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Article

Exploring Faculty Adoption of Natural Language Processing Tools in Teaching: An Exploratory Study in a Private University Context

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Abstract: Natural Language Processing (NLP) interfaces are becoming more common in higher education, but adoption by faculty is inconsistent in private universities with limited resources. Drawing on a study of a private university in Shanghai, we investigate institutional and individual determinants of how instructors adopt NLP tools (such as ChatGPT, Doubao and Kimi) for feedback, assessment, summarization, question generation, and instructional drafting. We employed an exploratory sequential mixed-methods design involving six interviews, as well as a survey ($n = 195$; ≈28% of faculty). Building on a TAM model enriched by Perceived Behavioral Control (PBC), University Facilitating Conditions (UFC), and Social Attitudes (SA), we tested a partial least squares structural equation model (PLS-SEM). Findings indicate that UFC is by far the most powerful predictor of adoption intentions and perceived control, while SA exerts a weaker but statistically significant influence which partially operates through PBC. PBC not only directly influences intention but also moderates the effects of UFC, indicating a central role of self-efficacy in instructor-focused interventions. These pathways are fleshed out by qualitative evidence that points to enabling policies, training, and aligned use cases as levers, and challenges around digital literacy, policy misalignment, and uneven infrastructure. We suggest professional development, incentives linked to pedagogical outputs, and ongoing resourcing for the integration of text-focused AI. The results extend TAM to the context of a private university setting by introducing institutional support and perceived control, which may be applied to similar institutions that are experiencing digital transformation.

Keywords: NLP (NLP); Teaching Innovation; Private Higher Education; Technology Acceptance Model (TAM); Institutional Support

1. Introduction

Higher education is undergoing digitalisation. Natural Language Processing (NLP) technology serves as a crucial catalyst for educational innovation [1]. It can enhance educational quality, for example by providing intelligent grading systems and personalised learning paths [2]. However, integrating NLP into writing instruction faces several barriers. These include teachers' technological literacy, institutional support, and cultural factors [3–6]. Compared to public institutions, private universities have limited funding and infrastructure [7]. But their teaching staff have more freedom in making teaching decisions. This adds complexity and uniqueness to the process of pedagogical innovation [8]. Still, there is very little evidence of NLP being adopted in private universities.

Throughout this article, NLP refers to a subset of artificial intelligence that enables computers to understand, generate, and evaluate human language in text-based educational tasks. In higher-education teaching, we operationalize NLP as faculty-facing tools for automated feedback on writing, rubric-aligned scoring, text summarization and question generation, and conversational assistants for drafting instructional materials and facilitating student practice.

Researchers base most existing literature on the extended Technology Acceptance Model (TAM). Davis and Venkatesh et al. developed this model to focus on perceived ease of use and usefulness [3, 4]. However, when studying private institutions, researchers often overlook the influence of institutional and cultural issues. Mishra & Koehler and Hew & Brush have well-documented how teacher training impacts technology use [9,10]. However, few studies have been conducted in resource-constrained environments. Gao et al. show that much artificial intelligence research focuses on NLP applications [11]. Yet, Celik et al. (2022) point out that these applications haven't fully integrated into teaching practices [12].

To address these gaps, this study examines NLP adoption behaviour among faculty at private universities by extending the TAM model to incorporate factors such as UFC and SA. Unlike the Unified Theory of Acceptance and Use of Technology (UTAUT) model, which broadly integrates individual and organisational factors [4], this study provides a more tailored theoretical perspective, specifically focusing on the context of resource constraints and faculty autonomy in private universities. The study addresses following five questions:

(1) How do private university teachers apply to NLP?
(2) What institutional and personal factors influence NLP teaching innovation?
(3) How do these factors influence NLP teaching effectiveness?
(4) How do wider contextual factors shape NLP teaching innovation?
(5) What strategies promote NLP adoption?

Based on this mixed-methods research, this study provides theoretical implications and practical suggestions.

2. Literature Review

2.1. Overview

The adoption of NLP in academic institutions is becoming increasingly popular as part of the digitalization push within education [1]. Studies have shown the proficiency of NLP in promoting language learning, programming teaching, and automatic evaluation [2]. However, the use of NLP in practice, especially among private university teachers, has not been well explored [3].

The present study aims to address this gap by examining the following factors: (1) NLP applications in teaching; (2) institutional and personal factors influencing adoption; (3) their interactions; and (4) external environmental influences.

2.2. NLP Applications in Teaching

In education, NLP is widely applied [13–16]. It is used for various tasks, such as language and programming learning, educational management, High-tech language education tools significantly enhance reading comprehension, grammar, and oral proficiency [17,18]. Tu & Nie [16] proposed that "automated scoring and feedback systems improve educational efficiency" in education management. Although the promise is great, NLP application in everyday educational settings has its challenges. According to scholars, model bias, data privacy, and teachers' lack of confidence are some of these limitations [19,20].

2.3. Institutional and Personal Factors in NLP Adoption

Institutional factors, such as policy support, training, and infrastructure, play an important role in NLP adoption [21, 22]. Structured practice improves teachers' confidence and skills [23–26]. Other individual factors, e.g., technology literacy and level of motivation, are also important [27]. Teachers' attitudes toward NLP tools are significantly affected by peer pressure. If peer teachers can use NLP tools effectively and receive good responses while teaching, there is a possibility that new teachers' acceptance of the use of NLP tools will increase [28]. Teachers' abilities and trust toward AI result in the adoption of NLP, as they feel their teaching improvement [26,29,30].

This research takes University Facilitating Conditions (UFC) as an institutional variable, as it closely influences technology in private universities [22]. UFC has a better empirical underpinning than other alternatives, such as organisational culture [23]. Social Attitudes (SA) encompass social forces [30]. On the other hand, Perceived Behavioral Control (PBC) integrates Perceived Ease of Use (PEU) and Perceived Usefulness (PU), designed to reflect teachers' sense of control [3].

2.4. Interaction of Institutional and Personal Factors

The decision to use NLP is influenced by both institutional and individual factors [31]. A progressive school culture supports NLP adoption, and policy action will lead to higher technology literacy [32,33]. However, the lack of support and training may induce burnout or resistance among teachers [34,35]. Further investigation is warranted in this regard, particularly within private universities.

2.5. External Environmental Influences

Yessimova et al. and Al-Zahrani & Alasmari argue that NLP adoption is widely influenced by external factors [22, 23]. These include aspects such as the policy environment, infrastructure, and sociocultural backgrounds. Lewis et al. argue that, in collectivist societies, even high institutional support is necessary for the acceptance of NLP. This is in direct contrast to individualistic cultures. As key components of the social environment external to the individual, these factors have been relatively underexplored in terms of their sociocultural influences. The intricate nature of sociocultural influences on NLP adoption requires further investigation. This study directly integrates SA to measure and examine such sociocultural effects.

2.6. Research Gaps and Theoretical Framework

Existing research reveals three gaps in the current understanding of the topic:

(1) The focus on private universities is limited [11].
(2) The analysis of institutional-personal interactions is insufficient [31].
(3) The effects of long-term adoption are neglected [36,37].

While a longitudinal perspective on sustained use remains a future task, a prerequisite to understanding long-term adoption is the first identification of the factors that motivate initial adoption intention. Our study addresses this foundational step.

In contrast to UTAUT's comprehensive integration of external variables [4], this study proposes a concise, context-specific model (UFC, SA, PBC) tailored to private universities, enhancing theoretical precision. Self-Determination Theory (SDT) further supports the role of PBC, positing that autonomy and competence, reflected in teachers' control over NLP, drive adoption behaviour, particularly in resource-constrained settings.

While UTAUT provides a comprehensive framework for institutional adoption, our setting, voluntary, instructor-facing use of text-centric NLP tools in a resource-constrained private university calls for a parsimonious expectancy, control and support specification. Accordingly, we adopted a TAM model augmented with PBC and Institutional Support. This reduced form avoids redundancy among expectancy constructs, preserves discriminant validity, and matches the causal grain of mechanisms observed in our qualitative results. We explicitly acknowledge UTAUT and note that its facilitating conditions are represented here via Institutional Support, while voluntariness/experience are handled through sampling heterogeneity and controls. Future studies will extend this model by testing UTAUT paths and moderators.

3. Method

3.1. Research Design

This study employs a mixed-methods approach with an exploratory sequential design [38] to investigate the factors influencing the adoption of NLP in teaching. Initially, qualitative interviews are employed to explore teachers' experiences, followed by quantitative analysis using Partial Least Squares Structural Equation Modeling (PLS-SEM) to validate key variables and relationships.

In this research, we concentrate on certain NLP tools that assist text understanding, production, assessment, and visualization in the educational domain. Tools like ChatGPT, Doubao, and KIMI use techniques including sentiment analysis, semantic parsing, and text summarization to help teachers automate feedback and enhance student outcomes.

The choice of these tools is based on their applicability in education and their success in enhancing teaching efficiency. The tools are indicative of both formative assessment and text generation NLP applications, which are central to how the authors understand the ways that NLP might enrich teaching. Their inclusion in this study is relevant, as AI-empowered tools are increasingly being incorporated into teaching workflows, thereby adding to the relevance of the present work with respect to trending indicators.

3.2. Participants and Data Sources

A sample of participants was recruited in University X, a leading private university in Shanghai. This university has 714 faculty members in diverse disciplines. It was chosen because, as Okstad & Dahlk and Ertürk noted, it faces the typical challenges of private institutions, such as resource limitations, infrastructure disparities, and faculty independence, while also boasting high academic prestige [7,8]. Moreover, Shanghai's globally internationalized background broadens the study's implications for private universities worldwide.

