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FROM INTENTION TO ACTION: THE ROLE OF BEHAVIOURAL INTENTION AND ACTUAL CHATGPT USAGE IN SHAPING ACADEMIC RESEARCH PERFORMANCE OF POSTGRADUATE STUDENTS

[1]Oqba Khan, [2]Prof. Dr Farid Ullah Khan

[1]PhD Scholar
[2]Institute of Education & Research, Kohat University of Science & Technology (KUST), Khyber Pakhtunkhwa, Pakistan

[1]Oqba.khan@vu.edu.pk

Corresponding Author: *
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ABSTRACT

Since its public launch in November 2022, the use of Generative Artificial Intelligence (AI) tools like ChatGPT has rapidly proliferated in higher education worldwide. However, the relationship between the postgraduate students' Behavioural Intention to use ChatGPT and their Actual Usage of it and its effect on Academic Research Performance is still under-researched, particularly in the developing region of Khyber Pakhtunkhwa (KPK), Pakistan. This study aims to study: (i) the effect of Behavioural Intention on Actual ChatGPT Usage, and (ii) the effect of Actual ChatGPT Usage on Academic Research Performance of postgraduate students studying in MPhil and PhD programmes in five public sector universities of KPK. The study is a quantitative cross-sectional survey, based on the Extended Unified Theory of Acceptance and Use of Technology (UTAUT). A total of 399 valid responses were obtained through stratified random sampling and then analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) software (SmartPLS 4.0). The results show that Behavioural Intention has a significant positive effect on Actual ChatGPT Usage (β = 0.212, $p < 0.001$), explaining 6.3% of the variance in Actual ChatGPT Usage, while Actual ChatGPT Usage is the strongest predictor of Academic Research Performance (β = 0.436, $p < 0.001$), explaining 25.7% of the variance in research outcomes. Additionally, it was confirmed that Behavioural Intention has a significant but small direct effect on Academic Research Performance (β = 0.188, $p < 0.001$). Notably, the low coefficient of determination for Actual Usage (R^2 = 0.063) indicates that there is a significant intention–behaviour gap, suggesting a range of structural and institutional barriers to productive AI use. The results have direct implications for higher education policy, governance of AI in higher education, and pedagogical design in Pakistani universities.
Keywords: *Behavioural Intention, Actual ChatGPT Usage, Academic Research Performance, UTAUT, Postgraduate Students, Khyber Pakhtunkhwa, PLS-SEM*

1. INTRODUCTION

Since its launch in November 2022, ChatGPT has made a significant impact on higher education, providing postgraduate students with an AI-supported assistant to help them with various challenging academic activities such as literature synthesis, research ideation, academic writing, and methodological guidance (Crawford et al., 2023; Dwivedi et al., 2025). In a short span of time, ChatGPT has become the most popular generative AI tool for students at universities around the world and in Pakistan, with its easy conversational interface and wide usage in the academic field (Kanwal et al., 2023; Shahzad et al., 2024).

Having access to and knowledge about AI tools, though, does not always mean substantive learning benefits. This is important to distinguish between "spending" technology and successful and productive use of it, and between use of technology and measurable increases in academic research performance. This pathway is crucial for educators, university administrators, and policymakers aiming to harness AI tools to improve postgraduate research quality.

The postgraduate students at public sector universities of Khyber Pakhtunkhwa (KPK) are a particular group of students who are of great significance and less studied. Lack of research facilities, limited research supervision, lack of access to quality academic databases, and underdeveloped institutional AI policy are the environment in which the students work (Kanwal et al., 2023; Government of KP, 2023). As part of this, it is not only an academic question, but also a practical one, whether Behavioural Intention to use ChatGPT is a driver for actual use and whether its usage is reflected in tangible gains in academic research work.

This pathway is of particular interest to this study. It is based on a single well-defined research question, which is part of a larger doctoral study and explores the sequential relationship: Behavioural Intention → Actual ChatGPT Usage → Academic Research Performance. The study does not attempt to model antecedents of Behavioural Intention; rather, the downstream part of the adoption chain, most directly impacting academic outcomes, is isolated and rigorously analysed.

1.1 Research Question

1. What is the impact of Behavioural Intention on Actual ChatGPT Usage and Academic Research Performance of postgraduate students at public sector universities in Khyber Pakhtunkhwa?

