

Perception of Higher Education Students on Digital Jobs in Cambodia: Case Study of BELTEI International University

IN Channdy¹, Dr. Prak Polla², CHAT Pound³

^{1,3}BELTEI International University, Phnom Penh, Cambodia

²Faculty of Education, Arts, and Humanities, Phnom Penh, Cambodia

ABSTRACT

Cambodia is like other countries in the world which is affected by the digital revolution, in particular the demand for and supply of digital related job market. This study aims to provide a comprehensive analysis of preferences for digital related jobs among the Cambodian workforce by examining key factors affecting their preferences and reasons behind it. Both quantitative and qualitative were employed in the research design. Data collection was done with 355 respondents on 26 digital related jobs using a 5-point Likert scale questionnaires. The respondents were students of Bachelor and Master) from four faculties of the BELTEI International University, Cambodia: Faculty of Law; Faculty of Education, Arts, and Humanities; Faculty of Information Technology; and Faculty of Business Administration. Simple descriptive statistics (percentages, frequencies, means and standard deviation) and inferential statistics analysis (independent t-test and one-way ANOVAs) were employed in analyzing the quantitative data. Open coding and thematic analysis were used to analyze the qualitative data. Result of study were: Quantitative, including 213 undergraduate (63.6%) and 119 graduate (35.5%) Doctoral Degree 2 (0.6%) and others 1 (0.3%) participants across four faculties: Qualitative, Descriptive statistics and inferential tests (independent samples t-tests and one-way ANOVAs) were used to analyze differences by gender, academic level, major, and age. Results indicated that the most preferred digital jobs were Electro Technology Engineers ($M = 4.18$, $SD = 0.79$), Digital Marketing and Strategy Specialists ($M = 4.17$, $SD = 0.73$), and System Engineers ($M = 4.16$, $SD = 0.75$), while the least preferred were Fin Tech Engineers ($M = 3.81$, $SD = 0.77$) and AI and Machine Learning Specialists ($M = 3.89$, $SD = 0.76$). In conclusion: Statistically significant differences were found across demographic groups, especially by gender and academic major.

How to cite this paper: IN Channdy | Dr. Prak Polla | CHAT Pound "Perception of Higher Education Students on Digital Jobs in Cambodia: Case Study of BELTEI International University"

Published in International Journal of Trend in Scientific Research and Development (ijtsrd), ISSN: 2456-6470, Volume-9 | Issue-4, August 2025, pp.441-455, URL: www.ijtsrd.com/papers/ijtsrd97255.pdf



Copyright © 2025 by author (s) and International Journal of Trend in Scientific Research and Development Journal. This is an Open Access article distributed under the terms of the Creative Commons Attribution License (CC BY 4.0) (<http://creativecommons.org/licenses/by/4.0>)



KEYWORDS: digital job preferences, higher education, Cambodia, mixed-methods, student perception, digital economy.

1. INTRODUCTION

Cambodia's digital economy has experienced remarkable growth in recent years, driven by increased internet penetration, mobile connectivity, and government initiatives aimed at digital transformation. According to the World Bank's Cambodia Digital Economy Assessment, the country has witnessed a significant shift towards digitalization across various sectors, creating new employment opportunities and changing traditional job market dynamics. This study seeks to provide a comprehensive analysis of preferences for digital jobs among the Cambodian workforce, examining factors such as skill requirements, compensation

expectations, work environment preferences, and career advancement opportunities in the digital sector.

1.1. Problem

Despite the growing availability of digital job opportunities in Cambodia, several challenges persist in matching workforce preferences with available positions. The International Labour Organization's "Future of Work in Cambodia" report identifies a skills gap between available digital jobs and workforce capabilities, while also noting varying levels of interest and awareness about digital career paths.

1.2. Research Questions

1. What kinds of digital jobs that higher education students prefer most?
2. What are the current preferences of university students regarding digital job opportunities?
3. How do the students in BIU differently perceive on digital jobs?

1.3. Research Objectives

1. To discover which digital jobs that higher education student prefer the most;
2. To discover which digital jobs that higher education student do not prefer the most;
3. To assess the extent of difference of BIU students 'preference on digital jobs by different demographics: major of study, sex and type of working institutions and expert of areas?

1.4. Significance

In light of Cambodia's expanding digital economy, this study is important because it offers insightful information about how college students, especially those at BELTEI International University, view and favor digital employment opportunities. The study offers support for initiatives to match university curricula with national digital workforce objectives and labor market demands by evaluating student preferences, skill gaps, and career expectations. In order to better prepare students for future work, policymakers, educators, and institutional leaders should use the findings to inform the development of focused interventions, such as career counseling and training in digital skills. Additionally, by raising students' awareness of new employment opportunities in the digital industry, the study empowers them and adds to the body of knowledge on digital job preparedness and the contribution of higher education to Cambodia's economic development.

2. Literature Review

2.1. Digital Jobs and Digital Economy

Digital jobs refer to employment opportunities that exist within or are created through digital technologies and platforms. These positions range from software development and data analysis to digital marketing and e-commerce management. According to the World Bank (2023), digital jobs are characterized by their reliance on digital tools and technologies as primary instruments for work performance and delivery. The concept encompasses both traditional jobs that have been transformed by digital tools and entirely new job categories that have emerged due to technological advancement. The digital economy represents the economic activity that results from billions of everyday online connections among people, businesses, devices, data, and

processes (Bukht & Heeks, 2018). It encompasses the production and consumption of digital technology, digital goods and services, as well as the infrastructure that enables digital interactions. In Cambodia, the digital economy has been rapidly developing, particularly after the COVID-19 pandemic, which accelerated digital adoption across various sectors.

2.2. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed by Davis (1989), provides a theoretical framework for understanding how users come to accept and use technology. This model is particularly relevant to studying preferences for digital jobs as it explains the factors that influence individuals' decisions to adopt new technologies and, by extension, pursue careers in digital fields. TAM posits that perceived usefulness and perceived ease of use are the primary determinants of technology adoption. In the context of digital job preferences in Cambodia, TAM can explain how perceived usefulness (the belief that a digital career will enhance job prospects and income) and perceived ease of use (the belief that digital skills can be acquired without excessive difficulty) influence Cambodian students' career choices in digital fields. Ly et al. (2023) applied TAM in their research on digital payment systems in Cambodia, finding that perceived ease of use significantly impacted attitudes toward digital technologies.

2.3. Digital Transformation Theory

Digital Transformation Theory examines how digital technologies fundamentally change business models, organizational structures, and operational processes (Vial, 2019). This theoretical framework helps explain the evolution of job markets and skill requirements in digitizing economies like Cambodia. The theory posits that digital transformation occurs in stages, with organizations and economies moving from digitization (converting analog to digital) to digitalization (using digital technologies to change business processes) to full digital transformation (fundamentally redesigning operations around digital capabilities). Cambodia's economy is currently transitioning through these stages, with various sectors at different points in the transformation process. This uneven development creates a complex landscape for career planning, as some sectors offer advanced digital opportunities while others remain primarily analog. Understanding this theoretical framework helps contextualize student preferences for digital careers within Cambodia's broader economic transformation.

