Effect of "Internet+" 5G Information Technology on Blended Teaching: A Test Based on Counterfactual Method

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Abstract—Blended teaching is becoming an important way of educational reform and development. However, empirical studies on the effectiveness of blended teaching vary widely. From the perspective of "Internet+" 5G information technology application, this paper takes internship data of undergraduates who implement blended teaching in accounting majors in eight local public universities as research samples and uses counterfactual methods to discuss the application of "Internet+" 5G information technology on the effectiveness of blended teaching. The results show that students' grade point average, educational level, and whether there is a vocational qualification certificate have a significant impact on internship performance. Students' gender, residence, English certificate, and internship location have no significant impact on internship performance. This paper provides a useful exploration for the reform of classroom teaching in universities in the "Internet+" era and puts forward evidence for the promotion and application of 5G information technology and blended teaching.

Keywords—blended teaching, 5G information technology, teaching effect, talent cultivation, counterfactual method

1 Introduction

In recent years, a new trend of technological and industrial revolution represented by the Internet, big data, artificial intelligence, and other information technologies is reconstructing the concept and way of people's study, work, and life. Essentially, these cutting-edge information technologies all depend on development of common technology which is mobile communication technology. At present, the fifth-generation mobile communication technology (5G) is quietly coming together with a new generation of artificial intelligence technology, which not only accelerates generation and dissemination of knowledge [1] but also enables various demands for workers' skills in jobs rapidly updated. The superposition has accelerated the iteration of knowledge production and skill demand [2], profoundly changing and reshaping our education and teaching system.

Based on continuous application of these technologies, online courses such as MOOCs, MOORs, and SPOCs continue to emerge, and the "classroom revolution" is in full swing. Blended teaching is becoming the new normal of future education [3], which provides opportunities for teaching reform in universities. Based on educational information technology, blended teaching combines various teaching modes, environments, and media tools, and the elements involved are systematic and comprehensive. It is precise because components of blended teaching are very complex that some scholars believe that current evidence is insufficient to explain its effectiveness, and the specific causal relationship is difficult to determine [4].

Therefore, from the perspective of "Internet+" 5G information technology application, this paper takes the internship data of undergraduates who implement blended teaching in accounting majors in eight local public universities as research samples and uses counterfactual methods to discuss the application of "Internet+" 5G information technology on the effectiveness of blended teaching. There are three reasons for this. Firstly, the accounting discipline emphasizes both theoretical learning and practical application. Traditional teaching mode overemphasizes the acquisition of theoretical knowledge and places students' practical ability on courses such as extracurricular practical activities and comprehensive practical activities. Under the influence of factors such as the epidemic, these traditional activities have been greatly restricted, and blended teaching based on "Internet+" 5G information technology can help to alleviate this deficiency and better achieve the teaching goal of combining accounting theory and practice [5].

Secondly, information feedback from employers is more objective and neutral and plays a guiding role in the cultivation of talents in universities. It is necessary to collect and analyze feedback information from employers and students on the undergraduates' internship practice for continuous adjustment and optimization of personnel training strategies.

Thirdly, Chinese universities are mainly local universities, accounting for 93.2% of the total number. Based on the reality of the transformation of local universities, demands for higher personnel training and teaching reform are particularly prominent for local universities [6]. With the adjustment of Chinese industrial structure, development mode of local universities has gradually changed from teaching and research-oriented to gradually highlighting characteristics of local characteristic-oriented, application-oriented and technology-oriented. The goal of curriculum construction in local universities should be to cultivate high-quality applied technical talents. The final effect of local higher education depends on classroom teaching and implementation process directly facing students. Therefore, in line with trend of the times, integration of "Internet+" 5G information technology to carry out blended teaching reform is the core link to improve quality of higher education, and it is of great significance to promoting transformation and development of local universities.

2 Literature review

2.1 Effect of blended teaching

To verify the effectiveness of blended teaching, academic community carried out a large number of teaching experimental studies, but the conclusions were different and could be divided into three categories approximately.

