Eurasian Journal of Educational Research 114 (2024) 285-317

Eurasian Journal of Educational Research
www.ejer.com.tr

The Impact of Digital Learning Infrastructure on Student Career Achievement in China

Huanhuan Wang[1]*, Mohd Shukri Ab Yajid[2], Jacquline Tham[3]

ARTICLE INFO

Article History:
Received: 01 August 2024
Received in revised form: 15 December 2024
Accepted: 30 December 2024
DOI: 10.14689/ejer.2024.114.016

Keywords
Student Career Achievement, Digitization, Government Policies, School Function, Teacher Quality

ABSTRACT

Background: Technological advancement has become a prevalent feature in learning institutions and their impact on students' career progression is still unknown. **Problem statement:** This study explores about the role of digital background, government policies, school functions and quality of teachers concerning the students' career achievement in the context of the increasing digitalization of education in China and the moderating role of students' motivation. The research issue is a lack of correspondence between technology-enhanced education activities and actual enhancement of students' employability. **Methodology:** For this research, self-completed structured questionnaires were administered to 500 university students in Heilongjiang Province and 479 completed questionnaires were collected. Statistical tests also included exploratory and confirmatory factor analysis using SPSS and AMOS, structural equation modeling (SEM), and bootstrapped mediation analysis. **Findings:** The findings show that motivation of students increases by digital background as well as school functions, which leads to better career outcomes. In addition, government policies and teachers have a direct as well as an indirect influence over the motive and thereby career prospects. The goodness of fit indicated that the model was a good fit for the data with a RMSEA of 0.047. CFI = 0.933. Outcomes: The outcomes indicate the need to ensure the adoption of learning technology, institutional support, and pivotal changes to the teacher education curriculum to help students develop the motivation, skills, and competencies valued in the workplace. **Conclusion:** The results of this research can be useful for policymakers and stakeholders in educational institutions that strive to boost graduate employment in digitally changing economies.

[1]PHD Candidate, Post Graduate Centre, Management and Science University, University Drive, Off Persiaran Olahraga, Section 13,40100, Selangor, Malaysia.
Lecturer, College of Economic and Managment, Qiqihar University: Qiqihar, Heilongjiang,161000, China
ORCID: https://orcid.org/0009-0009-2217-585X , Email: 18845211212@163.com
[2]Professor, Post Graduate Centre,Management and Science University,University Drive,Off Persiaran Olahraga,Section 13,40100, Selangor, Malaysia.
ORCID: https://orcid.org/0000-0001-5688-4392 , Email: shukri@msu.edu.my
[3]Associate professor, Post Graduate Centre,Management and Science University,University Drive, Off Persiaran Olahraga, Section 13,40100, Selangor, Malaysia.
ORCID: https://orcid.org/0000-0003-0966-2425 , Email: jacquline@msu.edu.my
*Correspondence: 18845211212@163.com

Introduction

Technological advancement has transformed both education and employment landscapes, placing university students within an evolving environment that prepares them for future occupational roles. As technology progresses, digitisation has emerged as a critical determinant in shaping students' readiness for the labour market (Parilla & Evangelista, 2025). However, an essential area remains insufficiently explored—namely, the extent to which digital technologies, structures, and methodologies influence students' trajectories of success. Furthermore, variables such as government policies, institutional roles, educator quality, and student motivation are among the most significant elements interacting to shape students' career ambitions. Understanding these interconnections is therefore essential for enhancing employability in the digital era, particularly as higher education institutions attempt to align academic provisions with industry demands (Hussain & Javed, 2019). The present study contributes to the growing corpus of scholarly and practical knowledge by investigating the interplay between digitisation and other determinants of student career achievement.

Drawing upon existing literature, digital technology use has been shown to improve students' competencies and adaptability to market demands through its integration into educational systems (Su & Shen, 2025). Moreover, governmental policies concerning infrastructure, technological access, and human capital development are identified as pivotal factors influencing disparities in employment opportunities. In a similar vein, institutional functions—such as curriculum innovation and student administration—play a partial yet meaningful role in equipping students for participation in a technologically sophisticated economy (Chávez-Márquez et al., 2023). Additionally, teacher quality remains a central component in fostering student engagement and motivation to achieve targeted learning outcomes and envisioned career paths. By examining these interconnected factors, this research seeks to offer policy-oriented recommendations and contribute constructive insights for policymakers, educators, and academic institutions.

Problem Statement

The returns on investments from educational reforms, particularly in terms of their translation into tangible career outcomes for students, remain somewhat ambiguous. Although digital resources and technical support have become more prevalent within higher education institutions, numerous domains continue to suffer from inadequate and ineffective implementation in relation to enhancing employment prospects. Moreover, many governmental policies addressing these challenges are enacted in environments where the alignment between policy frameworks and institutional practices intended to support students in navigating the demands of the contemporary labour market is insufficient. This misalignment often results in compromised quality.

Additionally, activities such as teacher training, curriculum development, resource distribution, and time allocation frequently exacerbate existing inequities in learning environments. This study addresses these issues by investigating the influence of digitisation, government initiatives, institutional functions, and teacher effectiveness on student motivation and career aspirations. In examining the impact of digitisation on education, it is no longer tenable to dismiss its potential to effect the anticipated transformations in student employability. The current research endeavours to assess the strength and nature of the relationships among these constructs, with the aim of offering actionable insights for enhancing the effectiveness of educational practices and policymaking.

Research Objectives

The study is guided by the following objectives:

1. To examine the influence of digitisation, governmental policies, institutional functions, and teacher quality on students' motivational levels.
2. To assess the extent to which digitisation, governmental policies, institutional functions, teacher quality, and student motivation affect students' career aspirations.
3. To investigate the mediating role of student motivation in the relationship between digitisation, governmental policies, institutional functions, and teacher quality, and students' career aspirations.

Significance of the Study

This research holds significant value for theory, practice, and policy. Theoretically, it addresses a range of issues raised in existing literature concerning the impacts of digitisation on education and learning. The study helps fill gaps in the literature regarding how technology-based tools and resources influence career outcomes. Additionally, it contributes to the body of knowledge by proposing an integrated framework encompassing government policies, institutional activities, teacher performance, and student motivation. From a practical standpoint, the findings of this study are valuable for educational institutions and practitioners seeking to enhance students' employability. The research offers actionable recommendations for improving motivation and aligning curriculum goals, identifying key factors that influence these aspects. For instance, institutions could use the insights from Fernández-Batanero et al. (2021) and Bond et al. (2021) to design tailored support measures that enhance digital competencies, improve mentoring quality, and promote collaboration with industry.

From a policy perspective, this study underscores the need for alignment between governmental and institutional actions in addressing employability gaps. Policymakers can use the findings to inform frameworks that integrate education and employment, particularly focusing on skills development, technology access, and support for disadvantaged groups. Furthermore, the study suggests that policies implemented within organisations should undergo periodic evaluation to assess the extent to which the intended objectives are achieved. Therefore, this research can be considered a relevant contribution to scholarship on education and labour in the context of emerging digital economies. By examining the relationship between digitisation, government policies, institutional roles, teacher effectiveness, and student motivation, the study provides valuable insights for stakeholders aiming to improve students' employment outcomes.

Literature Review

Overview of Vocational Education Digitization

Vocational education has undergone a transformation into a digital platform, making research in this domain highly pertinent, with a substantial body of studies assessing its impact on educational and employment outcomes. Scholars have consistently emphasised that digitisation is not merely a technological revolution but also a strategic adjustment driven by globalisation and economic changes. For example, Li and Fu (2024), who examined digital skills in vocational education within the context of the United Kingdom, highlighted that incorporating digital competencies into the curriculum enhances the marketability of vocational training and education. Their study underscored the necessity of integrating information technology skills across various business sectors to address the evolving challenges of the digital business landscape. Similarly, Wang (2024) identified digitisation as the central factor in reshaping vocational education in China. This research highlighted the urgent need to utilise existing governmental programmes to align educational systems with prevailing industry standards, thereby fostering an environment conducive to the digital revolution in education. In this context, the interplay between government policies, institutional roles, and teacher quality emerges as a crucial factor in the successful implementation of digitisation strategies.

Role of Government Policies in Education Digitization

A primary focus of governments is to support the digitisation of education, including ensuring equity in digital resources and governance. Similarly, as supported by Lin and Kee (2024), vocational education in the digital era must recognise the necessity of adapting to the demands of contemporary digital society. In their study of China's Vocational Education Reform, they highlight the critical role of government institutions in laying the groundwork for the development of digital infrastructures, while simultaneously integrating Information and Communication Technologies (ICT) into teaching and learning processes. Educational policies addressing issues related to digital literacy, teacher training, and curriculum development are thus vital.

Chinese authorities continue to guide the overall direction of digital education and its ongoing development. They have crafted policies and made significant investments to achieve ICT integration across the nation's educational institutions. These initiatives include establishing robust ICT facilities, increasing funding for digital resources, and implementing measures to digitalise both students and faculty. Zeng (2022) also discuss how these policies have fostered partnerships between academic institutions and industry sectors, creating environments where students can access relevant training and resources. Moreover, Hu and Zhang (2020) assess the impact of government policies on educational quality in Chinese universities, arguing that sustained investment in the digital environment positively influences student performance. Bajpai et al. (2019), who also acknowledge this, concur with studies indicating that meaningful technology integration requires strong policy support to bridge the gap between technology adoption and teachers' preparedness.

Advancements in Digital Learning Infrastructure

Chinese vocational education has recently been restructured with the integration of digital learning infrastructure, including virtual simulations, AI tools, and adaptive learning systems. These technologies enable differentiated instruction, enhancing efficiency and aligning with current job market demands. Dinesh and Subhashini (2025) highlighted AI's role in processing big data to tailor learning paths. This individualised approach supports skill acquisition and career readiness. Virtual simulations further provide practical experience, ensuring learners are prepared for workplace challenges. Overall, the shift reflects a move from rigid systems to flexible, student-centred, tech-based education.