The target population comprised all full-time faculty at X University. To reflect institutional heterogeneity, we used stratified purposive sampling by (a) academic discipline (humanities/social sciences, STEM, arts/design, business/management) and (b) NLP use background (non-users, light, moderate, heavy). The online survey ran for four weeks (15 March–12 April 2024). After preprocessing, 195 valid responses were retained (≈28% coverage of the faculty body). To deepen mechanism tracing, we then applied maximum-variation sampling to invite six survey participants for semi-structured interviews, balancing discipline, gender, teaching experience, and NLP usage. Age and academic experience were intentionally heterogeneous, allowing model controls and subgroup comparisons and improving external validity for a multi-disciplinary private university context.

To ensure diversity in the application areas of NLP (e.g., humanities, computer science, linguistics), six teachers were selected. Their teaching experience ranged from 3 to 15 years, and they had experience in classroom application. Semi-structured interviews were conducted with these teachers. With the participants' permission, the 40 to 60 minutes interviews were audio-recorded and then transcribed. The in-depth interviews covered topics like technology acceptance, perceived barriers, and institutional support.

A questionnaire was used to gather quantitative data from 195 teachers across all colleges. A random sampling method, as recommended by Zainal & Mohd Matore, was employed to obtain representative data [39]. The questionnaire incorporated a four-factor structure and used a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), as recommended by Joshi et al. [40].

3.3. Research Methods

3.3.1. Qualitative Method

An ethnographic approach was utilized in this research to understand an NLP-based teaching innovation, which has been found useful in understanding complex educational phenomena [41]. The interpretivist paradigm was used as the theoretical framework and focused on teachers' subjective experiences [41]. Thematic analysis was conducted to uncover factors and constructs through three iterations of coding: open coding, axial coding, and selective coding. Saturation was achieved after six interviews [42].

The qualitative part of this study sought to identify the main mechanisms affecting NLP adoption in teaching, and thus the analysis aimed to uncover relevant and highly impact themes from the interviews. Due to the exploratory nature of the study and the limited number of interviews ($n = 6$), the analysis was kept concise to ensure clarity and focus on theoretical and practical implications. Although a more detailed thematic exploration could be conducted in future studies with larger samples, the current qualitative analysis provides sufficient insight to inform the subsequent quantitative phase of the study.

3.3.2. Quantitative Method

In the overall design of the preference questionnaire, we adopted the Likert scale (1-strongly disagree; 5-strongly agree) as the primary question type, aiming to explore teachers' cognitive attitudes towards various dimensions of the particular policies, behaviors or attitudes. The Likert scale is highly suitable for studying enduring organization of beliefs and thought formed through social interactions [40, 43]. It also enables preferential thinking, emotions, and behaviour, phenomena that play a key role in the various manifestations of preferences [40,44], to be quantified objectively and scientifically [43], which aligns with our desire for a deeper understanding of perceptual aspects.

The measurement instrument was developed in accordance with TAM [3] and the qualitative results, focusing on four constructs: UFC, SA, PBC, and BI [45]. 5–8 items were used to measure each construct based on preexisting scales [3] and interview themes. PLS-SEM was chosen due to its appropriateness for small sample sizes (195 participants) and for an exploratory study [46] to examine path coefficients. Reliability and validity were assessed considering Cronbach's alpha (≥0.7), Composite Reliability (CR ≥ 0.7), and Average Variance Extracted (AVE ≥ 0.5) [47]. The limitations of PLS-SEM for model fit appraisal should be noted. The use of CB-SEM in future research could yield more accurate results [48]. Bias was controlled by using teaching experience (42% < 1 year) as a covariate.

3.4. Ethical Considerations and Limitations

The study has been performed in accordance with ethical standards, including informed consent and data confidentiality [41]. Limitations of the study are that it employed a sample from one institution, preventing broad generalization, and that only six teachers were interviewed qualitatively (although they had diverse disciplinary backgrounds), which is small. The study's cross-sectional nature does not allow for insights to be examined over time.

3.5. Research Contribution

This research is a mixed-methods design combining qualitative and quantitative methods. It enhances the TAM model by incorporating institutional and cultural factors, providing practical implications for the adoption of NLP in the private university. This is a positive step in the development of educational technology theory and practice.

4. Findings

4.1. Overview

The details of participants are shown in **Table 1**. This research employed a thematic analysis of semi-structured interviews with six university teachers at University X to explore NLP use in private universities. The analysis, which was performed in NVivo 12, revealed five major themes: (1) NLP uses; (2) institutional and personal factors; (3) interplay between institutional and personal factors; (4) environmental influences; and (5) new strategies. The results of this study indicated a multi-level interaction between personal, institutional, and broader environmental influences on NLP adoption, highlighting resources, policies, and technological literacy as paramount factors. This qualitative understanding forms the basis for the quantitative analysis that follows by extending TAM [3] in an educational technology environment.

Table 1. Participant information.

Name	Teaching Courses
Wang	College English
Yao	Principle of Database
Ma	An Introduction to Design Studies
Xia	Python Programming Fundamentals
Chen	Excel Advanced Applications
Li	BIM and Construction Project Management

4.2. Qualitative Findings

4.2.1. Keyword Extraction and Analysis

Word frequency in six Mandarin interview transcripts was analyzed to determine central issues in NLP adoption, using NVivo 12 (**Figure 1**). The most common word "□□" (teaching) (173 times) reflects teachers' concern about educational means, efficiency, and innovation. “NLP” (137 times) emphasizes the importance of NLP; “□□” (problem) was another high-frequency word, with 71 occurrences mentioning a problem that needs to be solved through using tools (53 times), as well as resource constraints and challenges such as students’ adaptability.

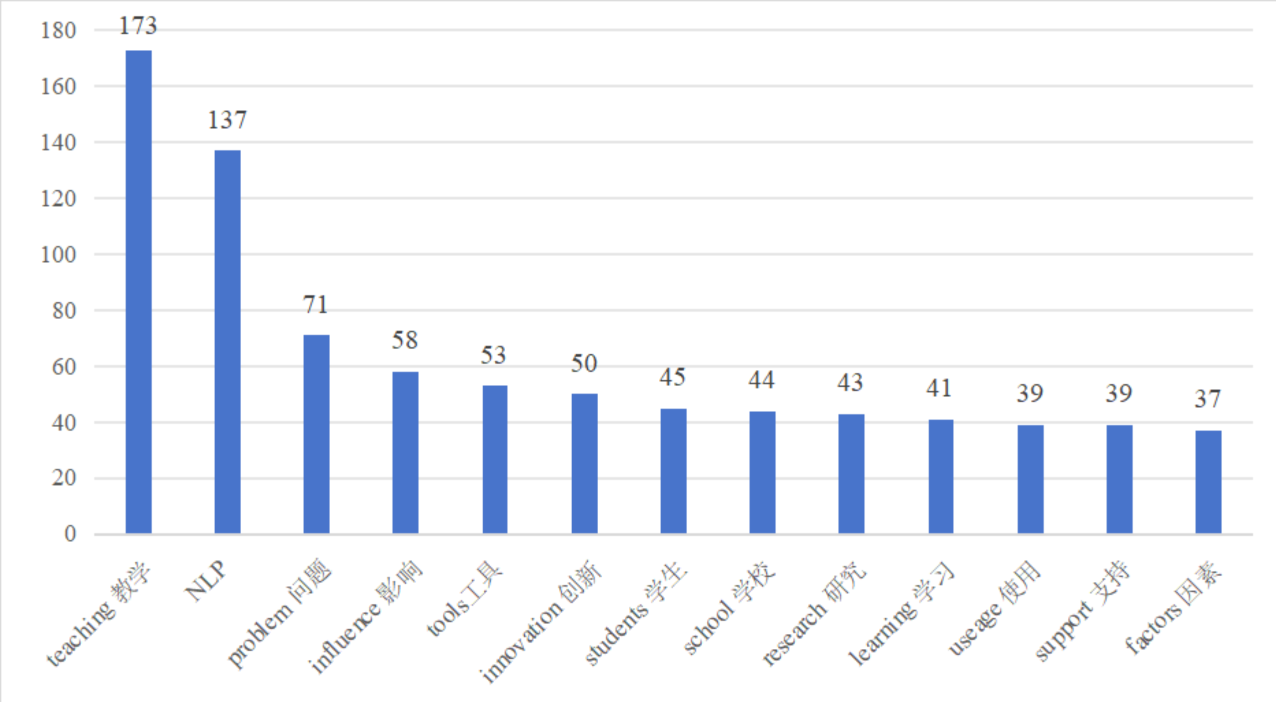

Figure 1. Word Frequency.

Institutional and personal factors emerged prominently. In terms of transformation and support at the institutional level, “innovation” (50) consistently underscores NLP’s ability to transform practice; “school” (44) reflects institutional enabling potential; and “support” (39) indicates training requirements associated with policy. It is indicated that the words “students” (45), “learning” (41), and “research” (43) are present because they relate to student flexibility and personal teacher characteristics influencing adoption. In the adoption context, the use of “factors” (37) is consistent with the interaction model of the study, thereby establishing a solid base for analyzing NLP.

4.2.2. Thematic Modelling Analysis

A three-level coding (open, axial, and selective) process was used to create a thematic model exploring NLP’s effective application in teaching (**Figure 2**) [49]. Complemented by word frequency analysis, this analysis explores the influence of institutional, personal, and environmental facilitators of adoption, which are considered in relation to the research questions. The consideration of word frequency data corroborated the thematic framework, resulting in two main themes: optimizing teaching and adoption barriers. From the data, five main themes were discovered. The face validity of these themes was confirmed by examination of the frequency analysis (**Table 2**).

