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# Digital Occupational Preferences in Cambodian Higher Education and Differences by Expertise and Age

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## ABSTRACT

*Digital transformation is changing the occupations that graduates can enter, yet little is known about which digital occupations Cambodian university students favor. Preference ratings for 26 digital occupations were collected from 335 respondents at BELTEI International University through a five-point questionnaire with good internal consistency (Cronbach's alpha = .879). Means and standard deviations ranked the occupations, independent samples t tests compared gender and type of institution, and one-way analyses of variance compared major of study, area of expertise, age group, and position. All occupations were rated favorably (M = 3.81 to 4.18). Electro technology engineers, digital marketing and strategy specialists, and system engineers ranked highest, whereas FinTech engineers and artificial intelligence and machine learning specialists ranked lowest. Area of expertise differed significantly for 24 occupations, age group for 18, and major of study for 15, and 40 of the 66 significant results remained significant after a Bonferroni adjustment. Gender, type of institution, and position produced only a few small differences that did not survive the adjustment. The findings suggest that universities should differentiate digital course offerings and career counseling by professional background and age, and should expose students to the data-intensive occupations in which interest was lowest. The cross-sectional, single-institution design limits generalization, and later studies should add post hoc tests, multiple institutions, and measures of the factors behind preference.*

**Keywords**: *Cambodia, Career Preferences, Digital Occupations, Higher Education, Technology Acceptance*

## INTRODUCTION

Digital technologies have changed which occupations employers seek and which skills they expect from the people they hire. Online vacancy data from the United States showed rapid growth in postings related to artificial intelligence between 2010 and 2018, and establishments that adopted such technologies hired fewer workers for non-AI positions (Acemoglu et al., 2022; Shen & Zhang, 2024; Tripathi, 2024). The same establishments also altered the skills requested in the postings that remained, which suggests that adoption changed the content of jobs as well as their number. Evidence of this kind indicates that digital transformation reshapes the structure of labor demand and not merely its volume (Huang, 2024). For students approaching graduation, such shifts make the choice of a first occupation more consequential, because expanding and contracting roles are not distributed evenly across fields of study (Corrales-Herrero & Rodríguez-Prado, 2024). The occupations that students decide to pursue will in turn influence whether the supply of digital talent keeps pace with what employers need, and whether the education system prepares people for the roles that grow (Zhao et al., 2025).

Professional practice illustrates the same movement, and auditing offers a clear example of how established occupations absorb new technologies. A systematic review of ten peer-reviewed articles published between 2020 and 2025 identified big data analytics, artificial intelligence, blockchain, robotic process automation, and cloud computing as the technological foundations of contemporary digital auditing (Herdiana & Nugrahanti, 2025). The review linked these technologies to improved audit quality and to changes in the role of the auditor. It also reported uneven adoption among firms and insufficient digital competency among practitioners, and it treated both as obstacles to implementation. Several of the technologies named in that review correspond to occupations listed in the survey underlying the present analysis, including big data specialists, artificial intelligence and machine learning specialists, blockchain developers, and process automation specialists. Employers cannot fill such roles unless enough graduates find them attractive and prepare for them. Whether students are drawn toward these occupations, or toward others, therefore determines how quickly competency gaps of the kind described above can close.

Technology acceptance research explains part of why individuals take up digital tools, and recent work in Indonesia and Cambodia shows how its core constructs operate in practice. A survey of 50 merchants in Surabaya, analyzed with partial least squares structural equation modeling, found that perceived usefulness significantly predicted the intention to use the QRIS digital payment standard (Firdausi & Antonio, 2025). Perceived ease of use influenced that intention only indirectly, by raising perceived usefulness, and the authors emphasized targeted training and support as conditions for wider adoption. In Cambodia, a cross-sectional survey of 369 university students integrated the Technology Acceptance

Model, the Unified Theory of Acceptance and Use of Technology, and Self-Determination Theory (Ly et al., 2024). The survey reported significant links among motivation, perceived ease of use, perceived usefulness, and the adoption of digital learning platforms. Both studies treated digital technology as something people use rather than as a field in which people seek work. Similar perceptions of usefulness and ease may plausibly inform occupational preferences as well, yet neither study examined preferences among digital occupations.

Evidence on occupational preference matters for universities because curriculum planning, course sequencing, and career guidance all depend on knowing what students actually want to pursue (Sarsenova & Duisenova, 2025). When preferences cluster around a narrow set of digital occupations, programs risk oversupplying some fields while others remain thinly staffed. When preferences diverge between groups, a single advising approach will serve some students better than others, which weakens the value of uniform guidance. The Cambodian studies reviewed for this article examined the adoption of learning technologies rather than the way students rank specific digital occupations against one another (Ly et al., 2024). As a result, institutions that wish to align their offerings with digital labor demand lack an empirical reference point for the occupations their own students find most attractive. Without such a reference point, decisions about new programs or specializations must rest on assumption or on labor market signals alone, and neither reveals the interests of the students who would enroll.

Group differences deserve separate attention because digital occupations are not perceived uniformly by all students, and the literature on gender offers a clear starting point. Research comparing IT students with IT professionals reported significant gender differences in how work in the IT sector was perceived (Pyrkosz-Pacyna et al., 2022). If comparable differences appear among Cambodian respondents, the appeal of a given occupation may depend on who is asked. Preferences may also vary with major of study, area of expertise, age, and position, because each of these characteristics can shape exposure to technology and to the occupations that rely on it. Respondents attached to public institutions may likewise differ from those in private institutions in the occupations they regard as attractive or attainable. Testing such variation occupation by occupation, rather than for digital work as a single category, can show where interest is uneven even when overall averages look similar.

A gap therefore remains between what is known about digital technology adoption and what is known about occupational preference. Technology acceptance studies explain why individuals use digital tools, labor market studies document which skills employers request, and gender-focused work describes how IT careers are perceived. The evidence reviewed did not combine these strands at the level of individual digital occupations for a Cambodian university community. Closing that gap requires a ranked preference profile for a broad set of digital occupations, together with tests of whether the profile differs across demographic and

institutional groups. The analysis reported here supplies such a profile for 26 digital occupations and tests differences by gender, type of institution, major of study, area of expertise, age group, and position. As far as the reviewed literature shows, an occupation-level and multi-group comparison of this kind has not been reported for Cambodia, which marks the novelty of the contribution.