School Functions and Curriculum Design

Vocational education must advanced digital transformation by means of school functions, namely curriculum design and student services, which also determine student motivation and career goals. As shown by Kurniati et al. (2022), boot camp models, like those which incorporate advanced digital technology, help student increase their practical competencies and improve their motivation by offering industry aligned practical course that is hands on, hence enhancing learning experience. In Pérez-Rivero et al. (2022), the authors noticed that curriculum redesigns were widespread during the COVID-19 pandemic that are focused on digital competencies and industry partnerships. In addition to motivating student more, these changes clarified career pathways and increased student goal orientation. In addition, Shambetaliev et al. (2023) stated that the digital teaching competence embeds itself better into restructured curricula equipping the students for professional challenges. In conclusion, in digitally evolves educational environments, redesigned curricula show evident contribution on increased student motivation and more clarity on student career aspirations.

Equity and Accessibility Challenges

In terms of the utilisation of digital learning infrastructure, a paradox of inequality exists in China, both geographically and in terms of the affordability of such resources. Key preparedness issues have been identified, including inadequate internet connectivity, a shortage of digital devices, and poor infrastructure in rural areas, all of which make it challenging for students to access the necessary tools and facilities for digital learning. According to Bi and Ishak (2025), students in rural regions are particularly affected, as they struggle to obtain resources of the same quality as their relatively more motivated counterparts in urban areas, thereby exacerbating the digital divide. This disparity not only impacts academic performance but also limits employment opportunities in those fields, thereby creating structural barriers to achievement.

Teacher Quality and Pedagogical Approaches

The quality of teachers has consistently been identified as a key factor in the effective delivery and application of robust learning processes, including the use of the internet. Competent educators, particularly those proficient in technology, are responsible for fostering a positive learning environment and enhancing students' capabilities. According to Méndez et al. (2022), to adequately prepare teachers for practice within the evolving educational landscape, professional development focused on the integration of technology into teaching and learning is essential. Huttayavilaiphan (2024) emphasised the importance of professional development in digital literacy to equip teachers with the specific skills needed to use technology effectively. Such programmes not only update educators on technical aspects but also teach them how to proactively design and enhance students' learning experiences. Teachers who are adept at using technology can motivate students, optimise their learning efforts, and better prepare them for the future workplace. They further pointed out that a lack of adequate training for teachers can undermine the effectiveness of even the most advanced ICT applications, highlighting the need for ongoing investment in teacher training. Providing opportunities for educators to fully utilise information technology ensures the creation of a digital learning environment that supports the achievement of educational goals and objectives. Cepa-Rodríguez and Murgiondo (2024) specifically addressed the enhancement of teachers' and students' digital literacy within the framework of experiential learning. Their studies demonstrated that through technology and various forms of experiential learning, student motivation is increased, along with the efficiency of acquiring the necessary knowledge and skills to secure employment in the market.

Student Motivation and Career Goals

Student motivation is a key moderating variable influencing the impact of digitisation, government policies, and teaching quality on career outcomes. Motivated students are more likely to use digital tools and pursue clear career goals. For instance, Tho et al. (2024) found increased engagement when students used structured digital platforms during COVID-19 remote instruction. Engagement is crucial for the effectiveness of educational technologies, supporting interaction, career planning, and goal attainment. Meeting learners' intrinsic needs—autonomy, competence, and relatedness—through adaptive tools fosters self-directed learning. Kastanya et al. (2023) noted that digital career guidance tools help students align education with career goals and develop relevant skills. Furthermore, Ithnin et al. (2024) argued that attrition can be mitigated by engaging students in digital skills competitions and project-based learning initiatives, which may inspire them to explore various career paths. The authors conclude that integrating career guidance and mentorship programmes would enhance student motivation and better prepare them for career opportunities as outlined in educational frameworks.

Integration of Variables and Systemic Impact

Digitisation, government policies, school functions, teacher quality, and student motivation collectively form a system that influences career aspirations. Tang et al. (2023) highlighted that these variables are not isolated but are interconnected forces driving the system. In China's vocational education system, it was found that studies adopting a comprehensive biosocial approach, focusing on both systemic and individual-level solutions, are more likely to yield positive outcomes. Mohd Rozi Bin Ismail (2024) also emphasised the importance of policy and institutional support in bridging the gap between learning outcomes and employment demands. As observed, collaboration between governments, universities, and industry organisations can effectively address other systemic barriers hindering student career success.

Literature Gap

Despite the progress made in digitisation and its integration into vocationally focused education, several deficits remain. While previous studies have concentrated on enhancing digital learning to improve career prospects for learners, the ways in which government policies, school functions, and teacher quality influence students' motivation and career interests have not been fully explored. Additionally, while earlier literature highlights the diverse opportunities afforded by digital tools, there is limited research on how these tools address equity gaps, either converging or diverging across various demographic dimensions. Furthermore, the relationship between digitisation and career success, with student motivation serving as a mediating variable, necessitates further comprehensive investigation. Moreover, the recursive relationship between digitisation and career outcomes, with a particular focus on the motivational role of students, has yet to be fully addressed. Prior research has often treated these factors as independent variables, overlooking the interaction between motivation, the digital learning environment, and career outcomes. To understand how motivation influences the levels of digitisation in fostering enduring professional achievements, multivariate complex research designs are essential.

Research Methodology

Research Model

This study primarily employs a quantitative research methodology to collect and analyse data from the public. According to Lazaraton (2005), the quantitative method incorporates various statistical techniques that involve systematic exploration through the analysis of statistical or numerical data. Quantitative research entails the gathering of data and its subsequent analysis to identify trends and assess relationships. This approach is exclusively deductive, where conclusions are drawn from the measurements. A key feature of the quantitative method is the formulation of hypotheses, followed by the application of various statistical analyses. In this study, a questionnaire survey is administered, including several demographic questions targeting college and university students.

Research Sample

College students in Heilongjiang Province were surveyed using a questionnaire. The sample includes 500 students, with data collected on gender, age group, academic grade, and major category for analysis.

Research Instruments and Procedure

A questionnaire survey was conducted using QuestionStar software, which facilitated the collection and validation of responses. The questionnaire included carefully designed demographic questions to gather student information. Clear guidelines were provided to both teachers and students to ensure accurate completion.

Preliminary Data Analysis

Organising data to address research questions is a crucial step in the analysis process. In the preliminary phase, the collected data are coded, inputted, edited, classified, and tabulated to prepare them for further analysis.

Encoding and Data Input

Data encoding is the first step in data preparation. The survey questionnaire is designed around four key dimensions: Digital Background (DI), Government Policies (GP), School Functions (SF), and Teacher Quality (TQ), with Student Motivation (ST) as the mediating variable. The data collected via the questionnaire are entered into SPSS for processing—this includes data entry, analysis, and output generation.

Editing Data

To ensure data accuracy and consistency, a pre-test is conducted before final data input. This involves thoroughly reviewing the collected survey responses to identify and correct errors, inconsistencies, and omissions. All questionnaire data are then edited accordingly. Particular attention is given to rectifying incorrect entries and missing information. Outliers are detected by examining maximum and minimum values and reviewing the frequency tables in SPSS.

Student Introduction

The participants in this study were college students from Heilongjiang Province, encompassing engineering institutions, comprehensive universities, and schools with medical specialisations. A total of 500 students participated, representing a diverse range of disciplines from first-year to fifth-year students. Following prior approval from the student teacher, the researchers administered the survey questionnaire. The questionnaire was then converted into a QR code, which was distributed to the student teacher. Students were instructed to scan the QR code and respond to the questions. The responses were automatically recorded in the QuestionStar software, which allowed for easy identification of both valid and invalid questionnaires. Ultimately, 479 valid responses were used for data analysis.

Basic Information of Pre-Test Students （N=96）

Descriptive Statistics

The pre-test sample of 96 students is presented with their general demographic data in Table 1. The study includes more female students at 75% than males at 25%. The participants primarily belong to two age groups that are 18–19 years old (50%) and 20–21 years old (42.7%) while those aged 22–25 constitute the smallest group. Most participants are freshmen with their first academic year (75%) while enrollment numbers decrease in subsequent academic years. The research indicates management encompasses the largest discipline group (46.9%) while economics falls second (27.1%) and science together with other disciplines and education come third (23.6%) and engineering positions last (1%).

Table 1

General Basic Information of Subjects' Statistical Analysis

Basic Information	Category	Frequency	Percentage (%)
Gender	Female	72	75.0
	Male	24	25.0
Age	18–19 years	48	50.0
	20–21 years	41	42.7
	22–23 years	6	6.3
	24–25 years	1	1.0
Grade	One	72	75.0
	Two	15	15.6
	Three	4	4.2
	Four	4	4.2
	Five	1	1.0
Category of Major Studied	Engineering	1	1.0
	Management	45	46.9
	Economics	26	27.1
	Education	9	9.4
	Science and Other Disciplines	15	15.6

Reliability Analysis of Pre-Testing

A reliability test in Table 2 is employed to assess whether the responses provided by survey participants remain consistent and reliable when gathered at different time points and locations. To evaluate the consistency and reliability of a questionnaire, statisticians often use Cronbach's alpha. The acceptable range for Cronbach's alpha, which can range from 0 to 1, typically lies between 0.65 and 0.70.