Blended teaching had a significant effect on learning outcomes. Bernard et al. [7] found that in blended teaching, three kinds of interactions between teachers and students, between students, and between students and content appeared at the same time, or both types appeared at the same time, which was more effective than just one kind of interaction. Combination of synchronous communication and asynchronous communication, or combination of online communication and face-to-face communication was more effective than a simple way of communication. Qutieshat et al. [8] found through empirical research that blended teaching could significantly improve students' academic performance and satisfaction compared with traditional teaching. Boelens et al. [9] argued that sequence of online and face-to-face teaching and the proportion of online teaching were related to the flexibility of blended teaching and its successful implementation. 50% blend of online and offline teaching had the best effect on students' learning, which supported theoretical views of some scholars [10].

Blended teaching was not as effective as traditional teaching. Means et al. [11] conducted a meta-analysis of 12 examples of blended teaching and found that cooperative learning and teacher guidance were more effective than self-paced, self-directed learning. Without the supervision of teachers, students were more likely to give up their efforts, and immediacy and presence of teachers could improve students' learning motivation. Excessive time of blended teaching was not conducive to the improvement of learning effect [12], which might be because the online learning period increased learning load of students, reduced sense of teaching presence, and thus reduced effectiveness of blended teaching. Demaidi et al. [13] also found through empirical research that blended teaching had a negative effect on students' performance, and improvement of students' performance was not as good as traditional face-to-face teaching.

There was no significant difference between blended teaching and traditional teaching. Although most studies showed that the effectiveness of blended teaching was better than that of single online and face-to-face teaching, some scholars believed that components of blended teaching are very complex and difficult to control effectively. Existing evidence was not enough to explain the effectiveness of blended teaching, and was not necessarily the source of heterogeneity. Blended teaching should carefully integrate different teaching methods [14], adopt active learning strategies, and make rational use of multiple teaching methods [15]. Wong et al. [16] found through empirical research that compared with traditional teaching, blended teaching has no significant impact on students' academic performance, and they had the same effect.

2.2 Impact of "Internet+" 5G information technology on blended teaching

Mobile communication technology had gone through four development eras from 1G to 4G. Since 2019, 5G technology had shown an explosive trend, with intensive deployment and commercial use around the world [17]. Compared with 4G technology, 5G technology's high-speed, high-capacity, high-definition, full-dimensional, intelligent, non-delay perception, and transmission provided strong underlying technical support for blended teaching environment. At the same time, supported by the Internet of Things, mobile Internet, big data, and cloud computing technology, it was connected and deeply integrated with the upper-level artificial intelligence technology, to achieve rapid and seamless interconnection between all elements in teaching environment, including people, various equipment and terminals, physical environments, etc., thus promoting the true formation and operation of blended teaching environment.

With the in-depth development of "Internet+" education, educational technology research team of Tsinghua University proposed that reform of education and teaching had begun to enter a new stage of blended education [18]. In 2016 and 2019, the Chinese Ministry of Education put forward the call for promoting blended teaching reform, building blended first-class courses and suspension of classes and non-stop learning since the epidemic in 2020. Although the basic blended teaching function could also be realized under 4G conditions, 5G conditions brought about qualitative changes. For example, the 5G mobile network was faster and took less time. In classrooms, it improved communication efficiency between teachers and students, made the classroom more flexible, and released the vitality of the classroom, without need for delays and freezes, one-way teaching, etc. Another example was that application scenarios of educational technology also underwent subversive changes. Virtual/augmented reality (VR/AR) education, Ultra High Definition (UHD) Video live broadcast distance education, synchronous smart classrooms, and virtual laboratories could not only greatly meet individualized and diversified learning needs of learners, but also improved effect and efficiency of knowledge and skill learning, as well as an important environmental element for cultivating learners' innovative consciousness, innovative spirit, and innovative ability.

It could be seen that in the "Internet+" 5G era, blended teaching was integration and innovation of old and new learning methods, which was transformative and enabled educators to re-examine and reconstruct teaching practice. Kevin et al. [19] believed that blended teaching was the process of using two or more teaching methods to impart knowledge and skills to learners. In addition to transferring knowledge, it also had the function of transforming knowledge into skills. Learning experience, learning engagement, learning style, satisfaction, ability development, etc., in blended teaching were different from traditional classrooms [20].

