International Journal of Social Science and Human Research

ISSN (print): 2644-0679, ISSN (online): 2644-0695

Volume 08 Issue 08 August 2025

DOI: 10.47191/ijsshr/v8-i8-53, Impact factor- 8.007

Page No: 6197-6204

Adoption of ChatGPT Among UK Business Companies: Application of The Technology Acceptance Model

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ABSTRACT: This study investigates the adoption of ChatGPT among UK business companies using an extended version of the Technology Acceptance Model (TAM). While previous research has examined the broader implications of generative AI (GenAI) across different sectors, few empirical studies have explored the specific drivers of ChatGPT adoption among UK business companies and comparable populations. This study investigates the adoption of ChatGPT among UK business companies using an extended version of the Technology Acceptance Model (TAM). While previous research has examined the broader implications of generative AI (GenAI) across different sectors, few empirical studies have explored the specific drivers of ChatGPT adoption among UK business companies and comparable populations. ChatGPT is considered a digital product, and the businesses adopting it are treated as organizational consumers, thereby linking the study to the marketing literature on technology acceptance and consumer behavior. To address this gap, this study also incorporates subjective norm and trust in the standard version of the TAM, which enables it to capture the social and relational influences on adoption behaviour. To address this gap, this study also incorporates subjective norm and trust in the standard version of the TAM, which enables it to capture the social and relational influences on adoption behaviour.

All data was collected through an online survey which was distributed to mid- and senior-level professionals across various UK industries, yielding 202 valid responses. Structural Equation Modelling (SEM) was used to test ten hypotheses derived from the TAM. The results show that perceived usefulness is the most influential predictor of both attitude toward use and behavioural intention. Attitude also strongly influences behavioural intention, which in turn predicts actual use, in line with the TAM assumptions. While trust and subjective norm significantly affect both perceived usefulness and ease of use, the effect of perceived ease of use on attitude is minimal, indicating a value-over-simplicity mindset among business users in the UK.

Although some measurement limitations were identified in the reliability test and confirmatory factor analysis, all constructs were retained due to their grounding in established theory. The findings offer theoretical insights into GenAI adoption models and practical guidance for improving ChatGPT integration in business settings. This includes the need to demonstrate clear value, build trust, and leverage social influence to drive effective adoption.

KEYWORDS: ChatGPT, UK Business Companies, Technology Acceptance Model (TAM), Perceived Usefulness; Perceived Ease of Us

I. INTRODUCTION

The rapid proliferation of generative artificial intelligence (GenAI) technologies has introduced significant shifts in how businesses approach automation, decision-making, and human–machine interaction. Among these technologies, OpenAI's ChatGPT has emerged as a transformative tool, providing advanced natural language processing capabilities that enable diverse applications, including customer service automation, content creation, internal knowledge management, and strategic decision support (Dwivedi et al., 2023). As such, ChatGPT is increasingly being explored and adopted by business enterprises seeking to enhance productivity, reduce operational costs, and innovate their service delivery models.

Despite growing academic and industrial interest in the integration of GenAI into organizational workflows, current literature offers limited empirical evidence on the specific factors influencing ChatGPT adoption within the business context—particularly in national settings such as the United Kingdom. Most existing studies focus on general AI adoption (Venkatesh et al., 2022; Rai et al., 2023), while few offer a nuanced view of how business professionals perceive and integrate conversational agents like

ChatGPT into their daily operations. Given the socio-technical complexity of GenAI systems, a deeper understanding of the psychological, relational, and contextual factors driving adoption is critical.

The Technology Acceptance Model (TAM), originally developed by Davis (1989), remains one of the most widely used frameworks for predicting and explaining users' acceptance of technology. Its core constructs—perceived usefulness and perceived ease of use—have proven effective across diverse technological contexts. However, as digital technologies become more socially embedded and ethically contested, scholars have increasingly called for extended models that integrate additional variables such as subjective norm, trust, and perceived risk (Gefen et al., 2003; Pavlou, 2003; Venkatesh & Bala, 2008). These variables are particularly relevant for GenAI adoption, where ethical concerns, transparency, and organizational culture may mediate user behavior (Dwivedi et al., 2024).