Table 2

Reliability Testing of Various Variables in the Questionnaire (Elsayed, 2012)

Variable	Measurement Items	CITY	Clone Bach after Deleting Item Alpha	Clone Bach Alpha
Digitization	B11	0.739	0.901	0.914
	B12	0.699	0.905	
	B13	0.683	0.907	
	B14	0.822	0.892	
	B15	0.761	0.899	
	B16	0.722	0.903	
	B17	0.734	0.901	
Government Policy	B21	0.793	0.872	0.899
	B22	0.768	0.875	
	B23	0.672	0.889	
	B24	0.673	0.889	
	B25	0.710	0.884	
	B26	0.753	0.877	

Table 2

Reliability Testing of Various Variables in the Questionnaire (Elsayed, 2012)

Variable	Measurement Items	CITY	Clone Bach after Deleting Item Alpha	Clone Bach Alpha
School Functions	B31	0.701	0.940	0.943
	B32	0.709	0.939	
	B33	0.733	0.938	
	B34	0.807	0.935	
	B35	0.754	0.937	
	B36	0.713	0.939	
	B37	0.751	0.938	
	B38	0.804	0.935	
	B39	0.751	0.938	
	B310	0.765	0.937	
	B311	0.782	0.936	
Teacher Quality	B41	0.732	0.830	0.868
	B42	0.735	0.829	
	B43	0.614	0.859	
	B44	0.640	0.853	
	B45	0.738	0.829	
Student Motivation	C1	0.870	0.889	0.916
	C2	0.674	0.910	
	C3	0.663	0.911	
	C4	0.769	0.901	
	C5	0.711	0.907	
	C6	0.740	0.904	
	C7	0.771	0.900	
Student Career Goals	D1	0.775	0.844	0.886
	D2	0.686	0.878	
	D3	0.775	0.844	
	D4	0.769	0.847	

This study includes 40 measurement items across six latent variables. The reliability analysis indicates strong internal consistency for all variables: digital background, government policies (α = 0.914), school functions (α = 0.943), teacher quality (α = 0.868), student motivation (α = 0.916), and student career objectives (α = 0.886). All reliability coefficients exceed the global benchmark of 0.7, confirming the credibility and consistency of the survey instruments. Moreover, the Corrected Item-Total Correlation (CITC) values for each latent variable exceed 0.5, indicating well-constructed item settings and satisfactory questionnaire consistency. However, to refine measurement precision, a procedure-specific approach is used to remove any poorly performing items from the observed variables.

Predictive Validity Analysis

To determine whether a scale is structurally valid, researchers must focus on examining, through factor analysis, whether the measurement variables of each latent variable demonstrate stable consistency or structure. The primary use of this metric is to assess the reliability of a scale intended for global use. The first step in applying factor analysis for validity assessment is to ensure that the factor analysis prerequisites are met. These prerequisites include Bartlett's sphericity test, which should have a significance level of less than 0.05, and the KMO value, which should exceed 0.7. If both conditions are satisfied, factor analysis can be deemed appropriate, indicating a high degree of correlation between the variables.

The results in Table 3 indicate that the survey data is appropriate for factor analysis, as evidenced by a KMO test value of 0.890, which exceeds the recommended threshold of 0.70. The scale demonstrates a robust rational structure, making it suitable for factor analysis. This is further validated by the Bartlett's test of sphericity, which yielded a chi-square value of 3069.524 with a significance level of 0.000 (P<0.01).

Table 3

Test for Sphericity for KMO and Bartlett (Shkeer & Awang, 2019)

KMO		**0.890**
Bartlett's Sphericity Test	Approximate Chi Square	3069.524
	Degree of Freedom	780
	Significance	0.000

Explanation of Total Variance in Pre-Testing

In the study's exploratory factor analysis, six factors with eigenvalues greater than 1 were extracted using principal component analysis. The cumulative variance explained by these six components was 69.044%, which exceeds the benchmark threshold of 60%. Based on this in Table 4, it can be concluded that the questionnaire exhibits high quality.

Table 4

Explanation of Total Variance

Component	**Initial Eigenvalue**			**Extracting the Sum of Squared Loads**			**The Sum of Squared Rotational Loads**		
	Total	**Variance**	**Cumulative %**	**Total**	**Variance**	**Cumulative %**	**Total**	**Variance**	**Cumulative %**
1	17.237	43.092	43.092	17.237	43.092	43.092	6.661	16.652	16.652
2	3.392	8.479	51.571	3.392	8.479	51.571	5.302	13.256	29.907
3	2.702	6.756	58.327	2.702	6.756	58.327	4.98	12.45	42.357
4	1.772	4.431	62.758	1.772	4.431	62.758	4.137	10.342	52.699
5	1.322	3.305	66.063	1.322	3.305	66.063	3.777	9.441	62.14
6	1.192	2.981	69.044	1.192	2.981	69.044	2.762	6.904	69.044
7	0.962	2.406	71.45						
8	0.879	2.197	73.647						
9	0.838	2.095	75.742						
10	0.768	1.921	77.663						
11	0.723	1.806	79.469						
12	0.658	1.646	81.115						
13	0.609	1.523	82.638						
14	0.572	1.430	84.068						
15	0.539	1.347	85.415						

Table 4(continued)

Explanation of Total Variance

Component	Initial Eigenvalue			Extracting the Sum of Squared Loads			The Sum of Squared Rotational Loads		
	Total	Variance	Cumulative %	Total	Variance	Cumulative %	Total	Variance	Cumulative %
16	0.497	1.241	86.656						
17	0.492	1.230	87.886						
18	0.426	1.064	88.95						
19	0.412	1.030	89.98						
20	0.372	0.931	90.912						
21	0.365	0.912	91.823						
22	0.315	0.787	92.611						
23	0.299	0.747	93.358						
24	0.278	0.694	94.052						
25	0.267	0.669	94.72						
26	0.245	0.614	95.334						
27	0.228	0.569	95.903						
28	0.216	0.540	96.443						
29	0.188	0.470	96.913						
30	0.178	0.446	97.359						
31	0.162	0.406	97.765						
32	0.155	0.388	98.152						
33	0.142	0.354	98.507						
34	0.116	0.291	98.797						
35	0.103	0.259	99.056						
36	0.100	0.251	99.307						
37	0.092	0.231	99.538						
38	0.069	0.173	99.711						
39	0.063	0.157	99.868						
40	0.053	0.132	100						

From the gravel plot in Figure 1, it is evident that out of the forty measurement items, six distinct factors emerged, each with eigenvalues greater than one. The trend levels off after the fifth factor, with the values stabilising from the sixth factor onward. These findings align with the results of the factor analysis presented in Table 4.

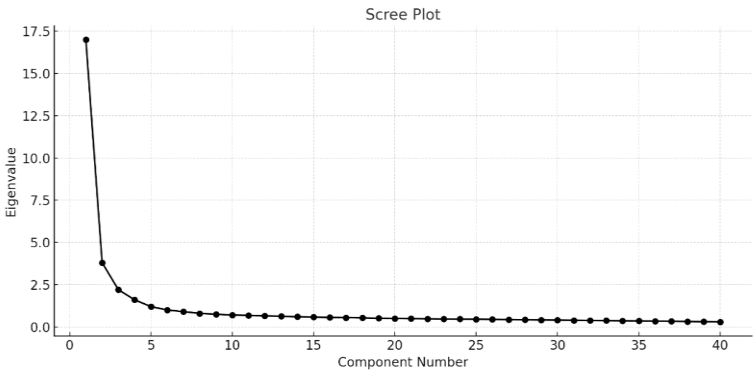

Figure 1: Scree Plot of Principal Component Analysis.

Pre-Test Rotation Component Matrix

Table 5 presents the rotated factor matrix based on maximum variance orthogonal rotation of 37 items. All factor loadings exceed 0.5, with no significant cross-loadings observed. This confirms strong content validity, as the items align well with the theoretical framework. The pre-test validity and reliability results indicate that the questionnaire items are well-constructed and appropriate for further testing on a larger sample.

Table 5

Rotation Component Matrix

Measurement Items	Component					
	1	2	3	4	5	6
B11		0.737				
B12		0.681				
B13		0.718				
B14		0.782				
B15		0.728				
B16		0.644				
B17		0.784				
B21				0.66		
B22				0.63		
B23				0.745		
B24				0.535		
B25				0.590		
B26				0.683		
B31	0.782					
B32	0.695					
B33	0.786					
B34	0.608					
B35	0.607					
B36	0.684					
B37	0.696					
B38	0.725					
B39	0.578					
B310	0.753					
B311	0.635					
B41					0.792	
B42					0.777	
B43					0.674	
B44					0.744	
B45					0.815	
C1			0.749			
C2			0.694			
C3			0.662			
C4			0.614			
C5			0.685			
C6			0.669			
C7			0.703			
D1						0.685
D2						0.629
D3						0.681
D4						0.628

Analysis of the Data and Discussion

Descriptive Statistical Analysis

Table 6 presents a descriptive analysis of the demographic characteristics of the 479 study participants, including gender distribution, age composition, academic year, and field of study. The sample exhibits a significant gender imbalance, with females representing 61.2% of participants compared to 38.8% males. Age distribution follows expected patterns for undergraduate populations, with 70.5% of participants falling within the 18-21 age range (39.2% aged 18-19 and 31.3% aged 20-21). The academic year distribution shows a concentration in second-year (53.2%) and fifth-year (35.5%) students, suggesting potential sampling biases that warrant consideration when interpreting results.

Table 6

Statistical Analysis of General Basic Information of Subjects

Basic Information	Category	Frequency	Percentage
Gender	Female	293	61.2
	Male	186	38.8
Age	18-19	188	39.2
	20-21	150	31.3
	22-23	124	25.9
	24-25	15	3.1
Grade	One	2	0.4
	Two	255	53.2
	Three	26	5.4
	Four	24	5
	Five	170	35.5
Category of Major Studied	Engineering	4	0.8
	Management	133	27.8
	Economics	109	22.8
	Education	46	9.6
	Science and Other Disciplines	102	21.3

Field of study analysis reveals a predominance of business-related disciplines, with Management (27.8%) and Economics (22.8%) collectively accounting for 50.6% of participants. STEM fields are notably underrepresented, particularly Engineering (0.8%), while "Science and Other Disciplines" comprise 21.3% of the sample. These demographic characteristics may influence the generalizability of study findings, particularly for gender-specific or discipline-related outcomes. The substantial representation of business students suggests findings may be most applicable to similar academic populations, while the limited representation of other disciplines cautions against broader generalizations.