Three questions structure the inquiry and correspond to the analyses reported in the Results section. The first concerns the overall preference profile, specifically which of the 26 digital occupations received the highest and lowest mean ratings from respondents at BELTEI International University (BIU). The second concerns whether preferences differed between male and female respondents and between respondents attached to public and private institutions. The third concerns whether preferences differed across major of study, area of expertise, age group, and position. Respondents were predominantly students at the bachelor's and master's levels, with a smaller number of lecturers and school leaders, so the findings describe a university community rather than undergraduates alone. The survey recorded preference ratings only, so the inquiry does not address salary expectations, workplace conditions, or opportunities for professional growth, which fall outside the scope of the data collected and remain open for later research.

Answers to these questions carry practical weight for BIU and comparable institutions that prepare students for digital work. A clear picture of which occupations attract students, and where interest differs by group, can guide the sequencing of digital courses, the content of career counseling, and the targeting of industry partnerships. Such evidence also gives policymakers a student-centered complement to employer-side data on skill demand. The design is cross-sectional and the ratings are self-reported, so the findings describe preferences at one point in time and cannot establish what drives them. Nor can the findings show whether stated preferences translate into actual career entry, which would require follow-up of respondents after graduation. Even with these limits, a documented preference profile gives educators and policymakers a starting point grounded in student responses, and it identifies the occupations on which later explanatory research could concentrate.

## LITERATURE REVIEW

### Digital Occupations and Their Skill Requirements

Digital occupations are understood here as roles whose core tasks depend on digital technologies, whether the role was newly created by those technologies or is an established role that has been reorganized around them (Lennon et al., 2023). The distinction matters because the two groups differ in the preparation they require and, in the way, students encounter them during their studies. Vial (2019) reviewed 282 works and described digital transformation as a process in which digital technologies create disruptions, organizations respond strategically to alter how

they create value, and structural changes and organizational barriers shape the positive and negative outcomes. That framework helps explain why occupations appear, change, and decline, since strategic responses to technological disruption alter which tasks organizations keep, automate, or create. Its unit of analysis is nevertheless the organization, so it says little about how individual students evaluate the occupations that result. Demand-side accounts of this kind therefore need a complementary perspective on the people who might fill the roles. The literature on digital occupations can accordingly be read as strong on what employers require and comparatively quiet on what prospective entrants want.

Research on competencies shows how demand is translated into expectations for graduates. Mei et al. (2023) observed that information technology labor demand and job characteristics have been shaped by Industry 4.0 and the digital age, and that universities are seeking to identify the skills expected of new digital workers. Using a fuzzy multi-criteria decision-making framework applied to an empirical case, they found that data and information processing was the most important competency for the future workforce implementing digital technologies in higher education, followed by the ability to interact with modern interfaces. These rankings are useful because they show that data-related and interface-related abilities are treated as central, yet they reflect the judgments of decision experts rather than the aspirations of students. The competencies were also evaluated in relation to the implementation of digital technologies within higher education institutions, which limits direct transfer to occupations in other sectors. A reasonable reading is that competency frameworks clarify what graduates need to be able to do while leaving open which digital roles graduates actually wish to pursue. Evidence on preference is therefore a necessary companion to competency evidence if institutions intend to match supply with demand.

Employability research adds a further layer by asking whether university activities improve the skills that labor markets reward. A systematic review of 87 papers on employability activities organized by higher education institutions found that institutions, students, and employers all value such activities, mainly because they develop skills desired in the labor market and reduce the risks of labor market entry (Scandurra et al., 2024). The same review concluded that the evidence base is dominated by small-scale case studies and evaluations that are not robust enough to support causal claims about student development or labor market outcomes. It also called for a more contextual understanding of employability that accounts for the interplay between individuals, a particular labor market, and a particular education system. Contextual evidence of this kind must be generated locally, because conclusions drawn from other labor markets and education systems may not transfer. For a university in Cambodia, the implication is that program design should be informed by evidence on the orientations of its own students and not by imported assumptions. Descriptive evidence on which digital occupations students

favor, and on how that varies by group, is one modest but concrete form of such local evidence.

**Theoretical Perspectives on Digital Occupational Preference**

The Technology Acceptance Model offers a widely used account of how individuals form intentions toward technology. Davis (1989) proposed that perceived usefulness and perceived ease of use are the two beliefs that most strongly determine whether people accept and use an information technology. Applied to occupations, the logic suggests that a student may favor a digital role when it appears to improve prospects and when its required skills appear attainable. This extension is analogical, because the model was built to explain technology use in organizational settings and not occupational choice. The model also centers on individual beliefs and gives limited weight to family expectations, institutional offerings, or labor market conditions, all of which can shape career decisions. Its value for the topic of digital occupational preference is therefore interpretive rather than predictive, since it supplies a vocabulary for reading preference patterns without being tested directly by them (Vîrjan et al., 2026).

Cambodian applications of the model show how its core constructs have been extended. Ly and Ly (2022) surveyed 391 users and added subjective norm to the Technology Acceptance Model to explain internet banking adoption, reporting that subjective norm shaped attitude, which ultimately influenced adoption. Ly and Ly (2024) later integrated the model with the Theory of Planned Behavior in a study of 359 participants and found that perceived usefulness played a critical role in digital payment adoption, extending to convenience, security, and transactional efficiency. The same study showed that financial literacy acted both as a determinant of adoption and as a mediator between public attitudes and adoption, and it identified behavioral nudges as a significant influence. In both studies the authors extended the original constructs with social, attitudinal, and literacy variables, which indicates that the base model was treated as a starting point and not as a complete explanation. Both studies concerned consumer technologies rather than occupations, so their findings cannot be transferred to career preference without caution. They nevertheless show that perceived usefulness and social influence are plausible candidates for explaining why some digital occupations attract more interest than others.

The two theoretical perspectives complement each other because they operate at different levels. Digital transformation theory describes how technological disruption and organizational response alter the set of occupations available, whereas the Technology Acceptance Model describes how individuals appraise technologies and, by extension, the roles built on them (Dash et al., 2023). Together they connect structural change to individual perception, which is the link that preference research needs. Each perspective also has limits in the Cambodian context. Vial's framework was derived from a review of works on organizational

transformation and does not address how students in a particular country evaluate the occupations that result, while the Cambodian applications of the Technology Acceptance Model located for this review concern consumer technologies. Because the questionnaire recorded only preference ratings, neither perspective is operationalized through its own constructs, and both serve as interpretive lenses for patterns in the ratings and not as models to be tested.

