Digital Transformation, Skills Gaps, and Digital Recruitment: Empirical Evidence from 220 Honduran Companies

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***Abstract*— Digital transformation and artificial intelligence (AI) are redefining the occupational profiles and competencies demanded by Latin American companies, yet empirical evidence in Central America remains scarce. This study analyzes the association between technological transformation, skills gaps, and digital recruitment in a non-probabilistic sample of 220 Honduran companies, concentrated in the western region and urban areas, using a quantitative, cross-sectional, descriptive-comparative design. A 15-item questionnaire covering three dimensions—skills gaps, recruitment and selection, and technological transformation—was administered, with reliability from acceptable to good (α = 0.789–0.851). Technological transformation obtained the highest rating (M = 2.75), highlighting the need for employee retraining (66.4% agreement). Main gaps reported were soft skills (57.3%) and digital/data-analysis skills (55.0%), while social media (34.5%) and job portals (25.9%) concentrated recruitment activity, versus marginal use of university-industry links (1.8%). The Kruskal-Wallis test showed no differences by economic sector, but did show differences by educational level, company size, and hiring intentions, all with small effect sizes. Under a high-agreement criterion (≥60%), only the hypothesis on profile modification and retraining (H2, 64.1%) was met; those on skills gaps (H1, 52.7%) and digital-channel use (H3, 55.5%) were not, though perceived usefulness of social media and digital portals individually reached 62.3%. These findings offer initial firm-level evidence on the convergence between technological innovation, emerging competencies, and digital recruitment in a Central American economy, with implications for university education, talent management, and regional-innovation policy*.

***Keywords*—** *digital transformation; skills gaps; digital recruitment; artificial intelligence; innovation and regional development; Honduran labor market.*

I. INTRODUCTION

Digital transformation and the incorporation of artificial intelligence (AI) into production processes are rapidly reshaping the occupational profiles, tasks, and competencies that companies require of their workforce. Recent international evidence has documented associations between corporate digitalization, the composition of employment, and the perception of jobs [1], [2], while simultaneously compelling organizations to redesign recruitment, training, and talent-management processes [3].

Although the international literature has documented associations among digital transformation, employment, competencies, and recruitment, empirical evidence remains limited on how these changes are perceived by Central American companies. In Honduras in particular, little information is available on skills gaps, the modification of job profiles, and the use of digital recruitment channels. This gap constrains the design of training, retraining, and university-industry linkage strategies.

In the Latin American context, and particularly in Honduras, this phenomenon overlaps with structural gaps in technical and digital training that hinder the filling of certain vacancies and that call for reskilling and upskilling strategies—dynamics that are relevant to examine through firm-level empirical evidence.

The objective of this article is to analyze how digital and technological transformation is associated with skills gaps and with recruitment and selection processes in a non-probabilistic sample of 220 Honduran companies, in order to descriptively evaluate three working hypotheses and to provide evidence that can inform skills training and the modernization of talent management in the country.

The contribution of the study is twofold. Conceptually, it integrates within a single empirical framework three dimensions that the literature usually addresses separately—skills gaps, recruitment and selection, and technological transformation—in dialogue with the propositions of skill-biased technological change and human-capital theory, which anticipate that technology adoption shifts demand toward higher-order digital and socio-emotional competencies. Empirically, it provides novel firm-level evidence for a small Central American economy with scarce prior coverage in the literature, identifies differences according to organizational characteristics, and derives implications for university education, talent management, employability policy, and regional innovation and entrepreneurship ecosystems.

The article is organized as follows: Section II presents the theoretical framework and the working hypotheses; Section III describes the methodology; Section IV presents the results; Section V develops the discussion; and Section VI presents the conclusions. The findings aim to contribute to the regional debate on innovation, talent development, and university-industry linkages in the face of technological change in the labor market.