Descriptive Statistical Analysis and Verification of Each Item

Descriptive statistical analysis involves examining the basic characteristics of participants' responses to each construct by presenting the mean and standard deviation of the variables under investigation. Table 7 provides a detailed statistical description and analysis of all the measurement items used in this study. Moreover, this study assesses whether the questionnaire data follow a normal distribution by examining skewness and kurtosis values for each item, as shown in the Table 7. Data are considered normally distributed if absolute skewness is below 3 and absolute kurtosis below 10. The sample data meet these criteria, supporting the use of reliability and validity analyses with accurate results. Additionally, the standard deviation of around 1 indicates low dispersion and consistent, reliable responses from participants.

Table 7

Statistical Analysis of Descriptive

Measurement Items	Mean	Standard Deviation	Variance	Skewness	Kurtosis	Minimum Value	Maximum Value
B11	3.67	1.002	1.003	-0.474	-0.284	1	5
B12	3.71	0.974	0.949	-0.464	-0.233	1	5
B13	3.78	0.982	0.964	-0.61	0.011	1	5
B14	3.81	1.003	1.006	-0.752	0.072	1	5
B15	3.75	0.978	0.957	-0.724	0.245	1	5
B16	3.76	0.998	0.997	-0.59	-0.112	1	5
B17	3.75	0.939	0.882	-0.476	-0.275	1	5
B21	3.80	1.078	1.162	-0.78	0.136	1	5
B22	3.60	1.158	1.341	-0.469	-0.614	1	5
B23	3.59	0.981	0.963	-0.377	-0.239	1	5
B24	3.58	1.069	1.144	-0.597	-0.072	1	5
B25	3.60	1.042	1.086	-0.544	-0.177	1	5
B26	3.54	1.058	1.119	-0.449	-0.289	1	5
B31	3.61	0.968	0.937	-0.367	-0.667	1	5
B32	3.59	0.964	0.929	-0.464	-0.281	1	5
B33	3.71	1.137	1.293	-0.64	-0.393	1	5
B34	3.63	1.136	1.291	-0.477	-0.62	1	5
B35	3.55	1.007	1.013	-0.338	-0.321	1	5
B36	3.60	1.062	1.127	-0.446	-0.326	1	5
B37	3.62	1.048	1.099	-0.517	-0.288	1	5
B38	3.54	1.102	1.215	-0.358	-0.618	1	5
B39	3.67	1.129	1.275	-0.582	-0.435	1	5
B310	3.62	1.083	1.173	-0.49	-0.477	1	5
B311	3.58	1.054	1.11	-0.488	-0.331	1	5
B41	3.45	1.134	1.286	-0.359	-0.694	1	5
B42	3.38	1.13	1.278	-0.079	-0.938	1	5
B43	3.43	1.066	1.137	-0.186	-0.67	1	5
B44	3.46	1.083	1.174	-0.257	-0.619	1	5
B45	3.43	1.044	1.09	-0.312	-0.515	1	5
C1	4.08	1.078	1.161	-1.257	1.083	1	5
C2	3.80	0.988	0.976	-0.556	-0.14	1	5
C3	3.74	0.959	0.919	-0.64	0.218	1	5
C4	3.96	1.046	1.095	-0.915	0.185	1	5
C5	3.77	1.036	1.073	-0.607	-0.199	1	5
C6	3.87	0.974	0.949	-0.753	0.278	1	5
C7	3.79	0.969	0.94	-0.568	-0.25	1	5
D1	3.84	1.075	1.155	-0.684	-0.362	1	5
D2	3.78	1.021	1.043	-0.718	0.098	1	5
D3	3.77	0.964	0.929	-0.572	-0.165	1	5
D4	3.84	1.049	1.100	-0.531	-0.609	1	5

Common Method Bias Testing

As the questionnaire survey data originates from the same group of participants and is conducted within the same environment, the relationship between various variables is susceptible to human interference, which may result in common method bias. Common method bias refers to the false internal consistency that can occur in questionnaire data. In other words, due to the shared source of the variable data, significant correlations between variables may arise. This is because the same respondent may tend to provide consistent responses when evaluating multiple variables. As a result, common method bias can introduce systematic errors, potentially distorting the relationships between observed variables and leading to measurement inaccuracies. To assess common method bias, this study followed Franco & Marradi (2013) and conducted a factor analysis of all items using non-rotated principal component analysis (Harman's single factor test) as shown in Table 8. The unrotated factor accounted for 38.078% of the total variance, which is below the 40% threshold. This indicates that common method bias is not a significant concern in the data, as no single factor explains the majority of the variance.

Table 8

Common Method Deviation Test

Component	Initial Eigenvalue			Extracting the Sum of Squared Loads		
	Total	Variance Percentage	Accumulated%	Total	Variance Percentage	Accumulated%
1	15.231	38.078	38.078	15.231	38.078	38.078
2	2.739	6.848	44.925	2.739	6.848	44.925
3	2.505	6.262	51.187	2.505	6.262	51.187
4	1.765	4.413	55.6	1.765	4.413	55.6
5	1.577	3.943	59.543	1.577	3.943	59.543
6	1.537	3.843	63.386	1.537	3.843	63.386
...	...	...	...			
40	0.174	0.436	100			

Reliability Analysis

This statistical method assesses the dependability and reliability of questionnaire responses collected from students across different times and locations. Cronbach's alpha, a common metric for reliability, indicates good dependability with values between 0.7 and 0.8, and excellent reliability with values between 0.8 and 0.9. The results are presented in Table 9.

Table 9

Reliability Testing of Various Variables in the Questionnaire

Variable	Measurement Items	CITY	Clone Bach Alpha after Deleting an Item	Clone Bach Alpha
Digital Background	B11	0.741	0.885	0.903
	B12	0.690	0.891	
	B13	0.693	0.891	
	B14	0.732	0.886	
	B15	0.704	0.890	
	B16	0.717	0.888	
	B17	0.709	0.889	

Table 9(continued)

Reliability Testing of Various Variables in the Questionnaire

Variable	Measurement Items	CITY	Clone Bach Alpha after Deleting an Item	Clone Bach Alpha
Government Policy	B21	0.792	0.863	0.894
	B22	0.741	0.871	
	B23	0.661	0.883	
	B24	0.694	0.878	
	B25	0.702	0.877	
	B26	0.704	0.877	
School Functions	B31	0.670	0.928	0.932
	B32	0.649	0.929	
	B33	0.733	0.925	
	B34	0.753	0.925	
	B35	0.703	0.927	
	B36	0.701	0.927	
	B37	0.708	0.927	
	B38	0.713	0.926	
	B39	0.752	0.925	
	B310	0.761	0.924	
	B311	0.755	0.924	
Teacher Quality	B41	0.703	0.816	0.855
	B42	0.659	0.828	
	B43	0.625	0.836	
	B44	0.657	0.828	
	B45	0.701	0.817	
Student Motivation	C1	0.773	0.870	0.895
	C2	0.676	0.882	
	C3	0.637	0.887	
	C4	0.726	0.876	
	C5	0.696	0.880	
	C6	0.702	0.879	
	C7	0.660	0.884	
Student Career Goals	D1	0.709	0.774	0.836
	D2	0.633	0.808	
	D3	0.641	0.805	
	D4	0.690	0.783	
	The Overall Reliability of the Scale			0.957

The reliability analysis results in the table above identify thirteen latent variables from forty measurement items. The overall scale reliability (α) is 0.957. Individual reliability coefficients include digital background (0.903), government policy (0.894), student motivation (0.895), and career objectives (0.836). All variables exceed the accepted threshold of 0.7, indicating strong reliability across the study.

Validity Analysis - Exploratory Factor Analysis

In order to find out how well the latent variables are measured; component analysis checks the scale's validity. To be considered suitable for analysis, the KMO value must be higher than 0.7 and the Bartlett's test significance must be lower than 0.05.

The survey data in Table 10 yielded a KMO test value of 0.950, which exceeds the threshold of 0.70, indicating that the questionnaire is appropriate for factor analysis. The scale is deemed suitable for factor analysis and demonstrates a robust structural strength, as confirmed by the Bartlett's test of sphericity results, which produced an estimated chi-square value of 11,795.185 with a significance probability of 0.000 (P<0.01).

Table 10

Sphericity Test for KMO and Bartlett

KMO		**0.950**
Bartlett's Sphericity Test	Approximate Chi Square	11795.185
	Degree of Freedom	780
	Significance	0.000

In this study, principal component analysis was employed to randomly identify six common factors with eigenvalues greater than 1, alongside exploratory factor analysis. The total variance explained by these six components was 63.386%, which exceeds the industry standard of 60%. Therefore, the validity of the questionnaire in table 11 is considered to be excellent.