2.4. Conceptual Model for the Study

Based on the literature review, this study proposes a conceptual model that integrates multiple theoretical perspectives to explain digital job preferences among Cambodian students. The model acknowledges that preferences are not simply individual choices but are shaped by complex interactions between personal, educational, cultural, and economic factors. The model positions digital job preferences as the outcome variable, influenced by four main categories of predictors:

- Individual characteristics: Digital self-efficacy, technology experience, academic performance, personal interests, and career aspirations
- Educational factors: Quality of digital education, curriculum relevance, instructor expertise, practical training opportunities, and exposure to industry professionals
- Social and cultural factors: Family influence, peer attitudes, cultural values regarding technology and career choices, and perceived social status of digital professions
- Economic and market factors: Perceived job availability, salary expectations, industry growth prospects, and economic stability of digital sectors. The model also recognizes moderating effects of demographic variables such as gender, socioeconomic status, and geographic origin, which may influence how the main predictors affect preferences. This comprehensive approach provides a framework for understanding the multifaceted nature of digital career preferences in Cambodia's unique context.
- Digital Skills Taxonomy for Cambodia

To effectively study preferences for digital jobs, it is essential to establish taxonomy of digital skills relevant to Cambodia's context. Based on the literature review, this study proposes a three-tier classification of digital skills:

1. Foundational digital skills: Basic digital literacy, computer operation, internet navigation, digital communication, information management, and online security awareness. These skills form the foundation for all digital careers and are increasingly necessary across all sectors of Cambodia's economy.
2. Intermediate digital skills: Content creation, data analysis, digital marketing, e-commerce management, social media management, customer relationship management systems, and productivity software proficiency. These skills are in high demand across multiple sectors in Cambodia's developing digital economy.
3. Advanced digital skills: Software development, web development, mobile app development, network administration, cybersecurity, artificial intelligence, machine learning, data science, and block chain technology. These specialized skills command premium compensation but require significant educational investment and are currently in limited supply in Cambodia.

This taxonomy provides a framework for examining which skill categories are most preferred by Cambodian students and why. It also enables analysis of how educational institutions like BELTEI International University are addressing each skill category and where gaps may exist between student preferences, educational offerings, and market demands.

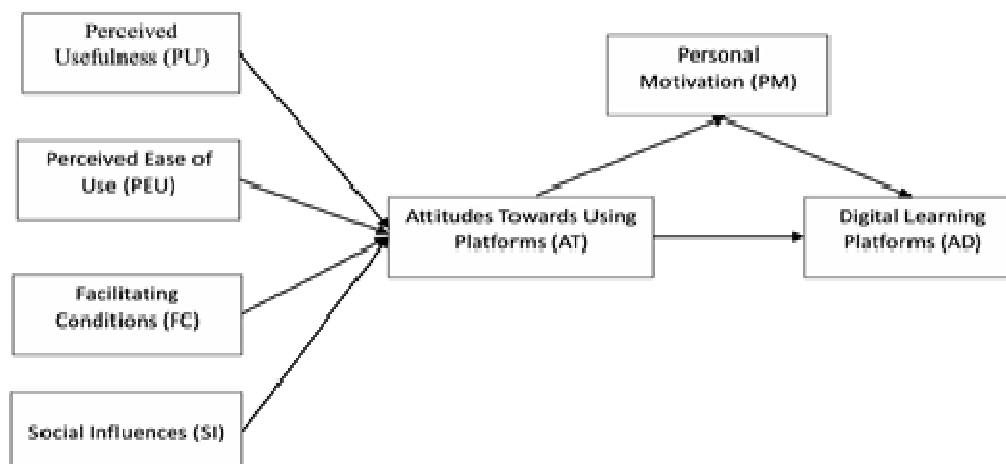


Figure 2: Research Framework

2.5. Conclusion of Literature Review

This comprehensive literature review provides a solid foundation for understanding digital job preferences among Cambodian students. The review has identified relevant theoretical frameworks, analyzed key scholarly contributions, examined practitioner perspectives, and highlighted important research gaps. The synthesis

reveals that while digital transformation presents significant opportunities for Cambodia's workforce development, realizing these opportunities requires coordinated efforts across educational, economic, and policy domains.

The literature demonstrates that digital job preferences are complex phenomena influenced by multiple factors operating at different levels. Understanding these preferences requires theoretical frameworks that acknowledge both individual agency and structural constraints. The review has established the conceptual foundation for empirical research that can contribute to evidence-based improvements in digital education and workforce development in Cambodia. Moving forward, the insights from this literature review will inform the design and implementation of empirical research at BELTEI International University. The study will build upon the theoretical foundations and address the research gaps identified in this review, ultimately contributing to enhanced understanding of digital career preferences and improved educational outcomes for Cambodian students preparing for the digital economy.

3. Research Methodology

The research design provides the framework for the collection and analysis of data (Bryman & Bell, 2019). This study employs a mixed-method research design, combining both quantitative and qualitative approaches to investigate preferences for digital jobs among students and recent graduates in Cambodia. The mixed-method approach allows for triangulation of data, providing a more comprehensive understanding of the research problem than either approach alone would offer (Creswell & Creswell, 2018).

3.1. Samples Selection Technique

To analyze the internal quality development on the basis of data availability, dependent variables, which are 26 digital jobs were listed for data collection with 335 respondents through a 5 scaled- questionnaire for this study were employed and analyzed to identify the respondents' most preference and less preferences on digital jobs and how differently the respondents perceive on these digital jobs in terms of their different group of demographics of the respondents. The 26 types of digital jobs include: Big data specialist, Fin Tech Engineers, AI and machine learning specialist, Software and applications developers, Security Management specialists, Data warehousing specialists, Internet of things specialists, Data analysts and scientists, Information security analysts, Robotics engineers, Block chain developers, Data engineers, Digital transformation specialists, Process automation specialists, System engineers, Online learning managers, Digital marketing and strategy specialists, Database and network professionals, ICT operations and user support technicians, E-commerce specialists, Social media strategists, Database architects, Develops engineers, Full stack engineers, Business intelligence analysts and Electro technology engineers.

3.2. Data Analysis

The data collected through questionnaire was coded and entered to computer by editing to avoid some errors and missing in the data collection and data analysis. To analyze the response gathered from the survey, the finding is produced and presented through simple descriptive statistics analysis in term of percentages, frequencies, means and standard deviation. Moreover, appropriate inferential statistics analysis in term of the independent t-test (two-tailed) and Analysis of Variances (one-way ANOVAs) were also employed in this data analyzing. Independent t-test were used to test the statistically significant differences of BIU's preference in digital jobs between genders and types of working institutions by presenting in terms of —Means, Standard Deviations, t-value and Significant level (2-tailed) or p-value. The ANOVA was employed to analysis for the difference in respondents' preference in digital jobs among the Major of Study or Name of faculty, Areas of working or expertise, Position and Age groups of respondents using ANOVA Analysis in term of F-value and significant value based on the degree of freedom for multiple comparisons. In addition, the graph on Mean Plot in the appendixes are additionally presented to understand the respondents' of preference in digital jobs by faculty major and areas of expertise, a number of graphics on Means Plots of respondents' preference on digital jobs by their Areas of Expertise, Major of Study, Position and Age Groups.

