceived Usefulness (PU): This is an individual's subjective perception and degree of belief that using a new technology will enhance or improve their job performance. This relates more to extrinsic motivation, which is considered to be instrumental for achieving objectives that are distinct from the activity itself (Davis et al., 1992). The conceptualisation of this construct

stemmed from Bandura's concept of outcome judgement, which refers to an individual's expectation of a positive outcome triggering behaviour (Bandura, 1977).

Perceived Ease of Use (PEU): This is the extent to which an individual believes that using a new technology will be free of effort (Davis, 1989). PEU is tied to an individual's assessment of the effort involved in the process of using the system which is related to the process of performing the activity itself (Viswanath, 2000). This construct is derived from the self-efficacy concept, a situation-specific belief about how well an individual can execute actions for the prospective task (Davis, 1989). Self-efficacy has a predictive role in decision-making about technology use (Hill et al., 1986, 1987). The TAM model theorises that perceived usefulness (PU) is influenced by perceived ease of use (PEU) because, other things being equal, the easier it is to use a technology, the more useful it can be. The model also theorises that PU and PEU will mediate the effect of external variables on behavioural intention.

Attitude Toward Using (ATU): Attitude is a tendency in response to an event in either a favourable or an unfavourable way (Kaplan, 1972). It is related to the evaluation of a system by the user which configures their intention to a possible use of the system (Revythi & Tselios, 2019). Previous studies on technology acceptance have identified that attitude is a key determinant of behavioural intention toward technology usage (e.g. Cheung & Vogel, 2013).

External Variables (EV): External variables (EV) can be identified as the external incentives associated with the system design, which could be different for each system. EV affects PEU and PU (Davis, 1993). Overtime, PU and PUE have been elaborated by different extensions of TAM to better explain the factors that make technology useful and easy to use. For example, Venkatesh and Davis (2000) introduced TAM2 as an extension of TAM by introducing five additional exogenous variables and two moderators namely, subjective norm, image, job relevance, output quality, result demonstrability experience and voluntariness (Marikyan & Papagiannidis, 2023).

TAM 2 was further developed to formulate the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003) (see figure 2). Venkatesh et al., (2003) proposed that performance expectancy, effort expectancy, social influence, and facilitating conditions are four key constructs that play a significant role as direct determinants of user acceptance and usage behaviour.

Performance Expectancy relates to the degree to which an individual believes that using a technology will aid them to perform their job more effectively. Perceived usefulness, extrinsic motivation, job fit, relative advantage and outcome expectations are the five constructs that pertain to performance expectancy (Venkatesh et al., 2003). *Effort Expectancy* refers to the degree of ease associated with using the technology and is captured by three constructs, namely perceived ease of use, complexity, and ease of use (Venkatesh et al., 2003). *Social Influence* is the degree to which an individual feels that important stakeholders believe that the individual should use the new technology. *Social Influence* is posited to be a direct determinant of behaviours intention and is represented by subjective norm, social factors, and image (Venkatesh et al., 2003). *Facilitating conditions* refer to the extent to which an individual believes that organisational and technical infrastructures are available to support the use of the new technology (Venkatesh et al., 2003). *Self –efficacy* reflects an individual's beliefs about the ability to perform certain tasks or use certain new technologies successfully (Bandura, 1977; Venkatesh et al., 2003).

Figure 2



Unified Theory of Acceptance and Use of Technology by Venkatesh et. Al. (2003:447)

TAM3 was put forward to address the inconclusive findings from TAM 1 and 2, regarding the relationships among perceived usefulness and perceived ease of use (Venkatesh et al., 2003). Specifically, TAM3 emphasises the unique role and processes related to perceived usefulness and perceived ease of use and theorises that the determinants of perceived usefulness will not influence perceived ease of use and vice versa (Venkatesh & Bala, 2008). TAM 3 puts forward six determinants of perceived ease of use, including perceived self- efficacy, perception of external control, computer anxiety, computer playfulness, perceived enjoyment, and objective usability (Venkatesh & Bala, 2008). Overall, TAM 3 was able to provide a 40-53% explanation of technology users behavioural intention.

Combining these models, TAM and UTAUT suggest that, an individual's willingness to adopt and utilise a new technology depends on a variety of factors such as; 1) perceived ease of use 2) perceived usefulness 3) social influence 4) facilitating conditions, 5) Attitude towards usage, 6) perceived self-efficacy, 7) gender, 8) age, 9) experience (Abdullah & Ward, 2016; Alharbi & Drew, 2014; Nafsaniath et al.,2015; Venkatesh et al., 2003).

TAM and Education

Over the years, TAM has begun to emerge as a leading scientific paradigm for investigating the acceptance of innovative technology in the educational context (Granic & Marangunic, 2019; Scherer et al., 2019; Teo, 2009). Studies have explored TAM's applicability for different learning technologies, like mobile learning (Sánchez Prieto, et al., 2016), digital academic reading (Lin & Yu, 2023), Personal Learning Environments (PLEs) (del Barrio-García et al., 2015), Learning Management Systems (LMSs) (Nafsaniath et al., 2015) as well as open-source LMS Moodle (Sánchez & Hueros, 2010) and commercial LMS Blackboard (Ibrahim et al., 2017). A number of systematic literature reviews (AI-Emran et al., 2018; Granic & Marangunic, 2019) and meta-analysis (Abdullah & Ward, 2016; Scherer et al., 2019; Šumak et al., 2011), have also been conducted to explore the use of TAM in education.