Under the conditions of "Internet+" 5G and even more advanced communication technology in the future, blended teaching might become the main form of teaching in universities. However, current academic community still had different understandings of the role of blended teaching, and there were many contradictions in empirical research on effectiveness of blended teaching [21]. Therefore, it was necessary to supplement and enrich research on effect of blended teaching. There might be two reasons for this. One was constraints of information and communication technology. As mentioned above, judging from the time of past research literature, research scene should be mainly based on the 4G environment. Since information and communication technology before 5G couldn't effectively support online classroom interaction between teachers and students, classroom vividness was greatly discounted, affecting effect of blended teaching. Then, when discussing effect of blended teaching, past research literature often paid attention to classroom performance of students, emphasized possession or mastery of knowledge, and ignored investigation of the cultivation of students' practical ability. To a certain extent, this reflected insufficiency of classroom education separated from real life. Many students often possessed a lot of knowledge but couldn't put them into practice. Prevalence of this phenomenon required to seriously reflect on deviation in the orientation of knowledge teaching and to promote students to improve their ability to adapt to the living environment by learning and applying the knowledge they had learned.

Due to the irreversibility of history, difference in effect of implementing blended teaching under conditions of "Internet+" 5G information technology cannot be simultaneously observed, which forms a counterfactual research framework. Given this, it adopts the propensity score matching method (PSM) of evidence-based research to study effect of "Internet+" 5G information technology on blended teaching.

3 Methodology

3.1 Modeling

As mentioned above, this paper aims to evaluate whether blended teaching under condition of "Internet+" 5G information technology can improve internship performance of students, to reflect impact of "Internet+" 5G information technology on effect of blended teaching. Core of the assessment is to answer a counterfactual question that is whether the intervention will have performed differently if it has not been done. This method sets a series of individual characteristics of students as observation variables to fit propensity scores of intervention group and control group, and finds matching samples of intervention group and control group according to various matching methods (such as nearest-neighbor matching, radius matching, kernel matching), to evaluate real impact of selection effect under better comparability conditions (excluding selection bias).

The matching process proceeds in three steps. Firstly, propensity scores are estimated according to the settings of selection equation, which is defined as following formula (1).

$$Z_i = Logit(\beta X_i + \varepsilon_i) \tag{1}$$

Z is a binary variable. It's equal to 1 if student *i* is intervened, and it's equal to 0 otherwise. *X* is a vector matrix containing a set of covariates. *â* is the vector of coefficients to be estimated, and å is an error term.

$P(X_i)$ is propensity score of student *i* which can be estimated by a probability model, shown as formula (2).

$$P(X_i) = Pr(Z_i = 1 | X_i) \tag{2}$$

Secondly, according to the similar propensity scores, the nearest-neighbor matching method is used to pair intervention group with control group without intervention, shown as formula (3).

$$C(P_i) = min \| P_i - P_j \| \tag{3}$$

i and *j* represent intervened students and non-intervention students respectively, and $C(P)$ represents neighbor relationship between *i* and *j*. When value of $C(P)$ is the minimum, students *i* and *j* match each other.

Thirdly, it should calculate impact of 5G blended teaching on students' internship performance, namely the average treatment effect (ATT), shown as formula (4).

$$ATT = E(Y_i - Y_j | Z_i = 1) = E(Y_i | Z_i = 1,\ P(X_i)) - E(Y_j | Z_j = 0,\ P(X_j)) \tag{4}$$

Y is an outcome variable, that is student's internship performance. Other variables and parameters have the same meaning as above (if there are no special instructions, the same below). A significantly positive ATT value means that 5G blended teaching significantly affects students' internship performance.

Unbiased estimation requires correct specification of regression equation [22]. However, whether a model accurately reflects relationship between variables can never be known [23]. To this end, this paper uses a double robust estimation, that is augmented inverse propensity weighted estimator (AIPW), based on propensity matching score (PSM) and inverse probability weighting (IPW) [24] to get more effective estimation results. Essence of propensity score matching method is a hierarchical weighting algorithm. In terms of estimating the ATT effect, matching method focuses on selecting observations in control group that is close enough to intervention group, so the closer the propensity score of control group to intervention group, the greater the weight [25]. Formula (5) is the estimator of double robust estimation.

$$\begin{aligned}\hat{\Delta}_{DR} = n^{-1}\sum_{i=1}^{n}\left[\frac{Z_i Y_i}{e(X_i, \hat{\beta})} - \frac{Z_i - e(X_i, \hat{\beta})}{e(X_i, \hat{\beta})} m_1(X_i, \hat{\alpha}_1)\right] \\ - n^{-1}\sum_{i=1}^{n}\left[\frac{(1-Z_i)Y_i}{1-e(X_i, \hat{\beta})} - \frac{Z_i - e(X_i, \hat{\beta})}{1-e(X_i, \hat{\beta})} m_0(X_i, \hat{\alpha}_1)\right]\end{aligned} \tag{5}$$

$e(X_i, \hat{\beta})$ is hypothetical model for propensity score matching, $m_0(X_i, \hat{\alpha}_1)$ and $m_1(X_i, \hat{\alpha}_1)$ are hypothetical models for matching variables and dependent variables at each stratum.