4. Findings

The total respondents took part in this study is 335 graduates. This made up of 144 respondents (43.0%) males and 191 (57.0%) females with 25.4% aged less than 20 years old, 47.5% of respondents aged between 21 and 30, 23.0 % aged between 31 and 40, and 4.2% aged between 41 and 50 years old. Respondents are from different positions, 4.2% are school directors and deputy directors, 31.0% are teachers and 64.8% are students. 11.9 % of the respondents are from public while 88.9 are from private institutions. 63.6% of the respondents are taking a bachelor program, while 35.5% were selected from master program and only 0.6 % are from doctoral program.

The respondents were also selected among those BIU students from four main faculties including from Faculty of Law (21.8%), Faculty of Education, Arts, and Humanities (56.7%), Faculty of Information Technology (8.7%). The respondents were selected from different Professional expert/area of expertise such as TEFL / TESOL (40.9%), Human Resource (8.4%), Management (17.4%), Finance & Business (11.0%) and Law (21.8%). See table 5.1.

Table 5.1 Demographic Characteristics of Respondents

Demographics		Frequency	Percent
Gender	Male	144	43.0
	Female	191	57.0
Age	Below 20 years old	85	25.4
	21 - 30 years old	159	47.5
	31 - 40 years old	77	23.0
	41 - 50 years old	14	4.2
Position	School Director & Deputy of school director	14	4.2
	Teacher/Lecturer	104	31.0
	Student	217	64.8
Types of organization or institutions	Public	40	11.9
	Private	295	88.9
Level of Academic Programs	Bachelor Degree	213	63.6
	Master's Degree	119	35.5
	Doctoral Degree	2	0.6
	Others	1	0.3
Name of faculties	Faculty of Law	73	21.8
	Faculty of Education, Arts, and Humanities	190	56.7
	Faculty of Information Technology	29	8.7
	Faculty of Business Administration	43	12.8
Professional expert/area of expertise	TEFL / TESOL	137	40.9
	Human Resource	28	8.4
	Management	60	17.9
	Finance & Business	37	11.0
	Law	73	21.8

N=335

4.1. Validity & Reliability

The quantitative data was analyzed by SPSS version 25.0. The 26-item questionnaire reported a reliability of $\alpha = .879$ (N=335). If a reliability of scale is more than .80, the internal consistency within a scale is very good (Malley & George, 2000). Table 5.2 shows the result of testing the validity and reliability of the scales used to measure all variables for all items (N=335), reporting a reliability of $\alpha = .879$, which means a reliability of internal consistency of the scale as the results of this research study.

Table 5.2: Cronbach's alpha

No.	Item Statistics	N	Cronbach's alpha
1	Big data specialist	335	0.879
2	Fin Tech Engineers	335	
3	AI and machine learning specialist	335	
4	Software and applications developers	335	
5	Security management specialists	335	
6	Data warehousing specialists	335	
7	Internet of things specialists	335	
8	Data analysts and scientists	335	
9	Information security analysts	335	
10	Robotics engineers	335	
11	Block chain developers	335	
12	Data engineers	335	
13	Digital transformation specialists	335	

14	Process automation specialists	335
15	System engineers	335
16	Online learning managers	335
17	Digital marketing and strategy specialists	335
18	Database and network professionals	335
19	ICT operations and user support technicians	335
20	E-commerce specialists	335
21	Social media strategists	335
22	Database architects	335
23	Develops engineers	335
24	Full stack engineers	335
25	Business intelligence analysts	335
26	Electro technology engineers	335

5. Major Findings

5.1. The Level of Preference of BIU Students on Digital jobs

This finding is related to the pre-identified research question 1: **RQ1: “What kinds of digital jobs that higher education students prefer most??”** Table 5.3 specified the number of total participants (N=335), Mean, Standard Deviations providing insights for research question 1. It is found five digital jobs indicate the highest Mean score that are meant the respondent perceived the highest preference from the respondents. The most preference on 5 digital jobs were identified including (1) Electro technology engineers (M=4.18 and SD=0.794), (2) Digital marketing and strategy specialists (M=4.17 and SD=0.733), (3) System engineers (Mean =4.16 and SD=0.754), (4) Social media strategists (Mean=4.16 and SD=0.794) and (5) Develops engineers (Mean=4.11 and SD=0.81). See table 5.3.

Table 5.3: Highest Level of Preference on Digital Jobs

Descriptive Statistics				
No	Variables	N	Mean	Std. Deviation
1	Electro technology engineers	335	4.18	0.794
2	Digital marketing and strategy specialists	335	4.17	0.733
3	System engineers	335	4.16	0.754
4	Social media strategists	335	4.16	0.794
5	Develops engineers	335	4.11	0.81
6	ICT operations and user support technicians	335	4.09	0.803
7	Online learning managers	335	4.08	0.819
8	Full stack engineers	335	4.08	0.779
9	Database and network professionals	335	4.07	0.801
10	E-commerce specialists	335	4.07	0.845
11	Security management specialists	335	4.06	0.742
12	Information security analysts	335	4.04	0.782
13	Data engineers	335	4.04	0.814
14	Digital transformation specialists	335	4.01	0.826
15	Database architects	335	4	0.874
16	Big data specialist	335	3.99	0.867
17	Data analysts and scientists	335	3.99	0.817
18	Software and applications developers	335	3.98	0.717
19	Process automation specialists	335	3.97	0.798
20	Robotics engineers	335	3.96	0.843
21	Block chain developers	335	3.95	0.86
22	Internet of things specialists	335	3.94	0.781
23	Data warehousing specialists	335	3.93	0.825
24	Business intelligence analysts	335	3.92	0.86
25	AI and machine learning specialist	335	3.89	0.762
26	Fin Tech Engineers	335	3.81	0.775
	Valid N (listwise)	335		

This finding is related to the pre-identified question 2: RQ2: ***“What are the current preferences of university students regarding digital job opportunities?”*** Table 5.4 specified the number of total participants (N=335), Mean, Standard Deviations providing insights for research question 1. It is found that five digital jobs indicate the lowest Mean score which mean that the respondent perceived the lowest preference in digital jobs. The five digital jobs that receive less preference were identified including (1) Fin Tech Engineers (M=3.81 and SD=0.775), (2) AI and machine learning specialist (M=3.89 and SD=0.762), (3) Business intelligence analysts (Mean =3.92 and SD=0.86), (4) Data warehousing specialists (Mean=3.93 and SD=0.825) and (5) Internet of things specialists (Mean=3.94 and SD=0.781). See table 5.4.