II. THEORETICAL FRAMEWORK

A. Technological Transformation, Automation, and Artificial Intelligence in Employment

Taken together, recent evidence shows that digital transformation reconfigures tasks, job profiles, and talent-management processes, while increasing demand for digital, analytical, and socio-emotional competencies and requiring strategies for staff upskilling and retraining. The international literature has documented associations between corporate digital transformation, the composition of employment, and firm performance: studies of Chinese companies show that it is associated with the level and composition of the workforce [1] and with the efficiency of internal technological innovation [4], as well as with the firm's operational and financial performance [5]. At the same time, evidence warns that digitalization can displace low-skilled employment [6], underscoring that its distributive effects are not neutral. Research on worker perceptions shows that digital transformation reshapes job characteristics as experienced by employees themselves [2], and recent studies document how automation and artificial intelligence alter the evolution of jobs [7], [8], [9] and call for employee-centered rather than management-imposed technology adoption [10]. These processes consistently require explicit reskilling and upskilling strategies [11] and translate into documented changes in job performance associated with the digital era [12].

B. Skills Gaps and Digital Competencies

The mismatch between the competencies available and those demanded by companies (skills mismatch) is a widely documented phenomenon. Studies in transition economies show that skills mismatch affects urban employment even in local labor markets [13], [14], and the European tourism industry reports persistent gaps in staff digital and soft skills [15], [16]. Skills shortages have also been associated with a measurable cost: lower per-worker productivity in high-tech firms [17] and more limited digital capabilities in traditional industries facing technological disruption [18]. Several authors highlight the need for dynamic models to analyze these competencies against the labor market [19], the importance of strengthening essential 21st-century skills—communication, critical thinking, digital literacy—[20], [21], and the need to anticipate how changing task content demands new training and values on-the-job training [22]. Emerging proposals even explore blockchain-based frameworks for standardizing competencies [23], gamified upskilling programs [24], bibliometric analyses of staff digital competencies [25], and artificial intelligence to reduce supply-demand mismatch in technology labor markets [26].

C. Digital Recruitment and Talent Management

Digitalization is also transforming talent attraction and selection processes. In the Ibero-American context, the use and valuation of online job portals are already a central part of labor-market access in the digital society [27]. The digital transformation of talent management is associated with better sustainable job performance and more innovative behaviors [3], and recent technical literature explores recommendation systems based on natural-language processing [28] and on graphs [29] to match vacancies and candidates, as well as the use of artificial intelligence and machine learning in selection processes [30], [31]. Other studies document what hiring managers actually look for in entry-level profiles [32], the role of social media as a competitive recruitment tool [33], and the continued relevance of e-recruitment in emerging economies [34], [35], where infrastructure limitations and organizational capabilities condition its adoption.

D. Companies, Organizational Size, and Regional Development

The capacity for technology adoption and for structuring talent-management processes is not homogeneous across companies of different sizes or across regions. Evidence on the impact of digital transformation on business growth and performance suggests that this impact depends on each organization's internal capabilities rather than on access to technology per se [36]. Micro and small enterprises tend to face greater resource constraints for investing in digitalization and formal training programs, whereas medium and large companies have greater capacity to structure recruitment and selection processes. This organizational heterogeneity constitutes a relevant axis for interpreting the results obtained among the sampled companies. The availability of talent with digital and socio-emotional competencies is, moreover, a strategic capability for innovation and business scaling: in regional economies such as Honduras's, difficulties in filling vacancies and updating staff skills may limit technology adoption, productivity, and the capacity of companies—particularly MSMEs—to integrate into more competitive markets and to participate actively in local innovation and entrepreneurship ecosystems.

E. Conceptual Model

The literature reviewed suggests that technological transformation, skills gaps, and digital recruitment are not isolated phenomena but stages of a single process of organizational change. This reading is consistent with two complementary frameworks: the skill-biased technological change hypothesis, which holds that technology adoption increases the relative demand for higher-order digital and analytical competencies, and human-capital theory, which links skills gaps to the need for continuous investment in training and retraining. From this perspective, technological transformation is associated with changes in tasks and job profiles and with new competency requirements. When the available capabilities do not meet these requirements, gaps emerge that call for reskilling and upskilling strategies. In parallel, companies modify their recruitment channels and criteria to attract profiles compatible with new technological needs. Fig. 1 summarizes this process, which connects directly with the three working hypotheses proposed below. The conceptual model organizes the study's dimensions and proposes an interpretive sequence linking technological transformation, profile change, skills gaps, and digital recruitment; however, the cross-sectional design does not allow the causal direction among these dimensions to be tested, so the model guides the interpretation

of the results without constituting a causal model tested in this study.