In the axial coding, the themes were developed into deeper connections. The open coding combined these themes to illuminate more general adoption practices and interconnections. This nested coding analysis can discern the present status and its challenges for NLP adoption while offering actionable insights into managing teaching innovation and maximizing pedagogical effectiveness.

Name	Files	Reference
1. Application and Effectiveness of NLP Techniques in Teaching and Learning	6	65
1.1Current Status of NLP Tool Application	6	31
(1) Types of Tools Used	6	16
(2) Scenarios of Tool Usage	5	15
1.2 Teaching Effectiveness of NLP Tools	6	15
(1) Teaching Efficiency	6	10
(2) Student Learning Outcomes	5	5
1.3 Student Feedback on the Integration of NLP Tools in Teaching	6	19
(1) Student Interest	6	6
(2) Student Participation	6	6
(3) Student Feedback	6	7
2. The influence of institutional and personal factors on NLP teaching innovations	6	126
2.1 Personal Background	6	63
(1) Educational Background	6	22
(2) Teaching Experience	6	34
(3) Other Work Experience	5	7
2.2 Personal Motivation	6	34
(1) Sources of Motivation	6	26
(2) Expected Goals	5	8
2.3 Personal Challenges	6	13
(1) Technical Challenges	5	8
(2) Psychological Challenges	3	5
2.4 Institutional Support	4	5
(1) Resource Support	3	4
(2) Training Support	1	1
2.5 Institutional Barriers	4	11
(1) Policy Limitations	3	5
(2) Resource Scarcity	4	6
3. The interaction of institutional and personal factors	6	13
3.1 Synergy between Policies and Personal Needs	6	9
(1) Policy Support	5	7
(2) Resource Matching	2	2
3.2 Conflicts between Institutional and Personal Factors	4	4
(1) Policy Obstacles	3	3
(2) Mismatched Needs	1	1
4. The impact of wider environmental factors on NLP teaching innovation	6	24
4.1 Social Trends	5	9
(1) Acceptance of NLP Technology by Society	4	6
(2) Economic Development Needs	1	1
4.2 Educational Trends	5	9
(1) Educational Policies	1	1
(2) Educational Reforms	3	3
4.3 Cultural Trends	1	1
(1) Cultural Background	0	0
4.4 Technological Trends	3	4
(1) Technological Development	1	1
(2) Technology Popularization	1	1
4.5 Policy Context	1	1
(1) National Policies	1	1
(2) Shanghai Municipal Policies	0	0
5. Strategies for promoting innovation in NLP teaching	6	24
5.1 Strategy Suggestions	6	14
(1) Teaching Strategies	6	10
(2) Teacher Training	4	4
5.2 Suggestions for Administrators or Policymakers	6	10
(1) Policy Support	5	6
(2) Resource Allocation	4	4

Figure 2. Theme model coding.

Table 2. Key Findings on NLP Adoption in Teaching: Influencing Factors and Frequency Analysis.

Category	Key Findings	Frequency	Implication
1. Application and effectiveness of NLP tools	Types of NLP tools Usage scenarios Improvement of teaching efficiency Learning effectiveness Importance of student feedback	31 16 10 5 19	NLP tools have the potential to enhance classroom interaction and improve learning quality
2. The influence of institutional and personal factors	problems Individual differences Educational background Teaching experience Work experience Personal motivation Expected goals Technical difficulties Psychological barriers	71 41 22 34 7 26 8 8 5	Teachers' acceptance of NLP is influenced by educational background, teaching experience, personal motivation, and institutional barriers.
3. Interaction between institutional and personal factors	Policy support Resource alignment Policy barriers Demand misalignment School Support	7 2 3 1 44 39	University policies and resource allocation significantly impact teachers' NLP adoption.
4. The role of external environmental factors	Impact Students Social trends Educational development Technological progress	58 45 9 9 4	Teachers consider not only classroom effects but also broader educational trends in adopting NLP.
5. Strategies to promote innovation in NLP teaching	Teaching method optimization Teacher training Policy support Resource allocation Innovation analysis	14 10 6 4 50	Teachers advocate policy incentives and resource optimization to facilitate NLP adoption.

4.2.3. Application and Effectiveness of NLP Techniques in Teaching and Learning

This research investigated the use and effectiveness of NLP in six teachers' classes at University X (**Figure 3**). NLP was most used in "*An Introduction to Design Studies*" (22.33%) where Ma employed GPT and image generation models to enhance creativity.

Excerpt from Ma:

> *"I use GPT to generate visual content such as flowcharts and schematics to stimulate creative thinking in students"* (Ma, 2024).

The "*BIM and Construction Project Management*" course (20.03%) utilized GPT for bilingual translation and speech processing, enhancing communication (Li).

Excerpt from Li:

> *"I often use GPT for bilingual translation and use speech processing tools to optimise classroom communication"* (Li, 2024).

In "*Excel Advanced Applications*" (19.31%), Chen employed NLP for content generation and assignment analysis, improving efficiency.

In the domain of educational programming, the use of AI, more specifically, generative pre-trained transformer (GPT) models, is increasingly receiving attention. In language education, GPT has been utilized for the creation of exam questions and real-time demonstrations in subjects such as "*Python Programming Fundamentals*" (Xia; 14.34%). Likewise, NLP is incorporated into interactive settings in "*Principles of Database*" (12.10%), as shown by Yao's method. In the field of *College English*, Wang's study focused on improving writing with GPT (11.89%).

The application of NLP differed among disciplines: in language teaching, it favored writing and analysis; in technical subjects, it was code and assessment based; and in design/management, it was interdisciplinary. Despite its promise, barriers to broader use of NLP in education include technical adaptation and student preparedness.

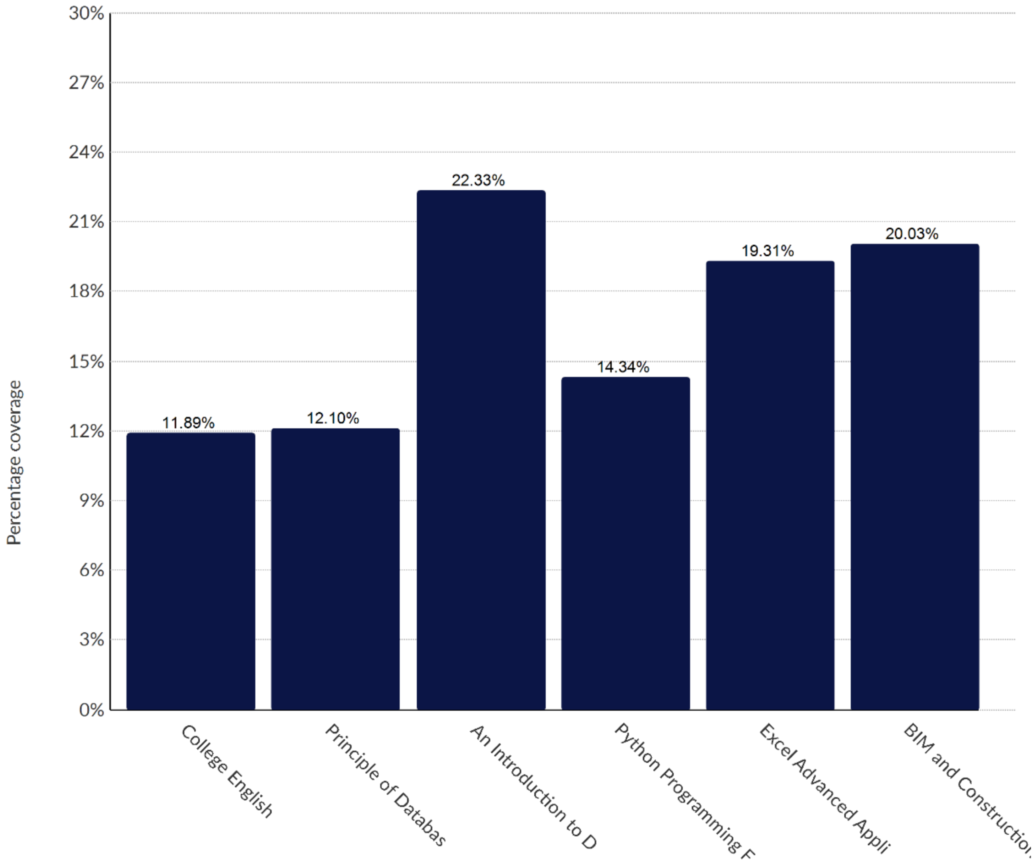

Figure 3. Coverage of the application and effectiveness of NLP tools in teaching and learning.

4.2.4. The Influence of Institutional and Personal Factors

In the above data, we have seen how institutional and personal factors affected NLP adoption in six teachers' courses at University X (see **Figure 4**). The course "*Principles of Database*" drew the most discussion (18.51%), and institutional support as well as self-motivation played an important role in Yao's class.

Excerpt from Yao:

"School policies provide a framework, but I still need to explore on my own and creatively integrate NLP tools into teaching" (Yao, 2024).

In "*An Introduction to Design Studies*" (17.38%), Ma relied on personal efforts to overcome limited resources.

Excerpt from Ma:

"Despite the limited resources at school, I endeavoured to incorporate NLP tools because they can stimulate students' creativity" (Ma, 2024).

"*College English*" (16.45%) highlighted Wang's focus on institutional support and student feedback.

Excerpt from Wang:

"Students' interaction and feedback are pivotal in determining the optimisation of the classroom application of NLP tools" (Wang, 2024).