**Demographic Differences in Digital Occupational Preference**

Gender is the demographic characteristic most often examined in research on technology careers, and the findings are not uniform. Serenko and Turel (2021) surveyed 185 university students who had not yet declared a major and found that implicit gender identity predicted choices of an information technology major and career among women but not among men. Explicit gender identity showed no such influence for either group, and social norms influenced the choices of men and women in a similar way. The authors also noted that earlier studies had reached conflicting conclusions, with some finding that gender and information systems career decisions were unrelated. Such inconsistency suggests that apparent gender effects depend on how gender is measured, on which occupations are considered, and on the social setting. The sample consisted of students at one United States university, so the results cannot be assumed to hold in Cambodia, where norms about technology work and gender may differ. Testing gender differences occupation by occupation in a Cambodian sample is therefore an empirical question and not a foregone conclusion.

Characteristics other than gender also appear in the literature as correlates of occupational interest, although the evidence is thinner. In the same study, information technology skills and work experience were associated with intentions to major in the field and to pursue a career in it, and the pattern differed between men and women (Serenko & Turel, 2021). Age had no significant effect once other variables were considered and was removed from the final model for parsimony. These results suggest that exposure to technology, rather than age alone, may account for differences in interest, which is consistent with expecting preferences to vary by major of study and area of expertise. Scandurra et al. (2024) likewise called for evidence that identifies heterogeneity across demographic groups, since average effects can conceal differences among students. For position and for the type of institution in which respondents' study or work, the literature reviewed offers little direct guidance, so those comparisons are treated as exploratory.

Technology acceptance research is often summarized in models such as the one shown in Figure 1, in which perceived usefulness, perceived ease of use, facilitating conditions, and social influences shape attitudes toward using digital platforms, and attitudes then lead to adoption both directly and through personal motivation. The model combines constructs from the Technology Acceptance Model with social and enabling conditions, which is consistent with the Cambodian

applications that added subjective norm, planned behavior, and financial literacy to the base model (Ly & Ly, 2022; Ly & Ly, 2024). It was framed around the adoption of digital learning platforms, so its extension to occupational preference is conceptual and not empirical. The questionnaire used here recorded preference ratings for 26 digital occupations together with the demographic characteristics of respondents, and it did not measure any of the constructs in Figure 1. The model is therefore retained as a reference framework and not as a hypothesized structure that the data test. Its value lies in identifying which constructs later studies could measure to explain why some occupations attract more interest than others and why preferences differ across groups. The empirical analysis reported here remains descriptive and comparative, treating occupational preference as the outcome and respondent characteristics as grouping variables.

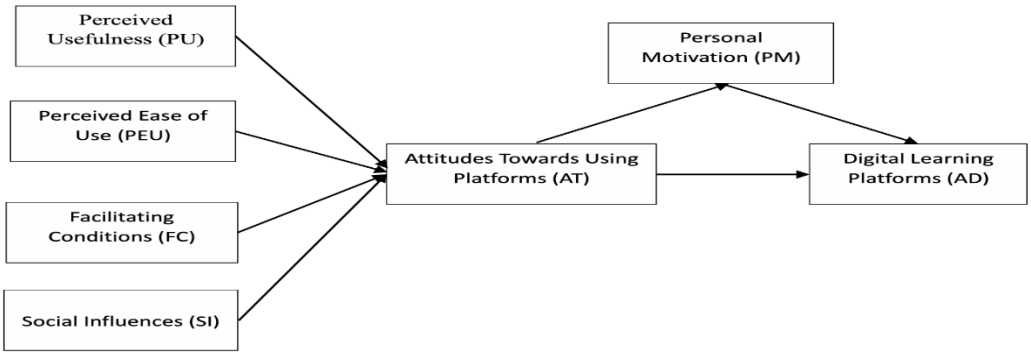


**Figure 1** Conceptual Model of Digital Technology Adoption among University Students
**Source:** Authors' Conceptual Model, Retained as a Reference Framework

Taken together, the reviewed work leaves three limitations in place. The first is that structural accounts of digital transformation and competency frameworks describe what economies and institutions need but rarely record what students themselves prefer. The second is that the Cambodian acceptance studies reviewed here addressed consumer technologies and did not address occupational preference. The third is that studies of demographic differences in technology careers produced mixed findings in settings that differ from Cambodia, and they usually concentrate on a single characteristic such as gender. Measuring preferences for a broad set of digital occupations and comparing them across six respondent characteristics responds directly to these limitations. The resulting evidence cannot explain why preferences arise, but it can show where interest is concentrated and where it diverges, which is the information that program planners require first.

## RESEARCH METHODOLOGY

A quantitative, cross-sectional survey design was adopted to measure preferences for digital occupations and to compare those preferences across

demographic groups (Creswell & Guetterman, 2024). The design suited the research questions because the aims were to describe levels of preference, to rank occupations, and to test whether group means differed, and none of these aims required manipulation of conditions or the tracking of respondents over time. Preferences were measured at one point in time through a structured questionnaire, so each respondent contributed a single set of ratings. The data were exclusively quantitative, and the design therefore did not draw on qualitative sources or on a mixed methods strategy. Analysis proceeded in three stages that matched the three research questions, namely descriptive ranking of the occupations, comparison of two-group means, and comparison of means across three or more groups. This sequence allowed overall patterns to be established before group differences were examined. Claims about causes or mechanisms were therefore beyond what the design could support.

The respondents were drawn from BIU, and the sample comprised 335 individuals. Of these, 144 were male and 191 were female. Students formed the largest group with 217 respondents, followed by 104 lecturers and teachers and 14 school directors and deputy directors. Most respondents were enrolled in bachelor's programs (213) or master's programs (119), while two were in doctoral programs and one reported another level. In terms of affiliation, 295 respondents were attached to private institutions and 40 to public institutions. Age was recorded in four bands, namely below 20 years, 21 to 30 years, 31 to 40 years, and 41 to 50 years, and respondents were also classified by faculty (Law, Education, Arts and Humanities, Information Technology, and Business Administration) and by area of expertise. The full distribution of each characteristic is reported in Table 1 of the Results section.