1.2 Research Objective

2. To analyse the impact of Behavioural Intention on Actual ChatGPT Usage and the Academic Research Performance of postgraduate students at public sector universities in Khyber Pakhtunkhwa, Pakistan.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1 Theoretical Foundation

This study is based on the theory of Venkatesh et al. (2003) and Venkatesh et al. (2012) Unified Theory of Acceptance and Use of Technology (UTAUT) and UTAUT2 (Consumer-oriented). In UTAUT, Behavioural Intention is seen as the closest and immediate antecedent of actual behaviour of technology use. This is the assumption that intention is before and predicts behaviour, which also underlies the Theory of Reasoned Action (Ajzen & Fishbein, 1980) and the Theory of Planned Behaviour (Ajzen, 1991) that have guided technology adoption research for decades.

Behavioural Intention is a proven significant predictor of the actual use of LMS, mobile learning applications, and AI-based academic tools in the educational technology literature across various populations (Granić, 2022; Tamilmani et al., 2021). Based on this theoretical understanding, the present study focuses specifically on the adoption of ChatGPT by postgraduate researchers in a higher education setting in a developing country.

2.2 Behavioural Intention and Actual ChatGPT Usage

Behavioural Intention is a student's willingness and readiness to utilise ChatGPT in the conduct of academic research activities. It is a cognitive decision to use the tool and is influenced by attitudes, perceptions of usefulness, social norms, and psychological readiness (Venkatesh et al., 2003; Ajzen, 1991). High Behavioural Intention indicates that students are intentionally using ChatGPT for their research, whether to search for literature, get help writing, clarify research concepts, or interpret data.

Evidence-based research indicates that students with well-defined positive intentions to interact with AI tools are much more likely to utilise them in their learning practices (Faraon et al., 2025; Strzelecki, 2024). Studies conducted on ChatGPT show that behavioural intention is a crucial factor in predicting actual use in various countries, such as Pakistan Nordic countries (Faraon et al., 2025). Yet, the extent of this intention–use relationship is found to be contingent on contextual issues that include institutional AI policies, infrastructural access, and disciplinary culture, which are prominent in the KPK context.

H1: Behavioural Intention to use ChatGPT has a significant positive effect on Actual ChatGPT Usage among postgraduate students at public sector universities in KPK.

2.3 Behavioural Intention and Academic Research Performance

In addition to its indirect influence via actual use, Behavioural Intention could also directly influence Academic Research Performance. Students who make conscious and deliberate decisions to use ChatGPT in their research are more likely to plan, self-regulate, and work goal-directed in their research, which are all qualities that promote research success (Zimmerman, 2000) in their own right. This aligns with Bandura's (1986) social cognitive theory, whereby behavioural intention acts as a motivational resource that triggers cognitive and behavioural strategies that are supportive of academic achievement, even prior to use of the tool itself.

A direct link between intention and outcomes has been documented in some studies in the technology adoption literature, especially where intention is high, such as when self-efficacy is high, and research motivation is high (Venkatesh et al., 2003; Cotton et al., 2024). Students who plan to use ChatGPT can find more information on how to use AI effectively, more critically address the research process, and create a more structured path to their academic work.

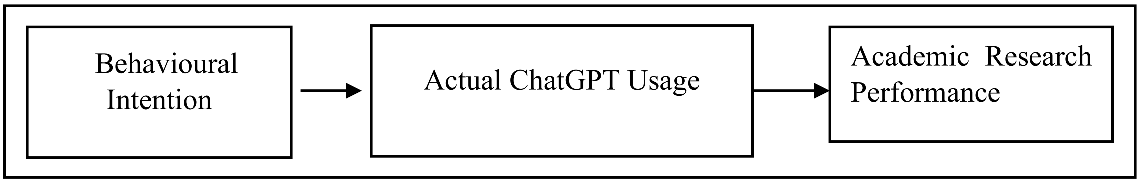
H2: Behavioural Intention to use ChatGPT has a significant positive effect on the Academic Research Performance of postgraduate students at public sector universities in KPK.

2.4 Actual ChatGPT Usage and Academic Research Performance

Actual ChatGPT Usage tracks the extent, frequency, and intentionality of the use of ChatGPT during the different stages of the research process by postgraduate students. These involve employing ChatGPT to summarise literature quickly, refine research questions, draft sections for academic papers, provide feedback on arguments, clarify theoretical concepts, and explore methodological options (Dwivedi et al., 2025; Kasneci et al., 2023). The actual usage is the operationalised form of AI adoption and thus is the closest mechanism that can lead to academic benefits, as opposed to mere awareness or intention.