The percentages for the courses "*Python Programming Fundamentals*" (16.37%), "*BIM and Construction Project Management*" (15.96%), and "*Excel Advanced Applications*" (15.72%) are affected by institutional and personal factors together. The results indicate that many institutional factors, such as policy support, hardware, and training for NLP applications, are insufficient in private universities and hinder the integration of NLP (Li; Wang). Personal circumstances, for example the degree of technological literacy and motivation, are significant in supporting acceptance, especially among veteran computers using teachers (Ma; Xia; Chen). Problems include workload issues and cross disciplinary boundaries (Yao; Wang; Ma; Xia).

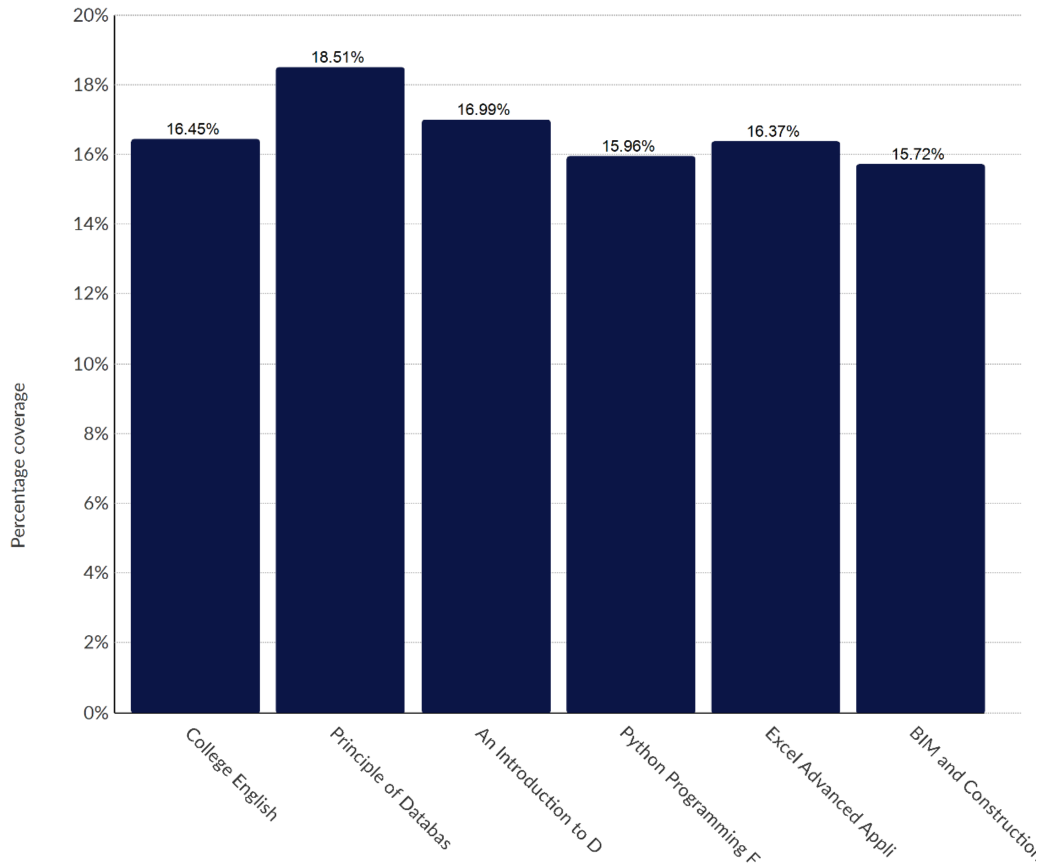

Figure 4. Coverage of the influence of institutional and personal factors.

4.2.5. The Interaction of Institutional and Personal Factors

The present research explored institutional and personal factors in the use of NLP in six courses at University X (see **Figure 5**). The "*Principles of Database*" course had the most discussion (20.59%), and Yao highlighted the mutualistic support between databases and personal innovation.

Excerpt from Yao:

"School policies provide a framework, but I still need to creatively integrate NLP tools into teaching" (Yao, 2024).

"BIM and Construction Project Management" (18.49%) highlighted Li's reliance on institutional AI curriculum reforms.

Excerpt from Li:

"The school's initiative to integrate AI into the curriculum system has provided me with the necessary support to explore the application of NLP in teaching in greater depth" (Li, 2024).

In "*An Introduction to Design Studies*" (18.91%), Ma effectively addressed issues of resource scarcity through personal initiative. On the other hand, Wang discussed conditions that help and hinder the spread of NLP for "*College English*" (14.71%) from institutional and personal aspects. The adoption rates of "*Python Programming Fundamentals*" (13.87%) and "*Excel Advanced Applications*" (13.45%) were lower; policy mismatches may explain the former, and conservatism may explain the latter.

The results suggest that at both the institutional and personal levels, "institutional support" and personal factors play roles in the adoption of NLP. Institutional limitations may require personal investment (Ma), and policy practice disconnections result in uncertainties (Li). Ineffective recent training compounds the problem (Wang; Yao), highlighting the necessity of facilitating cooperation to promote adoption.

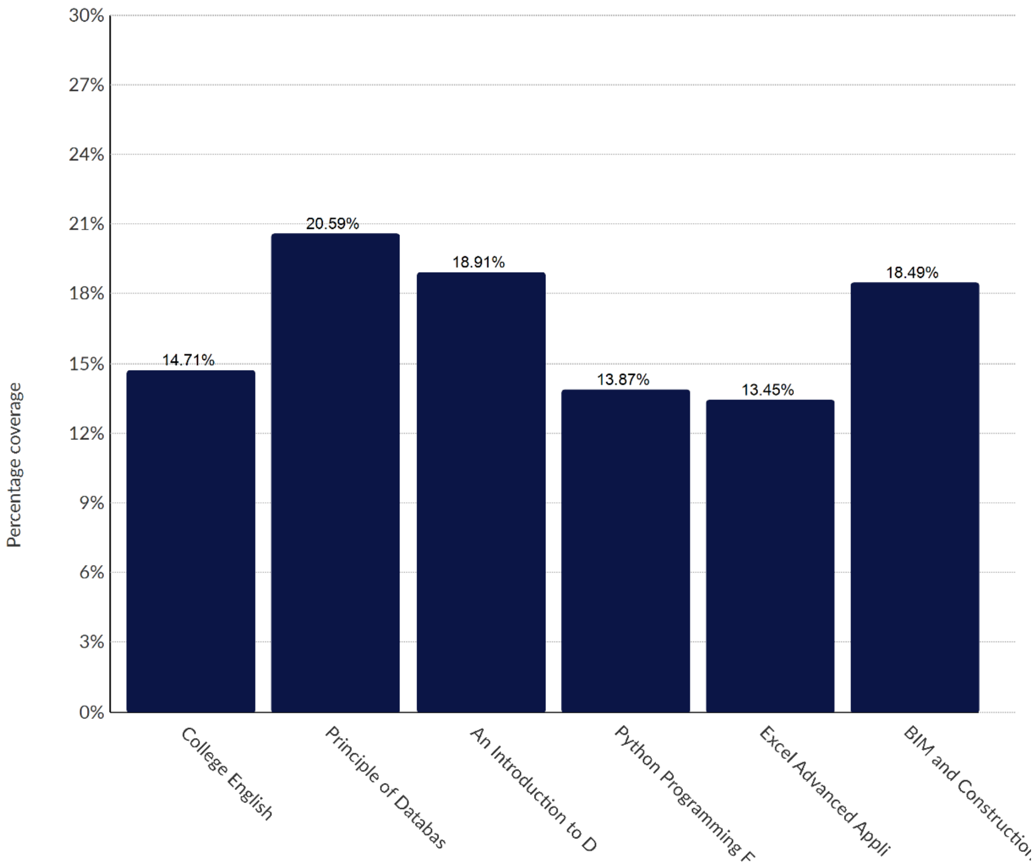

Figure 5. Coverage of the interaction of institutional and personal factors.

4.2.6. The Impact of Wider Environmental Factors on NLP Teaching Innovation

This survey examined the influence of the external environment on NLP adoption in teaching (**Figure 6**). The courses with the highest percentage of discussion were "*Principles of Database*" (20.87%) and "*BIM and Construction Project Management*" (20.68%), suggesting a strong environmental impact.

Excerpt from Yao:

"Shanghai's technological progress and cultural atmosphere provide an ideal environment for the application of NLP tools" (Yao, 2024).

Excerpt from Li:

"Shanghai's international environment and policy support have created opportunities for the application of NLP in teaching" (Li, 2024).

In "An Introduction to Design Studies" (19.09%), Ma noted technological advancements driving creativity. Excerpt from Ma:

"Shanghai's technological progress has inspired me to explore how NLP tools can enhance students'creativity and efficiency" (Ma, 2024).

Xia (*Python Programming*, 14.34%) highlighted digitalization's role, Wang (*College English*, 11.89%) noted cultural trends and challenges, and Chen (*Excel Advanced Applications*, 15.72%) emphasized resource constraints.
Excerpt from Xia:

"The development of digitalisation and artificial intelligence has provided a favourable environment for the application of technology" (Xia, 2024).

Excerpt from Wang:

"Cultural, technological and educational trends have influenced the innovation of NLP teaching, but challenges persist in terms of practical application" (Wang, 2024).

Excerpt from Chen:

"Despite Shanghai's leadership in finance and technology, educational institutions continue to face resource constraints, necessitate enhanced policy and resource support to promote the adoption of NLP" (Chen, 2024).

Findings indicate that technological trends, societal perceptions, and Shanghai's international context drive NLP adoption, though adaptation challenges and resource gaps remain (Xia; Wang; Li).