This study responds to these gaps by examining the adoption of ChatGPT among UK business professionals using an extended version of the TAM that incorporates subjective norm and trust. Through a survey-based methodology and Structural Equation Modelling (SEM), the research identifies key predictors of adoption intention and actual use, offering both theoretical refinement to the TAM and actionable insights for practitioners. By situating the analysis within the UK business context, the study also contributes to understanding regional adoption patterns and organizational readiness for GenAI deployment.

II. LITERATURE REVIEW

The growing adoption of GenAI and ChatGPT among business companies has led to extensive research into the impact and acceptance of these technologies across various sectors (e.g., Mohr and Kühl, 2021; Kelly et al., 2023; Haddud, 2024). An appropriate example in this direction is the research by Arman and Lamiya (2023), which provides an early indication regarding the influence of ChatGPT on business operations. This study conducts a comprehensive literature review to emphasise the efficiency gains of the technology, including improvements in customer service and reduced operational costs, but also challenges related to data privacy and integration issues. Similarly, George and George (2023) rely on a literature review to present a broader narrative and compare ChatGPT to landmark innovations that have historically transformed industries. According to the authors, this form of GenAI could be applied to sectors such as e-commerce, education, finance, and health, among others. However, the authors have also noted the disruptive effects of the technology as existing business structures would be significantly adapted. In addition, Cui (2023) conducts a series of qualitative interviews concerning the application of ChatGPT among small and medium-sized enterprises (SMEs) that operate in the European service sector. The study's findings show that ChatGPT can facilitate the growth of SMEs by contributing to human resource management, strategic decision-making, administrative tasks, and other areas.

A range of studies have applied different technology acceptance frameworks to better understand ChatGPT adoption (e.g., Jo and Bang, 2023; Limna et al., 2024; Ma et al., 2025). For example, Limna et al. (2024) have implemented the TAM by conducting in-depth interviews with eight business owners in Bangkok, Thailand, to understand local adoption of ChatGPT. The outcome of the study emphasises perceived ease of use and perceived usefulness as critical determinants of technology adoption. The study identifies a number of challenges as well, including concerns about data security and privacy which may negatively affect customer engagement. Tailored support of business needs and additional customisation options are also necessary for business companies to exploit the potential benefits of ChatGPT (Limna et al., 2024). By comparison, Ma et al. (2025) have employed the TAM in a quantitative study with 784 ChatGPT users from China. The results of the study confirm that there is correlation among perceived ease of use, perceived usefulness, behavioural intention, and use behaviour. The findings also highlight the effects of gender and urban-rural differences on technology adoption. Studies of ChatGPT adoption among students conducted by Budhathoki et al. (2024) and Saif et al. (2024) have also used the TAM to demonstrate the positive effect of anxiety on using the system. Extended to business companies, this means that perceived usefulness would be the primary driver of ChatGPT adoption.

Furthermore, Gupta and Yang (2024a) have introduced a GenAI technology adoption model that is tailored for entrepreneurs, and highlights the utilitarian and hedonic values of the technology. The authors argue that the initial perceptions concerning ChatGPT would influence subsequent emotional responses and behavioural intentions. Furthermore, Gupta and Yang (2024b) have published a related study protocol, which outlines a two-stage empirical investigation to validate their model in a startup context using Partial Least Squares Structural Equation Modelling (PLS SEM). These contributions offer novel frameworks for understanding the complex process of technology adoption as it applies to GenAI and ChatGPT. Moreover, Gupta and Yang (2024a, 2024b) expand considerably upon well-established frameworks such as the TAM while also showing how current innovations may affect startups and entrepreneurs.

While the above studies improve the overall understanding of the factors that influence the adoption of ChatGPT, there are at least two notable gaps that must be addressed. First, there is a noticeable lack of research focused specifically on the UK business context. Most studies adopt an international or global perspective, but they also focus on specific types of organisations, including startups, SMEs, and higher education institutions. Second, even as TAM has been applied in several contexts, there is limited work on empirical studies that employ the TAM to analyse ChatGPT adoption. The following sections show how the present study addresses these gaps.

III. HYPOTHESIS DEVELOPMENT

This study relies on an extended version of the TAM, as presented in the works of Davis (1989) and Kelly et al. (2023). Additional constructs included in the model are subjective norm (SN) and trust (T), which capture the social and relational factors that may shape the perceptions of ChatGPT among UK companies. In this direction, SN reflects the degree of social pressure that business leaders may feel to adopt ChatGPT, whereas T denotes the individuals' confidence in the reliability and integrity of the technology and its provider (Kelly et al., 2023; Wang et al., 2023). In principle, these concepts are more closely associated with the Theory of Planned Behaviour (TPB), but they are often used in an extended version of the original TAM (Schepers and Wetzels, 2007; Kelly et al., 2023).