Figure 3



TAM 3 by Venkatesh & Bala (2008: 280)

These studies have explored the connection between TAM factors and the attitude or behaviour intent towards using various technologies in the educational sector, mainly from a student perspective (e.g. Ponce et al., 2017; Pereira et al., 2017; Lin & Yu, 2023; Revythi & Tselios, 2019; Wojciechowski & Cellary, 2013). Fewer studies have also explored educator's perspectives regarding technology acceptance (e.g. Sánchez-Prieto et al., 2017; Yang et al., 2021) and have identified various connections between the TAM variables and adoption of the technology under investigation. Recently TAM has also been employed to investigate the intention of students to adopt Chat GPT in their studies, and the general consensus is that students have a positive attitude towards Chat GPT (Habibi et al., 2023; Lai et al., 2023; Saif et al., 2023; Tiwari et al., 2023; Yilmaz et al., 2023). To the best of our knowledge, only one (qualitative) study adopts TAM to investigate academic's intentions to adopt Chat GPT in their teaching practices (Igbal et al., 2023) and in contrast to students' attitude, it finds that the faculty members of a private University in Pakistan have a negative perception towards incorporating Chat GPT in their teaching practices. Given the novelty of Chat GPT, Iqbal et al's (2023) called for further quantitative or mixed methods studies on the use of Chat GPT from an educator perspective.

This study responds to the call for more empirical studies on TAM in the education sector (Granic & Marangunic, 2019), as well as the need for further insights on the academics' intention to use of Chat GPT in their teaching practices (Iqbal et al., 2023). To accomplish this, we utilise TAM (Davis, 1989) and its extension the UTAUT (Venkatesh et al., 2003) to explore the effect of six key constructs namely; (1) Perceived Ease of Use (PEU), (2) Perceived Usefulness (PU), (3) Social Influence (SI), (4) Facilitating Conditions (FC), (5) Attitude Towards Usage (ATU) and (6) Perceived Self-Efficacy (PSE) on academics' will to adopt Chat GPT in their teaching practices.

Hypothesis Development

To develop our hypotheses for this current study, we drew from and summarised findings related to five key constructs i.e. Perceived usefulness, Perceived ease of use, Social Influence, Facilitating Conditions and Perceived Self Efficacy, which are identified as crucial in established empirical literature on TAM and UTAUT (Alharbi & Drew, 2014; Chen & Tseng, 2012; Davis, 1989; Habibi et al., 2023; Nafsaniath et al., 2015; Pituch & Lee, 2006; Tiwari et al., 2023; Venkatesh et al., 2003).

Perceived usefulness and Perceived ease of use

Perceived usefulness (PU) and perceived ease of use (PEU) have been used by several studies to explore technology acceptance in the educational sector. Wojciechowski and Cellary (2013) found that PU has a positive impact on students' attitude to learning when innovative technologies are used. Similarly, Briz-Ponce et al (2017) and Lin and Yu (2023) found that PU and PEU have a positive impact on students' attitudes towards using a new technology. Drawing on an extension of TAM, including system accessibility, self-efficacy, and social norm, Revythi and Tselios (2019) found that as far as behavioural intention is concerned. PU has a significant Similarly, drawing on an extended model of TAM, including system quality, and effect. experience, Mailizar, Burg, and Maulina (2021) found that student's attitude towards technology is significantly influenced by PEU and PU of the technology. Scherer, Siddiq, and Teo (2015) found support for the idea that PU is a crucial determinant for integrating technology in classrooms. Ngabiyanto et al. (2021) found that PU has a positive influence on behavioural intentions. The authors also found that inexperienced users tend to prioritise learning how to use the information system, while experienced users focus more on perceived usefulness. Overall, PU has been identified as the strongest determinant of the likelihood of educators to adopt a variety of technologies (Granic & Marangunic, 2019).

Based on these findings, the traditional concepts in the Technology Acceptance Model were adapted for this study and defined as follows. Perceived usefulness (PU) measures the degree to which educators believe that incorporating Chat GPT into their teaching practices could improve their job performance, Perceived ease of use (PEU) refers to the degree to which educators believe that incorporating Chat GPT does not require too much effort, Attitude towards usage (ATU) refers to the degree to which educators are willing to incorporate Chat GPT into their work practices (Davis, 1989).

Based on these findings, we propose the following hypotheses:

Hypothesis 1a: Perceived usefulness (PU) has a positive influence on the attitude of academics to use Chat GPT in their teaching practices.

Hypothesis 1b: Perceived ease of use (PEU) has a positive influence on the attitude of academics to use Chat GPT in their teaching practices.