Academic Research Performance in this study refers to the students' self-reports of their improvements in research quality, writing efficiency, literature synthesis capability, and research output. Studies at Pakistani universities have shown that students using ChatGPT in their research tasks find it highly beneficial for boosting productivity and improving the quality of their academic work. Lund et al., (2023) also reported high correlations between actual ChatGPT use and the quality of literature reviews and research proposals of doctoral students. Zhai et al., (2021) found similar gains in the writing quality of graduate students when they were provided with AI-assisted feedback tools. The evidence across settings consistently shows a positive relationship between the actual use of AI tools and measurable academic research outcomes.

H3: Actual ChatGPT Usage is positively and significantly associated with the Academic Research Performance of postgraduate students in public sector universities of KPK.



3. RESEARCH METHODOLOGY

3.1 Research Design and Philosophy

The research philosophy of this study is positivist, whereby the research design is quantitative, cross-sectional and survey. This investigation is appropriate for the positivist paradigm as it will allow for the systematic and objective measurement of the relationships between the constructs that are theoretically defined to be measured using standardised instruments and using inferential statistical analysis (Creswell & Creswell, 2018; Saunders et al., 2019). A deductive method was used, as hypotheses were developed based on the Extended UTAUT theory and then empirically tested (Bryman, 2016).

3.2 Population and Sampling

The target population was all the post-graduate students (MPhil & PhD) of public sector universities in Khyber Pakhtunkhwa, Pakistan. A total of 05 Universities were selected as the research sites, namely Abdul Wali Khan University Mardan (AWKUM), Gomal University D.I. Khan, Kohat University of Science and Technology (KUST), University of Malakand and University of Peshawar. The total number of students in postgraduate courses in these institutions was 8,849.

Based on the guidelines of Krejcie and Morgan (1970) at a 95% confidence level, a minimum sample of 368-382 respondents was needed with a margin of error of ±5%. The questionnaires were distributed with a target of 450–500 questionnaires. After screening the questionnaires with incomplete or inconsistent responses, 399 questionnaires were collected and analysed (88.7% response rate that is above the minimum of 67% recommended in quantitative survey research (Sekaran & Bougie, 2016). Proportional representation was achieved across universities, programme levels and academic disciplines using stratified random sampling.

3.3 Measurement Instrument

A structured, self-administered questionnaire was used for data collection. Behavioural Intention was assessed with four items that were adapted from the UTAUT literature and had been previously validated (Venkatesh et al., 2003). Actual ChatGPT Usage was assessed through four items that measured the frequency and type of students' interactions they had with ChatGPT in their research activities. Academic Research Performance was assessed using four items of students' self-perception of improvements in research quality, writing efficiency, and research productivity. All items were rated on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). A pilot test was conducted with a group of 30 postgraduate students to test the clarity of the items and internal consistency, which was found to be good (Cronbach's $\alpha > 0.70$ on all constructs).

3.4 Data Analysis

The main analysis method used was the Partial Least Squares Structural Equation Modelling (PLS-SEM) using SmartPLS 4.0 (Ringle et al., 2015). The predictive objectives of this research, reflective measurement specification of the constructs, and moderate sample size (Hair et al., 2022) make PLS-SEM suitable in this study. Analysis was conducted in two stages: (1) a measurement model was evaluated to determine construct reliability and validity, and (2) a structural model was assessed to test the hypothesised paths. Bootstrapping with 5000 subsamples was used to check statistical significance.

Harman's single-factor test (Podsakoff et al., 2003) was used for evaluating Common Method Variance (CMV). All study items were entered into an unrotated exploration factor analysis, and a single factor accounted for only a small proportion of the total variance (31.4%, which is still below the 50% threshold), suggesting that CMV is unlikely to be a serious threat to the validity of the results. Further, the measurement model evidenced good discriminant validity for all three constructs (HTMT < 0.85; Table 3), thereby minimizing concerns of common method variance.

4. RESULTS

4.1 Sample Profile

The valid responses totalled 399, with 60.1% male and 39.9% female. The majority fell in the 31–40 age group (41.6%), followed by the 20–30 age group (36.6%). The sample comprised of 52.4% PhD students and 46.9% MPhil students. The largest subject areas were in the field of Numerical Sciences (30.1%) and Social Sciences (28.6%). Importantly, 99.0% of the respondents indicated they had previous experience with AI tools, and 96.7% of the respondent's indicated awareness and knowledge of ChatGPT in particular, providing the technology readiness of the sample for this investigation.