Existing studies have found that SN has positive effect on both perceived usefulness (PU) and perceived ease of use (PEU) by signalling endorsement by peers, industry bodies, and managers (Kelly et al., 2023; Wang et al., 2023), which is likely to be relevant to ChatGPT adoption. Therefore, hypotheses H1 and H2 are stated as follows:

H1. Subjective norm has a positive impact on the perceived usefulness of ChatGPT.

H2. Subjective norm has a positive impact on the perceived ease of use of ChatGPT.

The T variable should also reduce uncertainty in the application of ChatGPT as a novel technology, which in turn should positively affect the belief that the system will perform reliably and securely (Kelly et al., 2023; Wang et al., 2023). Therefore, the following hypotheses are used:

H3. Trust has a positive impact on the perceived usefulness of ChatGPT.

H4. Trust has a positive impact on the perceived ease of use of ChatGPT.

Consistent with the original version of the TAM by Davis (1989) and subsequent validations (Na et al., 2022; Kelly et al., 2023; Ma et al., 2025), it is expected that PEU will have direct positive effect on PU. This suggests that higher simplicity values would translate into higher perceived values:

H5. The perceived ease of use has a positive impact on the perceived usefulness of ChatGPT.

According to the TAM, PU and PEU shape attitudes toward use, which in turn drive behavioural intention (BI). Moreover, PU may have direct influence on BI as well. Ultimately, BI should result in actual use (AU) of the system (Davis, 1989; Ma et al., 2025). These relationships can be extended to the ChatGPT context:

H6. The perceived usefulness has a positive impact on the attitude toward using ChatGPT.

H7. The perceived ease of use has a positive impact on the attitude toward using ChatGPT.

H8. The perceived usefulness has a positive impact on the behavioural intention to use ChatGPT.

H9. The attitude toward using ChatGPT has a positive impact on the behavioural intention to use it.

H10. The behavioural intention to use ChatGPT has a positive impact on actual use of the system.

Overall, the above ten hypotheses enable a comprehensive test of how the standard TAM constructs interact with the SN and T variables to determine the level of ChatGPT adoption among UK business companies. A summary of the theoretical model is presented in Figure 1.

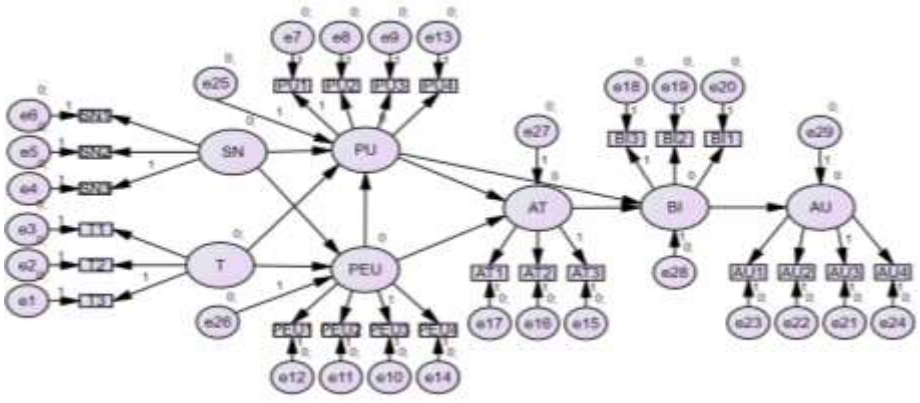

Figure 1. Theoretical Model

IV. RESEARCH METHODOLOGY

A. Data Collection

This study adopts a positivist, quantitative methodology to empirically test the ten hypotheses outlined above. An online survey has been defined where all the items are in line with Davis (1989), Kelly et al. (2003), Ma et al. (2025), and other works that use the TAM. The survey and the associated online link have been created using Google Forms, which enables efficient data collection from a geographically diverse sample of UK business companies. The target participants are mid- to senior-level managers and IT decision-makers among UK businesses from different sectors. A purposive sampling strategy, supported by snowball referrals, has been implemented to ensure that a sufficient number of responses have been collected. Invitations to

complete the survey have been distributed through professional networks (e.g., LinkedIn) and social media (e.g., Facebook) over a six-week period from late March to early May 2025. A minimum sample of 200 responses has been defined to satisfy the statistical requirements for Structural Equation Modelling (SEM) and related calculations (Hair Jr. et al., 2021). All items in the online survey questionnaire employ a five-point Likert scale (1 = "strongly disagree" to 5 = "strongly agree").