Table 5.4: Lowest Level of Preference on Digital Jobs

Descriptive Statistics				
No	Variables	N	Mean	Std. Deviation
1	Electro technology engineers	335	4.18	0.794
2	Digital marketing and strategy specialists	335	4.17	0.733
3	System engineers	335	4.16	0.754
4	Social media strategists	335	4.16	0.794
5	Develops engineers	335	4.11	0.81
6	ICT operations and user support technicians	335	4.09	0.803
7	Online learning managers	335	4.08	0.819
8	Full stack engineers	335	4.08	0.779
9	Database and network professionals	335	4.07	0.801
10	E-commerce specialists	335	4.07	0.845
11	Security management specialists	335	4.06	0.742
12	Information security analysts	335	4.04	0.782
13	Data engineers	335	4.04	0.814
14	Digital transformation specialists	335	4.01	0.826
15	Database architects	335	4	0.874
16	Big data specialist	335	3.99	0.867
17	Data analysts and scientists	335	3.99	0.817
18	Software and applications developers	335	3.98	0.717
19	Process automation specialists	335	3.97	0.798
20	Robotics engineers	335	3.96	0.843
21	Block chain developers	335	3.95	0.86
22	Internet of things specialists	335	3.94	0.781
23	Data warehousing specialists	335	3.93	0.825
24	Business intelligence analysts	335	3.92	0.86
25	AI and machine learning specialist	335	3.89	0.762
26	Fin Tech Engineers	335	3.81	0.775
Valid N (listwise)		335		

Students' Differences in Perception on Digital Jobs

This session present the data analysis for the research question 3. RQ3 ***“How do the students in BIU differently perceive on digital jobs?”*** using T-Test and ANOVA analysis. The summarized results of the differences of respondents' preference of digital jobs variable are shown in the following tables. Given the t-value ($\alpha=0.05$) or significant level of 5% to indicate that there is significant difference among the gender variable.

Difference of BIU students' preference on digital jobs by gender (T-Test Analysis)

This section investigated how the respondents' preference differs among the Gender variables. As indicated in the table 5.5, only 4 digital jobs the respondents perceived differently between male and female.

Fin Tech Engineers with the average score of male (M=3.69, SD=0.840), and of female (M=3.91, SD=0.709); and t-value, $t(335) = -2.637$, $p=0.009 \leq 0.05$ (two-tailed), indicates that there is statistically different in preference among male and female students regarding digital job **“Fin Tech Engineers”**. **Software and applications developers** with the average score of male (M=3.90, SD=0.782), and of female (M=4.05, SD=0.659); and t-value, $t(335) = -1.918$, $p=0.056 \leq 0.05$ (two-tailed), indicates that there is statistically different in preference among male and female students regarding Software and applications developers. **Data warehousing specialists** with the average score of male (M=3.83, SD=0.934), and of female (M=4.01, SD=0.725); and t-value, $t(335) = -$

2.031, $p=0.043$ (two-tailed), indicates that there is statistically different in preference among male and female students regarding **Data warehousing specialists. Block chain developers** with the average score of male ($M=3.83$, $SD=0.926$), and of female ($M=4.04$, $SD=0.797$); and t-value, $t(335)= -2.228$, $p=0.027$ (two-tailed), indicates that there is statistically different in preference among male and female students regarding **Data warehousing specialists. The rest of the digital jobs received no difference in preference from respondents.**

Table 5.5: Respondents' Preference on digital jobs by gender using T-Test

No.	Digital Jobs List	Male(N=144)		Female(N=191)		t-value	Sig. (2-tailed)
		Mean	Std.D	Mean	Std.D		
1	Big data specialist	4.02	0.942	3.96	0.807	0.655	0.513
2	Fin Tech Engineers	3.69	0.840	3.91	0.709	-2.637	0.009*
3	AI and machine learning specialist	3.83	0.796	3.94	0.734	-1.381	0.168
4	Software and applications developers	3.90	0.782	4.05	0.659	-1.918	0.056*
5	Security management specialists	3.98	0.832	4.13	0.661	-1.796	0.073
6	Data warehousing specialists	3.83	0.934	4.01	0.725	-2.031	0.043*
7	Internet of things specialists	3.94	0.887	3.95	0.694	-0.117	0.907
8	Data analysts and scientists	3.92	0.920	4.04	0.728	-1.332	0.184
9	Information security analysts	4.03	0.840	4.04	0.739	-0.083	0.934
10	Robotics engineers	3.93	0.833	3.99	0.852	-0.633	0.527
11	Block chain developers	3.83	0.926	4.04	0.797	-2.228	0.027*
12	Data engineers	4.02	0.857	4.06	0.783	-0.409	0.683
13	Digital transformation specialists	4.14	3.95	4.06	0.796	-1.165	0.245
14	Process automation specialists	3.91	0.810	4.02	0.788	-1.264	0.207
15	System engineers	4.15	0.732	4.17	0.772	-0.240	0.811
16	Online learning managers	4.03	0.836	4.12	0.806	-0.967	0.334
17	Digital marketing and strategy specialists	4.19	0.712	4.15	0.749	0.526	0.599
18	Database and network professionals	4.10	0.847	4.05	0.766	0.507	0.613
19	ICT operations and user support technicians	4.11	0.862	4.07	0.757	0.426	0.670
20	E-commerce specialists	4.08	0.886	4.06	0.816	0.201	0.841
21	Social media strategists	4.15	0.787	4.16	0.801	-0.109	0.914
22	Database architects	3.91	0.960	4.07	0.798	-1.701	0.090
23	Develops engineers	4.08	0.878	4.14	0.756	-0.668	0.505
24	Full stack engineers	4.06	0.846	4.09	0.727	-0.369	0.713
25	Business intelligence analysts	3.94	0.899	3.90	0.831	0.462	0.644
26	Electro technology engineers	4.21	0.860	4.15	0.742	0.644	0.520

** $P \leq 0.05$ for t-test value shows that there is significant difference*

Difference of BIU students' preference on digital jobs by Type of working institutions (T-Test Analysis)

This section investigated how the respondents' preference differs among the Gender variables. As indicated in the table 5.6, only 1 digital job that the respondents perceived differently between types of working institutions (public and private). ICT operations and user support technicians with the average score of public ($M=4.33$, $SD=0.730$), and of private ($M=4.06$, $SD=0.808$); and t-value, $t(335)= 1.985$, $p=.048^*$ (two-tailed), indicates that there is statistically different in preference among the respondents whose working institution are public and private in digital job "ICT operations and user support technicians". The rest of the digital jobs received no difference in preference from respondents.