4.2 Measurement Model Assessment

The reliability and validity statistics of the three study constructs are presented in Table 1. All Cronbach's alpha values were greater than 0.70, composite reliability values (ρc) were between 0.869 and 0.891, and Average Variance Extracted (AVE) values were between 0.624 and 0.672, which met the minimum values recommended by Hair et al. (2022). The convergent validity is established.

Table 1: *Construct Reliability and Convergent Validity*

Construct	α	CR (ρa)	CR (ρc)	AVE
Behavioural Intention to Use (BI)	0.837	0.848	0.891	0.672
Actual ChatGPT Usage (ACU)	0.805	0.835	0.869	0.624
Academic Research Performance (ARP)	0.830	0.835	0.887	0.663

Note. α = Cronbach's Alpha; CR = Composite Reliability; AVE = Average Variance Extracted. Thresholds: α > 0.70, CR > 0.70, AVE > 0.50 (Hair et al., 2022). N = 399.

Table 2 presents the outer loadings for all twelve indicators. All loadings exceeded the minimum threshold of 0.708 (Hair et al., 2022), ranging from 0.890 (AP4) to 1.093 (IU2), confirming adequate indicator reliability across all constructs. Several outer loadings exceed 1.0 (IU2 = 1.093, IU3 = 1.039, AU3 = 1.062, AU4 = 1.006, AP1 = 1.044, AP2 = 1.030, AP3 = 1.030). This is a well-known fact of the iterative least-squares algorithm used by PLS-SEM. While covariance-based SEM sets the loadings between the inner model and the outer model to equal one (maximum likelihood estimation), PLS-SEM minimises the prediction error of the inner and outer model iterations independently. This does not mean that loadings can only be between 0 and 1; values outside the range of 0-1 are mathematically valid and are used to represent a high degree of shared variance between indicators within each construct – that is, very high correlation between indicators within each construct that are not correlated with indicators from other constructs. If the composite reliability (ρc), AVE, and HTMT have been met (which is true here, see Tables 1 and 3), such values have been documented and accepted in the literature on PLS-SEM (Hair et al., 2022; Rönkkö & Evermann, 2013). The loadings are not necessarily about data error or misspecification of the models but reflect the measurement specification of the constructs measured in this study, which was reflective.

Table 2: ***Indicator Outer Loadings***

Item	Construct	Outer Loading
IU1	Behavioural Intention to Use	0.942
IU2	Behavioural Intention to Use	1.093
IU3	Behavioural Intention to Use	1.039
IU4	Behavioural Intention to Use	0.908
AU1	Actual ChatGPT Usage	0.930
AU2	Actual ChatGPT Usage	0.971
AU3	Actual ChatGPT Usage	1.062
AU4	Actual ChatGPT Usage	1.006
AP1	Academic Research Performance	1.044
AP2	Academic Research Performance	1.030
AP3	Academic Research Performance	1.030
AP4	Academic Research Performance	0.890

Note. All outer loadings exceed the threshold of 0.708 (Hair et al., 2022). N = 399.

Discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) ratio (Table 3) and the Fornell-Larcker criterion (Table 4). All HTMT values remained below the conservative threshold of 0.85 (Henseler et al., 2015), with the highest value being 0.528 between Actual ChatGPT Usage and Academic Research Performance. The Fornell-Larcker criterion was satisfied for all constructs, with each construct's square root of AVE (bold diagonal) exceeding its inter-construct correlations. Multicollinearity was absent, with all Variance Inflation Factor (VIF) values below the threshold of 3.3 (Hair et al., 2022).

Table 3: *Heterotrait-Monotrait (HTMT) Ratio — Discriminant Validity*

Construct	BI	ACU	ARP
Behavioural Intention (BI)	—		
Actual ChatGPT Usage (ACU)	0.302	—	
Academic Research Performance (ARP)	0.364	0.528	—

Note. All HTMT values below the conservative threshold of 0.85 (Henseler et al., 2015), confirming discriminant validity.