Data has been analysed using IBM SPSS Amos as it is considered an optimal tool for implementing SEM (Ong and Puteh, 2017). Additional use of Microsoft Excel and IBM SPSS has been used to apply basic formatting and descriptive statistics, respectively. Additional tests are performed to confirm construct reliability and validity, including Cronbach's Alpha analysis and confirmatory factor analysis (CFA). Ultimately, the theoretical model is tested by evaluating the path coefficients associated with hypotheses H1–H10.

B. Results

The online survey has resulted in a total of 217 responses. After excluding 15 responses for lacking consent or being incomplete, 202 responses are considered valid for analysis, which exceeds the pre-defined minimum requirement for proceeding with the tests.

The study participants represent a wide range of industry sectors. Retail and e-commerce are the largest group in the sample (46 respondents, 22.8% of total responses), followed by manufacturing (33, 16.3%), education and training (23, 11.4%), healthcare and pharmaceuticals (21, 10.4%), and finance and banking (20, 9.9%). The presented distribution suggests that the online survey has engaged both traditional and digitally oriented industries.

The size of companies varies, with the overwhelming share of study participants working in SMEs. Companies employing 1–49 people account for 39.6% (80 respondents) of the total, while those with 50–249 employees represent 43.6% (88).

The roles of respondents include both senior management and technical functions. Senior managers are the largest group in the sample (83, 41.1%), followed by department managers (54, 26.7%), and CEOs or founders (35, 17.3%). Furthermore, IT and technical specialists account for 11.9% (24), while all other roles (human resources, operations, finance) are just 3% (6). The implication here is that the collected responses concerning ChatGPT adoption generally reflect the perspective of decision makers.

The familiarity of study participants with ChatGPT is generally high. Namely, 46.5% (94) of participants report being very familiar with the technology, while 35.2% (71) are somewhat familiar. This indicates that the respondents have been sufficiently exposed to ChatGPT to provide informed evaluations concerning the technology.

The reported usage of ChatGPT further emphasises the active engagement of study participants with the system. The daily users are the largest segment (84, 41.6%), followed by weekly users (70, 34.7%), and monthly users (21, 10.4%). Only 10 respondents (4.9%) have reported not using ChatGPT at all. This suggests that the system is integrated in the business workflow of most organisations.

The familiarity of study participants with other GenAI tools shows a similar trend. For example, 34.7% (70) are somewhat familiar and 25.3% (51) very familiar, while 19.3% (39) are neutral. This suggests that most participants have broader experience with GenAI that extends beyond ChatGPT.

Overall, the sample is skewed toward SMEs and includes both traditional and digitally active industry sectors, with senior decision makers who are well acquainted with the technology and other GenAI tools. While large firms are under-represented, the diversity of industries and roles supports the generalisability of findings.

C. Reliability Analysis

The results of Cronbach's Alpha analysis indicate that all seven constructs exhibit high internal consistency, given that the associated coefficients are well above the threshold level of 0.70 (see Table 1). This implies that the results of hypothesis testing should be highly reliable. However, the high values of the coefficients, which are above 0.95 for all seven constructs, may also indicate that item redundancy exists. This would typically lead to re-evaluation of the constructs and elimination of redundant items, but the present study maintains the existing items as they are based on well-established literature (e.g., Davis, 1989; Kelly et al., 2023).

Table I. Cronbach's Alpha Analysis

Variable	Coefficient
Subjective Norm	.954
Trust	.973
Perceived Ease of Use	.975
Perceived Usefulness	.981
Attitude toward Use	.987
Behavioural Intention	.985
Actual Use	.964

D. Confirmatory Factor Analysis

The completed CFA utilises principal component analysis and oblimin rotation to indicate a three-factor solution that explains 89.46% of the total variance, which is notably high. Component 1 alone accounts for 75.21%, indicating a dominant latent dimension, while Components 2 and 3 contribute 9.07% and 5.18%, respectively.