Table 5.6: Respondents' Preference on digital jobs by Types of Working Institutions using T-Test

Digital Jobs List	Public		Private		t-value	Sig. (2-tailed)
	Mean	Std. Deviation	Mean	Std. Deviation		
Big data specialist	4.08	0.764	3.97	0.880	0.699	0.485
Fin Tech Engineers	3.80	0.687	3.82	0.787	-0.130	0.897
AI and machine learning specialist	4.03	0.733	3.87	0.766	1.172	0.242
Software and applications developers	4.03	0.768	3.98	0.712	0.403	0.687
Security management specialists	4.03	0.660	4.07	0.753	-0.342	0.733
Data warehousing specialists	3.90	0.810	3.94	0.828	-0.256	0.798
Internet of things specialists	4.03	0.620	3.93	0.801	0.704	0.482
Data analysts and scientists	4.03	0.800	3.98	0.820	0.329	0.742
Information security analysts	4.05	0.677	4.04	0.797	0.096	0.923
Robotics engineers	3.85	0.736	3.98	0.857	-0.912	0.362
Block chain developers	3.90	0.709	3.95	0.879	-0.362	0.717
Data engineers	3.93	0.656	4.06	0.833	-0.967	0.334
Digital transformation specialists	3.98	0.733	4.02	0.839	-0.301	0.764
Process automation specialists	4.00	0.751	3.97	0.805	0.227	0.821
System engineers	4.23	0.768	4.16	0.753	0.543	0.588
Online learning managers	4.05	0.749	4.08	0.829	-0.227	0.821
Digital marketing and strategy specialists	4.10	0.709	4.18	0.737	-0.645	0.520
Database and network professionals	4.03	0.862	4.08	0.794	-0.392	0.695
ICT operations and user support technicians	4.33	0.730	4.06	0.808	1.985	0.048*
E-commerce specialists	4.25	0.707	4.04	0.860	1.473	0.142
Social media strategists	4.08	0.730	4.17	0.803	-0.706	0.481
Database architects	4.03	0.768	4.00	0.888	0.170	0.865
Develops engineers	4.10	0.778	4.11	0.815	-0.087	0.931
Full stack engineers	4.10	0.744	4.08	0.785	0.168	0.867
Business intelligence analysts	4.10	0.778	3.89	0.868	1.418	0.157
Electro technology engineers	4.18	0.813	4.18	0.793	-0.009	0.992

* $P \leq 0.05$ for t-test value shows that there is significant difference

Differences in Democratic Engagement by ANOVA Analysis

Difference in Difference of BIU students' preference on digital jobs by Major of Study using ANOVA Analysis

The analysis of variance (ANOVA) is a hypothesis test approach to test for equality of means across multiple populations, which analysis for the differences of the sample means of a numeric random variable come from the same population, or whether at least one sample mean comes from a different population. The test statistic used to test this hypothesis is called the F-statistic (Wegner, 2013).

This section employs ANNOVA test to see whether how different or not among the respondent with different demographics variables and how different preference of digital JOBS among different majors of study. Based on the F-statistic table, the F-statistic value at the degree of freedom (3,331) is 2.21 (the region of acceptance the research null hypothesis (H_0) is $F \leq 2.21$). If the P Value is 0.05 or below for ANOVA Test value, it shows that there is significant difference between difference groups of independent variables.

As seen in the table 5.7, most digital jobs show difference in respondents' preference by different major of study or faculty. These digital jobs include: *AI and machine learning specialist*, $F(3,331) = 6.231$ and $P = 0.000$, *Software and applications developers* $F(3,331) = 5.507$, and $P = 0.001$, *Security management specialists*, $F(3,331) = 7.55$ and $P = 0.000$, *Data warehousing specialists*, $F(3,331) = 3.558$, and $P = 0.015$, *Internet of things specialists*, $F(3,331) = 3.712$ and $P = 0.012$, *Information security analysts*, $F(3,331) = 5.675$ and $P = 0.001$, *Robotics engineers*, $F(3,331) = 3.103$, and $P = 0.027$, *Block chain developers*, $F(3,331) = 2.775$ and $P = 0.041$, *Data engineers* $F(3,331) = 5.238$ and $P = 0.002$, *Process automation specialists*, $F(3,331) = 5.714$ and $P = 0.001$, *System engineers*, $F(3,331) = 5.899$ and $P = 0.001$, *Online learning managers*, $F(3,331) = 6.371$ and $P = 0.000$, *E-commerce specialists*, $F(3,331) = 4.570$, and $P = 0.004$, *Social media strategists*, $F(3,331) = 3.917$ and $P = 0.009$,

and Business intelligence analysts, $F(3,331) = 3.159$ and $P = 0.025$. Therefore, there is a statistically significant difference in preference between the respondents 'major of study or faculty'.

Table 5.7: Respondents' Preference on digital jobs by Major of Study/ Faculty using ANOVA Test

ANOVA			
Digital Jobs	df	F-value	Sig.
Big data specialist	(3,331)	2.194	0.089
Fin Tech Engineers	(3,331)	1.845	0.139
AI and machine learning specialist	(3,331)	6.231	0.000*
Software and applications developers	(3,331)	5.507	0.001*
Security management specialists	(3,331)	7.552	0.000*
Data warehousing specialists	(3,331)	3.558	0.015*
Internet of things specialists	(3,331)	3.712	0.012*
Data analysts and scientists	(3,331)	0.721	0.540
Information security analysts	(3,331)	5.675	0.001*
Robotics engineers	(3,331)	3.103	0.027*
Block chain developers	(3,331)	2.775	0.041*
Data engineers	(3,331)	5.238	0.002*
Digital transformation specialists	(3,331)	2.074	0.103
Process automation specialists	(3,331)	5.714	0.001*
System engineers	(3,331)	5.899	0.001*
Online learning managers	(3,331)	6.371	0.000*
Digital marketing and strategy specialists	(3,331)	1.361	0.255
Database and network professionals	(3,331)	1.499	0.215
ICT operations and user support technicians	(3,331)	1.933	0.124
E-commerce specialists	(3,331)	4.570	0.004*
Social media strategists	(3,331)	3.917	0.009*
Database architects	(3,331)	2.205	0.087
Develops engineers	(3,331)	2.105	0.099
Full stack engineers	(3,331)	0.573	0.633
Business intelligence analysts	(3,331)	3.159	0.025*
Electro technology engineers	(3,331)	0.418	0.740

* $P \leq 0.05$ for ANOVA Test value which shows that there is significant difference.

df=degree of freedom

Difference in Difference of BIU students' preference on digital jobs by Respondents' Areas of Expertise using ANOVA Analysis