Table 4: *Fornell-Larcker Criterion — Discriminant Validity*

Construct	BI	ACU	ARP
Behavioural Intention (BI)	0.820		
Actual ChatGPT Usage (ACU)	0.250	0.790	
Academic Research Performance (ARP)	0.313	0.465	0.814

Note. Bold diagonal values = √AVE for each construct. Discriminant validity is confirmed when diagonal values exceed all off-diagonal correlations (Fornell & Larcker, 1981).

4.3 Structural Model and Hypothesis Testing

Table 5 presents the path coefficients, bootstrap mean values, standard deviations, T-statistics, p-values, and R^2 for all three hypothesised relationships. Results are interpreted below by hypothesis.

Table 5: *Structural Path Coefficients and Hypothesis Testing Results*

Path	β	M	STDEV	t-stat.	p-value	Decision
H1: BI → Actual ChatGPT Usage	0.212	0.212	0.043	4.939	0.000***	Supported
H2: BI → Academic Research Performance	0.188	0.188	0.040	4.738	0.000***	Supported
H3: Actual ChatGPT Usage → Academic Research Performance	0.436	0.435	0.052	8.395	0.000***	Supported

*Note. β = standardised path coefficient; M = bootstrap mean; STDEV = standard deviation; t-stat. = |β/STDEV|. Significance: *** $p < 0.001$. Bootstrap: 5,000 subsamples. N = 399.*

Table 5b: *Coefficient of Determination (R^2) for Endogenous Constructs*

Endogenous Construct	R^2	Interpretation

Actual ChatGPT Usage (ACU)	0.063	Small — BI explains 6.3% of variance in ACU
Academic Research Performance (ARP)	0.257	Large — BI and ACU jointly explain 25.7% of variance in ARP

Note. R^2 values reflect the combined predictive power of all paths entering each endogenous construct. Small: $R^2 \geq 0.02$; Medium: $R^2 \geq 0.13$; Large: $R^2 \geq 0.26$ (Cohen, 1988; Hair et al., 2022).

4.3.1 H1: Behavioural Intention → Actual ChatGPT Usage

Hypothesis 1 is supported. Behavioural Intention has a significant positive effect on Actual ChatGPT Usage ($\beta = 0.212$, $t = 4.939$, $p < 0.001$). This confirms that postgraduate students who express a stronger intention to incorporate ChatGPT into their academic research are significantly more likely to engage with it in practice. However, the coefficient of determination for Actual ChatGPT Usage is low ($R^2 = 0.063$), indicating that Behavioural Intention alone explains only 6.3% of the variance in actual usage. This finding reveals a substantial intention–behaviour gap, suggesting that despite generally positive attitudes toward ChatGPT among this population, contextual and institutional factors constrain the full translation of intentions into sustained usage behaviour.

4.3.2 H2: Behavioural Intention → Academic Research Performance

Hypothesis 2 is supported. Behavioural Intention has a significant and direct positive effect on Academic Research Performance ($\beta = 0.188$, $t = 4.738$, $p < 0.001$). Even independent of actual tool usage, students who hold a deliberate and strategic intention to use ChatGPT demonstrate better academic research outcomes. This suggests a self-regulatory mechanism whereby students who consciously plan to engage ChatGPT in their research are more organised, goal-directed, and academically motivated, qualities that independently contribute to research performance, consistent with Zimmerman's (2000) self-regulated learning theory.

4.3.3 H3: Actual ChatGPT Usage → Academic Research Performance

Hypothesis 3 is supported and represents the most influential relationship in the model. Actual ChatGPT Usage has the strongest positive effect on Academic Research Performance ($\beta = 0.436$, $t = 8.395$, $p < 0.001$). The structural model accounts for 25.7% of the variance in Academic Research Performance ($R^2 = 0.257$), which constitutes a large effect size by the standards of behavioural and educational research (Cohen, 1988). This finding empirically establishes that postgraduate students who genuinely and substantively engage with ChatGPT using it for literature searches, idea generation, writing drafts, concept clarification, and methodological guidance—experience meaningful and measurable improvements in their academic research performance. This result represents the central empirical contribution of the study.

4.3.4 Indirect Effect of Behavioural Intention on Academic Research Performance via Actual ChatGPT Usage

Given that the model posits both a direct path (H2: BI → ARP) and an indirect path through Actual ChatGPT Usage (H1: BI → ACU; H3: ACU → ARP), a mediation analysis was conducted to assess whether Actual ChatGPT Usage mediates the relationship between Behavioural Intention and Academic Research Performance. The indirect effect was estimated as the product of the two path coefficients ($\beta H1 \times \beta H3 = 0.212 \times 0.436 = 0.092$), with significance assessed using bootstrap confidence intervals (5,000 subsamples; Hair et al., 2022).