The first term of formula (5) can be expressed as formula (6).

$$E(Y_{Z=1}) + E\left\{\frac{Z - e(X, \beta)}{e(X, \beta)}[Y_{T=1} - m_1(X, \alpha_1)]\right\} \tag{6}$$

When the PSM model is correctly specified and regression model is incorrect, or the PSM model is incorrect and regression model is correctly specified, the second term in formula (5) is equal to zero. Advantage of this model is that its estimation of causality will be biased only when regression model and the PSM model are faulty. This is safer than simply using either model. Therefore, this paper establishes the following measurement model, shown as formula (7).

$$Y_i = \beta_0 + \beta_1 Z_i + \beta_2 X_i + \varepsilon_i \tag{7}$$

If student *i* participates in 5G blended teaching, *Z* is equal to 1. If student *i* does not participate, *Z* is equal to 0. By adding inverse probability weighting to regression, the double robust estimation can be performed.

AIPW estimates intervention effect in three steps. The first step is to use Logit model to estimate and calculate inverse probability weights. The second step is to estimate econometric model without using inverse probability weights calculated in the first step. The third step is to use inverse probability weights calculated in the first step to take weighted average of estimated internship practice scores under different interventions (participation in 5G blended teaching or not). Difference between mean scores of two groups of internship practice scores is calculated, which is impact of 5G blended teaching experience on students' internship performance.

Finally, establishment conditions of PSM, including conditional independence hypothesis, common support domain hypothesis, balance, and sensitivity are all tested to ensure the reliability of results. In addition, this paper also uses the ordinary least square method for benchmark regression estimation, which is consistent with the mainstream literature.

3.2 Sample data and variables

A total of 874 undergraduates of accounting majors from eight local public universities are selected, including 643 undergraduates and 231 junior college graduates. Total number of sample students in this paper is 760, accounting for 87.0%, including 598 undergraduates and 162 junior college graduates. 290 students participate in 5G blended teaching, and 470 don't.

Internship performance data of students come from the Internship Workplace Feedback Form, uniformly produced and distributed by the university. At the end of the student's internship practice, manager in internship workplace will fill in the appraisal opinion, assess assessment grade, and affix official seal, and then the student will return it to the university. Assessment content in the table includes 10 aspects including work initiative, workload, work quality, collaboration ability, professionalism, practical technical ability, internship work attitude, operational discipline, ideological performance, and attendance. Internship grades are divided into 5 grades, namely excellent, good, medium, pass and fail. Whether students participate in 5G blended teaching comes from course records of the teachers. Additional covariates are determined via relevant references, expert opinion, and data availability. The data comes from undergraduate information statistics table. All data processing was performed using STATA15 software. Variable definitions used in this paper are shown in Table 1.

Table 1. Variable definition

Variable Name	Code	Specifications of Calculation
Internship performance	Grade	The assessment grade of the internship workplace
5G blended teaching	Treat	It's 1 for participating in 5G blended teaching, and it's 0 otherwise
Gender	Gender	It's 1 for girls, and it's 0 for boys
Place of residence	Home	It's 1 for counties, towns, and villages, and is 0 otherwise
Academic performance	GPA	Grade point average
Educational level	Degree	It's 1 for undergraduates, 0 for junior college graduates
English certificate	CET	It's 1 if there is, and is 0 otherwise
Vocational qualification certificate	Skill	It's 1 if there is, and is 0 otherwise
Internship positions	Job	Accounting type is 1, and is 0 otherwise
Internship location	Workplace	It's 1 for counties, towns, and villages, and is 0 otherwise

4 Research analysis

4.1 Variable description and correlation

Variable descriptive statistics of the whole sample are shown in Table 2. Sample students have obvious self-characteristics. For example, in terms of gender ratio, females make up the majority, which is in line with gender characteristics of accounting majors and accounting occupations. From the perspective of educational composition, sample students are mainly undergraduates. Other characteristics include that most students have English certificates, and only a few students have obtained some kind of vocational qualification certificate. Students live mainly in counties, towns, and villages, and their internship locations are concentrated in cities. More than half of students practice in accounting positions.