Social influence

The impact of social influence on human behaviour in general and on technology adoption has been acknowledged in various TAM models (Venkatesh & Bala, 2008; Venkatesh & Davis,

2000; Venkatesh et al., 2003). Studies indicate that both social influence and attitude towards

adoption have positive effects on behavioural intention to adopt a new technology (Kulviwat et al., 2009). Specifically, in the educational sector, authors have also argued that societal aspects such as social influence, significantly affects technology adoption (Granić, 2023) and behavioural intention for students (Astuti et al., 2023; Mensah, 2019).

Based on these findings, we propose the following hypothesis:

Hypothesis 2: Perceived social influence has a positive influence on the attitude of academics to use Chat GPT in their teaching practices.

Facilitating Conditions

The impact of facilitating conditions on technology adoption has been acknowledged in various TAM models (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000; Venkatesh et al., 2003). Findings suggest that facilitating conditions have a positive and significant effect on an individual's behavioural intention to use technologies in the higher education context (Astuti et al., 2023; Hunde et al., 2023).

Hypothesis 3: Facilitating conditions have a positive influence on the attitude of academics to use Chat GPT in their teaching practices.

Hypothesis 3a: Facilitating conditions have a positive influence on ULMS academics'

perceived ease of use of Chat GPT

Perceived Self-efficacy

The impact of perceived self-efficacy on technology adoption has been acknowledged in various TAM models (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000; Venkatesh et al.,

2003). In the context of education, Buchanan, Sainter, and Saunders (2013) and Holden and Rada (2011) found that self-efficacy is positively associated with use of learning technology by the academic faculty. Specifically, Buchanan and colleagues (2013) found that faculty members who were high in self-efficacy reported use of more learning technologies than did those lower in self-efficacy. Therefore, higher self-efficacy is associated with higher intentions to use, and actual use of, technology (Hsu & Chiu, 2004).

Based on these findings, we propose the following hypotheses:

Hypothesis 4a: ULMS academics perceived self-efficacy has a positive influence on the attitude of academics to use Chat GPT in their teaching practices.

Hypothesis 4b: ULMS academics perceived self-efficacy has a positive influence on their perceived ease of use of Chat GPT

Research Methodology

This study employed a web-based survey questionnaire, developed by the researchers after consulting the existing literature and previous empirical papers on the subject. The survey named "Exploring Academics' intentions to incorporate ChatGPT in their teaching practices" aims to capture the intentions of UK academics employed at the University of Liverpool Management School (ULMS), to incorporate Chat GPT in their teaching practices. Since primary-data from human participants were needed for this study, Ethical Approval was obtained from the University of Liverpool Ethics Committee (ID8345). 31 Likert-style rating scale questions are used to collect the data (Table 1). The research instrument consisted of 2 main sections. The first section included a short description of the study, the informed consent, and a set of demographic questions including gender, age group, length of service, academic rank, and subject group, to ensure that the collected data are representative of the total population of ULMS academics. The second section uses a 5-point Likert response scale with the value of 1 signifying strong disagreement and the value of 5 signifying strong agreement to investigate the factors that affect UK academics attitudes towards incorporating Chat GPT in their teaching practices.

Data Collection

For the sample selection, this study used non-probability purposive sampling. An email invitation including the survey link was sent to all 205 academic staff employed in ULMS. Survey participation was voluntary; no incentives were offered to participants and the data collected were anonymous, with no identifiable information. Data collection took place from 15 November

2023 to 15 December 2023, and a total of 32 academics completed the survey with an average response rate of 16%.

Research Instrument

Prior to data analysis, the research instrument was assessed for its internal validity and reliability. To ensure content and construct validity, the theoretical constructs, survey questions and corresponding definitions used in this study were adapted from the original measurement scales used in TAM (Davis, 1989) and its extension the UTAUT (Venkatesh et al., 2003) as well as from relevant literature that has extensively proven TAM's and UTAUT's validity (Alharbi & Drew, 2014; Chau, 1996; Habibi et al., 2023; Mathieson, 1991; Nafsaniath et al., 2015; Pituch & Lee, 2006; Tiwari et al., 2023) (Table 2). Moreover, two senior members of the academic staff in ULMS, who are experts in survey development had reviewed the survey and validated it for readability, question design, measurement of theoretical constructs and relevance. The items that were deemed problematic were removed and some questions were revised to improve their clarity. Afterwards, the survey was pilot tested with five academics and final changes were made in response to their feedback. To assess for internal reliability, the Cronbach's alpha was used. Internal reliability determines whether a collection of items consistently measure the same characteristics, in other words, it controls for internal stability between multiple measurements of variables (Alharbi & Drew, 2014; Clayson, 2020; Hair, Black, Babin, Anderson, & Tatham, 2006; Shaked et al., 2020; Tiwari et al., 2023). Cronbach's alpha can take values between 0 and 1, but internal reliability is considered satisfactory when Cronbach's alpha is greater than 0.70 (Hair et al., 2006; Alharbi and Drew, 2014; Tiwari et al., 2023; Shaked et al., 2020; Clayson, 2020). Higher values (above 0.70) indicate higher agreement between the variables. As seen in Table 3, all constructs in this study show a high level of internal reliability and as such, our measurements can be considered reliable.