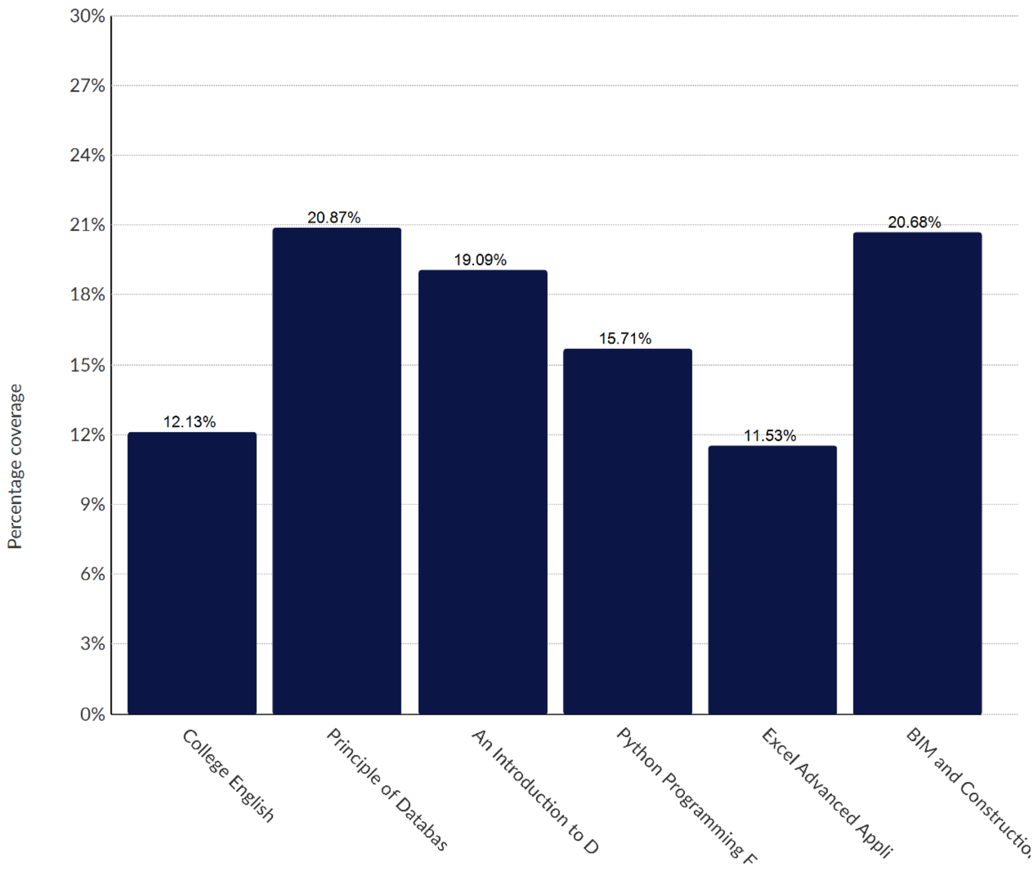

Figure 6. Coverage of the impact of wider environmental factors on NLP teaching innovation.

4.2.7. Strategies for Promoting Innovation in NLP Teaching

This study identified strategies for enhancing the adoption of NLP across six teachers' courses (**Figure 7**). The "*Principles of Database*" course (27.77%) had the highest proportion of discussion, with Yao emphasising incentives.

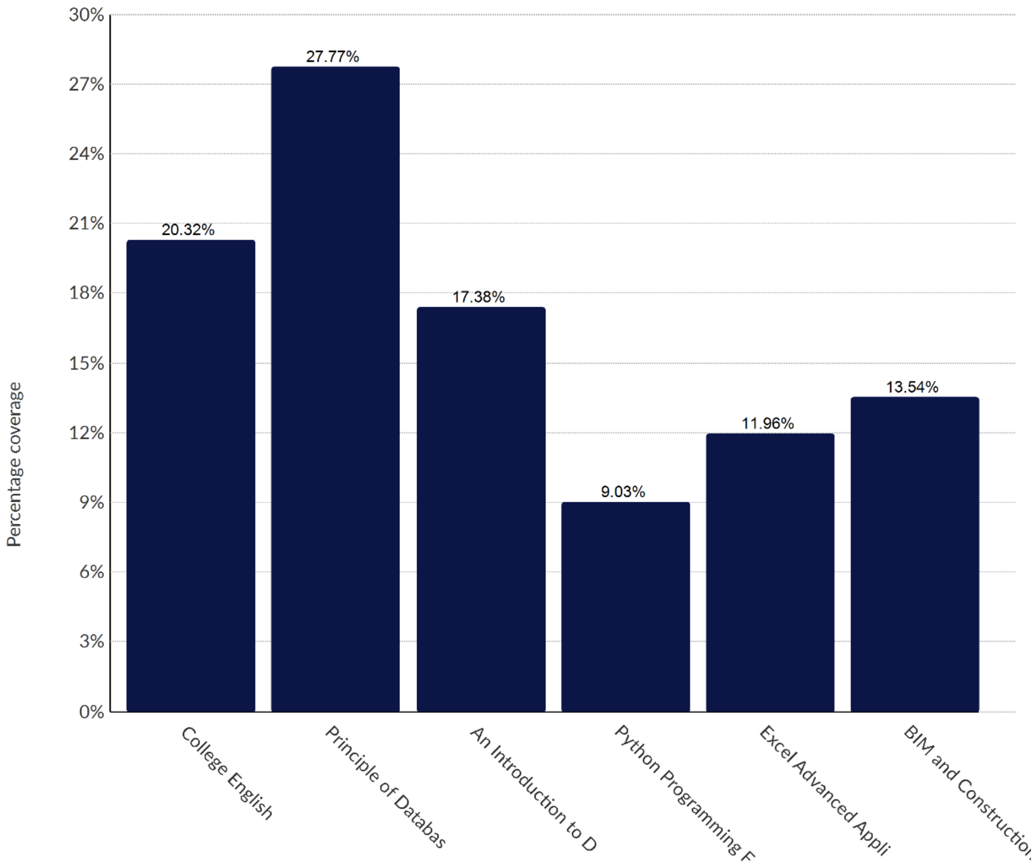

Figure 7. Coverage of Strategies for promoting innovation in NLP teaching.

Excerpt from Yao:

"The necessity for clear incentives to be established, such as teaching competition awards, to promote the application of NLP techniques" (Yao, 2024).

"College English" (20.32%) saw Wang advocate for training and assessment adjustments.
Excerpt from Wang:

"Policy support and training can help teachers use NLP tools more effectively in English teaching" (Wang, 2024).

In "*An Introduction to Design Studies*" (17.38%), Ma promoted student use of NLP for creativity.
Excerpt from Ma:

"Encouraging students to use NLP tools in the classroom can help stimulate creativity and critical thinking" (Ma, 2024).

"*BIM and Construction Project Management*" (13.54%) emphasized seminars and reforms (Li), "*Excel Advanced Applications*" (11.96%) proposed pilot programs (Chen), and "*Python Programming Fundamentals*" (9.03%) focused on enterprise projects (Xia).

Excerpt from Li:

"Seminars and teaching reforms are crucial to exploring the application of NLP in education" (Li, 2024).

Excerpt from Chen:

"The piloting of NLP in elective courses, with equipment and training support, is needed" (Chen, 2024).

Excerpt from Xia:

"Integrating NLP tools into practical projects helps students apply the technology in real-world scenarios" (Xia, 2024).

Key strategies include enhanced training (Yao), optimized policy support (Li), interdisciplinary collaboration (Ma), and increased student participation (Wang).

4.2.8. Results of Qualitative

Qualitative analysis of the study suggests that the integration of NLP in the private university is different. NLP adoption is higher in technology driven areas like computer science and engineering, as they are more compatible with NLP tools, compared to humanities and management fields, which have lower rates of adoption due to adaptation and literacy problems. The success of adoption depends on teacher motivation, technology familiarity, and institutional resources, while barriers mainly result from inadequate support [3].

Alongside institutional and personal factors (policy, resources, training, and literacy skills), external environmental factors such as technological development and internationalisation also interplay. Such private universities can contribute to the promotion of NLP use. The results provide some evidence for TAM [3], based on perceived ease of use, perceived usefulness, attitude toward using, and intention to use. To substantiate these relations, PLS-SEM quantitatively assesses an expanded TAM, investigating PBC, institutional impacts, environmental effects, and the relationship yielding solid theory-based incentives for educational technology.

Although a sample of six interviews may seem small to generalize, the sample size is appropriate in an exploratory sequential design. In this strategy, qualitative depth rather than breadth is emphasized in exploring the central themes and mechanisms (which then inform the later quantitative phase). The interviews included a wide variety of participants from different disciplines and at different levels of NLP use and were selected using maximum variation sampling. These qualitative interview findings were triangulated and extended with a survey covering 28% of faculty. This triangulation ensures anatomy and sociality in the study's conclusions.

4.3. Quantitative Findings

The objective of the quantitative section of this study is to investigate how NLP tools are used and accepted among teachers. Furthermore, a flowchart has been designed to represent the diffusion and adoption of NLP tools, including teachers' behaviour toward the use of this technology.

4.3.1. Theoretic Framework

The variables in the quantitative study were developed in accordance with TAM and refined to a desired form by means of thematic analysis. TAM represents the basic framework, augmented with modifications suggested by qualitative research. TAM is the most popular model for the investigation of computer-based information system acceptance (**Figure 8**), focusing on PU, PEU, AT, and BI [3].