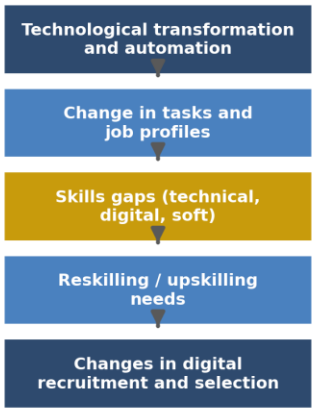


Fig. 1. Conceptual model of the digital transformation process and change in job competencies.

F. Working Hypotheses

From the conceptual model and the literature reviewed, three descriptive working hypotheses are proposed, each linked to a specific subset of instrument items (Section III.B). Because the high-agreement threshold (≥60%) constitutes a descriptive criterion rather than an inferential statistical test, the hypotheses are evaluated against this threshold rather than through formal statistical testing. Accordingly, H1–H3 are best understood as descriptive propositions or prevalence criteria—statements about the proportion of favorable responses observed in this sample—rather than as hypotheses in the inferential sense. Testing them as formal statistical hypotheses would require, at minimum, a prespecified benchmark, a corresponding significance test (e.g., a one-sample proportion test against the 60% cutoff), and confidence intervals around each observed agreement percentage; none of these is undertaken here, and the descriptive labels H1–H3 are retained for expositional convenience only:

H1 (skills gaps): participating companies report substantial gaps in the competencies required to fill available positions, particularly regarding work experience (E02.1), technical competencies (E02.2), and soft skills (E02.3).

H2 (technological transformation): participating companies perceive that technological transformation modifies job profiles (E07.2) and increases the need for employee reskilling (E07.4).

H3 (digital recruitment): participating companies use and perceive digital channels as relevant mechanisms for recruitment and selection, assessed through the average of items E03.1 and E03.2, related to the use of multiple channels and the usefulness of social media and digital portals. E03.1 and E03.2 are combined here because H3 concerns overall channel relevance rather than either behavior alone; both are also reported and interpreted separately in Sections IV.B and IV.D, where they diverge (48.6% versus 62.3%).

III. METHODOLOGY

A. Design and Sample

The study adopted a quantitative, non-experimental, cross-sectional, descriptive-comparative approach. A total of 220 questionnaires administered to Honduran companies were analyzed, distributed across different geographic regions, areas of operation (urban and rural), economic sectors, and organizational sizes. Non-probabilistic convenience sampling was used because of the accessibility of participating companies; therefore, the results describe the sample analyzed and are not intended to statistically represent the entirety of Honduran companies. Data were collected between February and April 2026.

The questionnaires were completed by business owners, general managers, human resource officers, and other executives familiar with the companies' recruitment and talent-management processes. Companies were contacted through students and research faculty, as well as through chamber-of-commerce and municipal databases. The questionnaire was administered in both digital and in-person format, depending on the access conditions of each area, with an approximate response time of seven to ten minutes. A total of 235 questionnaires were received; 15 were excluded due to duplication or incomplete responses prior to statistical processing, yielding a final database of 220 valid records. Duplication was identified by consulting the surveyors, who determined that the questionnaire had been sent twice to the same participants; the corresponding repeated submissions were removed prior to analysis.

Participation was voluntary. Participants were informed of the academic purpose of the study, and the confidentiality and aggregate treatment of the information were guaranteed. No institutional ethics-committee protocol number is reported here, as the survey involved no sensitive data or vulnerable populations and collected only aggregate organizational information under informed, voluntary consent. The anonymized item-level dataset underlying the analyses reported in this article is available from the corresponding author upon reasonable request.