Table 11

Explanation of Total Variance

Component	**Initial Eigenvalue**			**Extracting the Sum of Squared Loads**			**Sum of Squared Rotational Loads**		
	Total	Variance %	Accumulated %	Total	Variance %	Accumulated %	Total	Variance %	Accumulated %
1	15.231	38.078	38.078	15.231	38.078	38.078	6.494	16.235	16.235
2	2.739	6.848	44.925	2.739	6.848	44.925	4.623	11.559	27.793
3	2.505	6.262	51.187	2.505	6.262	51.187	4.278	10.695	38.489
4	1.765	4.413	55.6	1.765	4.413	55.6	3.904	9.76	48.249
5	1.577	3.943	59.543	1.577	3.943	59.543	3.383	8.458	56.707
6	1.537	3.843	63.386	1.537	3.843	63.386	2.672	6.679	63.386
7	0.803	2.007	65.393						
8	0.742	1.854	67.247						
9	0.707	1.768	69.015						
10	0.7	1.75	70.765						
11	0.645	1.612	72.377						
12	0.617	1.542	73.919						
13	0.595	1.487	75.406						
14	0.579	1.448	76.854						
15	0.566	1.415	78.269						
16	0.543	1.358	79.628						
17	0.531	1.328	80.956						
18	0.511	1.277	82.233						
19	0.496	1.24	83.473						
20	0.473	1.183	84.656						
21	0.46	1.149	85.805						
22	0.432	1.079	86.884						
23	0.414	1.036	87.92						
24	0.395	0.987	88.906						
25	0.382	0.954	89.86						

Table 11(continued)

Explanation of Total Variance

Component	Initial Eigenvalue			Extracting the Sum of Squared Loads			Sum of Squared Rotational Loads		
	Total	Variance %	Accumulated %	Total	Variance %	Accumulated %	Total	Variance %	Accumulated %
26	0.377	0.942	90.803						
27	0.346	0.864	91.667						
28	0.336	0.84	92.507						
29	0.324	0.809	93.316						
30	0.306	0.766	94.082						
31	0.291	0.728	94.809						
32	0.282	0.706	95.515						
33	0.274	0.686	96.201						
34	0.268	0.671	96.872						
35	0.245	0.611	97.483						
36	0.232	0.581	98.064						
37	0.22	0.55	98.613						
38	0.197	0.493	99.107						
39	0.183	0.457	99.564						
40	0.174	0.436	100						

The results from the scree plot in Figure 2 indicate that six components with eigenvalues greater than 1 were extracted from the forty measurement questions. After the sixth component, the trend begins to level off. These findings are consistent with the results of the factor analysis. Moreover, the rotated factor matrix Table 12 shows six distinct variable groups identified from 40 items using maximum variance orthogonal rotation. All factor loadings exceed 0.5, with no significant cross-loadings. This confirms strong content validity, as the measurement items are well grouped according to the theoretical framework.

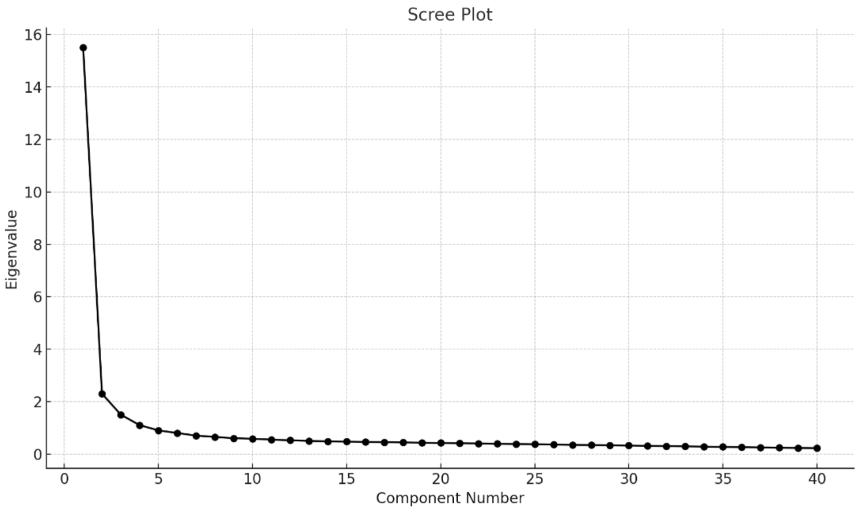

Figure 2: Scree Plot of Exploratory Factor Analysis (Formal Test).

Table 12

Rotation Component Matrix

Measurement items	Component					
	1	2	3	4	5	6
B11		0.772				
B12		0.708				
B13		0.749				
B14		0.718				
B15		0.696				
B16		0.705				
B17		0.745				
B21				0.714		
B22				0.674		
B23				0.681		
B24				0.695		
B25				0.698		
B26				0.707		
B31	0.703					
B32	0.676					
B33	0.653					
B34	0.688					
B35	0.634					
B36	0.651					
B37	0.631					
B38	0.679					
B39	0.709					
B310	0.749					
B311	0.722					
B41					0.78	
B42					0.764	
B43					0.725	
B44					0.751	
B45					0.778	
C1			0.71			
C2			0.688			
C3			0.63			
C4			0.709			
C5			0.71			
C6			0.659			
C7			0.666			
D1						0.733
D2						0.706
D3						0.714
D4						0.715

Validity Test - AMOS Confirmatory Factor Analysis

The reliability of a survey is primarily assessed through AMOS confirmatory factor analysis (CFA). This method in Figure 3 involves performing a statistical analysis of the survey data collected using the AMOS software. The main aim of this approach is to assess whether the pre-established variable structure set by the researcher is reasonable and whether the descriptive relationships between survey variables and their corresponding measurement items are appropriate.

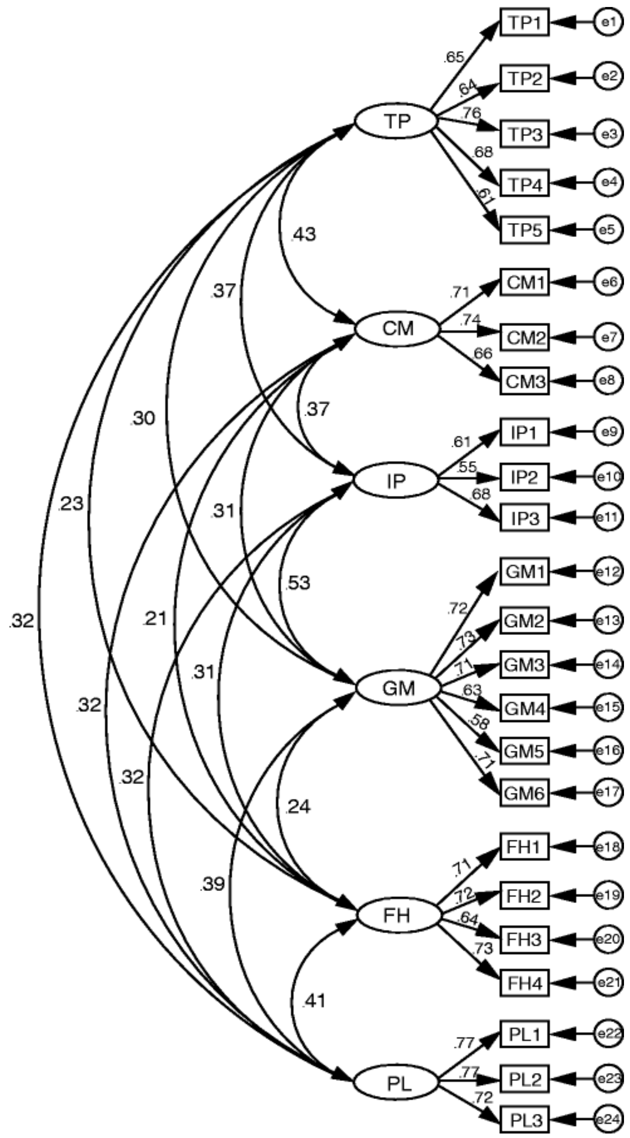

Figure 3: Confirmatory Factor Analysis Model Diagram

Model Goodness of Fit Test

When conducting factor analysis, key fit indices should be examined first. The χ^2/df ratio should ideally be below 3, though values under 5 are acceptable. Important indicators such as GFI, AGFI, and NFI are used to assess model fit; NFI values above 0.8 suggest acceptable fit, while values above 0.9 indicate good fit. For excellent model fit, TLI and CFI should exceed 0.9. Additionally, an RMSEA below 0.08 signifies a reasonably good model fit.

The fitting index results in Table 13 from the CFA model indicate that the X^2/df ratio is 2.045, which is below the standard threshold of 3, as suggested in the literature. Additional relevant index values include: IFI (0.934), CFI (0.933), TLI (0.928), and RMSEA (0.047), all of which are below the acceptable threshold of 0.08. Based on these results, it can be concluded that the model used for CFA in this study is effective, and the survey data fits within the established standards. All goodness-of-fit indicators for this model have met or exceeded the general recommended values.

Table 13

Confirmatory Factor Analysis Model Fitting Indicators

Fit Index	Judgment Criteria	Actual Value
Chi Square Degree of Freedom Ratio X ²/ Df	<5 Acceptable;< 3 Ideals	2.045
Goodness of Fit Index GFI	>0.8 Acceptable;> 0.9 Ideal	0.872
Adjusted Goodness of Fit Index AGFI	>0.8 Acceptable;> 0.9 Ideal	0.856
Normalized Fit Index (NFI)	>0.8 Acceptable;> 0.9 Ideal	0.878
Correction Fitting Index IFI	> 0.9	0.934
Comparative Fit Index (CFI)	> 0.9	0.933
Non-Norm Fitting Index NNFI (TLI)	> 0.9	0.928
Approximation Error Square Root Index RMSEA	< 0.08	0.047

The confirmatory factor analysis results in Table 14 show that all standardized factor loadings exceed 0.5, with standard errors below 0.5, meeting validity requirements. This indicates the questionnaire items accurately represent their constructs. CR, which measures internal consistency, should exceed 0.7 to demonstrate strong reliability, while AVE values above 0.5 indicate good convergent validity. The findings reveal that all measurement items meet these thresholds, confirming that the questionnaire's variables are both reliable and valid according to theoretical standards.