We decided to integrate PU and PEU into PBC not only because of their theoretical correspondence with TAM and the consistency of TPB (Theory of Planned Behavior), but also because of the particular background of our study. In TPB, PBC includes both PU and PEU as its antecedents. It represents an overall measure of perceived control to perform behavior. Since adoption in this research is voluntary, treating PU and PEU as components of PBC was accepted, which makes for a more parsimonious but theoretically sound model. This strategy eliminates possible redundancy and collinearity between PU and PEU, in accordance with modeling parsimony. In addition, the PBC framework more realistically represents instructors' lack of control over using NLP tools, which influences their actual use.

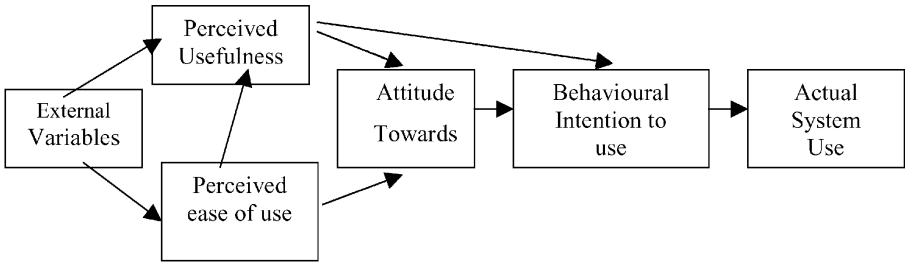

Figure 8. Technology Acceptance Model [3,50].

In this study, we decided to combine PU and PEU into a single construct of PBC. This decision is conceptually grounded, rather than empirically tested, and aligns with the theoretical framework established in the Technology Acceptance Model (TAM). According to Venkatesh and Davis, PU and PEU are central to understanding technology adoption, yet in our study, we found that PBC, which reflects users' sense of control over the technology, inherently encompasses both the PEU and PU. By combining these two variables into PBC, we aim to simplify the model and avoid redundancy, while still capturing the full scope of teachers' perceptions of NLP tools.

In our conceptual framework, PBC not only reflects the perceived control over the technology but also integrates the aspects of both PU and PEU, providing a more parsimonious and comprehensive measure of the faculty's adoption behavior in the context of private universities. This integration is consistent with TAM and is supported by prior research that has demonstrated the effectiveness of combining these constructs in similar settings.

Conversely, the original PU and PEU variables in TAM are not applicable in full, based on the findings of this study. These two variables prioritise users' personal experience and emphasize their distinct attitudes towards technology adoption [51]. However, the findings of our qualitative research do not demonstrate the necessity of separating PU and PEU as independent factors.

A fundamental reason for this is that the present study focuses on the adoption of NLP in private universities, where the integration of external and internal factors plays a dominant role in adoption decisions, rather than purely personal perceptions. In light of these findings, we have combined PU and PEU into a single variable, termed PBC, to more accurately reflect teachers' adoption behaviors in real classroom settings. Similarly, to achieve a more parsimonious model that consists with our qualitative research priority on decisive behavioral factors, we have integrated AT and "Behavioural Intention to Use" into the final "Behavioural Intention (BI)" variable. This approach can simplify the model by focusing on the intention construct. Furthermore, the "Actual System Use" variable, while acknowledged in the TAM framework, is positioned for further consideration in this study, as the primary focus is predicting adoption intention rather than tracking long term usage behavior.

With regard to external variables, Davis proposed that multiple external factors can be incorporated into the TAM [3], a notion that is supported by our qualitative findings [52]. The results of the study indicate two major external influences:

1. Social Attitudes

Encompassing broader social-environmental factors, including public awareness and understanding of NLP tools in China, which may be influenced by educational trends and domestic social trends.

2. University Management

Covering financial and policy support for NLP development, shaped by various institutional conditions.

Based on these adjustments, our study proposes four key variables contributing to the theoretical framework of NLP adoption in Chinese private universities (**Figure 9**).

We assessed overall model fit using SRMR for both the saturated and estimated models, supplemented by SRMR < 0.08 and NFI exceeding 0.90 indicated acceptable fit; the observed values met their bootstrap quantiles (**Table 3**).

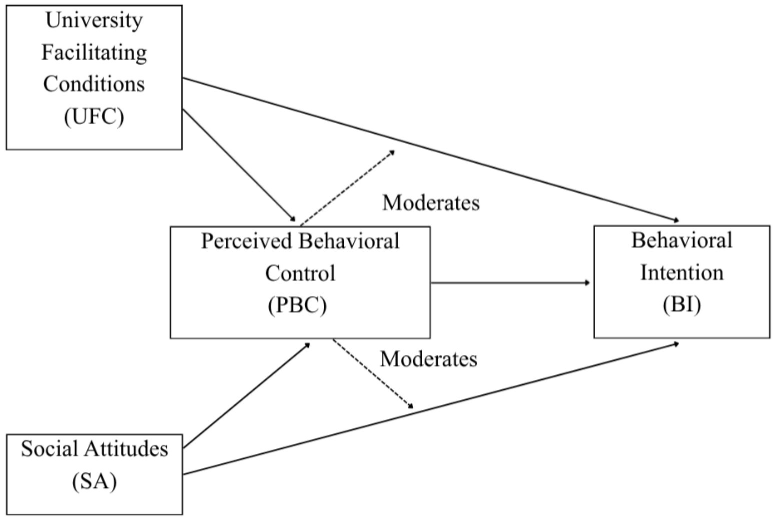

Figure 9. Potential model on teachers using NLP in private University.

Table 3. Model fit.

	Estimated Model
SRMR	0.074
NFI	0.97

4.3.2. Research Hypotheses

For this study, researchers do not have strong expectations for the data and intend to seek the construction of the theory and the formation of the model inside the latent data of NLP acceptance between teachers. The research aligns with explanatory factors analysis (EFA), that allows researchers explore the key variables from the observed data and creates the construction of a model and discovery the plausible theory [53–57].

The study does not commence with strong expectations regarding the data. The objective is to construct a theoretical framework and develop a model based on latent patterns in NLP acceptance among teachers. The hypotheses for this study are outlined in **Figure 10**.

H1: *UFC positively influences PBC.*

H2: *SA positively influences PBC.*

H3: *UFC positively influences BI.*

H4: *SA positively influences BI.*

H5: *PBC positively influences BI.*

H6: *PBC moderates the relationship between UFC and BI.*

H7: *PBC moderates the relationship between SA and BI.*

4.3.3. Quantitative Results

This questionnaire survey was conducted among 195 teachers from University X, covering all secondary colleges (**Table 4**).

In the participants, 113 teachers hold master's degrees, while 47 hold doctoral degrees (see **Table 4**). Teaching experience varies widely, ranging from less than one year to over 16 years (see **Table 5**). However, most respondents have relatively short teaching experience, with 82 teachers (42%) reporting less than one year (see **Table 5**).

Regarding time served as a faculty member at University X, most respondents have worked there for less than five years, but others report longer periods (**Table 6**). We can compare the absolute and relative numbers of the

195 teachers who took part in the research, organized according to University X (**Table 7**). Although the sample is not proportional in terms of demographic variables, there is great diversity among the teachers participating in the study, which contributes to high representativeness and variability.

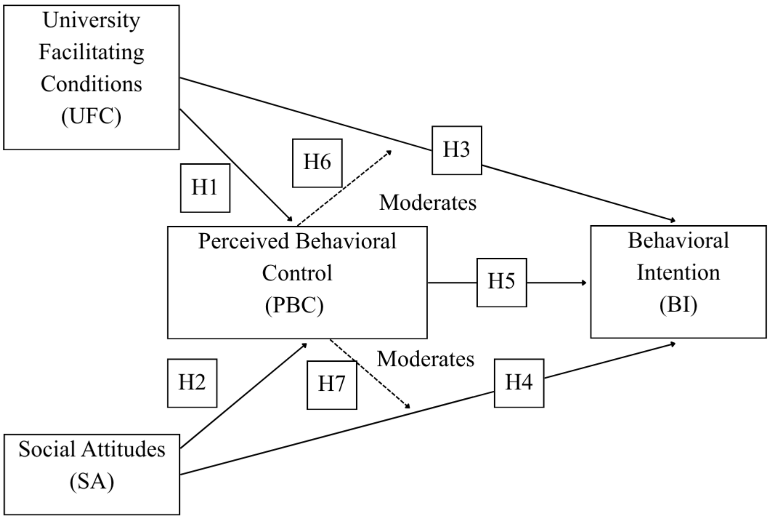

Figure 10. Hypothesis on teachers using NLP in private University.

Table 4. Participants information on academic discipline.

Academic Discipline	N	%
Philosophy	8	4.1
Economy	2	1.0
Education	19	9.7
Arts	22	11.3
History	1	0.5
Social science	49	25.1
Engineering	52	26.7
Agriculture	1	0.5
Medicine	23	11.8
Military	2	1.0
Management	6	3.1
Fine arts	10	5.1
Total	195	100.0

Table 5. Participants' information on academic level.

Academic Level	N	%
Bachelor degree	30	15.4
Master degree	113	57.9
Doctoral degree	47	24.1
Others (professional degree etc.)	5	2.6
Total	195	100.0

Table 6. Participants' information on teaching experience.

Teaching Experience	N	%
0–5 years	82	42.1
6–10 years	48	24.6
11–15 years	28	14.4
Over 16 years	37	19.0
Total	195	100.0

Table 6. *Cont.*

University X Teaching Experience	N	%
0–5 years	129	66.2
6–10 years	41	21.0
11–15 years	8	4.1
Over 16 years	17	8.7
Total	195	100.0

Table 7. Participants information on secondary college in University X.