B. Instrument

Items were developed based on a review of the literature on skills gaps, digital recruitment, and technological transformation (Section II), and organized into a 15-item questionnaire structured across three dimensions: (1) skills gaps (5 items, code E02), (2) recruitment and selection (5 items, code E03), and (3) technological transformation (5 items, code E07). Responses were recorded on a four-point Likert scale (1 = strongly disagree; 4 = strongly agree). For each item, the percentage of agreement (responses 3 and 4) was calculated and classified according to the criterion: high (≥60%), medium (45%-59.9%), and low (<45%). The 60% threshold was adopted as an operational criterion to identify a clear majority of favorable responses; this cutoff was used solely for descriptive purposes, both to classify items and to evaluate the working hypotheses (Section II.F), and it does not constitute a

criterion of statistical significance. The 60% cutoff was chosen to exceed a simple majority (>50%) by a margin signaling reasonably consistent agreement, following common survey-research convention rather than a formal power calculation. Because several percentages lie close to this cutoff (Section IV.D), classifications should be read as sensitive to it; a sensitivity analysis at nearby thresholds (55% and 65%), together with bootstrap confidence intervals for each hypothesis, was therefore conducted and is reported in Section IV.D. The instrument underwent review by five experts in methodology, business management, and human talent, who assessed the clarity, relevance, coherence, and sufficiency of the items; their observations were incorporated into the final version of the questionnaire prior to its administration. As a preliminary analysis, overall internal consistency was estimated on a random 30% subsample of the cleaned database (α = 0.965); in the complete sample, dimension-specific coefficients were calculated (Section III.C, between 0.789 and 0.851), considered more appropriate than a single coefficient given the multidimensional nature of the instrument. The expert review provided evidence of content validity, while Cronbach's alpha allowed internal consistency to be estimated. A post hoc exploratory factor analysis of the three-dimension structure was subsequently conducted and is reported, together with corrected item-total correlations, in Section III.D; its results offer only partial support for the intended structure and should not be equated with confirmatory validation. The high overall alpha obtained in the subsample should therefore be interpreted as preliminary evidence of internal consistency rather than sufficient proof of structural validity.

No selection quotas were applied by region, sector, or company size, which contributed to the territorial and urban concentration of the sample. No sensitive personal data or information intended to individually identify participants were collected.

C. Reliability

The internal consistency of each dimension was estimated using Cronbach's alpha coefficient, with the conventional criterion of $\alpha \geq 0.70$ as an acceptable threshold. All three dimensions exceeded this threshold (Fig. 2).

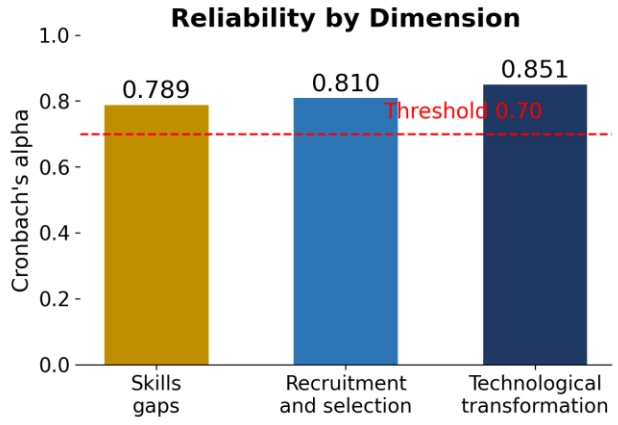


Fig. 2. Reliability (Cronbach's alpha) by dimension.

D. Structural Validity (Exploratory Factor Analysis)

To assess the three-dimension structure, an exploratory factor analysis (EFA, principal-axis, post hoc, N = 220) was conducted. Sampling adequacy was acceptable (KMO = 0.893; Bartlett's $\chi^2(105) = 1628.8$, $p < .001$). Retention criteria disagreed: Kaiser's rule suggested four factors, a parallel analysis against 1,000 random datasets supported only two (third eigenvalue 1.22 vs. random 95th percentile 1.34), and the a priori model specified three. A three-factor solution (promax rotation) was extracted for comparability with the instrument's design, explaining 63.6% of the common variance.