However, the loading structure in the pattern matrix does not align with the theoretical constructs defined in the extended TAM. Some constructs, such as SN and T, show strong loadings on Component 3, but others, such as PU, AT, BI, and AU all load heavily onto Component 1. This suggests that there is potential construct overlap or multicollinearity. Furthermore, the PEU items load clearly on Component 2, but the near-perfect correlations indicate redundant items or issues with discriminant validity, which is in line with the results of Cronbach's Alpha analysis. Despite these irregularities, the constructs are retained in their original form, as they are based on established theoretical frameworks.

E. Structural Equation Model

Analysis of the SEM model shows that there is acceptable, but not ideal fit. Namely, the $\chi 2/df$ ratio is 4.362, which is within the acceptable range (< 5) and thus indicates moderate model fit. Furthermore, the CFI value is 0.917, while TLI is 0.906, with both being slightly below the ideal threshold level of 0.95, but above the 0.90 cutoff for adequate fit. The RMSEA value is 0.129, which exceeds the recommended maximum of 0.08, and therefore indicates a poor absolute fit. Finally, the Parsimony-adjusted indices are strong, reflecting a reasonably efficient model structure.

Analysis of the path coefficients shows that the strongest relationship is between PU and AT ($\beta = 0.96$), which indicates that the beliefs of users concerning the utility of ChatGPT heavily influence their overall attitude (see Table 2). Similarly, BU strongly predicts AU ($\beta = 0.90$), confirming that intention is a strong driver of system use.

Table II. PLS SEM Path Coefficients

Path			Unstandardised estimate	S.E.	Standardised estimate	C.R.	P	Conclusion
SN	--->	PU	0.283	0.055	0.296	5.127	***	Supports hypothesis H1
SN	--->	PEU	0.407	0.065	0.4	6.287	***	Supports hypothesis H2
T	--->	PU	0.544	0.055	0.562	9.834	***	Supports hypothesis H3
T	--->	PEU	0.357	0.064	0.346	5.551	***	Supports hypothesis H4
PEU	--->	PU	0.148	0.056	0.158	2.630	0.009	Weakly support hypothesis H5
PU	--->	AT	0.939	0.034	0.959	27.704	***	Strongly supports hypothesis H6
PEU	--->	AT	0.015	0.024	0.016	0.611	0.541	Does not support hypothesis H7
PU	--->	BI	0.412	0.109	0.396	3.760	***	Supports hypothesis H8
AT	--->	BI	0.613	0.112	0.577	5.488	***	Supports hypothesis H9
BI	--->	AU	0.88	0.048	0.903	18.244	***	Strongly supports hypothesis H10

Furthermore, T plays a significant role, influencing both PU ($\beta = 0.56$) and PEU ($\beta = 0.35$), which suggests that confidence in the given technology increases both perceived effectiveness and overall usability. There is also evidence that SN has a positive effect on both PU ($\beta = 0.30$) and PEU ($\beta = 0.40$), which means that social influence increases the perceived utility and the ease of use.

By contrast, PEU has a weak effect on AT ($\beta = 0.02$), suggesting that ease of use does not significantly shape attitudes toward ChatGPT. However, PEU does still influence PU ($\beta = 0.16$), although this link is weak. Finally, both PU ($\beta = 0.40$) and AT ($\beta = 0.58$) have meaningful effects on BI, with attitude being the stronger of the two.

Analysis of the standardised indirect effects also shows that T and SN exert strong indirect influence on both BI (0.589 and 0.345, respectively) and AU (0.532 and 0.312) (see Table 3). This is achieved primarily through PU and AT. Given that PU itself has a high indirect effect on AU (0.858), it can be confirmed that it of critical importance in shaping adoption of ChatGPT among UK business companies. Even though PEU has limited direct influence, it does have some indirect effects on AT (0.152), BI (0.159), and AU (0.144).

Table III. PLS SEM Indirect Path Coefficients Using Standardised Estimates

	T	SN	PEU	PU	AT	BI	AU
PEU	.000	.000	.000	.000	.000	.000	.000
PU	.055	.063	.000	.000	.000	.000	.000
AT	.597	.351	.152	.000	.000	.000	.000

	T	SN	PEU	PU	AT	BI	AU
BI	.589	.345	.159	.554	.000	.000	.000
AU	.532	.312	.144	.858	.521	.000	.000

Overall, the model confirms that PU is the key driver of both AT and BI (see Figure 2). At the same time, T and SN are both essential antecedents of PU and PEU. Interestingly, PEU has a limited role in shaping attitude as hypothesis H7 is not supported), which suggests that business professionals evaluate ChatGPT more on its practical value than its user-friendliness. Finally, the model appears to align rather well with extended TAM despite the identified issues with the survey items.