Secondary College	N	%
College of Information Technology	49	25.1
College of Mechanical and Electrical Engineering	19	9.7
College of Business	10	5.1
College of Foreign Languages	15	7.7
College of Journalism and Communication	23	11.8
College of Art and Design	6	3.1
College of Gems and Jewelry	2	1.0
College of Education	19	9.7
College of International Design	5	2.6
College of International Education	4	2.1
College of Health Management	29	14.9
College of Vocational and Technical	13	6.7
College of Marxism	1	0.5
Total	195	100.0

PLS-SEM is used to conduct the main analysis of data collected with the scale. The motivation behind the quantitative analysis is to produce an NLP tools adoption theory for private universities by further enriching the model.

PLS-SEM is an appropriate statistical method for this purpose, as it can evaluate causal models from a prediction-oriented viewpoint [58]. Furthermore, it facilitates a more profound examination of extant frameworks, enabling the analysis of intricate relationships and real-world adoption patterns [58].

The R-squared of each unit of UFC and SA on PS is 0.526, and the R-squared of each unit of UFC, SA, and PBC on BI is 0.860. Both are greater than 0.742, indicating that UFC and SA have a greater impact on PBC and BI (**Figure 11**).

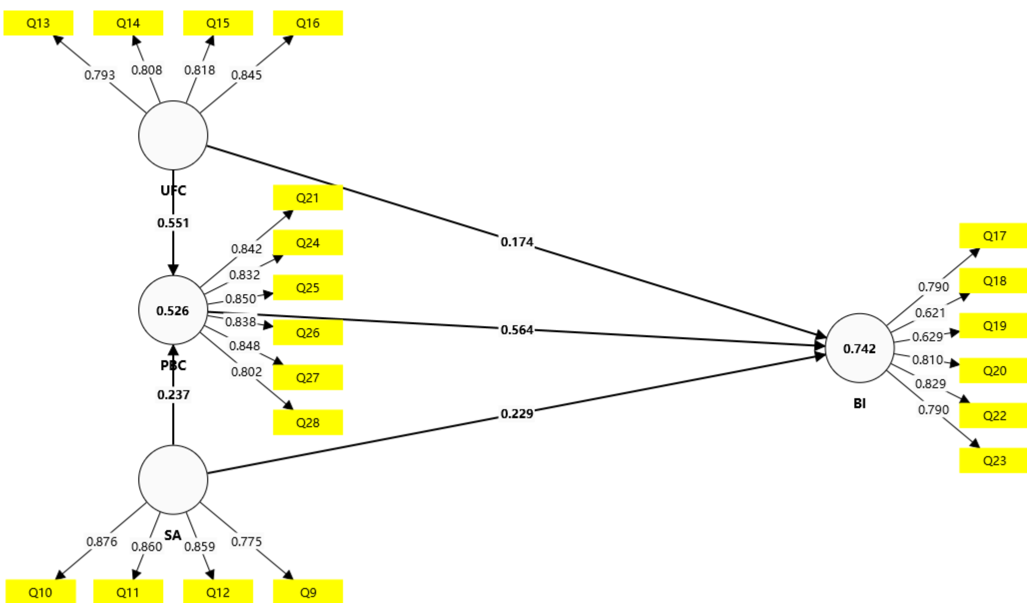

Figure 11. Model results diagram.

To address concerns that elevated R^2 might reflect common method bias (CMB), we applied the full-collinearity VIF test appropriate for PLS-SEM. Each latent construction was regressed on all other constructions, and all full-collinearity VIFs were < 3.3, suggesting CMB is unlikely to threaten the validity of the explained variance.

The load factor for each item is significant (**Table 8**).

Table 8. Load factor table for each item.

	Origin Sample	Mean	Std.	*T* Statistics	*P* Values
Q10 ← SA	0.876	0.876	0.018	49.960	0.000
Q11 ← SA	0.860	0.858	0.024	35.852	0.000
Q12 ← SA	0.859	0.859	0.022	38.565	0.000
Q13 ← UFC	0.793	0.791	0.036	21.906	0.000
Q14 ← UFC	0.808	0.807	0.034	23.648	0.000
Q15 ← UFC	0.818	0.816	0.033	24.504	0.000
Q16 ← UFC	0.845	0.844	0.026	31.918	0.000
Q17 ← BI	0.790	0.788	0.036	21.821	0.000
Q18 ← BI	0.621	0.619	0.059	10.449	0.000
Q19 ← BI	0.629	0.626	0.061	10.396	0.000
Q20 ← BI	0.810	0.810	0.038	21.491	0.000
Q21 ← PBC	0.842	0.841	0.029	29.126	0.000
Q22 ← BI	0.829	0.828	0.029	28.921	0.000
Q23 ← BI	0.790	0.789	0.035	22.684	0.000
Q24 ← PBC	0.832	0.831	0.038	22.130	0.000
Q25 ← PBC	0.850	0.849	0.024	35.286	0.000
Q26 ← PBC	0.838	0.836	0.033	25.151	0.000
Q27 ← PBC	0.848	0.847	0.026	33.132	0.000
Q28 ← PBC	0.802	0.800	0.043	18.579	0.000
Q9 ← SA	0.775	0.773	0.045	17.055	0.000

AVE is greater than 0.5, which indicates good convergent validity, and CR is greater than 0.7, which indicates good internal consistency (**Table 9**).

Table 9. Cronbach's alpha, composite reliability, and average variance extracted (AVE).

	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
BI	0.842	0.858	0.884	0.562
PBC	0.913	0.915	0.933	0.698
SA	0.864	0.878	0.908	0.711
UFC	0.833	0.833	0.889	0.666

Model fit and path coefficient analysis are as below.

This study employed PLS-SEM to analyse teachers' adoption behaviour of NLP tools. The findings suggest that the model demonstrates adequate fit and substantial explanatory power. Among the key predictors, UFC and SA have been identified as the most significant factors influencing perceived PBC and BI, with R^2 values of 0.526 and 0.860, respectively. These values exceed 0.742, thereby confirming their critical role in the adoption of technology by teachers.

The findings of the path analysis are presented as follows (**Table 10**):

Table 10. The structural equation modeling results.

	Original Sample	Mean	Std.	*T* Statistics	*P* Values	Conclusion
PBC → BI	0.564	0.561	0.077	7.355	0.000	Significance
SA → BI	0.363	0.361	0.068	5.311	0.000	Significance
SA → PBC	0.237	0.234	0.074	3.216	0.001	Significance
UFC → BI	0.485	0.487	0.069	7.011	0.000	Significance
UFC → PBC	0.551	0.553	0.069	7.972	0.000	Significance
SA → PBC → BI	0.134	0.131	0.046	2.936	0.003	Significance
UFC → PBC → BI	0.311	0.309	0.051	6.107	0.000	Significance

PBC → BI ($\beta = 0.564$, $p < 0.001$). PBC is significantly associated with teachers' intention to use technology, such that higher self-efficacy could result in greater acceptance of NLP application.

It revealed a significant association between SA and the intention to use NLP tools ($\beta = 0.363$, $p < 0.001$). SA factors have also been shown to influence teachers' adoption intentions, indicating that external context and social cognition play a role in shaping decisions.

The inter-relationships between SA and PBC were found to have the following effects: SA also influences PBC, which suggests that peer support boosts teachers' technological self-efficacy.

UFC → BI ($\beta = 0.485$, $p < 0.001$). The result highlights the importance of organizational resources, policy support, and training for NLP tools adoption, suggesting that UFC are important determinants of BI formation.

UFC → PBC ($\beta = 0.551$, $p < 0.001$). Institutional support has a positive effect on PBC, which suggests that teachers will become more confident and feel more control over using NLP tools when they receive sufficient support.

Finally, SA directly predict BI ($\beta = 0.134$, $p = 0.003$) according to the data. Social perceptions may have an indirect effect on BI through PBC, suggesting that self-efficacy mediates the relationship between social perception and adoption intention.

UFC → PBC → BI ($\beta = 0.311$, $p = 0.8$). Cronbach's alpha ($\alpha > 0.8$) and Composite Reliability (CR > 0.7) were used to test internal consistency and overall scale reliability.

The AVE for all measures (AVE > 0.5) showed strong convergent validity.

Discriminate validity was high, as the Fornell-Larcker test showed that the latent variables were distinct.

These findings indicate that the measurement model is reliable for assessing teachers' NLP adoption behaviour, contributing to a proportionate basis for further structural equation modelling analysis.

The findings of the study emphasize UFC as a determining factor in teachers' adoption of NLP. The impact of UFC on teachers' attitudes towards adoption is far greater than that observed with SA. SA still retains significance in influencing teachers' attitudes toward adoption. Perceived PBC functions as a prominent mediator. Teachers' self-efficacy has a direct effect on their adoption behaviour, and it mediates the effects of institutional support and SA on BI.

Results also provide evidence of the effect of PU in TAM. Teachers' acceptance of NLP is clearly significant. The current findings support TAM's position. They highlight the importance of institutional support, self-efficacy, and teachers' PEU in NLP adoption.

To increase the uptake of NLP among teachers, it is suggested that universities focus on three main issues:

1. Strengthening Institutional Support

It is recommended to support systemic NLP training, policy incentives, and resource allocation. Increased motivation for teachers in technology adoption. It is suggested to increase teachers' motivation regarding technology adoption through a change in attitudes.

2. Enhancing Social Awareness

Actions to improve public attitudes towards NLP and its role in serving education are proposed. This aims to reduce resistance to new technology and stimulate a more supportive environment.

3. Building Teachers' Technological Confidence

Targeted training programs to enhance technology literacy and self-efficacy should be constructed if NLP is to be effectively incorporated into teaching methodologies.