The rotated pattern offers partial support for the intended structure (the complete 15-item loading matrix and corrected item-total correlations are reported in Appendix A). Items E02.1-E02.3 and E07.3-E07.4 loaded cleanly on their intended factors (λ = 0.83-0.96), consistent with the skills-gaps and transformation dimensions. However, E07.1 loaded instead on the recruitment factor (λ = 0.76), and E02.4/E02.5 showed low communalities (0.245, 0.142) without a salient loading on any factor; E03.5 split weakly across two factors. Item-total correlations ranged from 0.30 (E02.5) to 0.75. Overall, the structure is workable but imperfect once E02.4, E02.5 and E07.1 are set aside; a confirmatory factor analysis on an independent, larger sample, and a review of these items, is recommended before further use of the instrument.

E. Statistical Analysis

Descriptive statistics were calculated by item and by dimension, with 95% confidence intervals. Dimension scores were compared across firm characteristics using the nonparametric Kruskal-Wallis test. Statistical significance was established at $p < 0.05$ across 18 global comparisons, and effect sizes were estimated using epsilon squared (ε^2; criterion: small < 0.06, medium 0.06-0.14, large > 0.14). No general correction for multiple comparisons was applied to these 18 global tests, so their results were interpreted as exploratory. For variables with significant global differences, post hoc comparisons were performed using Dunn's test, applying the Holm adjustment to pairwise p-values. Finally, the three hypotheses were evaluated descriptively against a single high-agreement percentage threshold (≥60%)—the same criterion already defined for classifying the instrument's items—by calculating, in all three cases, the average percentage of agreement of the specific items linked to each hypothesis (Section II.F). This procedure constitutes a descriptive synthesis criterion and not an inferential statistical test.

IV. RESULTS

A. Profile of Participating Companies

Table I summarizes, for each firm characteristic, the predominant category and its percentage of the total sample (N = 220). The variable “required educational level” refers to the educational level required by the company to fill its positions or vacancies, not to the educational level of currently employed staff; the category “not applicable” corresponds to companies that did not specify an educational requirement and should not

be interpreted as an additional educational level comparable to primary, secondary, university, or postgraduate (see also Section V).

TABLE I. FIRM PROFILE (N = 220)

Variable	Predominant category	%
Geography	Western region	56.4%
Area of operation	Urban	86.4%
Economic sector	Trade	35.9%
Company size	Large (151+)	32.3%
Reported vacancies	1-2	39.1%
Required educational level	Primary	43.2%
Hardest position to fill	Administrative	26.8%
Recruitment channel	Social media	34.5%
Future hiring	Yes	55.0%

The sample is concentrated in the western region (56.4%) and in urban areas (86.4%). The sector with the highest participation was trade, with 35.9%, followed by the "other" category, with 18.2%, and services, with 16.4% (Fig. 3). In terms of company size, the distribution was more balanced, with a predominance of large (32.3%) and small (30.0%) companies (Fig. 4).

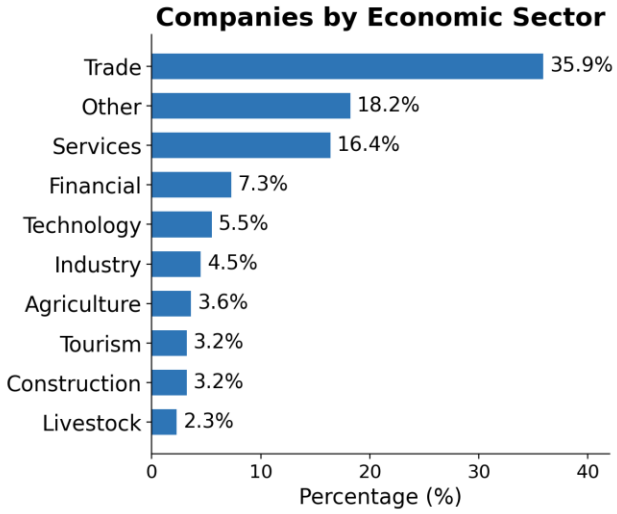


Fig. 3. Distribution of companies by economic sector.