Table 14

Standardized Factor Loadings, Combined Reliability (CR), Convergent Validity (AVE)

Variable	Measurement	Standardized Factor Load	S.E.	T	P	CR	AVE
Digital Background	B11	0.780				0.903	0.572
	B12	0.735	0.055	16.781	***		
	B13	0.728	0.055	16.591	***		
	B14	0.782	0.056	18.099	***		
	B15	0.752	0.055	17.256	***		
	B16	0.768	0.055	17.708	***		
	B17	0.745	0.052	17.062	***		
Government Policy	B21	0.855				0.894	0.586
	B22	0.800	0.048	20.996	***		
	B23	0.701	0.043	17.323	***		
	B24	0.737	0.046	18.603	***		
	B25	0.743	0.045	18.821	***		
	B26	0.747	0.045	18.949	***		

Table 14(continued)

Standardized Factor Loadings, Combined Reliability (CR), Convergent Validity (AVE)

Variable	Measurement	Standardized Factor Load	S.E.	T	P	CR	AVE
School Functions	B31	0.686				0.933	0.557
	B32	0.666	0.071	13.696	***		
	B33	0.770	0.084	15.670	***		
	B34	0.788	0.084	16.016	***		
	B35	0.737	0.074	15.049	***		
	B36	0.730	0.078	14.917	***		
	B37	0.743	0.077	15.164	***		
	B38	0.738	0.081	15.071	***		
	B39	0.782	0.084	15.895	***		
	B310	0.780	0.080	15.857	***		
	B311	0.780	0.078	15.856	***		
Teacher Quality	B41	0.778				0.856	0.543
	B42	0.720	0.060	15.499	***		
	B43	0.689	0.056	14.777	***		
	B44	0.721	0.057	15.508	***		
	B45	0.773	0.055	16.700	***		
Student Motivation	C1	0.831				0.895	0.551
	C2	0.714	0.046	17.272	***		
	C3	0.678	0.045	16.138	***		
	C4	0.775	0.047	19.333	***		
	C5	0.731	0.047	17.845	***		
	C6	0.755	0.044	18.651	***		
	C7	0.702	0.045	16.909	***		
Student Career Goals	D1	0.799				0.837	0.563
	D2	0.702	0.054	15.332	***		
	D3	0.712	0.051	15.570	***		
	D4	0.784	0.055	17.281	***		

Differential Validity

According to the standard criteria for discriminant validity, the correlation coefficient between latent variables must be regulated and kept below or within the critical value of 0.85. Correlations exceeding 0.85 suggest that the variables or dimensions are too strongly correlated, which means they have not achieved the desired level of discriminant validity. To assess whether discriminant validity is satisfactory, the square root of the AVE values for each variable or dimension is compared with the magnitude of the correlation coefficients between the variables. Good discriminant validity is confirmed when the square root of each variable's AVE value is greater than the correlation coefficient between the variables. Based on the data presented in Table 15, there is a relationship between the latent variables, although it is not particularly strong, as none of the correlation coefficients exceed the threshold of 0.85. All variables demonstrate excellent discriminant validity, as the square roots of their AVE values are greater than the corresponding correlation coefficients.

Table 15

Distinguished Validity

	1	2	3	4	5	6
1. Digital Background	0.756					
2. Government Policies	0.47	0.765				
3. School Functions	0.521	0.68	0.747			
4. Teacher Quality	0.329	0.397	0.371	0.737		
5. Student Motivation	0.579	0.55	0.618	0.38	0.742	
6. Student Career Goals	0.457	0.507	0.555	0.378	0.518	0.751

Note: In bold font are the square root values of the Average Variance Extracted (AVE), while below the diagonal are the correlation coefficients between each variable.

Correlation Analysis

The variables in this study were analysed using Pearson correlation, which is crucial for determining the presence of a mutual association between them. A correlation is considered significant if it passes the statistical significance test, thereby providing a solid statistical foundation for the subsequent regression analysis. Table 16 presents the correlation analysis results, indicating that all six latent variables exhibit Pearson correlation coefficients greater than 0.1, with statistically significant p-values below the 0.05 threshold. These findings confirm that the correlations are significant, demonstrating strong relationships among the latent variables. Consequently, the observed correlations align with the study's hypotheses, offering preliminary empirical support for the theoretical framework. The analysis now proceeds to examine the causal impact relationships.

Table 16

Descriptive Statistical Analysis and Correlation Analysis

	Average Value	Standard Deviation	1	2	3	4	5	6
1. Digital Background	3.749	0.781	1					
2. Government Policies	3.619	0.861	.470**	1				
3. School Functions	3.612	0.822	.521**	.680**	1			
4. Teacher Quality	3.430	0.869	.329**	.397**	.371**	1		
5. Student Motivation	3.859	0.790	.579**	.550**	.618**	.380**	1	
6. Student Career Goals	3.807	0.842	.457**	.507**	.555**	.378**	.518**	1

Note: * * Significant correlation at. 01 level (bilateral)

AMOS Structural Equation Model

SEM, also known as Structural Equation Analysis or Covariance Structural Analysis, is a statistical technique used to examine the relationships between variables by analysing their covariance matrices. SEM is a multivariate method that simultaneously evaluates a system of interconnected causal relationships, combining elements of factor analysis and multiple regression. Unlike traditional multiple regression, SEM can accommodate latent variables, correlated independent variables, measurement errors, and multiple dependent variables, making it a more robust and flexible analytical tool. In this study, the researcher employed AMOS 21 software to construct a structural equation model aligned with the proposed theoretical framework, as illustrated in Figure 4. This approach allows for testing the model's validity using the collected sample data through structural equation analysis.

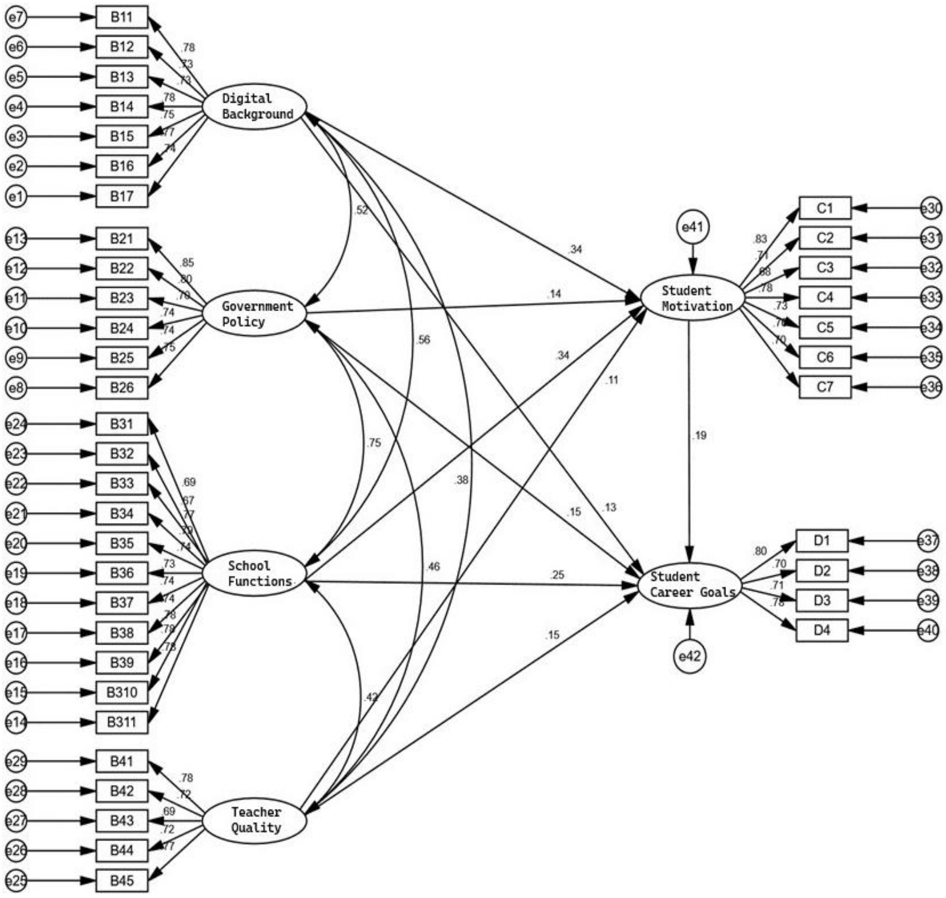

Figure 4: Structural Equation Model Depicting Relationships Among Digital Background, Government Policy, School Functions, Teacher Quality, Student Motivation, and Student Career Goals

Model Goodness of Fit Test

In statistics, the initial step in determining the adequacy of a structural equation model involves evaluating the model fit indices. Key fit indices include the Chi-square to degrees of freedom ratio (χ^2/df), which ideally should be less than 3, though values below 5 are generally acceptable. To indicate good model fit, indices such as the GFI, AGFI, and NFI should exceed 0.8, with values above 0.9 reflecting better model performance. For a model to be considered an excellent fit, the TLI and CFI should both be greater than 0.9. Additionally, a RMSEA below 0.08 is regarded as a reasonable indicator of model fit and adaptability.

Based on the data presented in the Table 17, the test results for the model fit indices are as follows: $\chi^2/df = 2.045$, which is below the ideal threshold of 3; GFI = 0.872, AGFI = 0.856, NFI = 0.878, IFI = 0.934, CFI = 0.933, and TLI = 0.928. All these goodness-of-fit indicators meet or exceed the commonly accepted standards, indicating that the structural equation model developed in this study is well-fitted to the data collected from the questionnaires. This confirms the robustness and suitability of the proposed model.