Data were collected with a questionnaire that listed 26 digital occupations, and respondents rated their preference for each occupation on a five-point Likert-type scale. A higher mean rating indicated stronger preference for the occupation concerned. The occupations were big data specialists, FinTech engineers, artificial intelligence and machine learning specialists, software and applications developers, security management specialists, data warehousing specialists, Internet of things specialists, data analysts and scientists, information security analysts, robotics engineers, blockchain 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, development engineers, full stack engineers, business intelligence analysts, and electro technology engineers. Preference for each occupation served as the dependent variable, and the demographic characteristics of the respondents served as the grouping variables. Ratings were treated as continuous scores for the calculation of means, standard deviations, t tests, and analyses of variance. The questionnaire recorded preference ratings only

and did not measure salary expectations, workplace conditions, self-efficacy, or other antecedents of preference, and its scope therefore set the boundaries within which the findings could be interpreted.

Internal consistency was examined with Cronbach's alpha, which was calculated across the 26 items using the data from all 335 respondents. The coefficient was .879, which indicated good internal consistency for the scale as a whole. Because the items were distinct occupations and not interchangeable indicators of a single construct, the coefficient was best read as evidence that respondents who rated one digital occupation highly tended to rate other digital occupations highly as well. It did not show that the occupations formed a unidimensional scale, and alpha values for individual items were not reported. The occupation-level analyses therefore treated each occupation as a separate rating and not as part of a composite score. Composite indices were not computed, so every comparison in the Results section refers to a single occupation.

Responses were coded and entered into SPSS version 25.0, and the entries were edited to reduce errors before analysis. Descriptive statistics, namely frequencies, percentages, means, and standard deviations, were used to profile the respondents and to rank the 26 occupations by mean preference, which addressed the first research question, and approximate 95% confidence intervals around the means were calculated to describe the precision of the ranking. Independent samples t tests with two-tailed significance were used to compare mean preference ratings between male and female respondents and between respondents attached to public and private institutions, which addressed the second research question. For each occupation, the means, standard deviations, t values, and p values were reported. One-way analysis of variance was used to compare mean preference ratings across faculties of study, areas of expertise, positions, and age groups, which addressed the third research question, and the F values and p values were reported for each occupation. Effect sizes were expressed as Cohen's d for the t tests and eta squared for the analyses of variance, and a significance level of .05 was applied throughout.

Each comparison was conducted separately for each of the 26 occupations, which produced a family of 26 tests for each grouping variable and 156 tests in total. No correction for multiple comparisons was applied to the primary tests, so the probability of at least one false positive within a family exceeded the nominal level of .05. A Bonferroni-adjusted threshold of .0019 (.05 divided by 26) was therefore applied afterward as a sensitivity check, and results that were significant at .05 but not at the adjusted threshold were interpreted as tentative. Post hoc comparisons were not conducted after the analyses of variance, so a significant F value indicated only that at least one group mean differed and did not identify which groups differed. The group sizes were also uneven, with 40 respondents attached to public institutions against 295 attached to private institutions and 29 respondents from the Faculty of Information Technology against 190 from the Faculty of

Education, Arts, and Humanities, which limited the precision of the smaller groups. The ranking of occupations was descriptive, and no inferential test was applied to the differences between neighboring means. The ordering of closely clustered occupations was therefore read as approximate and not as a strict hierarchy.

## RESULT AND DISCUSSION

### Respondent Profile and Overall Preference for Digital Occupations

Female respondents (57.0%) outnumbered male respondents (43.0%) in the sample of 335, and nearly half of all respondents (47.5%) were aged 21 to 30 years. Students formed the largest position group (64.8%), followed by lecturers and teachers (31.0%) and school directors and deputy directors (4.2%). Respondents in bachelor's programs accounted for 63.6% of the sample and those in master's programs for 35.5%, while doctoral respondents and one respondent at another level made up the remainder. Most respondents were attached to private institutions (88.1%), and they came mainly from the Faculty of Education, Arts, and Humanities (56.7%) and the Faculty of Law (21.8%). TEFL and TESOL was the most common area of expertise (40.9%), followed by law (21.8%), management (17.9%), finance and business (11.0%), and human resource (8.4%). The sample therefore leaned toward education, language, and law backgrounds, and the results describe a university community that is not evenly spread across technical disciplines.

**Table 1** Demographic Profile of Respondents (N = 335)

| **Characteristic** | **Category** | **n** |
|---|---|---|
| Gender | Male | 144 |
| | Female | 191 |
| Age group | Below 20 years | 85 |
| | 21 to 30 years | 159 |
| | 31 to 40 years | 77 |
| | 41 to 50 years | 14 |
| Position | School director or deputy director | 14 |
| | Teacher or lecturer | 104 |
| | Student | 217 |
| Type of institution | Public | 40 |
| | Private | 295 |
| Academic program | Bachelor's degree | 213 |
| | Master's degree | 119 |
| | Doctoral degree | 2 |
| | Other | 1 |
| Faculty | Law | 73 |
| | Education, Arts, and Humanities | 190 |
| | Information Technology | 29 |

| Characteristic | Category | n |
|---|---|---|
| | Business Administration | 43 |
| Area of expertise | TEFL and TESOL | 137 |
| | Law | 73 |
| | Management | 60 |
| | Finance and business | 37 |
| | Human resource | 28 |

*Note.* Percentages are calculated from the counts and may not sum exactly to 100 because of rounding

**Source:** Analysed by the researcher (2026)

Preference for digital occupations was uniformly favorable. Mean ratings of the 26 occupations ranged from 3.81 to 4.18 on the five-point scale, and the average of the 26 means was 4.03, so every occupation received a mean above the scale midpoint of 3. Standard deviations ranged from 0.717 to 0.874, which indicated moderate and fairly even dispersion of ratings across occupations. Table 2 ranks all 26 occupations by mean rating and answers the first research question. Because the full range of means spanned only 0.37 points, differences between neighboring occupations were small in absolute terms, and the ranking is best read as a pattern and not as a precise ordering. Approximate 95% confidence intervals, calculated from the reported means and standard deviations, extended roughly 0.08 to 0.09 points on either side of each mean.