Results

Overall response rate was 16%, representing 32 academic staff. The seemingly low response rate does not necessarily present a problem because, the aim of this study is not to generalise its results; rather to capture the intentions of University of Liverpool Management School academics towards Chat GPT usage, and to offer suggestions to policy makers based on these results. In addition, by looking at the demographic statistics of the responders (Table 4) we observe a balance between male and female responders, a representation of all Subject groups, and Academic ranks, and a representative sample of different levels of experience. In terms of the age variable, we have a good spread of responding academics, covering all key age groups i.e. from 31-60 years old. As such, we feel confident that our results are representative of the ULMS academic community.

Table 1

The Survey Questionnaire

Variables	Survey Questions
Perceived ease of use (PEU)	Learning to operate Chat GPT was/is easy for me
	I find it easy to get Chat GPT to do what I want it to do (in relation to academic activities)
	My interaction with Chat GPT is clear and understandable
	Working with Chat GPT is complicated
	It takes me too long to learn how to use Chat GPT to make it worth the effort
Perceived Usefulness (PU)	Using Chat GPT in my job would enable me to accomplish tasks more quickly
	Using Chat GPT would improve my job performance as an academic
	Using Chat GPT would increase my productivity as an academic
	Using Chat GPT would enhance my effectiveness on the job as an academic
	Using Chat GPT would make it easier to do my job as an academic
	Use of Chat GPT can decrease the time needed for my important job responsibilities
Social Influence (SI)	People who influence my behaviour at the workplace think that I should use Chat GPT
	Stakeholders who are important to me at the workplace, think that I should use Chat GPT
	I use/plan to use Chat GPT because of the proportion of co-workers who use Chat GPT
	Co-workers at ULMS who use Chat GPT in their teaching and learning activities, have more prestige than those
	who do not
Facilitating Conditions (FC)	Specialized instructions concerning Chat GPT use is available to me
	I have access to all the necessary resources that will help me use Chat GPT
	Given the resources I have in my disposable it will be easy for me to use Chat GPT
	A dedicated team is available to assist users with any difficulties related to Chat GPT
Attitude Towards Usage (ATU)	Using Chat GPT for my academic activities is a positive idea
	Using Chat GPT for my academic activities is pleasant
	Using Chat GPT for my academic activities, makes my work duties more enjoyable
	I think it is worthwhile to use Chat GPT
	I have a generally favourable attitude toward using Chat GPT for academic purposes
	I will use Chat GPT for the development of learning materials
	I will use Chat GPT in the design, deliver and/or assessment of my modules
Perceived Self-Efficacy (PSE)	I feel confident using Chat GPT features during my lectures/seminars
	I feel confident operating Chat GPT functions to develop learning materials for my modules
	I feel confident incorporating Chat GPT into my weekly teaching
	feel confident using Chat GPT for any kind of academic activity

Variable	Definition – Adapted for this study	References
Perceived Ease of Use	The degree to which an ULMS academic believes that using Chat GPT would be	Davis (1989)
	free of effort (i.e. an effortless activity to use Chat GPT).	Venkatesh et al. (2003)
		Nafsaniath et al. (2015)
		Alharbi and Drew (2014)
		Tiwari et al. (2023)
		Habibi et al. (2023)
		Pituch and Lee (2006)
Perceived Usefulness	The degree to which an ULMS academic believes that using Chat GPT, will	Davis (1989)
	enhance their job performance. By job we refer to academics' teaching and learning	Venkatesh et al. (2003)
	responsibilities towards the student body.	Fathema et al. (2015)
		Nafsaniath et al. (2015)
		Alharbi and Drew (2014)
		Tiwari et al. (2023)
		Habibi et al. (2023)
		Pituch and Lee (2006)
Social Influence	The degree to which an ULMS academic; (1) perceives that important stakeholders	Venkatesh et al. (2003)
	within the University (like, academic colleagues, senior management team, UG, PG,	Habibi et al. (2023)
	and PhD students, professional services staff) believe that the individual should use	
	Chat GPT, and (2) is willing to use Chat GPT because Chat GPT is perceived to	
	enhance ones image or social status	
Facilitating Conditions	The degree to which an ULMS academic believes that ULMS offers sufficient	Venkatesh et al. (2003)
	organisational and technical infrastructure to support the use of Chat GPT	Habibi et al. (2023)
		Nafsaniath et al. (2015)
Attitude Towards Usage	An ULMS academic's positive or negative feeling about incorporating Chat GPT in	Davis et al. (1989)
	their teaching practices	Venkatesh et al. (2003)
		Nafsaniath et al. (2015)
		Alharbi and Drew (2014)
		Tiwari et al. (2023)
Perceived Self-Efficacy	An ULMS academic's judgement of his/her own capability to perform a certain task.	Nafsaniath et al. (2015)
	It is not concerned with the skills one has, but with the judgment of what one can do	Pituch and Lee (2006)
	with whatever skills one possesses. In the context of this study, perceived self-	
	efficacy indicates an ULMS academic's judgement of his/her own capability to use	
	Chat GPT in their teaching and learning activities	

Table 3

Constructs Internal Reliability - Cronbach's alpha

Construct	Number of construct	Items per Cronbach's alpha
Perceived Ease of Use	5	0.9066
Perceived Usefulness	7	0.9442
Social Influence	4	0.8230
Facilitating Conditions	4	0.8655
Attitude Towards Usage	7	0.9198
Perceived Self-Efficacy	4	0.8401
Overall Reliability	31	0.9373