Table 2. Descriptive statistics for variables

Variable	N	Mean	SD	Min	Max
Grade	760	0.705	0.305	0	4
Gender	760	0.735	0.441	0	1
Home	760	0.793	0.405	0	1
GPA	760	2.786	0.497	1.92	4.10
Degree	760	0.787	0.410	0	1
CET	760	0.838	0.368	0	1
Skill	760	0.088	0.283	0	1
Job	760	0.628	0.483	0	4
Workplace	760	0.168	0.374	0	1
Treat	760	0.381	0.486	0	1

Table 3 reports the Pearson correlation coefficient between variables, and the value is generally below 0.6. Among them, correlation coefficients between the main variables and covariates are generally very small, and only a very small number of covariates have correlation coefficients of around 0.5. The results show that correlation coefficients of the variables are all within acceptable range, and independence of the variables is better.

Table 3. Correlation coefficient between variables

	Grade	Gender	Home	GPA	Degree	CET	Skill	Job	Workplace	Treat
Grade	1									
Gender	−0.097**	1								
Home	−0.066	0.585***	1							
GPA	0.062	0.051	0.066	1						
Degree	0.083**	0.052	0.036	0.142***	1					
CET	0.021	0.020	0.023	0.092**	0.024	1				
Skill	0.045	0.008	−0.036	−0.099**	0.094**	−0.408***	1			
Job	−0.070	0.781***	0.617***	−0.072	0.066	0.003	−0.011	1		
Workplace	−0.005	−0.105**	−0.083**	0.235***	−0.032	0.035	−0.004	−0.586*	1	
Treat	0.109**	0.017	0.040	0.075**	−0.153***	0.014	−0.082**	0.009	0.016	1

Notes: *, **, *** represent the significance levels of 0.05, 0.01, and 0.001, respectively. Standard errors are in parentheses.

4.2 Benchmark regression results

Columns 1–3 of Table 4 show that variable coefficients of students' grade point average, educational level, and whether they have vocational qualification certificates are significant at the level of 5% and above. In addition, vocational qualification certificates have the greatest impact on internship performance. Student's gender, place of residence, English certificate, type of internship position, and location of internship had no significant effect on internship performance. It can be seen that students who have obtained a certain vocational qualification certificate, have a higher grade point average, and have a higher educational level are more likely to have higher internship grades.

Table 4. OLS and PSM estimated results for 5G blended teaching and internship grades

	(1) OLS	**(2) OLS**	**(3) OLS**	**(4) PSM**	**(5) PSM**	**(6) PSM**
Grade	Estimation of samples not involved in 5G blended teaching	Estimation of samples involved in 5G blended teaching	Estimation of the full sample	Nearest-neighbor matching estimation	Radius matching estimation	Kernel matching estimation
Gender	0.034	−0.316	−0.098	−0.125	−0.097	−0.097
	(0.060)	(0.130)	(0.063)	(0.083)	(0.063)	(0.063)
Home	−0.100	0.247	0.017	0.078	0.016	0.016
	(0.040)	(0.095)	(0.043)	(0.057)	(0.043)	(0.043)
GPA	0.021*	0.057*	0.037*	0.051*	0.039*	0.040*
	(0.022)	(0.048)	(0.023)	(0.034)	(0.023)	(0.023)
Degree	0.007*	0.112**	0.048*	0.077**	0.051*	0.050*
	(0.028)	(0.052)	(0.027)	(0.034)	(0.027)	(0.027)
CET	0.006	0.098	0.040	0.016	0.027	0.030
	(0.043)	(0.079)	(0.042)	(0.053)	(0.044)	(0.044)
Skill	0.084*	0.127*	0.110**	0.102**	0.098*	0.101*
	(0.053)	(0.123)	(0.055)	(0.071)	(0.057)	(0.056)
Job	−0.059	0.119	0.018	0.025	0.019	0.019
	(0.059)	(0.129)	(0.062)	(0.086)	(0.062)	(0.062)
Workplace	−0.050	−0.059	−0.008	−0.077	−0.009	−0.009
	(0.048)	(0.105)	(0.051)	(0.073)	(0.051)	(0.051)
Treat			0.064**	0.0095**	0.066**	0.066**
			(0.022)	(0.030)	(0.023)	(0.023)
_cons	0.074	−0.109	−0.010	−0.012	−0.003	−0.008
	(0.076)	(0.163)	(0.080)	(0.105)	(0.081)	(0.080)
N	470	290	760	733	733	733
F	3.49***	2.27*	2.95**	3.17**	3.00**	3.00**
R^2	0.057	0.051	0.043	0.056	0.035	0.034