Table 17

Structural Equation Model Fitting Indicators

Fit Index	Judgment Criteria	Actual Value
Chi-Square Degree of Freedom Ratio $X^2/$ Df	<5 Acceptable;< 3 Ideals	2.045
Goodness of Fit Index GFI	>0.8 Acceptable;> 0.9 Ideal	0.872
Adjusted Goodness of Fit Index AGFI	>0.8 Acceptable;> 0.9 Ideal	0.856
Normalized Fit Index (NFI)	>0.8 Acceptable;> 0.9 Ideal	0.878
Correction Fit Index IFI	> 0.9	0.934
Comparative Fit Index (CFI)	> 0.9	0.933
Non-Norm Fit Index NNFI (TLI)	> 0.9	0.928
Approximation Error Square Root Index RMSEA	< 0.08	0.047

The path analysis in Table 18 results provide substantial evidence supporting all hypothesised relationships within the study. The digital background exhibits a significant positive influence on student motivation, with a standardised path coefficient of 0.341 ($t = 6.884$, $p < 0.001$), thereby confirming Hypothesis H5. Government policies also positively affect student motivation, as evidenced by a coefficient of 0.136 ($t = 2.162$, $p < 0.05$), substantiating Hypothesis H6. Similarly, school function demonstrates a strong positive impact on student motivation, with a coefficient of 0.336 ($t = 5.288$, $p < 0.001$), supporting Hypothesis H7. Teacher quality is found to positively influence student motivation, with a path coefficient of 0.108 ($t = 2.461$, $p < 0.05$), thereby confirming Hypothesis H8.

Table 18

Path Coefficient

Assuming Path			Standardized Path Coefficient	S.E.	C.R.	P
Student Motivation	<---	Digitization	0.341	0.063	6.884	***
Student Motivation	<---	Government Policy	0.136	0.071	2.162	0.031*
Student Motivation	<---	School Functions	0.336	0.069	5.288	***
Student Motivation	<---	Teacher Quality	0.108	0.049	2.461	0.014*
Student Career Achievement	<---	Digitization	0.129	0.072	2.206	0.027*
Student Career Achievement	<---	Government Policy	0.153	0.078	2.135	0.033*
Student Career Achievement	<---	School Functions	0.249	0.078	3.344	***
Student Career Achievement	<---	Teacher Quality	0.149	0.054	2.962	0.003**
Student Career Achievement	<---	Student Motivation	0.185	0.066	2.701	0.007**

Note: * * * P < 0.001, * * P < 0.01, * P < 0.05

In terms of student career aspirations, the digital background significantly contributes to shaping students' career goals, with a coefficient of 0.129 ($t = 2.206$, $p < 0.05$), supporting

Hypothesis H1. Government policies also play a crucial role, as indicated by a coefficient of 0.153 ($t = 2.135$, $p < 0.05$), affirming Hypothesis H2. The function of schools further enhances career aspirations, with a coefficient of 0.249 ($t = 3.344$, $p < 0.001$), thus substantiating Hypothesis H3. Teacher quality is another significant contributor, reflected in a coefficient of 0.149 ($t = 2.962$, $p < 0.01$), thereby supporting Hypothesis H4. Lastly, student motivation is shown to have a meaningful positive effect on professional goals, with a coefficient of 0.185 ($t = 2.701$, $p < 0.01$), confirming Hypothesis H9. Collectively, these findings validate the model and affirm the theoretical assumptions underpinning the study.

Amos Bootstrap Mediation Effect Test

Table 19 presents the analysis of mediating effects among various variables, conducted using AMOS 21.0. The Bootstrap method was employed with a confidence level of 95%, and the mediating effects were assessed based on 5000 resampling iterations performed by the software. To determine whether a significant mediating effect exists, the upper and lower bounds of the 95% confidence interval were examined alongside the corresponding significance P-values. If the confidence interval does not include zero and the P-value is less than the conventional threshold (typically 0.05), the mediating effect is considered statistically significant. This method ensures robust estimation of mediation and enhances the reliability of the conclusions drawn from the model.

Table 19

Bootstrap Mediated Effect Test

Intermediary	Estimate	Lower	Upper	P
Digitization - Student Motivation - Student Career Goals	0.063	0.012	0.126	0.014
Government Policy - Student Motivation - Student Career Goals	0.025	0.002	0.072	0.027
School Functions - Student Motivation - Student Career Goals	0.062	0.015	0.131	0.009
Teacher Quality - Student Motivation - Student Career Goals	0.020	0.003	0.055	0.013

The test results presented in Table 19 were obtained using the Bootstrap method in AMOS software to evaluate the mediating effects. A total of 5,000 bootstrap samples were generated, and a 95% confidence interval was calculated. The findings indicate that the indirect effect of the mediating pathway involving digital background, student motivation, and student career aspirations is 0.063, with the 95% confidence interval entirely positive and excluding zero. The corresponding p-value is below the significance threshold of 0.05, confirming a significant mediating effect and thereby supporting the related hypothesis. Similarly, the indirect effect of the mediating pathway through government policy, student motivation, and student career objectives is 0.025, with a 95% confidence interval that is positive and excludes zero. The p-value is also below 0.05, indicating a significant mediation and validating the hypothesis.

For the pathway involving school function, student motivation, and student career ambitions, the indirect effect is 0.062, with a 95% confidence interval that remains positive and excludes zero. The p-value is below 0.05, signifying a significant mediating impact and confirming the hypothesis. Finally, the mediating pathway comprising teacher quality, student motivation, and student career aspirations has an indirect effect of 0.020. The 95% confidence interval is positive and excludes zero, with a p-value below 0.05, demonstrating a significant mediating effect and supporting the hypothesis posited in this research. In summary, all tested mediating pathways show significant indirect effects, validating the hypothesised mediating role of student motivation in the relationships between the independent variables and student career objectives.

Difference Analysis

An independent sample t-test was conducted to compare gender differences across the various variables within the scale. The analysis in Table 20 revealed statistically significant differences between genders in terms of digital background, student motivation, and student career goals, with P-values less than 0.05, indicating meaningful gender-based disparities in these dimensions. Conversely, no significant differences were observed in the remaining variables, as their corresponding P-values exceeded the 0.05 threshold. These findings suggest that gender plays a differential role in shaping participants' digital experiences, motivational levels, and career aspirations, while its influence on other aspects measured by the scale appears limited.

Table 20

Differences in Scale Variables between Different Genders

Variable	Gender	Average Value	Standard Deviation	t	Sig.
Digitization	Female	3.674	0.825	-2.771	0.006
	Male	3.868	0.693		
Government Policy	Female	3.596	0.884	-0.736	0.462
	Male	3.655	0.826		
School Functions	Female	3.575	0.849	-1.258	0.209
	Male	3.672	0.777		
Teacher Quality	Female	3.433	0.898	0.099	0.922
	Male	3.425	0.824		
Student Motivation	Female	3.787	0.841	-2.631	0.009
	Male	3.972	0.689		
Student Career Goals	Female	3.738	0.880	-2.255	0.025
	Male	3.915	0.768		

The findings presented were obtained through ANOVA, which examined the influence of age across multiple covariates. The analysis in Table 21 revealed statistically significant differences among participants from different age groups in relation to student career ambitions, as indicated by a P-value below 0.05. This suggests that age plays a meaningful role in shaping students' career-related aspirations. In contrast, no significant age-related differences were identified for the remaining variables, as their P-values exceeded the 0.05 threshold. These results highlight the specific impact of age on career ambition, while suggesting uniformity across age groups concerning other measured dimensions.

Table 21

Differences in Scale Variables among Different Ages

Variable	Age	Average Value	Standard Deviation	F	Significance
Digitization	18-19 Years Old	3.690	0.837	1.535	0.191
	20-21 Years Old	3.811	0.749		
	22-23 Years Old	3.713	0.751		
	24-25 Years Old	4.105	0.539		
	Over 26 Years Old	4.214	0.101		
Government Policy	18-19 Years Old	3.575	0.912	0.543	0.704
	20-21 Years Old	3.662	0.841		
	22-23 Years Old	3.600	0.839		
	24-25 Years Old	3.856	0.626		
	Over 26 Years Old	3.833	0.000		
School Functions	18-19 Years Old	3.554	0.875	2.128	0.076
	20-21 Years Old	3.663	0.764		
	22-23 Years Old	3.570	0.824		
	24-25 Years Old	4.115	0.498		
	Over 26 Years Old	4.182	0.129		
Teacher Quality	18-19 Years Old	3.418	0.889	1.059	0.377
	20-21 Years Old	3.400	0.881		
	22-23 Years Old	3.447	0.847		
	24-25 Years Old	3.813	0.644		
	Over 26 Years Old	2.800	0.000		
Student Motivation	18-19 Years Old	3.792	0.865	1.943	0.102
	20-21 Years Old	3.882	0.767		
	22-23 Years Old	3.868	0.728		
	24-25 Years Old	4.343	0.252		
	Over 26 Years Old	4.286	0.202		
Student Career Goals	18-19 Years Old	3.707	0.868	3.084	0.016
	20-21 Years Old	3.807	0.830		
	22-23 Years Old	3.883	0.826		
	24-25 Years Old	4.267	0.438		
	Over 26 Years Old	5.000	0.000		

The results presented in Table 22 were derived from ANOVA examining the impact of academic major on various variables. The analysis revealed statistically significant differences across participants from different disciplines with respect to government policies, school functions, student motivation, and student career goals ($p < 0.05$). Conversely, no significant differences were observed in the remaining variables ($p > 0.05$). These findings suggest that students' academic backgrounds may influence their perceptions of institutional support, motivation levels, and career aspirations, but not other factors examined in the study.