As seen in the table 5.8, most digital jobs show difference in respondents' reference by different major of study or faculty. These digital jobs include: Big data specialist, $F(4,330) = 11.216$ and $P = 0.000$, AI and machine learning specialist, $F(4,330) = 10.700$ and $P = 0.000$, Software and applications developers, $F(4,330) = 4.664$ and $P = 0.001$, Security management specialists, $F(4,330) = 5.479$ and $P = 0.000$, Data warehousing specialists, $F(4,330) = 10.374$ and $P = 0.000$, Internet of things specialists, $F(4,330) = 13.279$ and $P = 0.000$, Data analysts and scientists, $F(4,330) = 10.171$ and $P = 0.000$, Information security analysts, $F(4,330) = 24.796$ and $P = 0.000$, Robotics engineers, $F(4,330) = 20.733$ and $P = 0.000$, Block chain developers, $F(4,330) = 18.399$ and $P = 0.000$, Data engineers $F(4,330) = 8.942$ and $P = 0.000$, Digital transformation specialists, $F(4,330) = 5.395$ and $P = 0.000$, Process automation specialists, $F(4,330) = 7.014$ and $P = 0.000$, System engineers, $F(4,330) = 5.310$ and $P = 0.000$, Digital marketing and strategy specialists, $F(4,330) = 4.201$ and $P = 0.002$, Database and network professionals, $F(4,330) = 7.898$ and $P = 0.000$, ICT operations and user support technicians, $F(4,330) = 11.202$ and $P = 0.000$, E-commerce specialists, $F(4,330) = 8.742$ and $P = 0.000$, Social media strategists, $F(4,330) = 8.900$ and $P = 0.000$, Database architects, $F(4,330) = 7.995$ and $P = 0.000$, Develops engineers, $F(4,330) = 7.923$ and $P = 0.000$, Full stack engineers, $F(4,330) = 5.927$ and $P = 0.000$, Business intelligence analysts $F(4,330) = 11.700$ and $P = 0.000$, Electro technology engineers, $F(4,330) = 2.689$ and $P = 0.031$. Therefore, there is a statistically significant difference in preference between the respondents 'areas of expertise'.

Table 5.8: Respondents' Preference on digital jobs by Respondents' Areas of Expertise using ANOVA Test

ANOVA			
	df	F	Sig.
Big data specialist	(4,330)	11.216	0.000*
Fin Tech Engineers	(4,330)	1.285	0.275
AI and machine learning specialist	(4,330)	10.700	0.000*
Software and applications developers	(4,330)	4.664	0.001*
Security management specialists	(4,330)	5.479	0.000*
Data warehousing specialists	(4,330)	10.374	0.000*
Internet of things specialists	(4,330)	13.279	0.000*
Data analysts and scientists	(4,330)	10.171	0.000*
Information security analysts	(4,330)	24.796	0.000*
Robotics engineers	(4,330)	20.733	0.000*
Block chain developers	(4,330)	18.399	0.000*
Data engineers	(4,330)	8.942	0.000*
Digital transformation specialists	(4,330)	5.395	0.000*
Process automation specialists	(4,330)	7.014	0.000*
System engineers	(4,330)	5.310	0.000*
Online learning managers	(4,330)	0.846	0.497
Digital marketing and strategy specialists	(4,330)	4.201	0.002*
Database and network professionals	(4,330)	7.898	0.000*
ICT operations and user support technicians	(4,330)	11.202	0.000*
E-commerce specialists	(4,330)	8.742	0.000*
Social media strategists	(4,330)	8.900	0.000*
Database architects	(4,330)	7.995	0.000*
Develops engineers	(4,330)	7.923	0.000*
Full stack engineers	(4,330)	5.927	0.000*
Business intelligence analysts	(4,330)	11.700	0.000*
Electro technology engineers	(4,330)	2.689	0.031*

* $P \leq 0.05$ for ANOVA Test value which shows that there is significant difference.
df=degree of freedom

Difference of BIU students' preference on digital jobs by Respondent's Age Group using ANOVA Analysis

Table 5.9, most digital jobs shows the difference in preference by different age groups of the respondents. These digital jobs include: Big data specialist, $F(3,331)= 6.611$ and $P=0.000$, and Fin Tech Engineers $F(3,331)= 3.564$ and $P=0.015$, Security management specialists, $F(3,331)= 4.147$ and $P= 0.007$, Internet of things specialists, $F(3,331) = 3.765$ and $P= 0.011$, Data analysts and scientists, $F(3,331)= 2.348$ and $P= 0.073$, Information security analysts $F(3,331)= 5.100$ and $P= 0.002$, Robotics engineers, $F(3,331)= 10.941$ and $P= 0.000$, Block chain developers, $F(3,331)= 11.672$ and $P= 0.000$, Data engineers, $F(3,331)= 4.754$ and $P=0.003^*$, Digital transformation specialists, $F(3,331)= 4.870$, and $P=0.003^*$, Process automation specialists, $F(3,331)= 10.453$ and $P=0.000$, System engineers, $F(3,331)= 2.531$ and $P= 0.057^*$, Online learning managers $F(3,331)= 4.798$ and $P= 0.003^*$, ICT operations and user support technicians, $F(3,331)= 6.435$ and $P= 0.000^*$, E-commerce specialists, $F(3,331) = 13.484$ and $P= 0.000^*$, Social media strategists, $F(3,331)= 6.775$ and $P= 0.000^*$, Database architects, $F(3,331)= 8.689$ and $P=0.000^*$, Develops engineers, $F(3,331)= 2.651$ and $P= 0.007^*$, Full stack engineers, $F(3,331)= 4.454$ and $P= 0.000^*$, Business intelligence analysts, $F(3,331) = 12.054$ and $P= 0.000^*$. The digital jobs that show no significance in preference between age groups include: AI and machine learning specialist, $F(3,331)=0.838$ and $P=0.474$, Software and applications developers, $F(3,331)=1.168$ and $P=0.322$, Digital marketing and strategy specialists, $F(3,331)=1.364$ and $P= 0.254$, and Database and network professionals, $F(3,331)=2.411$ and $P= 0.067$. Therefore, there is a statistically significant difference in preference between the respondents 'age groups.

Table 5.9: Respondents' Preference on digital jobs by Respondents' Age Group using ANOVA Test

ANOVA			
	df	F	Sig.
Big data specialist	(3,331)	6.611	0.000*
Fin Tech Engineers	(3,331)	3.564	0.015*
AI and machine learning specialist	(3,331)	0.838	0.474
Software and applications developers	(3,331)	1.168	0.322
Security management specialists	(3,331)	4.147	0.007*
Data warehousing specialists	(3,331)	1.264	0.287
Internet of things specialists	(3,331)	3.765	0.011*
Data analysts and scientists	(3,331)	2.348	0.073
Information security analysts	(3,331)	5.100	0.002*
Robotics engineers	(3,331)	10.941	0.000*
Block chain developers	(3,331)	11.672	0.000*
Data engineers	(3,331)	4.754	0.003*
Digital transformation specialists	(3,331)	4.870	0.003*
Process automation specialists	(3,331)	10.453	0.000*
System engineers	(3,331)	2.531	0.057*
Online learning managers	(3,331)	4.798	0.003*
Digital marketing and strategy specialists	(3,331)	1.364	0.254
Database and network professionals	(3,331)	2.411	0.067
ICT operations and user support technicians	(3,331)	6.435	0.000*
E-commerce specialists	(3,331)	13.484	0.000*
Social media strategists	(3,331)	6.775	0.000*
Database architects	(3,331)	8.689	0.000*
Develops engineers	(3,331)	2.651	0.007*
Full stack engineers	(3,331)	4.454	0.000*
Business intelligence analysts	(3,331)	12.054	0.000*
Electro technology engineers	(3,331)	0.969	0.203

* $P \leq 0.05$ for ANOVA Test value which shows that there is significant difference.

df=degree of freedom

Difference in Difference of BIU students' preference on digital jobs by Respondents' Position using ANOVA Analysis