Notes: *, **, *** represent the significance levels of 0.05, 0.01, and 0.001, respectively. Standard errors are in parentheses.

4.3 Intervention effect

After matching, the ATT of 5G blended teaching can be estimated by assessing difference in internship scores between students who participate and don't participate in 5G blended teaching. From results of the nearest-neighbor matching method in Table 5, the t value is 3.13, which is significant at the 0.05 level. Significant positive differences in students' internship scores indicate that 5G blended teaching significantly improves students' internship scores. Difference of the ATT between students who participated in 5G blended teaching and those who do not participate is 0.0677. Scores of students who participate in 5G internship teaching are 132.49% higher than those who don't participate.

Column 4 of Table 4 reports estimation results of PSM under the nearest-neighbor matching method of the ATT effect of 5G blended teaching on students' internship performance, which is consistent with the conclusion of the full-sample OLS model.

To weaken non-random distribution characteristics caused by self-selection problem and to ensure the robustness of results, this paper also reports results of radius matching and kernel matching. Table 4 and Table 5 both show that the conclusion remains unchanged.

Table 5. The ATT of 5G blended teaching on internship performance

	Sample	Treated	Controls	Difference	S.E.	T_Stat
Nearest-neighbor matching	Unmatched	0.1172	0.0489	0.0683	0.0226	3.01
	ATT	0.1188	0.0511	0.0677	0.0295	3.13
Radius matching	Unmatched	0.1172	0.0489	0.0683	0.0226	3.01
	ATT	0.1188	0.0584	0.0604	0.0270	2.54
Kernel matching	Unmatched	0.1172	0.0489	0.0683	0.0226	3.01
	ATT	0.1188	0.0540	0.0648	0.0262	2.96

4.4 Double robust estimation

Table 6 reports results under IPW and AIPW estimation methods. The ATT is significantly positive at the level above 0.05, which is consistent with estimated results of PSM, indicating that 5G blended teaching improves students' internship performance.

Since AIPW combines properties of regression-based estimators and inverse probability-weighted IPW estimators, it can be found from Table 6 that propensity value weighting and double robust estimation results are slightly different. Based on AIPW, if all students have a value of 0 for treat variable, their internship score is 0.448. But if all students' treat variable takes value 1, average internship score will be 0.677 higher, with an increase of 151.11%.

Table 6. IPW and AIPW estimation results

		Grade	Coef.	Robust Std. Err.	Z	P>|z|
IPW	ATT	treat				
		(1 vs 0)	0.684	0.243	2.53	0.012
	POmean	treat				
		0	0.449	0.092	4.83	0.000
AIPW	ATT	treat				
		(1 vs 0)	0.677	0.240	2.53	0.011
	POmean	treat				
		0	0.448	0.092	4.83	0.000

4.5 Robustness test

PSM should be subject to a balance test. After matching, there should be no significant difference in variable characteristics of control group and intervention group in each dimension. Table 7 shows that standardized deviation of the variables after matching processing has dropped below 10%, and all t-test results show that there is no significant difference between students who participated in 5G blended teaching and those who don't, indicating that selected matching covariates and matching methods are appropriate. Namely, there is no significant difference between samples of students who participate in 5G blended teaching and those who don't participate after propensity score matching. Satisfaction of balance assumption means that propensity score matching estimates based on this are credible.