**Table 2** Mean Preference Ratings for the 26 Digital Occupations (N = 335)

| Rank | Occupation | M | SD | Position in ranking |
|---|---|---|---|---|
| 1 | Electro technology engineers | 4.18 | 0.794 | Highest five |
| 2 | Digital marketing and strategy specialists | 4.17 | 0.733 | Highest five |
| 3 | System engineers | 4.16 | 0.754 | Highest five |
| 4 | Social media strategists | 4.16 | 0.794 | Highest five |
| 5 | Development engineers | 4.11 | 0.810 | Highest five |
| 6 | ICT operations and user support technicians | 4.09 | 0.803 | |
| 7 | Online learning managers | 4.08 | 0.819 | |
| 8 | Full stack engineers | 4.08 | 0.779 | |
| 9 | Database and network professionals | 4.07 | 0.801 | |
| 10 | E-commerce specialists | 4.07 | 0.845 | |
| 11 | Security management specialists | 4.06 | 0.742 | |
| 12 | Information security analysts | 4.04 | 0.782 | |
| 13 | Data engineers | 4.04 | 0.814 | |
| 14 | Digital transformation specialists | 4.01 | 0.826 | |
| 15 | Database architects | 4.00 | 0.874 | |
| 16 | Big data specialists | 3.99 | 0.867 | |
| 17 | Data analysts and scientists | 3.99 | 0.817 | |

| Rank | Occupation | M | SD | Position in ranking |
|---|---|---|---|---|
| 18 | Software and applications developers | 3.98 | 0.717 | |
| 19 | Process automation specialists | 3.97 | 0.798 | |
| 20 | Robotics engineers | 3.96 | 0.843 | |
| 21 | Blockchain developers | 3.95 | 0.860 | |
| 22 | Internet of things specialists | 3.94 | 0.781 | Lowest five |
| 23 | Data warehousing specialists | 3.93 | 0.825 | Lowest five |
| 24 | Business intelligence analysts | 3.92 | 0.860 | Lowest five |
| 25 | Artificial intelligence and machine learning specialists | 3.89 | 0.762 | Lowest five |
| 26 | FinTech engineers | 3.81 | 0.775 | Lowest five |

*Note.* Occupations are ordered by mean rating, and higher means indicate stronger preference.

**Source:** Analysed by the researcher (2026)

The five most preferred occupations were electro technology engineers (M = 4.18, SD = 0.794), digital marketing and strategy specialists (M = 4.17, SD = 0.733), system engineers (M = 4.16, SD = 0.754), social media strategists (M = 4.16, SD = 0.794), and development engineers (M = 4.11, SD = 0.810). The five least preferred occupations were FinTech engineers (M = 3.81, SD = 0.775), artificial intelligence and machine learning specialists (M = 3.89, SD = 0.762), business intelligence analysts (M = 3.92, SD = 0.860), data warehousing specialists (M = 3.93, SD = 0.825), and Internet of things specialists (M = 3.94, SD = 0.781). The highest group combined engineering-oriented roles with marketing and communication roles, whereas the lowest group consisted largely of data-intensive and emerging-technology roles. Other occupations built on data or advanced computing also fell in the lower half of the ranking, including big data specialists (rank 16), process automation specialists (rank 19), and blockchain developers (rank 21). The confidence intervals of the top five overlapped one another, so the order within that group should not be treated as definitive. The interval for FinTech engineers (approximately 3.73 to 3.89) did not overlap with that of the fifth-ranked occupation (approximately 4.02 to 4.20), which suggests a genuine separation between the two ends of the ranking.

**Differences in Preference Across Respondent Groups**

Group comparisons were run separately for each of the 26 occupations, and Tables 3 and 4 report the outcomes for the second and third research questions. Gender produced three significant differences at the .05 level, all with female respondents giving higher ratings. Female respondents rated FinTech engineers higher than male respondents did (female M = 3.91, SD = 0.709, male M = 3.69, SD = 0.840), $t(333) = -2.64$, $p = .009$, and the same pattern appeared for data warehousing specialists (male M = 3.83, female M = 4.01), $t(333) = -2.03$, $p = .043$,

and for blockchain developers (male M = 3.83, female M = 4.04), t(333) = −2.23, p = .027. The difference for software and applications developers did not reach significance, t(333) = −1.92, p = .056. The effect sizes were small (Cohen's d between 0.22 and 0.29), and none of the three differences remained significant when the threshold was adjusted to .0019 (.05 divided by 26). Female respondents also gave higher mean ratings than male respondents for 19 of the 26 occupations, so the broader pattern was one of slightly higher female ratings and not of male dominance in digital preference.

Type of institution produced a single significant difference. Respondents attached to public institutions rated ICT operations and user support technicians higher (M = 4.33, SD = 0.730) than respondents attached to private institutions (M = 4.06, SD = 0.808), t(333) = 1.99, p = .048, with a small to moderate effect (d = 0.34). This difference did not remain significant under the adjusted threshold, and one significant result among 26 tests is close to the 1.3 expected by chance at the .05 level, so it was treated as tentative. Public institutions supplied only 40 respondents, which made the estimate less precise than those for larger groups. Mean ratings were higher for public respondents in 13 of the 26 occupations, so no consistent advantage in either direction was evident. The comparisons across faculties, expertise, and age produced a much larger set of differences.

**Table 3** Mean Preference Ratings by Gender and by Type of Institution

| Occupation | Male M (SD) | Female M (SD) | t(333) | p | Public M (SD) | Private M (SD) | t(333) | p |
|---|---|---|---|---|---|---|---|---|
| Electro technology engineers | 4.21 (0.860) | 4.15 (0.742) | 0.64 | .520 | 4.18 (0.813) | 4.18 (0.793) | −0.01 | .992 |
| Digital marketing and strategy specialists | 4.19 (0.712) | 4.15 (0.749) | 0.53 | .599 | 4.10 (0.709) | 4.18 (0.737) | −0.65 | .520 |
| System engineers | 4.15 (0.732) | 4.17 (0.772) | −0.24 | .811 | 4.23 (0.768) | 4.16 (0.753) | 0.54 | .588 |
| Social media strategists | 4.15 (0.787) | 4.16 (0.801) | −0.11 | .914 | 4.08 (0.730) | 4.17 (0.803) | −0.71 | .481 |
| Development engineers | 4.08 (0.878) | 4.14 (0.756) | −0.67 | .505 | 4.10 (0.778) | 4.11 (0.815) | −0.09 | .931 |
| ICT operations and user support technicians | 4.11 (0.862) | 4.07 (0.757) | 0.43 | .670 | 4.33 (0.730) | 4.06 (0.808) | 1.99 | .048* |
| Online learning managers | 4.03 (0.836) | 4.12 (0.806) | −0.97 | .334 | 4.05 (0.749) | 4.08 (0.829) | −0.23 | .821 |
| Full stack engineers | 4.06 (0.846) | 4.09 (0.727) | −0.37 | .713 | 4.10 (0.744) | 4.08 (0.785) | 0.17 | .867 |
| Database and network professionals | 4.10 (0.847) | 4.05 (0.766) | 0.51 | .613 | 4.03 (0.862) | 4.08 (0.794) | −0.39 | .695 |