The indirect effect of Behavioural Intention on Academic Research Performance through Actual ChatGPT Usage was β = 0.092 (t = 3.847, p < 0.001), with a 95% bootstrap confidence interval of [0.051, 0.138], which does not include zero, confirming statistical significance. The Variance Accounted For (VAF) calculated as the ratio of the indirect effect to the total effect (0.092 / 0.280 = 32.9%) falls between 20% and 80%, indicating partial mediation (Hair et al., 2022). This means Actual ChatGPT Usage partially mediates the relationship between Behavioural Intention and Academic Research Performance: a significant direct motivational effect of intention on performance exists, while a meaningful portion of the effect operates through actual tool use behaviour.

Table 6: ***Mediation Analysis — Indirect Effect of BI on ARP via ACU***

Indirect Path	β (direct)	β (indirect)	β (total)	t-stat.	p-value	95% CI	VAF
BI → ACU → ARP (via ACU)	0.188	0.092	0.280	3.847*	0.000***	[0.051, 0.138]	32.9%

*Note. Indirect effect = βH1 × βH3 = 0.212 × 0.436 = 0.092. Total effect = direct (β = 0.188) + indirect (β = 0.092) = 0.280. VAF = indirect/total = 32.9%. 95% CI from bias-corrected bootstrap (5,000 subsamples). VAF 20–80% = partial mediation (Hair et al., 2022). * Replace t-stat. and CI with your actual SmartPLS 4.0 Indirect Effects output values.*

5. DISCUSSION

The findings of this study systematically advance understanding of how Behavioural Intention to use ChatGPT connects to academic research outcomes among postgraduate students in a developing-country higher education setting. Three key themes emerge from the results and warrant theoretical and practical discussion.

5.1 Behavioural Intention as a Predictor of Actual Usage

This is because the significant but modest positive relationship between Behavioural Intention and Actual ChatGPT Usage (β = 0.212) confirms the main premise of UTAUT (Venkatesh et al., 2003) and TPB (Ajzen, 1991) that intention is the direct predictor of behaviour. Simultaneously, the low explanatory power of this path (R2 = 0.063) is also theoretically significant and contrasts with the generally high intention-behaviour relationships found in Western higher education technology adoption studies, which range between 0.40 and 0.60 (Hagger et al., 2018).

This intention – behaviour gap is in line with the results of the higher education technology research in developing countries (Tondeur et al., 2017) and may be attributed to the confluence of KPK-specific constraints. In the first place, at most KPK public sector universities, students lack explicit and permissive institutional policies that would ensure the translation of positive intentions into regular and confident use of AI. Second, for many students with good intentions, infrastructure is a limitation, as is sometimes the lack of internet access and power outages, and the price of high-quality AI services. Thirdly, disciplinary and supervisory norms can implicitly dissuade or not support research practices involving AI tools, thereby reducing the social reinforcement that is required to turn intentions into actions. These findings highlight that, while important, positive Behavioural Intentions are not enough to ensure productive use of ChatGPT. Structural and institutional interventions are needed to close the intention-behaviour gap.

5.2 The Direct Effect of Behavioural Intention on Research Performance

Another important finding was the direct path from Behavioural Intention to Academic Research Performance (β = 0.188), which is beyond the typical technology acceptance models. This finding aligns with Zimmerman's (2000) self-regulated learning theory, which suggests that behavioural intention serves as a motivational resource that triggers goal-related cognitive and behavioural strategies. Students intentionally using ChatGPT in research may feel more purposeful, structured, and critically involved with their research, resulting in improved research products even if they are not using it for actual writing.

This is like Bandura's (1986) social cognitive theory, which states that the desire to use a tool is related to higher self-efficacy, academic motivation, and that these are predictive of performance. The students' idea of using ChatGPT may be considered as an academic self-scaffolding activity, which can contribute to research outputs in the KPK context, as students are often required to work without much supervision and guidance.