Based on the F -statistic table, the F -statistic value at the degree of freedom (3,331) is 2.21 (the region of acceptance the research null hypothesis (H_0) is $F \leq 2.21$). If the P Value is 0.05 or below for ANOVA Test value, it shows that there is significant difference between difference groups of independent variables. Table 5.10 shows there is no significant difference in preference in digital jobs by different positions of the respondents. These digital jobs include: Big data specialist, $F(3,331) = 0.393$ and $P = 0.758$, Fin Tech Engineers, $F(3,331) = 0.601$ and $P = 0.614$, AI and machine learning specialist, $F(3,331) = 0.570$ and $P = 0.635$, Software and applications developers, $F(3,331) = 1.335$ and $P = 0.263$, Security management specialists, $F(3,331) = 1.829$ and $P = 0.142$, Data warehousing specialists, $F(3,331) = 0.461$ and $P = 0.710$, Internet of things specialists, $F(3,331) = 1.645$ and $P = 0.179$, Data analysts and scientists, $F(3,331) = 0.239$ and $P = 0.869$, Information security analysts, $F(3,331) = 0.486$ and $P = 0.693$, Robotics engineers, $F(3,331) = 0.617$ and $P = 0.604$, Block chain developers, $F(3,331) = 2.360$ and $P = 0.071$, Data engineers, $F(3,331) = 1.155$ and $P = 0.327$, Digital marketing and strategy specialists, $F(3,331) = 0.395$ and $P = 0.757$, Database and network professionals, $F(3,331) = 0.252$ and $P = 0.860$, ICT operations and user support technicians, $F(3,331) = 0.458$ and $P = 0.712$, E-commerce specialists, $F(3,331) = 1.019$ and $P = 0.384$, Social media strategists, $F(3,331) = 0.667$ and $P = 0.573$, Database architects, $F(3,331) = 1.324$ and $P = 0.267$, Develops engineers, $F(3,331) = 1.161$ and $P = 0.325$, Full stack engineers, $F(3,331) = 0.248$ and $P = 0.863$, and Electro technology engineers, $F(3,331) = 0.255$ and $P = 0.858$.

Table 5.10 also shows there is a significant difference in preference in digital jobs by different positions of the respondents. These digital jobs include: Process automation specialists $F(3,331) = 2.709$, and $P = 0.045$, System engineers, $F(3,331) = 3.399$ and $P = 0.018$, Online learning managers, $F(3,331) = 4.539$ and $P = 0.004$, Business

intelligence analysts, $F(3,331)= 3.423$ and $P= 0.018$, and Digital transformation specialists, $F(3,331)= 4.342$ and $P= 0.005$.

Therefore, there is a statistically significant difference in preference in most digital jobs between the respondents' positions, while a few digital jobs have no significant difference.

Table 5.10: Respondents' Preference on digital jobs by Respondents' Positions using ANOVA Test

ANOVA			
	df	F	Sig.
Big data specialist	(3,331)	0.393	0.758
Fin Tech Engineers	(3,331)	0.601	0.614
AI and machine learning specialist	(3,331)	0.570	0.635
Software and applications developers	(3,331)	1.335	0.263
Security management specialists	(3,331)	1.829	0.142
Data warehousing specialists	(3,331)	0.461	0.710
Internet of things specialists	(3,331)	1.645	0.179
Data analysts and scientists	(3,331)	0.239	0.869
Information security analysts	(3,331)	0.486	0.693
Robotics engineers	(3,331)	0.617	0.604
Block chain developers	(3,331)	2.360	0.071
Data engineers	(3,331)	1.155	0.327
Digital transformation specialists	(3,331)	4.342	0.005*
Process automation specialists	(3,331)	2.709	0.045*
System engineers	(3,331)	3.399	0.018*
Online learning managers	(3,331)	4.539	0.004*
Digital marketing and strategy specialists	(3,331)	0.395	0.757
Database and network professionals	(3,331)	0.252	0.860
ICT operations and user support technicians	(3,331)	0.458	0.712
E-commerce specialists	(3,331)	1.019	0.384
Social media strategists	(3,331)	0.667	0.573
Database architects	(3,331)	1.324	0.267
Develops engineers	(3,331)	1.161	0.325
Full stack engineers	(3,331)	0.248	0.863
Business intelligence analysts	(3,331)	3.423	0.018*
Electro technology engineers	(3,331)	0.255	0.858

* $P \leq 0.05$ for ANOVA Test value which shows that there is significant difference.
df=degree of freedom

References

- [1] VAR, S., & SOK, S. (2024). Making Cambodia's Higher Education Responsive to the Labor Market in the Digital Transformation Era.
- [2] Chan, K. N. (2015). Investigating Communities of Practice and ELT Teacher Research in Cambodia.
- [3] Kassy S. Sereyrath Em (2023). Attitudes and perceptions of using zoom: a survey of Cambodian University Students.
- [4] CHET, C., KENG, C., KEAN, T., VAR, S., & SOK, S. (2024). The Cambodia Journal of Basic and Applied Research. Royal University of Phnom Penh.
- [5] Chan, K. N., (2015). Investigating Communities of Practice and ELT Teacher Research in Cambodia. Department of Linguistics Faculty of Human Sciences Macquarie University Sydney.
- [6] Kassy, S., & Sereyrath, E. (2023). Jurnal As-Salam, Vol. 7 No. 1.
- [7] Bora, L., Bunhorn, D., & Son, N. (2024). Computers in Human Behavior Reports. Elsevier Ltd. <https://www.sciencedirect.com/journal/computers-in-human-behavior-reports>
- [8] Sam, V, A., & Wareerat, K. (2017). Kasetsart Journal of Social Sciences. Elsevier B.V. <http://www.elsevier.com/locate/kjss>