| Occupation | Male M (SD) | Female M (SD) | t(333) | p | Public M (SD) | Private M (SD) | t(333) | p |
|---|---|---|---|---|---|---|---|---|
| E-commerce specialists | 4.08 (0.886) | 4.06 (0.816) | 0.20 | .841 | 4.25 (0.707) | 4.04 (0.860) | 1.47 | .142 |
| Security management specialists | 3.98 (0.832) | 4.13 (0.661) | −1.80 | .073 | 4.03 (0.660) | 4.07 (0.753) | −0.34 | .733 |
| Information security analysts | 4.03 (0.840) | 4.04 (0.739) | −0.08 | .934 | 4.05 (0.677) | 4.04 (0.797) | 0.10 | .923 |
| Data engineers | 4.02 (0.857) | 4.06 (0.783) | −0.41 | .683 | 3.93 (0.656) | 4.06 (0.833) | −0.97 | .334 |
| Digital transformation specialists | 3.95 (n.r.) | 4.06 (0.796) | −1.17 | .245 | 3.98 (0.733) | 4.02 (0.839) | −0.30 | .764 |
| Database architects | 3.91 (0.960) | 4.07 (0.798) | −1.70 | .090 | 4.03 (0.768) | 4.00 (0.888) | 0.17 | .865 |
| Big data specialists | 4.02 (0.942) | 3.96 (0.807) | 0.66 | .513 | 4.08 (0.764) | 3.97 (0.880) | 0.70 | .485 |
| Data analysts and scientists | 3.92 (0.920) | 4.04 (0.728) | −1.33 | .184 | 4.03 (0.800) | 3.98 (0.820) | 0.33 | .742 |
| Software and applications developers | 3.90 (0.782) | 4.05 (0.659) | −1.92 | .056 | 4.03 (0.768) | 3.98 (0.712) | 0.40 | .687 |
| Process automation specialists | 3.91 (0.810) | 4.02 (0.788) | −1.26 | .207 | 4.00 (0.751) | 3.97 (0.805) | 0.23 | .821 |
| Robotics engineers | 3.93 (0.833) | 3.99 (0.852) | −0.63 | .527 | 3.85 (0.736) | 3.98 (0.857) | −0.91 | .362 |
| Blockchain developers | 3.83 (0.926) | 4.04 (0.797) | −2.23 | .027* | 3.90 (0.709) | 3.95 (0.879) | −0.36 | .717 |
| Internet of things specialists | 3.94 (0.887) | 3.95 (0.694) | −0.12 | .907 | 4.03 (0.620) | 3.93 (0.801) | 0.70 | .482 |
| Data warehousing specialists | 3.83 (0.934) | 4.01 (0.725) | −2.03 | .043* | 3.90 (0.810) | 3.94 (0.828) | −0.26 | .798 |
| Business intelligence analysts | 3.94 (0.899) | 3.90 (0.831) | 0.46 | .644 | 4.10 (0.778) | 3.89 (0.868) | 1.42 | .157 |
| Artificial intelligence and machine learning specialists | 3.83 (0.796) | 3.94 (0.734) | −1.38 | .168 | 4.03 (0.733) | 3.87 (0.766) | 1.17 | .242 |
| FinTech engineers | 3.69 (0.840) | 3.91 (0.709) | −2.64 | .009* | 3.80 (0.687) | 3.82 (0.787) | −0.13 | .897 |

*Note.* The groups were 144 male, 191 female, 40 public, and 295 private respondents. Occupations follow the order of Table 2. * $p < .05$. None of the starred results remained significant at the Bonferroni-adjusted threshold of .0019. n.r. means not reported

**Source:** Analysed by the researcher (2026)

Major of study was associated with significant differences for 15 of the 26 occupations, with F(3, 331) values from 2.78 to 7.55 and eta squared values from .025 to .064, which are small effects. The largest differences appeared for security management specialists ($F = 7.55$, $p < .001$), online learning managers ($F = 6.37$, $p < .001$), artificial intelligence and machine learning specialists ($F = 6.23$, $p < .001$), and system engineers ($F = 5.90$, $p < .001$). Eight of the 15 differences remained significant under the adjusted threshold. Eleven occupations showed no significant difference by major, namely big data specialists, FinTech engineers, data analysts and scientists, digital transformation specialists, digital marketing and strategy specialists, database and network professionals, ICT operations and user support technicians, database architects, development engineers, full stack engineers, and electro technology engineers. Two of the five most preferred occupations, electro technology engineers ($p = .740$) and digital marketing and strategy specialists ($p = .255$), did not differ by major, which suggests that their appeal was shared across faculties. No post hoc tests were run, so the specific faculties that differed could not be identified, and the mean plots in the appendices show the direction of each difference.

Area of expertise produced the strongest and most widespread differences. Twenty-four of the 26 occupations differed significantly across expertise groups, F(4, 330) values ranged from 2.69 to 24.80, and 22 of the 24 remained significant under the adjusted threshold. Effect sizes were larger than for any other grouping variable, with eta squared reaching .231 for information security analysts ($F = 24.80$), .201 for robotics engineers ($F = 20.73$), and .182 for blockchain developers ($F = 18.40$), and a median of .097 across the significant results. These three occupations, together with Internet of things specialists ($F = 13.28$, $\eta^2 = .139$), are technical roles whose appeal appears to depend heavily on professional background. Only FinTech engineers ($p = .275$) and online learning managers ($p = .497$) showed no significant difference by expertise. Because post hoc comparisons were not conducted, the results establish that expertise matters but not which fields prefer which occupations.

Age group was associated with significant differences for 18 of the 26 occupations, with eta squared values from .023 to .109, and 10 of these remained significant under the adjusted threshold. The largest differences appeared for e-commerce specialists ($F(3, 331) = 13.48$), business intelligence analysts ($F = 12.05$), blockchain developers ($F = 11.67$), and robotics engineers ($F = 10.94$). Eight occupations showed no significant difference by age group, namely artificial intelligence and machine learning specialists, software and applications developers, data warehousing specialists, data analysts and scientists, system engineers ($p = .057$), digital marketing and strategy specialists, database and network professionals, and electro technology engineers. Position was associated with significant differences for only five occupations, namely digital transformation specialists, $F(3, 331) = 4.34$, $p = .005$, online learning managers, $F = 4.54$, $p = .004$,

system engineers, F = 3.40, p = .018, business intelligence analysts, F = 3.42, p = .018, and process automation specialists, F = 2.71, p = .045. The effect sizes for position were small ($\eta^2$ from .024 to .040), and none of the five differences survived the adjusted threshold. Differences were therefore concentrated in the grouping variables that capture professional background and life stage and not in position, gender, or institution type.