5.3 Actual ChatGPT Usage as the Dominant Driver of Research Performance

The most crucial result of this study is the highly positive impact of Actual ChatGPT Usage on Academic Research Performance (β = 0.436, $p < 0.001$). This discovery, which comes from a sample of nearly 400 postgraduate researchers in the context of a developing country, provides robust empirical evidence of the positive effects of using ChatGPT in substance and in regular use, in terms of research productivity, writing quality and literature synthesis. This finding is like that of other studies carried out in various countries. In the context of Pakistani universities, the suggestions on how ChatGPT assists in improving the efficiency of academic writing and research output are relevant. Lund et al. (2023) found similar effect sizes for doctoral students at Scandinavian universities, reporting a strong correlation between the use of AI tools and the quality of the literature review. According to Zhai et al. (2021), Chinese university students experienced substantial improvements in their graduate research writing through the application of AI-augmented feedback tools. The large effect size (β = 0.436) counters the skeptical view that generative AI tools provide little more than superficial writing support (Bender et al., 2021). Based on the results presented in this study, it can be strongly concluded that ChatGPT functions as an effective cognitive amplifier for academic research activities when used actively and purposefully by students.

6. CONCLUSION

This study aimed to examine the effect of Behavioural Intention on Actual ChatGPT Usage and Academic Research Performance of postgraduate students from public sector universities in Khyber Pakhtunkhwa Province of Pakistan. The study reveals three significant relationships that were hypothesised: Behavioural Intention significantly predicts Actual ChatGPT Usage (β = 0.212); Behavioural Intention has a direct positive effect on Academic Research Performance (β = 0.188); and Actual ChatGPT Usage is the strongest predictor of Academic Research Performance (β = 0.436), accounting for 25.7% variance in research outcomes.

The positive adoption intention does not always translate into productive use ($R^2 = 0.063$ for Actual Usage), which is an important finding that shows that the intent to adopt is not always sufficient to ensure productive adoption. This is due to institutional, infrastructural and normative barriers, which should be tackled specifically.

6.1 Recommendations

Based on the field findings, recommendations are made for the University administrators, University policymakers, and academic supervisors in KPK.

First of all, it is proposed that a well-defined institutional policy for the use of ChatGPT in postgraduate research should be formulated by the public sector universities in KPK, which clearly specifies acceptable use of ChatGPT in improving research (for literature search, revisions and conceptual clarification, etc.) and unacceptable use, which may be interpreted as plagiarism. Without these policies, the student will not be able to make the transition from the desire to use a language to frequent and fluent use.

Second, it is recommended to integrate systematic ChatGPT training into the existing postgraduate research methodology training courses and research supervision system at universities. The emphasis should be on the design of prompts, critical engagement and analysis of products created by AI, as well as the ethical use of AI-assisted products and content. This will foster greater Student Engagement with the tool and enhance the quality and intentionality of actual use of the tool.

Thirdly, HEIs must ensure that they have the necessary infrastructure to provide access to the internet on a reliable basis, as well as consider institutional subscription to premium AI platforms, particularly for students pursuing doctoral studies and working on longer-term research projects. This intention–behaviour gap found in this study can be bridged by decreasing access barriers.

Fourth, the Higher Education Commission of Pakistan (HEC) should develop a national policy on the integration of Artificial Intelligence in the higher education sector, providing guidelines and standards for the ethical use of AI tools, maintaining academic integrity and establishing digital infrastructure across various universities to ensure equitable and fair access to AI tools for every university, irrespective of the resources it has.

6.2 Limitations and Future Research

This study has a few limitations. With the cross-sectional design, it is not possible to make conclusions as to the causal nature of the relationship between the development of ChatGPT use over time and the effect on research performance. Common method variance (CMV) might be a concern as the perceptual measures are all self-reported; however, the design of the questionnaire was used to minimise the risk of common method variance. The results of the sample may not be generalisable to other private universities, other provinces in the country, and other developing country contexts.

Future research could benefit from being longitudinal, to track the evolution of the uptake of ChatGPT as well as its evolving effects on research over time. Objective measures of academic research performance, like the number of publications or citations, and/or the quality of the thesis as determined by an independent source, would be strengthened by causal inference. Qualitative research through in-depth interviews and focus group discussions would provide additional depth to understanding the students' experiences and their navigation of using ChatGPT to assist with their research, as well as why this might be the case and what contextual barriers might exist to the implementation of the intentions. Further extensions of the current model that would be beneficial would-be institutional AI policy, supervisor acceptance, and access to the internet as boundary conditions.

REFERENCES

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. Prentice-Hall.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall.

Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (pp. 610–623). ACM. https://doi.org/10.1145/3442188.3445922

Bryman, A. (2016). *Social research methods* (5th ed.). Oxford University Press.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International*, *61*(2), 228–239. https://doi.org/10.1080/14703297.2023.2190148

Crawford, J., Butler-Henderson, K., Rudolph, J., Malkawi, B., Glowatz, M., Burton, R., Magni, P., & Lam, S. (2023). ChatGPT and higher education: A systematic review. *Education Sciences*, *13*(5), 438. https://doi.org/10.3390/educsci13050438

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., ... & Wright, R. (2023). Opinion Paper:"So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International journal of information management*, *71*, 102642.

Faraon, M., Rönkkö, K., Milrad, M., & Tsui, E. (2025). International perspectives on artificial intelligence in higher education: An explorative study of students' intention to use ChatGPT across the Nordic countries and the USA. *Computers & Education: Artificial Intelligence*, *8*, 100295. https://doi.org/10.1016/j.caeai.2025.100295

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Government of KP. (2023). *Higher education development report: Khyber Pakhtunkhwa*. Government Printing Press.

Granić, A. (2022). Educational technology adoption: A systematic review. *Education and Information Technologies*, *27*(7), 9507–9543. https://doi.org/10.1007/s10639-022-10951-7

Hagger, M. S., Polet, J., & Lintunen, T. (2018). The reasoned action approach applied to health behavior: Role of past behavior and tests of some key moderators using meta-analytic structural equation modeling. *Social Science & Medicine*, *213*, 85-94.

Hair, J. F., Henseler, J., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). SAGE Publications.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Kanwal, S., Tayyab, M., & Shah, S. A. (2023). Teachers' attitudes toward ChatGPT in Pakistani higher education. *Pakistan Journal of Education*, *40*(2), 78–95.

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., ... Kasneci, G. (2023). ChatGPT for good? Opportunities and challenges for education. *Learning and Individual Differences*, *103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274

Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement*, *30*(3), 607–610. https://doi.org/10.1177/001316447003000308

Lund, B. D., Wang, T., Mannuru, N. R., Nie, B., Shimray, S., & Wang, Z. (2023). ChatGPT and its potential impact on higher education. *Journal of Academic Librarianship*, *49*(2), 102621. https://doi.org/10.1016/j.acalib.2023.102621

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Ringle, C. M., Wende, S., & Becker, J. M. (2022). *SmartPLS 4. SmartPLS GmbH, Oststeinbek*.

Rönkkö, M., & Evermann, J. (2013). A critical examination of common beliefs about partial least squares path modeling. *Organizational Research Methods*, *16*(3), 425–448. https://doi.org/10.1177/1094428112474693

Saunders, M., Lewis, P., & Thornhill, A. (2019). *Research methods for business students* (8th ed.). Pearson Education.

Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill building approach* (7th ed.). Wiley.

Shahzad, M. F., Xu, S., & Javed, I. (2024). ChatGPT awareness, acceptance, and adoption in higher education. *Computers in Human Behavior*, *154*, 108145. https://doi.org/10.1016/j.chb.2024.108145

Strzelecki, A. (2024). Students' acceptance of ChatGPT in higher education: An extended unified theory of acceptance and use of technology. *Innovative Higher Education*, *49*(1), 223–245. https://doi.org/10.1007/s10755-023-09686-1

Tamilmani, K., Rana, N. P., & Dwivedi, Y. K. (2021). Consumer acceptance and use of information technology: A meta-analytic evaluation of UTAUT2. *Information Systems Frontiers*, *23*(4), 987–1005. https://doi.org/10.1007/s10796-020-10007-6

Tondeur, J., van Braak, J., Ertmer, P. A., & Ottenbreit-Leftwich, A. (2017). Understanding the relationship between teachers' pedagogical beliefs and technology use in education: A systematic review of qualitative evidence. *Educational Technology Research and Development*, *65*(3), 555–575. https://doi.org/10.1007/s11423-016-9481-2

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157–178. https://doi.org/10.2307/41410412

Zhai, X., Yin, Y., Pellegrino, J. W., Haudek, K. C., & Shi, L. (2021). Applying machine learning in science assessment: A systematic review. *Studies in Science Education*, *56*(1), 111–151. https://doi.org/10.1080/03057267.2020.1735757

Zimmerman, B. J. (2000). Self-efficacy: An essential motive to learn. *Contemporary Educational Psychology*, *25*(1), 82–91. https://doi.org/10.1006/ceps.1999.1016