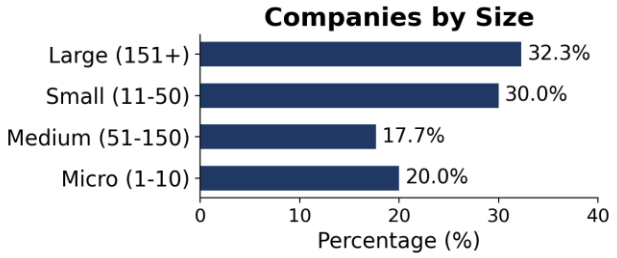


Fig. 4. Distribution of companies by size.

Regarding the number of available vacancies, 39.1% of companies reported between one and two vacancies, while 8.2% indicated that no vacancies currently exist. Administrative, sales, and managerial positions were the most frequently reported hard-to-fill occupational categories (26.8%, 21.8%, and 13.6%, respectively); although technological positions showed a lower frequency (5.0%), filling them may require specialized profiles, an aspect that should be explored further in future research (Fig. 5).

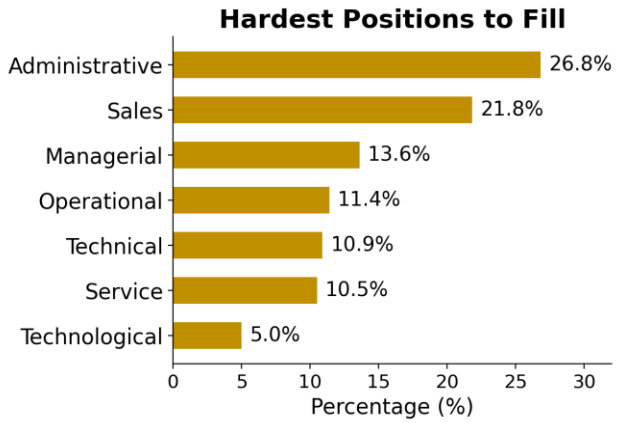


Fig. 5. Hardest positions to fill.

Social media (34.5%) and job portals (25.9%) were the main recruitment channels reported by participating companies, well above employment agencies (5.5%) and university links (1.8%), indicating that digital channels play a prominent role in talent-attraction processes (Fig. 6).

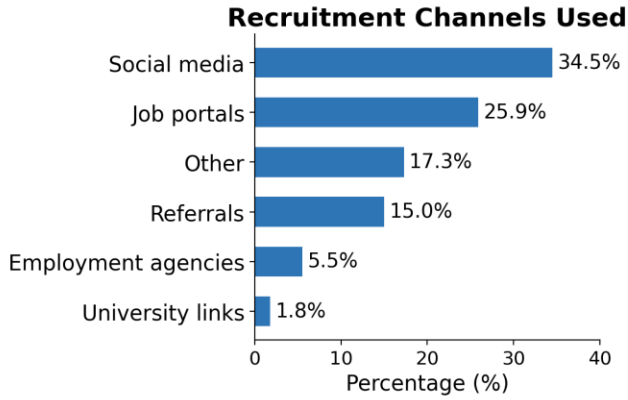


Fig. 6. Recruitment channels used.

B. Results by Dimension

Tables II-A and II-B present the code, wording, and percentage of agreement of the instrument's 15 items, as a reference for interpreting the figures in this section.

TABLE II-A. ITEM GLOSSARY: SKILLS GAPS AND RECRUITMENT

Code	Indicator assessed	%	95% CI
E02.1	Lack of experience	50.0%	43.4-56.6%
E02.2	Lack of technical competencies	50.9%	44.3-57.4%
E02.3	Lack of soft skills	57.3%	50.7-63.6%
E02.4	Digital and data skills	55.0%	48.4-61.4%
E02.5	English proficiency	32.3%	26.4-38.7%
E03.1	Use of multiple channels	48.6%	42.1-55.2%
E03.2	Usefulness of social media/portals	62.3%	55.7-68.4%

Code	Indicator assessed	%	95% CI
E03.3	Applications meet requirements	51.4%	44.8-57.9%
E03.4	Recording of the selection process	55.0%	48.4-61.4%
E03.5	Slower process due to profile mismatch	64.5%	58.0-70.6%

95% CI = Wilson score interval for the proportion of agreement (responses 3-4).