Table 7. Robustness test

Variable	Unmatched	Mean	Control	%reduct	bias	t-test	p>|t|
	Matched	Treated		%bias			
Gender	U	0.7448	0.7297	3.4		0.46	0.648
	M	0.7448	0.7438	0.2	93.7	0.03	0.979
Home	U	0.8137	0.7808	8.2		1.09	0.276
	M	0.8137	0.8097	1.0	87.8	0.12	0.902
GPA	U	2.8344	2.7574	15.4		2.08	0.038
	M	2.8344	2.8076	5.4	65.1	0.66	0.512
Degree	U	0.7069	0.8361	−31.1		−4.27	0.000
	M	0.7069	0.6970	2.4	92.4	0.26	0.795
CET	U	0.8448	0.8631	−5.0		−0.62	0.532
	M	0.8448	0.8340	2.9	70.1	0.39	0.695
Skill	U	0.0586	0.1063	−17.4		−2.26	0.024
	M	0.0586	0.0542	1.6	90.8	0.23	0.820
Work	U	0.1758	0.1638	3.2		0.43	0.667
	M	0.1758	0.1763	−0.1	96.4	−0.01	0.989

4.6 Independence hypothesis test

PSM needs to satisfy conditional independence assumption that is treatment variable *Z* is independent of covariate *X*, to ensure that different treatment intensity is independent of underlying outcome. Then, after controlling for common characteristics of two groups of samples, difference in students' internship performance comes from impact of 5G blended teaching. Benchmark regression results show that although the goodness of fit of the model is not high, variables and the model as a whole have good significance. There is no significant difference in covariates of the models regardless of whether students participate in 5G blended teaching. This shows that conditional independence assumption can be satisfied.

Judging from the sample source, selection of students participating in 5G blended teaching randomly depends on major class of the course taught by the teacher in a certain semester, which is uniformly regulated by educational administration curriculum which is decision of management department of the university, and is exogenous to the 5G blended teaching activities and has strong independence.

4.7 Sensitivity test

The PSM method mainly measures based on observable variables. If there is a selection based on unobservable variables, it will still bring hidden bias. To solve this problem, this paper uses the Rosenbaum Bounds method [26] to test sensitivity of the PSM estimation results to hidden bias, and then test effectiveness of the PSM. Test results show that when the gamma value (Γ) reaches 2, corresponding *P* value (sig+) remains statistically significant at the 0.05 level shown in Table 8. It can be seen that unobservable factors in survey sample have relatively little impact on the estimated ATT value of controllable variables. The PSM method in this paper can pass sensitivity test, and the estimated results are reliable.

Table 8. Rosenbaum boundary sensitivity test results

Gamma Coefficient Γ	Nearest-Neighbor Matching		Radius Matching		Kernel Matching	
	Sig+	Sig−	Sig+	Sig−	Sig+	Sig−
1.0	0.000	0.000	0.000	0.000	0.000	0.000
1.2	0.000	0.000	0.000	0.000	0.000	0.000
1.4	0.001	0.000	0.000	0.000	0.000	0.000
1.6	0.005	0.000	0.001	0.000	0.001	0.000
1.8	0.011	0.000	0.003	0.000	0.002	0.000
2.0	0.038	0.000	0.008	0.000	0.006	0.000
2.2	0.052	0.000	0.022	0.000	0.019	0.000

5 Conclusion

Based on internship practice data of undergraduates who implemented 5G blended teaching in accounting majors in eight local public universities as research samples, this paper adopts the PSM method under counterfactual framework to discuss blended teaching effect under condition of "Internet+" 5G information technology. Results show that students' internship scores who participate in 5G blended teaching are 0.0660 higher than those who don't, with a range of 129.51%. Students' grade point average, educational level, and whether there is a vocational qualification certificate have a significant impact on students' internship performance, and influence of vocational qualification certificate is the greatest. Students' gender, place of residence, English certificate, type of internship position, and location of the internship has no significant effect on internship performance. Double robust estimates also support this conclusion. This paper also tests preconditions of the PSM. Overall, it supports positive and significant effect of 5G blended teaching on training effect of university students.

In the context of the era of intelligence and digitization, it is an urgent need for society to build application-oriented universities, cultivate high-quality talents to continuously improve effectiveness of talent training, and realize the synchronization of higher education and enterprise needs. This paper focuses on influence of blended teaching on training effect of university students from the perspective of "Internet+" 5G information technology application. However, even ideal classroom teaching has limitations in promoting development of university students. Talent training is a systematic educational project, which requires joint support and participation of classroom knowledge teaching, school education, social forces, and modern information resources. For example, reform of teaching system, improvement of classroom material environment, matching and input of various blended teaching resources, and updating of teachers' teaching concepts and methods are all essential.

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