- [9] Jonathan, M, M., Marivic, C, G., Renz E, M, & Mark, B, U., (2024). Social Sciences & Humanities Open. <https://www.sciencedirect.com/journal/social-sciences-and-humanities-open>
- [10] Rany, S, Hak, Y, Morin, T, & Sarith, C., (2024). Factors Influencing English-Speaking Anxiety Among EFL Learners: A Case Study in Cambodian Higher Education.
- [11] Demetri L. Morgan, & Charles H.F. Davis III. (2020). STUDENT ACTIVISM, POLITICS, AND CAMPUS CLIMATE IN HIGHER EDUCATION. Library of Congress Cataloging-in-Publication Data
- [12] Yeon, S, K., & Jee, H, L. (2023). Positive Student Satisfaction And University Education System Welfare Policy In Cambodia.
- [13] Edman, F. (2025). Digital transformation in Cambodian higher education: Current trends and future directions. Learning Gate. <https://www.researchgate.net/publication/388046663>
- [14] Kao, D., Dr. Apichart., I, Asst., & Prof. Dr. Sirion, C. (2016). The Influencing Factors toward Brand Loyalty of Smartphone in Phnom Penh, Cambodia.
- [15] Sophearith, Y. (2022). Factors Influencing Perceived Ease of Use, Attitude and Behavioral Intention to Enhance ICT Learning Motivation in Higher Education in Cambodia. AU-GSB e-Journal Vol 15 No 1 (2022) 207-218
- [16] Syahril, R, E, D., Masrawati, P., Imran,A., & Muhammad, Q., (2023). MODERNITY IN THE MANAGEMENT OF THE UMSU FACULTY OF ISLAMIC STUDIES.
- [17] Keo,V., Sam,R., Lan,B., & Rouet, W. (2024). Students' perceptions and effects of technology integration in English learning: A case study at National University of Battambang. Journal of English and Education (JEE). Journal of English and Education (JEE)
- [18] SOKSAN, D. (2015). EFFECTS OF LANGUAGE DEVELOPMENT ON BILINGUALS' CONCEPT SELECTIONS: A CASE STUDY OF LANGUAGE SPEECH PRODUCTION TASK IN THE KHMER-ENGLISH BILINGUAL CONTEXT.
- [19] KAKADA, B. (2019). DEVELOPMENT OF 21ST CENTURY SKILLS ASSESSMENT CRITERIA FOR UNDERGRADUATE STUDENTS IN CAMBODIA.
- [20] Anthony, C., & Brian S, R. (2009). How to Recruit and Retain Higher Education Students. Taylor & Francis e-Library, 2009
- [21] HAROLD, S. (2019). A HIGHER EDUCATION. Taylor & Francis (Printers) Ltd, Basingstoke.
- [22] Kalwant, B & Martin, M. (2025). RACE, RACISM, AND HIGHER EDUCATION. British Library Cataloging-in-Publication Data
- [23] N.V. Varghese & Jinusha, P. (2022). India Higher Education Report 2021. British Library Cataloging-in-Publication Data
- [24] Nichole, M, G. (2025). LatinX Students in Higher Education. Library of Congress Cataloging-in-Publication Data.
- [25] N.V. Varghese & Nidhi S. Sabharwal. (2024). INDIA HIGHER EDUCATION REPORT 2022. Routledge is an imprint of the Taylor & Francis Group, an informa business.
- [26] Guofeng, L & Gulbahar H, B. (2023). "STRANGERS" OF THE ACADEMY. 4 Park Square, Milton Park, Abingdon, Oxon OX14 4RN.
- [27] Mario C. Martinez. (2021). THE SCIENCE OF HIGHER EDUCATION. Routledge is an imprint of the Taylor & Francis Group.
- [28] Than, C. (2025). A Study of Teacher Feedback Impact on Cambodian EFL Students' L2 Writing: Perception, Performance, and Attribution. JEILT Publisher.
- [29] Jayson, R. (2009). Diffusion of technology adoption in Cambodia: The test of a theory. (IJEDICT), 2009, Vol. 5, Issue 3, pp. 157-171
- [30] Geoffrey, K & Irene, T. (2013). A framework for the integration of e-learning in higher education institutions in developing countries. IJEDICT), 2013, Vol. 9, Issue 2, pp. 19-36.
- [31] Un, N., & Dr. Ngoy, Y. (2024). Factors Influencing Users' Satisfaction and Continued Usage Intention of Mobile Apps among Food and Beverage SMEs in Phnom Penh. <http://www.arjhss.com/>.
- [32] Da, B. (2025). Challenges and suggestions for improving the quality of higher education in Cambodia. Cambodian Education Forum. <https://doi.org/10.62037/cjer.2025.05.01.03>.
- [33] A publication of CDRI - Cambodia's leading independent development policy research institute. (2020). A Cambodia Development Review.

- [34] CHANMONITA, S. (2020). THE USE OF PEER FEEDBACK ACTIVITY THROUGH CANVAS LMS TO ENHANCE EFL STUDENTS' WRITING ABILITY.
- [35] Bunteng, L. (2024). Factors Influencing Digital Trust Among Young People in Phnom Penh: The Adoption of Expectation Confirmatory Theory. *CJBPP Cambodia Journal for Business and Professional Practice*, Vol 1 ISSN: 3078-4131. <https://doi.org/10.71215/cjbpp.202415>.
- [36] Kimkong, H., & Koemhong, S. (2023). *Cambodian Journal of Educational Research*. Cambodian Education Forum. <https://www.researchgate.net/publication/373170005>
- [37] Fay, P. (2017). Deconstructing Internationalization: Advocating Glocalization in International Higher Education. <https://digitalcommons.lindenwood.edu/jigs/vol8/iss2/4>
- [38] Samuel D, M, & Peter N., K. (2009). Deconstructing the Model Minority Myth and How It Contributes to the Invisible Minority Reality in Higher Education Research. *NEWDIRECTIONS FOR INSTITUTIONAL RESEARCH*.
- [39] Chheng, L. (2024). Quality Enhancement of Higher Education in Cambodia. *SRWUNG: Journal of Social Sciences and Humanities*. <https://journal.jfpublisher.com/index.php/jssh>
- [40] QUYNH, X, L, & MA. (2013). Fostering learner autonomy in language learning in tertiary education: an intervention study of university students in hochiminh city, vietnam.
- [41] Chhoun, K. (2024). Early Cybersecurity Education Key to Digital Future.
- [42] Riccardo, C., Erica, P., Gert, v., & d, W. (2011). Undergraduate Students' Experiences of the Use of MOOCs for Learning at a Cambodian University. MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.
- [43] Álvaro, A, S., Diego, V., & PabloFernández, A. (2011). Self-Assessment of Soft Skills of University Teachers from Countries with a Low Level of Digital Competence. MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.
- [44] Emmanuel C., L. (2015). *The Primer Series on ICTD for Youth*. Republic of Korea
- [45] Qiu, T, C., Cai, L, T., Gregory, B., Chee, P, W., Hoang, M, D., & Rozainee, K. (2015). Drug abuse, relapse, and prevention education in Malaysia: perspective of university students through a mixed methods approach. *Frontiers | Drug Abuse, Relapse, and Prevention Education in Malaysia: Perspective of University Students Through a Mixed Methods Approach*
- [46] Phany, S. (2014). Youths' Experiences and Perceptions of Gender Equality in Cambodia.
- [47] Kimkong, H. (2024). Understanding Cambodian Provincial University Students' Perspectives on Cambodia's Vision to Become a Knowledge-Based Society.
- [48] Francesc M. Esteve-, M., Ana, Y, P., & Fuentes, L, C. (2021). A strategic approach of the crucial elements for the implementation of digital tools and processes in higher education. John Wiley & Sons Ltd.
- [49] Edman, F., & Udam, M. (2024). Digital Transformation in Cambodian Higher Education and Its Impact on Teaching and Learning Outcomes. *Journal of Accounting, Finance, Economics, and Social Sciences*.
- [50] ANE, C-P. (2023). Flexible Learning in Higher Education Institution: Experiences of Instructors in a Private Higher Institution. *JPAIR Multidisciplinary Research* is licensed under a Creative Commons Attribution-Noncommercial 4.0 International (CC BY-NC 4.0).