**Table 4** One-way ANOVA Results by Major of Study, Area of Expertise, Age Group, and Position

| Occupation | Major F | p | Expertise F | p | Age F | p | Position F | p |
|---|---|---|---|---|---|---|---|---|
| Electro technology engineers | 0.42 | .740 | 2.69* | .031 | 0.97 | .408 | 0.26 | .858 |
| Digital marketing and strategy specialists | 1.36 | .255 | 4.20* | .002 | 1.36 | .254 | 0.40 | .757 |
| System engineers | 5.90† | <.001 | 5.31† | <.001 | 2.53 | .057 | 3.40* | .018 |
| Social media strategists | 3.92* | .009 | 8.90† | <.001 | 6.78† | <.001 | 0.67 | .573 |
| Development engineers | 2.11 | .099 | 7.92† | <.001 | 2.65* | .049 | 1.16 | .325 |
| ICT operations and user support technicians | 1.93 | .124 | 11.20† | <.001 | 6.44† | <.001 | 0.46 | .712 |
| Online learning managers | 6.37† | <.001 | 0.85 | .497 | 4.80* | .003 | 4.54* | .004 |
| Full stack engineers | 0.57 | .633 | 5.93† | <.001 | 4.45* | .004 | 0.25 | .863 |
| Database and network professionals | 1.50 | .215 | 7.90† | <.001 | 2.41 | .067 | 0.25 | .860 |
| E-commerce specialists | 4.57* | .004 | 8.74† | <.001 | 13.48† | <.001 | 1.02 | .384 |
| Security management specialists | 7.55† | <.001 | 5.48† | <.001 | 4.15* | .007 | 1.83 | .142 |
| Information security analysts | 5.68† | <.001 | 24.80† | <.001 | 5.10† | .002 | 0.49 | .692 |
| Data engineers | 5.24† | .002 | 8.94† | <.001 | 4.75* | .003 | 1.16 | .327 |
| Digital transformation specialists | 2.07 | .103 | 5.40† | <.001 | 4.87* | .003 | 4.34* | .005 |
| Database architects | 2.21 | .087 | 8.00† | <.001 | 8.69† | <.001 | 1.32 | .266 |
| Big data specialists | 2.19 | .089 | 11.22† | <.001 | 6.61† | <.001 | 0.39 | .758 |
| Data analysts and scientists | 0.72 | .540 | 10.17† | <.001 | 2.35 | .073 | 0.24 | .869 |
| Software and applications developers | 5.51† | .001 | 4.66† | .001 | 1.17 | .322 | 1.34 | .263 |

| Occupation | Major F | p | Expertise F | p | Age F | p | Position F | p |
|---|---|---|---|---|---|---|---|---|
| Process automation specialists | 5.71† | <.001 | 7.01† | <.001 | 10.45† | <.001 | 2.71* | .045 |
| Robotics engineers | 3.10* | .027 | 20.73† | <.001 | 10.94† | <.001 | 0.62 | .604 |
| Blockchain developers | 2.78* | .041 | 18.40† | <.001 | 11.67† | <.001 | 2.36 | .071 |
| Internet of things specialists | 3.71* | .012 | 13.28† | <.001 | 3.77* | .011 | 1.65 | .179 |
| Data warehousing specialists | 3.56* | .015 | 10.37† | <.001 | 1.26 | .287 | 0.46 | .710 |
| Business intelligence analysts | 3.16* | .025 | 11.70† | <.001 | 12.05† | <.001 | 3.42* | .018 |
| Artificial intelligence and machine learning specialists | 6.23† | <.001 | 10.70† | <.001 | 0.84 | .474 | 0.57 | .635 |
| FinTech engineers | 1.85 | .139 | 1.29 | .276 | 3.56* | .015 | 0.60 | .615 |

*Note.* Degrees of freedom were 3 and 331 for major of study, age group, and position, and 4 and 330 for area of expertise. Occupations follow the order of Table 2. * $p < .05$. † $p < .0019$ (.05 divided by 26).

**Source:** Analysed by the researcher (2026)

Across all 156 tests, 66 were significant at the .05 level, whereas about eight would be expected by chance if no true differences existed. Forty of the 66 remained significant under the Bonferroni-adjusted threshold, and all 40 came from the analyses by area of expertise, age group, and major of study. Gender, type of institution, and position therefore produced only tentative differences, while professional background and age produced differences that were robust to the adjustment. Effect sizes followed the same pattern, being largest for area of expertise and small for the remaining variables. The differences by expertise, age, and major also appeared across a wide range of occupations, which suggests that they reflect broad differences in orientation toward digital work and not isolated quirks in single items. Because the adjustment was applied after the main analyses, it is best read as a sensitivity check and not as the primary decision rule.

The uniformly high ratings suggest that respondents view digital occupations as attractive as a whole, and the ranking shows where that interest is strongest. The most preferred occupations are applied roles with visible everyday outputs, such as marketing, social media, systems, and engineering roles, whereas the least preferred are data-intensive and frontier-technology roles that respondents may seldom meet in their studies or daily lives. The composition of the sample supports this reading, since TEFL and TESOL, law, management, and finance accounted for more than nine in ten respondents by expertise, while information technology accounted for under a tenth by faculty. Familiarity may therefore explain part of the ranking,

although familiarity was not measured and the explanation remains an inference. The small gap between the highest and lowest means also implies that lower-ranked occupations are not rejected and are only comparatively less attractive. For curriculum planners, the more useful signal is the relative position of occupations and the groups that diverge, and not the absolute level of preference.