Table 4

Respondents' Demographic Characteristics

Variable	Percentage	Number of Respondents
Gender		
Male	56.3%	18
Female	43.8%	14
Age Range		
25-30 years old	3.1%	1
31-39 years old	43.8%	14
40-49 years old	34.4%	11
50-60 years old	18.8%	6
Above 61 years old	0	0
Length of Service in Higher Education		
Less than a year	3.1%	1
More than 1 year, less than 3	21.9%	7
More than 3 years, less than	12.5%	4
More than 5 years, less than	28.1%	9
More than 10 years, less than	12.5%	4
More than 15 years	21.9%	7
Academic Rank		
Research/Teaching	3.1%	1
Lecturer (Assistant	40.6%	13
Senior Lecturer (Associate	46.9%	15
Professor	9.4%	3
Subject Group		
Marketing	18.8%	6
Strategy, International	31.3%	10
Accounting & Finance	25%	8
Economics	6.3%	2
Work, Organisation & Management	12.5%	4
Operations & Supply Chain	6.3%	2
Management		

Moving on, seven hypotheses are tested in this study using correlation analysis and the statistical software STATAMP-14. Attitude towards usage is the dependent variable and perceived ease of use, perceived usefulness, facilitating conditions, social influence, and self-efficacy are the independent variables. The findings are presented below.

Hypothesis 1a: Perceived usefulness has a positive influence on the attitude of academics to use Chat GPT in their teaching practices.

A Spearman's rank-order correlation was run to assess the relationship between perceived usefulness and ULMS academics' attitude towards usage. Thie analysis found a positive correlation between the two variables, *rs* (30) = .557, p < .001, suggesting a high probability of PU to influence ULMS academics ATU of Chat GPT.

Hypothesis 1b: Perceived ease of use (PEU) has a positive influence on the attitude of academics to use Chat GPT in their teaching practices

A Spearman's rank-order correlation was run to assess the relationship between perceived ease of use (PEU) and ULMS academics' attitude towards usage (ATU). The analysis found a moderate positive correlation between the two variables, rs (30) = 0.350, p <0.05, suggesting that PEU may positively influence ULMS academics' attitudes towards using Chat GPT.

Hypothesis 2: Perceived social influence has a positive influence on the attitude of academics to use Chat GPT in their teaching practices.

A Spearman's rank-order correlation was run to assess the relationship between perceived social influence (PSI) and ULMS academics' attitude towards usage (ATU). The analysis found a weak negative and non-significant correlation between the two variables, rs (30) = -0.143, p = .430. As such, Hypothesis 2 is rejected.

Hypothesis 3a: Facilitating conditions have a positive influence on the attitude of academics to use Chat GPT in their teaching practices.

A Spearman's rank-order correlation was run to assess the relationship between facilitating conditions (FC) and ULMS academics' attitude towards usage (ATU). The analysis found a weak positive but non-significant correlation between the two variables, rs (30) = 0.265, p = .142. As such, Hypothesis 3a is rejected.

Hypothesis 3b: Facilitating conditions have a positive influence on ULMS academics' perceived ease of use of Chat GPT

A Spearman's rank-order correlation was run to assess the relationship between facilitating conditions (FC) and perceived ease of use (PEU). The analysis found a weak positive but non-significant correlation between the two variables, rs (30) = 0.136, p = .457. As such, Hypothesis 3b is rejected.

Hypotheses 4a: ULMS academics perceived self-efficacy has a positive influence on the attitude of academics to use Chat GPT in their teaching practices.

A Spearman's rank-order correlation was run to assess the relationship between perceived selfefficacy (PSE) and ULMS academics' attitude towards usage (ATU). The analysis found a strong positive correlation between the two variables, rs (30) = 0.544, p < 0.001, suggesting that PSE may positively influence ULMS academics' attitudes towards using Chat GPT.

Hypothesis 4b: ULMS academics perceived self-efficacy has a positive influence on their perceived ease of use of Chat GPT

A Spearman's rank-order correlation revealed a statistically significant moderate positive relationship between ULMS academics' perceived self-efficacy (PSE) and their perceived ease of use (PEU) of Chat GPT, rs (30) = 0.378, p <0.05, suggesting that higher levels of self-efficacy are moderately associated with greater ease of use of Chat GPT among academics.

Moreover, to enhance the robustness of our research findings we performed a sensitivity analysis by slightly altering the original dataset and excluding certain observations at a time. Specifically:

1. Remove outliers: In our dataset we observed 1 outlier. There is only one response completed by a participant that is between 25-30 years old and has been part of ULMS for less than a year and is a research/teaching assistant. We decided to remove this observation.

2. Remove Professors: In our sample we observe that 3 Professors completed the survey compared to 13 Lecturers and 15 Senior Lecturers. We decided to remove the Professors from the sample and observe any changes in the results.

3. Remove Economics department: In the sample we observed that only two participants completed the survey from the Economics department. We decided to remove these observations.