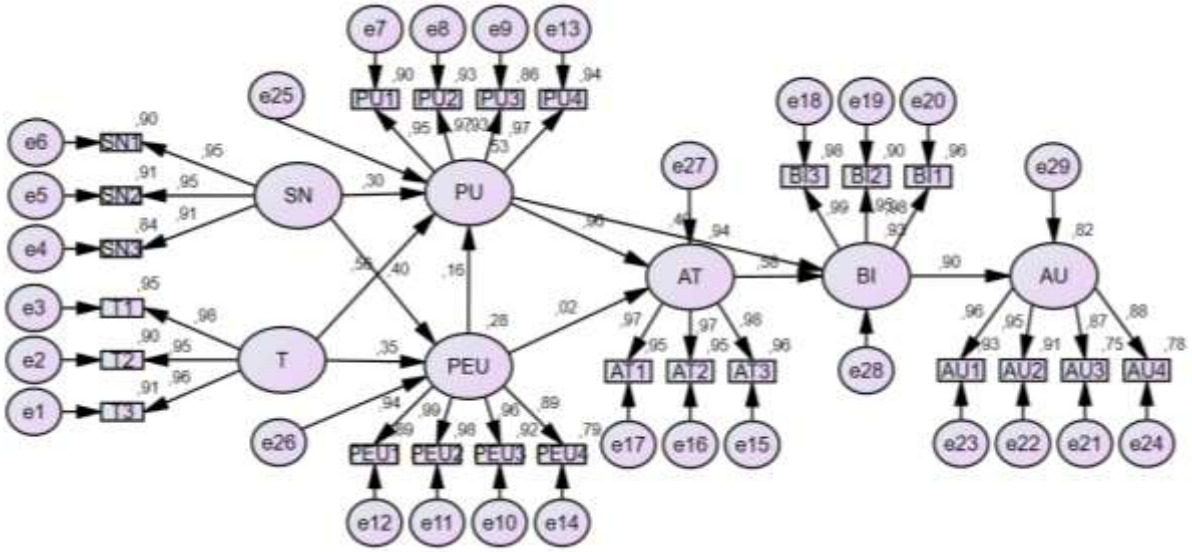

Figure 2. Structural Model

V. CONCLUSION AND DISCUSSION

With respect to relevant theory, the results of this study confirm the relevance and adaptability of the TAM in the context of GenAI and ChatGPT adoption. The completed SEM analysis indicates that perceived usefulness is the single most influential predictor in shaping both attitude toward use and behavioural intention related to ChatGPT. By contrast, perceived ease of use has a weak influence on attitude, implying that this variable is less critical than expected in shaping the behaviour of the respondents. This finding also indicates that utility outweighs simplicity, which is generally in line with the reviewed literature. Moreover, trust and subjective norm have influence with respect to both perceived usefulness and perceived ease of use. This confirms the importance of social context and confidence in the given technology when studying the adoption of new technologies, including GenAI in general and ChatGPT in particular. The strong link between behavioural intention and actual use further validates the structure of the TAM.

The practical implication of the study for UK business companies is that promoting ChatGPT adoption should focus on demonstrating clear benefits that are relevant to the completion of the users' deliverables. By comparison, emphasising ease of use is expected to have lower impact. The results of analysis also show that building organisational trust in the technology and encouraging visible support from leadership and peers should also drive adoption of ChatGPT. At the same time, the identified concerns around data privacy, which are reflected in the lower trust scores, may limit the adoption level, which is fully in line with previous studies on GenAI and ChatGPT. To address this challenge, business companies that promote the use of ChatGPT should prioritise transparency and ensure that personal and corporate data is secure.

The above insights offer actionable guidance for mid- to senior-level managers and IT decision-makers that focus on ChatGPT integration in their workflows. While this study is relevant primarily to UK business companies, its results could potentially be generalised to other environments as well. Future studies should explore how the relationships identified in this study evolve over time as ChatGPT becomes more useful and more deeply embedded in daily business operations.

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