TABLE II-B. ITEM GLOSSARY: TECHNOLOGICAL TRANSFORMATION

Code	Indicator assessed	%	95% CI
E07.1	Use of platforms for vacancies	61.4%	54.8-67.6%
E07.2	Technology modifies profiles	61.8%	55.2-68.0%
E07.3	Automation transforms positions	60.5%	53.9-66.7%
E07.4	Need for employee retraining	66.4%	59.9-72.3%
E07.5	Difficulty in emerging occupations	58.2%	51.6-64.5%

95% CI = Wilson score interval for the proportion of agreement (responses 3-4).

Table III presents the mean, the 95% confidence interval (computed from the t-distribution as mean ± t-critical × standard error, with n − 1 degrees of freedom), and the reliability of each dimension, with increasing values from skills gaps (2.43) to technological transformation (2.75). Because the underlying items are ordinal, the median and interquartile range (IQR) of each dimension score are also reported as a distribution-free complement to the mean: skills gaps, Md = 2.40 (IQR 1.80-3.00); recruitment and selection, Md = 2.80 (IQR 2.20-3.20); technological transformation, Md = 2.80 (IQR 2.20-3.40). The medians and IQRs support the same ordering as the means and are used, rather than the means, wherever a distribution-free summary is preferable (e.g., the post hoc comparisons in Table V).

TABLE III. MEAN (95% CI) AND RELIABILITY

Dimension	Mean (95% CI)	Alpha	Level
Skills gaps	2.43 (2.32-2.53)	0.789	Acceptable
Recruitment and selection	2.64 (2.54-2.75)	0.810	Good
Technological transformation	2.75 (2.64-2.87)	0.851	Good

1) Skills gaps (M = 2.43): soft skills represented the most frequently reported competency gap (57.3%, medium-agreement range, close to the high threshold), followed by the need for digital and data-analysis skills (55.0%). English-language proficiency received the lowest level of agreement, at 32.3% (Fig. 7, top panel).

2) Recruitment and selection (M = 2.64): the most notable finding, classified as high agreement, was that selection processes became slower when candidates did not meet the required profile (64.5%). The perceived usefulness of social media and digital portals (62.3%, high agreement) shows that these channels occupy a relevant place in participating companies' talent-attraction processes (Fig. 7, middle panel).

3) Technological transformation (M = 2.75): technological transformation received the highest mean score among the three dimensions. Four of the five items reached or exceeded the high-agreement threshold (≥60%), while the item on difficulty in emerging occupations (58.2%) fell within the medium-agreement range, although close to the established threshold. The need for employee retraining (66.4%) was the most notable result of the entire study, followed by the recognition that technology modifies job profiles (61.8%) and that automation transforms existing positions (60.5%) (Fig. 7, bottom panel).