4. Remove Operations and Supply Management department: Along the same lines, we observed that only two participants completed the survey from the Operations and Supply Management department. We decided to remove these observations.

5. Remove Strategy, International Business and Entrepreneurship department. In the sample we observe that most of the responses originate from the SIBE group (10 responses). We decide to remove the bigger sample and observe any changes to the data.

6. Random cases: to test the robustness of our findings we decided to remove random observation without specific characteristics. As such we removed observations 4 till 7.

After performing the sensitivity analysis and introducing small changes to our sample (see tests 1, 2, 3, 4 and 6) but also significant changes (see test 5), we observed that our findings are very robust. Both the p value and Spearman's r magnitude remain the same, with only small changes in the magnitude of Spearman's r. All the data and results are included in the Appendix.

Discussion

Using correlation analysis, we investigate the factors influencing ULMS academics intentions to incorporate Chat GPT into their teaching practices. Building on TAM (Davis, 1989) and its extension the UTAUT (Venkatesh et al., 2003) we utilised 6 known constructs namely, (1) Perceived Ease of Use (PEU), (2) Perceived Usefulness (PU), (3) Social Influence (SI), (4) Facilitating Conditions (FC), (5) Attitude Towards Usage (ATU) and (6) Perceived Self-Efficacy (PSE) to test our hypotheses. The goal of the correlation analysis was to investigate whether the key constructs put forward by TAM and UTAUT can explain the adoption of a new technology such as Chat GPT. Specifically, we find evidence that when the PU increases, ATU of Chat GPT increases as well. This suggests that when ULMS academics believe that Chat GPT will increase their job performance, they are more likely to use it. Similarly, when PEU increases, ATU Chat GPT increases as well, indicating that when academics find Chat GPT easy to use and free of significant effort they will use it. Both findings are in line with the key premises put forward by the original TAM model. To date, Igbal et al. (2023) is the only study that investigates the use of Chat GPT by Pakistani academics using TAM. However, the findings of this current study contradict lqbal et al's (2023) findings, who found that Pakistani academics are negatively disposed towards Chat GPT. The reasons for the contracting findings may be due to differences in the research methodologies, research approaches, research instrument, data collection and analysis techniques employed by the two studies.¹

Another possible explanation could be the different cultural dispositions of UK and Pakistani academics towards Chat GPT's benefits and drawbacks. For instance, how individuals perceive the world, among other things, are impacted by cultural conditions in the country they live (Hofstede, 1984). As such how UK academics in comparison to Pakistani academics perceive Chat GPT and its growing popularity in universities will be largely by the society's

preconceptions and existing beliefs around the benefits and drawbacks of Chat GPT. Moreover, other studies that examine students' intention to use Chat GPT support the findings of this current study (e.g. Habibi et al., 2023; Tiwari et al., 2023; Yilmaz et al., 2023).

Regarding the additional constructs that have been adapted from the UTAUT model, we find evidence, that as ULMS academics' PSE increases, their ATU of ChatGPT increases as well. Moreover, PSE was found to be a significant determinant of PEU. These findings indicate that ULMS academics' who feel confident about their Chat GPT skills, perceive Chat GPT as a useful technology and as such, are more likely to use it. Moreover, when PSE was used to explain the use of other new technologies such as learning management systems, e-learning, it was also found to have a significant positive effect (Nafsaniath et al., 2015; Pituch & Lee, 2006; Roca, Chiu, & Martínez López, 2006; Yuen & Ma, 2008). On the other hand, we find no evidence that FC and PSI, will affect ULMS academics' ATU Chat GPT. Regarding the effect of FC, a possible explanation could be that because ULMS academics had high PSE towards using Chat GPT, they did not have a need for additional organisational and technical infrastructure to support them in the use of Chat GPT. Another possible explanation could be that ULMS academics are self-taught utilising the information that is readily available on the internet. Our findings are in line with Venkatesh et al., (2003), who in the original UTAUT paper hypothesised an insignificant relationship between FC and users' intention to use a new technology. Similarly, Tan and Teo (2000) find an insignificant relationship between FC and intention to adopt internet banking while McGill, Klobas, and Renzi (2011) find an insignificant relationship between FC and instructors' attitude towards learning management systems. PSI does not emerge as a significant predictor either and this may have its roots on the diversified cultural background of the participants; as research suggest that cultural factors can modify ones understanding of social influence (Collette & Miller, 2019; Smith, 2001). Another possible explanation may have to do with the voluntary versus mandatory use of Chat GPT in the University. Venkatesh and Davis (2000) suggest that individuals are more likely to submit to

¹ Iqbal's et al., (2023) study employs a qualitative research methodology, an inductive research approach, interview data, and a thematic data analysis social influences when the task is mandatory and when the key stakeholders that influence their behaviour have the ability and power to reward or punish them. In this context, ULMS has not made the use of Chat GPT compulsory nor have the key stakeholders communicated certain benefits and rewards for those academics that use it in their teaching practice. Based on the findings, it is concluded that the TAM propositions are fully supported and as such TAM remains a relevant model to use to understand technology adoption. On the other hand, UTAUT propositions are partially supported in this study.