This research validates the potential use of the TAM for examining NLP adoption by teachers in private universities. The results contribute to the theoretical framework of research on educational technology adoption and provide empirical evidence for policy development in higher education.

5. Discussion

5.1. Discussion of the Main Findings

This mixed-method research employed PLS-SEM and qualitative interviews to examine the antecedents of NLP adoption in teaching at a private university. It can be concluded from the analysis that technological literacy, PU, UFC, SA, and PBC have a significant effect on NLP adoption. These results illustrate an expansion of the Technology Acceptance Model (TAM) [3]. In this sense, the present study adds to prior literature by extending TAM with specific institutional dynamics, rather than the abstract external factors discussed in UTAUT [4]. The theoretical generalization is supported by actual prior work, such as Scherer et al's study, which offers an in-depth and well-informed perspective on the issue [5].

Q1. Practical Application of NLP

The use of NLP differs across academic fields. In engineering-related applications like computer science, developers leverage NLP to analyze, understand, and judge code (Yao, 2024). Although there are certainly similar boundaries in other sciences, the humanities use it primarily for text analysis (Wang, 2024). PU ($\beta = 0.572$, $p < 0.001$) and UFC ($\beta = 0.485$, $p < 0.001$) are positive factors that drive the utilization of NLP in academia. However, concerns about accuracy and privacy remain [22]. Given our experience in Shanghai, the results may have implications for other private universities with low capacity but a keen interest in integrating technology [30].

Q2. Institutional and Personal Factors

Our analysis showed that UFC is the most powerful predictor of the current phenomenon ($\beta = 0.485$, $p < 0.001$), and this strength is stronger than that of SA ($\beta = 0.363$, $p < 0.001$). Education and resources can drive adoption, as evident from Li [48] and Al-Zahrani & Alasmari [23]. It is also interesting to note that the OsZhord-Confidence relationship is significantly mediated by PBC, indicating that confidence ($\beta = 0.564$, $p < 0.001$) plays an important role [37]. Findings from previous research have indicated that literate teachers can innovate under constraints, unlike their non-technical counterparts.

Q3. Interaction Factors

The results in the study reveal that institutional support has a strong positive effect on adoption, as reflected in the generated beta coefficient of 0.485, which is statistically significant at the 0.001 level. This effect is mediated by PBC (the beta coefficient = 0.564, statistically significant at the $p < 0.001$ level). However, the results also show that the device is used very little without training. The opportunity for self-adaptation aligns with SDT (Self-Determination Theory), which is based on autonomy and competence from a motivational perspective.

Q4. Environmental Factors

The study found that SA has a weak influence on BI ($\beta = 0.363$, $p < 0.001$), with UFC having a greater impact than broader trends [30]. The internationalisation and technological atmosphere of Shanghai, in contrast to less globalised regions (e.g. inland China), promote acceptance through cross-national collaborations.

Q5. Effective Strategies

A number of strategies have been proposed to enhance the effectiveness of these programmes, including the strengthening of UFC ($\beta = 0.485$, $p < 0.001$) through low cost training (Li, 2024), and the enhancement of SA ($\beta = 0.363$, $p < 0.001$) through publicity [22]. The enhancement of PBC ($\beta = 0.564$, $p < 0.001$) through targeted programmes [26] and the promotion of interdisciplinary collaboration ($\beta = 0.472$, $p < 0.001$) are also recommended.

5.2. Research Contributions

This study makes three significant contributions, both theoretically and practically, to advance the field of Educational Technology.

The study is an innovative extension of the TAM [3] by integrating university faculty members' UTAUT security acceptance model. In contrast to the conventional TAM, which operates at a micro-level only, the model of this study also includes institutional and media-contextual factors. This inclusion results in a more comprehensive model for explaining the adoption of NLP, particularly among private universities. By incorporating these two factors, the research broadens TAM's dimensionality in higher education [4].

Our model borrows from TAM but adapts it to the context of voluntary adoption of NLP tools for teaching, a domain that is not fully explained by either TAM or UTAUT. By integrating PBC as core construct, our model directs attention to personal instructors' perceptions of control and the institutional context, which can further deepen the understanding of text-based AI tools adoption. This variation allows for a more nuanced insight into voluntary adoption mechanisms, which is a significant issue in the field of educational technology acceptance. While UTAUT primarily focuses on general contextual and social aspects, our model focuses more closely on personal level determinants, representing an extension of existing adoption theories in context.

By identifying the determinants of initial adoption intention, our work provides a baseline and theoretical groundwork for future research. Our results offer a theoretical basis for why faculty begin to use NLP, which is a necessary prerequisite for continued use. Additionally, this study addresses a critical research gap by examining the factors that influence the initial adoption of NLP tools, particularly in the context of private universities, which has been underexplored in the existing literature.

The research design is mixed, combining qualitative interviews and PLS-SEM to develop strong responses. For thematic analysis, it relies on NVivo, while for path confirmation, structural equation modeling is used. This approach offers a stringent and replicable foundation for future educational technology research [47].

The paper provides useful recommendations for private universities on how to foster the uptake of NLP. These recommendations include targeted training, resource maximization, and policy incentives. Emphasizing the significance of PBC, this study highlights the importance of improving teachers' confidence and skills for effective NLP adoption.

5.3. Practical Recommendations

The outcomes of the research lead to four recommendations that could improve the adoption of NLP in private university teaching. These suggestions revolve around teachers' engagement with pragmatic edtech.

First, universities should provide systematic training and concrete rewards. As Yessimova et al. (2024) proposes, they can offer NLP training sessions and incentives for adoption. These rewards can come in the form of technology competitions and research grants. Second, social publicity is crucial. Media can be leveraged by universities to promote NLP and reduce resistance. A positive side effect of using government and industry support is that it could increase the perceived value of NLP [22]. Third, with appropriate training programs, it would be possible to improve technological self-efficacy and the effective use of NLP [26]. Finally, NLP projects that foster cross disciplinary collaboration could enhance cross disciplinary understanding.

Training, incentives, and promotion are well-known constructs in the literature, but we have designed our recommendations to focus specifically on the case of NLP tool adoption within higher education.

Given that context-driven training should prioritize pedagogical integration over technical skill, we must also educate instructors on how NLP can support richer writing feedback, content generation online, and task automation in teaching environments. Incentives should be related to innovation in teaching that directly compensate teachers for using NLP tools to improve their pedagogical practices.

Spreading the news should focus on pedagogical success and how NLP tools enhance teaching, rather than emphasizing the idea of saving time and energy for activities like playing games. Aligning these recommendations with the university's strategic goals for digital transformation can help institutions consolidate their adoption efforts with longer term teaching and learning aims, thus contributing to the sustainability and scalability of NLP adoption.

These recommendations address both the private universities and personal obstacles, providing practical plans that private universities can use to implement NLP.

5.4. Limitations and Future Research Directions

This study has limitations, although it adds value to education and information knowledge.

First, the sample was only representative of one private university in Shanghai, which may lead to non-generalizable findings [41]. Therefore, future research should cover various regions and multiple disciplines to improve external validity. Secondly, methodological constraints were identified. PLS-SEM is applicable for exploratory analyses but does not provide as much precision in model fit as CB-SEM [48]. Future studies using CB-SEM may improve causal inference.

The rapid developments in NLP technology may have rendered the findings from this study outdated. To gain a dynamic perspective, it is suggested that longitudinal designs be used to monitor long-term adoption [30]. The following directions will help overcome the existing limitations, making the study more applicable and robust.

Although the data is specific to one private university with 28% faculty participation, our stratified multi-discipline sample and explicit depictions of boundary conditions allow for analytical crossover to other similar institutions. We urge further multi-site replications within the public/private sector and in other regions to validate the identified mechanisms.

Though a single private institution was the subject of the study, this limited scope allowed for depth in exploration and an understanding of factors that are contextual to NLP adoption. The selected university is a typical private institution in China, and its experiences offer significant insights into the particular issues and prospects of such universities. A 28% sample coverage (n = 195) was employed to ensure generalization within this organization. The next steps include multi-center replications at other institutions to verify the robustness and generalizability of these findings.

6. Conclusions

Because this is a mixed-methods study, TAM [3] has been extended to include the theoretical models of UFC, perceived performance control, and subjective norms to explain NLP tools adoption. This finding suggests that UFC was the most significant factor, although PBC also influenced adoption intentions. The inclusion of institutional and social aspects strengthens the relevance of TAM within the context of private higher education.

The findings imply that universities need to develop training programs, incentives, and resources, as well as manage AI perception to minimize resistance, which provides practical implications for educational technology adoption. The sample for this study comes from Shanghai, which may limit its representativeness and the ability to generalize to the wider population. Additionally, the small qualitative sample size may not reflect all differing opinions. However, the futurestudies might consider considering multiple institutions, using longitudinal research designs, and investigating interdisciplinary collaborations to promote NLP innovation.

Author Contributions

Conceptualization, Y.L.; methodology, S.B. and Z.S.; investigation, Z.B. and C.L.; formal analysis, S.B.; writing—original draft, Y.L.; writing—review & editing, Y.L. and Z.S.; supervision, A.B.M.A.; project administration, Y.L. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

This study was approved by the Ethics Committee of Shanghai Jianqiao University (Approval No. SJQU-2023-ETH-012).

Informed Consent Statement

All participants provided written informed consent prior to data collection.

Data Availability Statement

De-identified interview transcripts and survey data that support the findings of this study are available from the corresponding author upon reasonable request. Ethical restrictions apply to the sharing of raw identifiable data.

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Conflicts of Interest

The authors declare no conflict of interest.

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