Table 22

Differences in Scale Variables among Different Majors

Variable	Major	Average Value	Standard Deviation	F	Significance
Digitization	Engineering	3.750	0.744	1.544	0.188
	Operate	3.680	0.861		
	Economics	3.941	0.561		
	Education	3.658	0.815		
	Science and Other Disciplines	3.838	0.782		
Government Policy	Engineering	3.550	0.842	3.551	0.007
	Operate	3.523	0.859		
	Economics	3.953	0.565		
	Education	3.515	0.965		
	Science and Other Disciplines	3.785	0.843		
School Functions	Engineering	3.595	0.817	3.074	0.016
	Operate	3.483	0.823		
	Economics	3.943	0.610		
	Education	3.542	0.919		
	Science and Other Disciplines	3.706	0.765		
Teacher Quality	Engineering	3.338	0.794	1.857	0.117
	Operate	3.362	0.883		
	Economics	3.596	0.862		
	Education	3.398	0.960		
	Science and Other Disciplines	3.600	0.834		
Student Motivation	Engineering	3.853	0.765	4.702	0.001
	Operate	3.843	0.836		
	Economics	4.199	0.457		
	Education	3.637	0.916		
	Science and Other Disciplines	3.966	0.675		
Student Career Goals	Engineering	3.808	0.848	3.063	0.016
	Operate	3.615	0.922		
	Economics	3.978	0.732		
	Education	3.772	0.843		
	Science and Other Disciplines	3.992	0.737		

Research Implication

This study undertook a comprehensive statistical analysis of the collected data to evaluate the research hypotheses outlined at the beginning of the chapter and to ensure the data were appropriately prepared for subsequent analyses. Initially, descriptive statistical analysis was conducted, accompanied by a summarising table to provide an overview of the key variables. This was followed by confirmatory factor analysis (CFA) to validate the measurement model, ensuring that the observed variables reliably reflected the latent constructs. Subsequently, a series of bivariate correlation analyses were performed to examine the interrelationships among the variables. These were complemented by regression analyses to test the proposed hypotheses and determine the strength and direction of the relationships.

Future Directions

This study has made a meaningful contribution to the existing body of knowledge and has offered valuable practical insights. Nevertheless, certain limitations remain within the current literature that merit further exploration. Primarily, this study employed SPSS and AMOS software to conduct the analysis of questionnaire data—a method widely adopted in academic research. While this approach is robust and reliable, future research could benefit from incorporating mixed-methods strategies. For instance, in addition to administering questionnaires to students, which provided an adequate sample size meeting standard data collection requirements, supplementary data could be obtained through random interviews. The inclusion of qualitative data may enrich the analysis, potentially yielding more nuanced and precise conclusions that reflect the complexity of the studied phenomena.

References

Bajpai, N., Biberman, J., & Ye, Y. (2019). *ICT for education: Lessons from China*. https://doi.org/10.7916/d8-5scg-7845

Bi, B., & Ishak, N. (2025). Digital Learning and Social Inequality in China: Assessing the Barriers to Access and Engagement in Online Education. *Uniglobal Journal of Social Sciences and Humanities*, *4*(1), 192-198. https://doi.org/10.53797/ujssh.v4i1.23.2025

Bond, M., Bedenlier, S., Marín, V. I., & Händel, M. (2021). Emergency remote teaching in higher education: mapping the first global online semester. *International journal of educational technology in higher education*, *18*(1), 50-50. https://doi.org/10.1186/s41239-021-00282-x

Cepa-Rodríguez, E., & Murgiondo, J. E. (2024). Digital competence among 1st and 4th year primary education undergraduate students: a comparative study of face-to-face and on-line teaching. *Education and Information Technologies*, *29*(18), 24881-24898. https://doi.org/10.1007/s10639-024-12828-3

Chávez-Márquez, I. L., Ordóñez Parada, A. I., & Flores Morales, C. R. (2023). Digital Competencies in University Students through Educational Innovations: A Review of the Current Literature. *Apertura*, *15*(2), 74-87. https://doi.org/10.32870/ap.v15n2.2398

Dinesh, D., & Subhashini, S. (2025). AI In Vocational And Technical Education: Revolutionizing Skill-Based Learning. *Epra International Journal of Multidisciplinary Research (IJMR)*, 9-23. https://doi.org/10.36713/epra20462

Elsayed, E. A. (2012). Overview of Reliability Testing. *IEEE Transactions on Reliability*, *61*(2), 282-291. https://doi.org/10.1109/tr.2012.2194190

Fernández-Batanero, J. M., Román-Graván, P., Montenegro-Rueda, M., López-Meneses, E., & Fernández-Cerero, J. (2021). Digital teaching competence in higher education: A systematic review. *Education Sciences*, *11*(11), 689. https://doi.org/10.3390/educsci11110689

Franco, G. D., & Marradi, A. (2013). *Factor analysis and principal component analysis*. FrancoAngeli. http://digital.casalini.it/9788891700827

Hu, Y., & Zhang, H. (2020). ICT in Education in China. In *Lecture Notes in Educational Technology* (pp. 15-35). Springer Singapore. https://doi.org/10.1007/978-981-15-

6157-3_2

Hussain, S., & Javed, T. (2019). Determination of Motivational Behavior by Implementation of Theory of Planned Behavior: A Study on Teachers of Higher Education Sectors of Punjab. *International Journal of Academic Research in Business and Social Sciences*, *9*(3). https://doi.org/10.6007/ijarbss/v9-i3/5792

Huttayavilaiphan, R. (2024). Digital Competence and Anxiety in Thai University English Education: Impacts on Teachers and Students. *World Journal of English Language*, *15*(1), 225. https://doi.org/10.5430/wjel.v15n1p225

Ithnin, H. S., Nasir, N. M., Syeddin, S. N. a., Salim, N. Z. M., & Murad, M. A. (2024). Enhancing Student Engagement: Analysing the Role of ARCS Motivation Model in Online Learning Tools for Higher Education. *International Journal of Research and Innovation in Social Science*, *VIII*(IIIS), 4958-4968. https://doi.org/10.47772/ijriss.2024.803368s

Kastanya, M. O., Ilham, M., Ipijei, I., & Romdioni, A. N. (2023). The Influence Of Motivation and Self Efficacy On Students' Interest In Careers In Taxation With Voluntability As Moderation. *Southeast Asia Journal Of Graduate Of Islamic Business And Economics*, *1*(3), 152-158. https://doi.org/10.37567/sajgibe.v1i3.1652

Kurniati, M., Suwandi, S., & Setyawan, B. (2022). *The Impact of Implementing Emergency Curriculum on Students' Creativity during Covid-19 Pandemic Learning* Proceedings of the International Conference in Industrial & Mechanical Engineering and Operations Management (IMEOM), http://dx.doi.org/10.46254/bd05.20220358

Lazaraton, A. (2005). Quantitative Research Methods. In *Handbook of Research in Second Language Teaching and Learning*. https://www.taylorfrancis.com/chapters/10.4324/9781410612700-16

Li, J., & Fu, W. (2024). Vocational Education Personnel Training under the Background of Digital Transformation. *Journal of Education and Educational Research*, *8*(3), 353-357. https://doi.org/10.54097/9f87yr11

Lin, M., & Kee, C. n. L. (2024). Enhancing Digital Literacy and Technological Integration: A Case Study at Henan's Vocational College. *Asian Journal of Research in Education and Social Sciences*, *6*(2), 668-680. https://doi.org/10.55057/ajress.2024.6.2.61

Méndez, D., Méndez, M., & Anguita, J. M. (2022). Digital Teaching Competence in Teacher Training as an Element to Attain SDG 4 of the 2030 Agenda. *Sustainability*, *14*(18), 11387. https://doi.org/10.3390/su141811387

Mohd Rozi Bin Ismail, Y. X. (2024). The Correlational Study between Teachers' characteristic on Students' Academic Performance and the Role of Students' Motivation in Chinese Vocational Institutions. *Sumerianz Journal of Medical and Healthcare*(73), 28-36. https://doi.org/10.47752/sjell.73.28.36

Parilla, E. S., & Evangelista, J. (2025). From Campus to Career: A Qualitative Exploration of Graduate Employability and Workforce Readiness in Ilocos Norte. *Advanced Qualitative Research*, *3*(1), 62-77. https://doi.org/10.31098/aqr.v3i1.2818

Pérez-Rivero, C. A., de Obesso, M. d. l. M., & Núñez-Canal, M. (2022). Digital competence among university professors: analysis of the impact of the COVID crisis. *Economic Research-Ekonomska Istraživanja*, *36*(3). https://doi.org/10.1080/1331677x.2022.2155859

Shambetaliev, K., Babaev, D., Shatmanaliev, B., & Amanova, N. (2023). Experiences Of Distance Education In Vocational Secondary Education During The Covid-19 Pandemic With The Support Of Information And Communication Technologies.

Alatoo Academic Studies, *23*(1), 162-168. https://doi.org/10.17015/aas.2023.231.17

Shkeer, A. S., & Awang, Z. (2019). Exploring The Items For Measuring The Marketing Information System Construct: An Exploratory Factor Analysis. *International Review of Management and Marketing*, *9*(6), 87-97. https://doi.org/10.32479/irmm.8622

Su, M., & Shen, Y. (2025). The Impact of Digital Education on Innovation Performance of Postgraduate Students. *Education, Language and Sociology Research*, *6*(1), p88. https://doi.org/10.22158/elsr.v6n1p88

Tang, Y., Wareewanich, T., & Yue, X.-G. (2023). The impact of organizational inclusion on teachers' internal motivation for professional development in vocational colleges: The case of China. *Problems and Perspectives in Management*, *21*(3), 138-152. https://doi.org/10.21511/ppm.21(3).2023.11

Tho, H. T. C., Dinh, N. V., Vinh, N. T. T., Thuy, L. T. T., & Phuong, N. T. (2024). Factors Influencing Student Learning Outcomes through Learning Motivation: A Case Study at A University in Vietnam. *Journal of Ecohumanism*, *3*(8). https://doi.org/10.62754/joe.v3i8.5143

Wang, Y. (2024). Digital Transformation of Vocational Education: Connotation, Challenges and Pathways. *Region - Educational Research and Reviews*, *6*(12), 43. https://doi.org/10.32629/rerr.v6i12.2996

Zeng, W. (2022). An empirical research on China's policy for ICT integration in Basic Education from 1988 to 2021. *Educational technology research and development : ETR & D*, *70*(3), 1059-1082. https://doi.org/10.1007/s11423-022-10079-y