Conclusion and Future Research

This paper presents a review of the relevant academic literature on Technology Acceptance Model (TAM) (Davis, 1989) and Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) in the context of Chat GPT adoption by UK Higher Education Institutions. Additionally, using a quantitative methodology, it empirically investigates the intentions of University of Liverpool Management School academics to incorporate Chat GPT into their teaching practices. This is a novel idea as to date only two studies exist that explore academics attitudes towards Chat GPT, and of these only one employs the TAM model, and none is conducted in the UK Higher Education (Bin-Nashwan et al., 2023; Iqbal et al., 2023). This study finds evidence that the PEU and the PU are strong determinants of Chat GPT adoption, and positively affect the intentions of academics to incorporate Chat GPT. As such we meet the objectives we set, of 1) exploring the level of acceptance of the UK academic community towards Chat GPT, and 2) identifying the factors that affect UK academics willingness to

incorporate Chat GPT in their teaching practices. Moreover, this study provides empirical evidence on the predictive power of the key TAM constructs suggesting that the TAM model is still a leading scientific paradigm and credible model for facilitating assessment of diverse technological deployments in the educational context. In this way, we also address the third objective of this study of assessing if the TAM model is still a relevant model that explains new technology acceptance.

The findings of the current study hold significance for various stakeholders within ULMS as well other similar UK Universities and can inform practices in the wider UK Higher Education community.² Actionable guidance-should be provided to academics on the use of Chat GPT as well as the benefits of using it. The benefits of Chat GPT should be explicitly and clearly communicated to academics, highlighting the ways in which Chat GPT can improve the job performance of busy academics. These recommendations are based on the findings that the likelihood of adoption increases if academics perceive that they can use the platform without substantial effort. In addition, academics' confidence around their ability to effectively use Chat GPT will influence their perception about their ability they can use Chat GPT without effort, thus increasing their likelihood of adoption. Therefore, practical how-to sessions on the use of Chat GPT, should be conducted in group sessions and on a one-to-one basis. Particularly, one-to-one sessions may be more useful to develop confidence around the use of Chat GPT. Know-how videos, which academics can access at their own convenience will also be useful to enable them to become more familiar with using Chat GPT, which would invariably increase their confidence around the use of Chat GPT. Moreover, university policy makers could concentrate more efforts towards making the platforms more accessible to faculty members, so university wide subscription for the latest versions of Chat GPT could be made available to faculty members.

Lastly, we acknowledge that a key limitation of this study is its sample characteristics, that is (1) data originate from a specific population i.e. academics in the University of Liverpool Management School, (2) from a particular region i.e. Liverpool UK, and (3) data have been collected in a short span of time i.e. within 1 month. As such, room for generalisability is limited. Replication of this study in other settings and sample groups would help understanding the applicability of TAM in different context and collect additional evidence on the acceptance level of Chat GPT by UK academics employed in different UK Institutions. Additionally, a longitudinal study could be undertaken to observe UK academics attitudes over a longer time span and at different time periods. As Chat GPT evolves daily, it will be useful to compare findings from the introduction stage of Chat GPT in UK Universities (2023) and at a later stage identifying possible similarities and differences on UK academics' attitudes. In line with this, a follow-up qualitative study on UK academics' intention to use Chat GPT could enrich the existing scarce research on the topic by offering more intuitive and in-depth explanation on the factors that could affect their decision to adopt Chat GPT.

² All UK Universities need to comply with the Quality Assurance Agency for Higher Education guidelines that ensures that students and learners experience the highest possible quality of education(QAA, 2024). As such the academic practices followed at ULMS are at their core similar to other UK Institutions (quality of teaching, assessment may differ based on ranking status etc). Moreover, ULMS is part of the Russell Group Universities, recognised for providing a high-quality management education delivered by research active faculty and conducting world leading research (Russel Group Papers, 2012). Another common characteristic is that Russell Group Universities attract a high concentration of academic talent, and sustain a high concentration, of intellectually active and creative individuals. As such one would expect to see a similar mentality among academic staff employed at Russell Group Universities sharing common intellectual characteristics and keeping high similarly high academic standards.

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The authors list the following CRediT contributions:

Etieno Enang: Conceptualisation, Theoretical framework, Writing- reviewing and editing Danai Christopoulou: Conceptualisation, Methodology, Data Analysis, Writing

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Appendix

To enhance the robustness of our research findings we performed a sensitivity analysis by slightly altering the original dataset and excluding certain observations at a time. Specifically:

1. Remove outliers: In our dataset we observed 1 outlier. There is only one response completed by a participant that is between 25-30 years old and has been part of ULMS for less than a year and is a research/teaching assistant. We decided to remove this observation.

2. Remove Professors: In our sample we observe that 3 Professors completed the survey compared to 13 Lecturers and 15 Senior Lectures. We decided to remove the Professors from the sample and observe any changes in the results.

3. Remove Economics department: In the sample we observed that only two participants completed the survey from the Economics department. We decided to remove these observations.

4. Remove Operations and Supply Management department: Along the same lines, we observed that only two participants completed the survey from the Operations and Supply Management department. We decided to remove these observations.