The ranking connects directly to evidence on employer demand for digital skills. Acemoglu et al. (2022) documented rapid growth in vacancies related to artificial intelligence in the United States and a shift in the skills requested in other postings, yet artificial intelligence and machine learning specialists ranked 25th of 26 occupations among the present respondents (M = 3.89). Herdiana and Nugrahanti (2025) identified big data analytics, artificial intelligence, blockchain, and robotic process automation as technological foundations of digital auditing, and they reported insufficient digital competency among practitioners. Respondents in the present data placed big data specialists, process automation specialists, and blockchain developers in the lower half of the ranking, at ranks 16, 19, and 21. These parallel patterns suggest that competency shortfalls in professional practice may be sustained partly by modest interest in the very occupations that the technologies create, although neither earlier study measured student preference and the comparison across settings is indirect. The finding therefore adds a supply-side observation to demand-side evidence, namely that rising demand for advanced data and automation skills does not guarantee strong preference among prospective entrants.

Technology acceptance research offers one way to read the same pattern. Firdausi and Antonio (2025) found that perceived usefulness significantly predicted the intention to use the QRIS payment standard among merchants in Surabaya, and they stressed training and support as conditions for wider adoption. Ly et al. (2024) reported significant links among motivation, perceived ease of use, perceived usefulness, and the adoption of digital learning platforms among 369 Cambodian university students. The uniformly favorable ratings in the present data are consistent with the positive orientation toward digital technology that Ly et al. (2024) observed in a similar population, and they extend that orientation from the adoption of learning platforms to the choice of digital occupations. The large differences by area of expertise and age are consistent with the emphasis that Firdausi and Antonio (2025) placed on training and support, since exposure and preparation plausibly shape how useful and attainable an occupation appears. Perceived usefulness and ease of use were not measured here, so these links are interpretive and would need direct testing in later work.

Evidence on gender is mixed in the literature, and the present results qualify the stronger claims. Pyrkosz-Pacyna et al. (2022) reported significant gender differences in how IT students and IT professionals perceived work in the IT sector, which would lead to an expectation of clear gender gaps in occupational preference. In the present data, gender differences reached significance for only three of 26

occupations, the effects were small, none survived adjustment for multiple comparisons, and female respondents gave the higher ratings. The direction of these differences is the reverse of what a male-dominated image of technology work would predict. Several explanations are possible, including a sample dominated by education, language, and law backgrounds in which female respondents were more numerous, an early stage of digital career formation in which gender typing may not yet be entrenched, and the difference between perceiving a sector and rating personal preference for a named occupation. These explanations are speculative because the data do not separate them, but they indicate that gender gaps in digital occupational preference should not be assumed to transfer across settings.

The findings carry practical implications for BIU and comparable institutions. The strong association between expertise and preference suggests that digital course offerings and career counseling should be differentiated by professional background and not delivered uniformly, with particular attention to data-intensive and frontier occupations in which interest is lowest. Age differences for roles such as e-commerce specialists and business intelligence analysts indicate that different age groups may need different guidance on entry routes and reskilling. Early exposure through practical projects, industry speakers, or short courses could be tested as ways to narrow the gap for lower-ranked occupations, although the present data do not show that such measures would work. From a theoretical standpoint, the findings can be read through technology acceptance and digital transformation perspectives but do not test them. Later work that measures perceived usefulness, ease of use, and self-efficacy alongside preference could show which mechanisms drive the differences, and replication with post hoc comparisons would identify which groups differ.

In summary, the results support, extend, and qualify earlier research. They support evidence from Cambodia that university students hold a favorable orientation toward digital technology (Ly et al., 2024). They are also consistent with the emphasis on training and support in Firdausi and Antonio (2025) and with the competency shortfalls noted by Herdiana and Nugrahanti (2025), because differences by expertise and age were large and robust, although the present data measure neither competency nor training. They extend labor market and technology acceptance studies by moving from the adoption of tools and the growth of vacancies to the preferences of prospective entrants, and by showing that interest is weakest in data-intensive and frontier occupations (Acemoglu et al., 2022; Firdausi & Antonio, 2025). They contradict, or at least qualify, the expectation of substantial gender differences drawn from Pyrkosz-Pacyna et al. (2022), because the few gender differences found were small, not robust, and favored female respondents. Whether this divergence reflects Cambodia's context, the composition of the sample, or the use of occupation-specific ratings cannot be determined from the present data. These classifications rest on a cross-sectional, self-reported, single-

institution sample and on comparisons across different constructs, so they should be treated as provisional.

## CONCLUSION

Preference for digital occupations among respondents at BIU was uniformly favorable, with mean ratings from 3.81 to 4.18 on a five-point scale and an average of 4.03. Electro technology engineers, digital marketing and strategy specialists, system engineers, social media strategists, and development engineers were the most preferred occupations, whereas FinTech engineers, artificial intelligence and machine learning specialists, business intelligence analysts, data warehousing specialists, and Internet of things specialists were the least preferred. Interest was therefore strongest for applied engineering, marketing, and communication roles and weakest for data-intensive and frontier-technology roles, even though the gaps between occupations were small. Group differences were concentrated in professional background and life stage, since area of expertise differed significantly for 24 of the 26 occupations, age group for 18, and major of study for 15. A substantial share of these differences remained significant after a Bonferroni adjustment. Gender, type of institution, and position produced only a few small differences that did not survive the adjustment, and the gender differences that appeared favored female respondents.

These conclusions should be read within several limitations. The data were self-reported ratings collected at one point in time from a single university, so the findings describe preferences in that community and cannot show what drives them or whether they translate into career entry. The sample leaned toward education, language, and law backgrounds, with relatively few respondents from information technology, and several comparison groups were small. Each comparison was run separately for each occupation, no correction was applied to the primary tests, and post hoc comparisons were not conducted, so the specific groups behind each difference remain unidentified. The questionnaire measured preference only and did not capture perceived usefulness, ease of use, self-efficacy, family influence, or salary expectations. No qualitative data were gathered to explain the patterns that the ratings revealed.

The findings suggest practical steps for BIU and for Cambodian higher education more broadly. Because expertise and age were the strongest correlates of preference, digital course offerings and career counseling may work better when they are differentiated by professional background and life stage than when they are delivered uniformly. Early exposure to data-intensive and frontier occupations, through practical projects, short courses, or industry engagement, could be piloted to raise familiarity with the lowest-ranked roles. Policymakers planning digital skills programs could also read student preference data alongside employer demand data, so that curricula respond to both sides of the labor market. Later research

should recruit multi-institution samples with balanced disciplinary representation, apply post hoc tests and corrections for multiple comparisons, measure the antecedents of preference that were absent here, and combine surveys with interviews. Following respondents after graduation would show whether the preferences recorded here predict actual entry into digital occupations.

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