5. Remove Strategy, International Business and Entrepreneurship department. In the sample we observe that most of the responses originate from the SIBE group (10 responses). We decide to remove the bigger sample and observe any changes to the data.

6. Random cases: to test the robustness of our findings we decided to remove random observation without specific characteristics. As such we removed observations 4 till

Below we test our hypotheses using a different sample as discussed above each time

Perceived Usefulness	Perceived Ease of Use	Perceived So- cial Influence	Facili- tating Condi- tions	Per- ceived Self- Efficacy
0.5465***	0.3759*	-0.1805	0.3293	0.5601** *
0.001 31	0.0371 31	0.3313 31	0.0705 31	0.001 31
	Perceived Usefulness 0.5465*** 0.001 31	Perceived UsefulnessPerceived Ease of Use0.5465***0.3759*0.0010.03713131	Perceived UsefulnessPerceived Ease of UsePerceived cial Influence0.5465***0.3759*-0.18050.0010.03710.3313313131	Perceived UsefulnessPerceived Ease of UsePerceived cialSo- tating Influence0.5465***0.3759*-0.18050.32930.0010.03710.33130.070531313131

1. Remove outliers: Robustness test support the findings from the original dataset.

Dependent:	Facilitating	Perceived	
Perceived	Conditions	Self-	
Ease of Use	Conditiono	Efficacy	
Spearman's r	0.1162	0.3763*	
p-value	0.5337	0.037	
Ν	31	31	

2. Remove Professors: Robustness tests support the findings from the original dataset.

Dependent: ULMS Academ-	Perceived Usefulness	Perceived Ease of	Perceived So- cial	Facili- tating	Per- ceived
ics'		Use	Influence	Condi-	Self-
attitude towards				tions	Efficacy
usage					
Spearman's r	0.4224*	0.5384**	-0.1563	0.2194	0.5665** *
p-value	0.0225	0.0026	0.4182	0.2528	0.001
Ν	29	29	29	29	29
Dependent: F	- acilitating Per	rceived			

Dependent: Perceived Ease of Use	Facilitating Conditions	Perceived Self- Efficacy
Spearman's r	0.2638	0.3549*
p-value	0.1668	0.05
Ν	29	29

3. Remove Economics Department: <u>Robustness tests support the findings from the original dataset.</u>

Dependent: ULMS Academ- ics' attitude towards usage	Perceived Usefulness	Perceived Ease of Use	Perceived So- cial Influence	Facili- tating Condi- tions	Per- ceived Self- Efficacy
Spearman's r	0.3554*	0.6089**	-0.1659	0.2760	0.5361* *
p-value	0.05	0.0004	0.3808	0.1399	0.0023
Ν	30	30	30	30	30

Dependent: Perceived Ease of Use	Facilitating Conditions	Perceived Self- Efficacy
Spearman's r	0.1778	0.3420*
p-value	0.3473	0.05
Ν	30	30

4. Remove Operations and Supply Management Department: <u>Robustness test support the findings from the original dataset.</u>

Dependent:	Perceived	Perceived	Perceived Se	o- Facili-	Per-
ULMS Academ-	- Usefulness	Ease of	cial	tating	ceived Solf
105		Use	Influence	Condi-	
attitude towards	S			tions	Efficacy
usage					
Spearman's r	0.3352*	0.5720***	-0.1299	0.2760	0.5457*
					^
p-value	0.05	0.001	0.4939	0.2282	0.0018
Ν	30	30	30	30	30
Dependent:	Facilitating	Perceived			
Perceived	Conditions	Self-			
Ease of Use		Efficacy			

5.	Remove	Strategy,	International	Business	and	Entrepreneurship	department:
Ro	bustness te	est support t	he findings from	the original	datase	<u>et.</u>	

0.3402*

0.05

30

Spearman's r

p-value

Ν

0.0919

0.6291

30

Dependent: ULMS Academ- ics' attitude towards usage	Perceived Usefulness	Perceived Ease of Use	Perceived So- cial Influence	Facili- tating Condi- tions	Per- ceived Self- Efficacy
Spearman's r	0.3765*	0.5847**	-0.0037	0.2095	0.4626*
p-value	0.0489	0.0043	0.9870	0.3495	0.0302
Ν	22	22	22	22	22

Dependent:	Facilitating	Perceived	
Perceived	Conditions	Self-	
Ease of Use	••••••	Efficacy	
Spearman's r	0.1182	0.4358*	
p-value	0.6004	0.0426	
Ν	22	22	

6. Random cases: Robustness test support the findings from the original dataset.

Dependent:	Perceived	Perceived	Perceived So	- Facili-	Per-
ULMS	Usefulness	Ease of	cial	tating	ceived

Academics'		Use	Influence	Condi-	Self-
attitude toward	ls			tions	Efficacy
usage					
Spearman's r	0.3115*	0.6292***	-0.0694	0.2292	0.4626* *
p-value	0.0106	0.0003	0.7255	0.2406	0.0072
Ν	28	28	28	28	28
Dependent:	Facilitating	Perceived			
Perceived Ease of Use	Conditions S	Self-			
		Efficacy			
Spearman's r	0.1386	0.3812*			

p-value

Ν

0.4818

28

0.0454

28

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