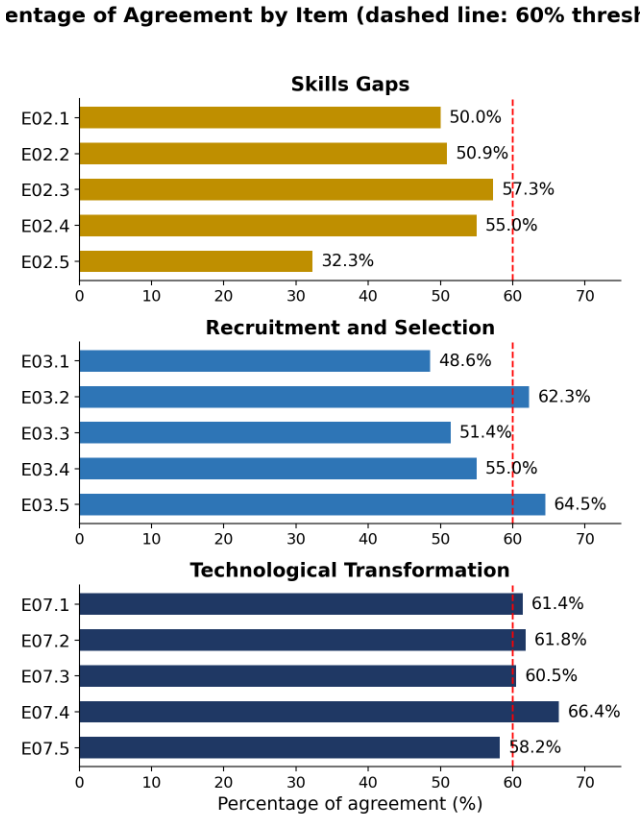


Fig. 7. Percentage of agreement by item, for skills gaps, recruitment and selection, and technological transformation. Dashed line: high-agreement threshold (60%).

C. Comparisons by Firm Characteristics

The Kruskal-Wallis test was applied to compare the scores of the three dimensions across the categories of six firm characteristics. Table IV presents the full Kruskal-Wallis statistics (H, degrees of freedom, sample size, effect size, and raw, Holm-, and FDR-adjusted p-values) for these 18 comparisons.

TABLE IV. KRUSKAL-WALLIS RESULTS BY VARIABLE AND DIMENSION, WITH MULTIPLE-COMPARISON CORRECTION

Comparison	H (df)	ε²	p raw / Holm / FDR
Sector × Gaps	4.06 (9)	-0.024	0.908 / 1.000 / 0.908
Sector × Recruitment	13.55 (9)	0.022	0.139 / 1.000 / 0.478
Sector × Transf.	10.50 (9)	0.007	0.312 / 1.000 / 0.510
Vacancies × Gaps	5.16 (5)	0.001	0.396 / 1.000 / 0.594
Vacancies × Recruitment	9.72 (5)	0.022	0.084 / 1.000 / 0.376
Vacancies × Transf.	1.62 (5)	-0.016	0.899 / 1.000 / 0.908
Hard-to-fill × Gaps	8.71 (6)	0.013	0.191 / 1.000 / 0.491
Hard-to-fill × Recruitment	7.84 (6)	0.009	0.250 / 1.000 / 0.500
Hard-to-fill × Transf.	4.67 (6)	-0.006	0.587 / 1.000 / 0.677
Company size × Gaps	1.86 (3)	-0.005	0.602 / 1.000 / 0.677
Company size × Recruitment	8.41 (3)	0.025	0.038 / 0.612 / 0.229
Company size × Transf.	2.07 (3)	-0.004	0.559 / 1.000 / 0.677
Educ. level × Gaps	16.55 (5)	0.054	0.005 / 0.093 / 0.049
Educ. level × Recruitment	6.20 (5)	0.006	0.287 / 1.000 / 0.510

Comparison	H (df)	ε²	p raw / Holm / FDR
Educ. level × Transf.	6.71 (5)	0.008	0.243 / 1.000 / 0.500
Future hiring × Gaps	1.42 (2)	-0.003	0.492 / 1.000 / 0.677
Future hiring × Recruitment	11.27 (2)	0.043	0.004 / 0.064 / 0.049
Future hiring × Transf.	3.67 (2)	0.008	0.159 / 1.000 / 0.478

H = Kruskal-Wallis statistic; df = k − 1; n = 220 for every comparison; ε² = (H − k + 1) / (n − k) (Tomczak & Tomczak, 2014). p-values: raw, Holm-, and FDR-adjusted. Under Holm, none of the 18 remain significant at α = .05; under FDR, two do (Educ. level × Gaps, p = .049; Future hiring × Recruitment, p = .049).

No statistically significant differences were identified across economic sectors, number of vacancies, or type of hard-to-fill position, in any of the three dimensions. There was insufficient statistical evidence to state that skills-gap, digital-recruitment, and technological-transformation scores differ across the economic sectors, vacancy levels, or position types represented in the sample.

Three statistically significant relationships were identified, all with small effect size according to the $\varepsilon^2 < 0.06$ criterion (Fig. 8): (a) company size was globally associated with recruitment and selection, $H(3) = 8.411$, $p = 0.038$, $\varepsilon^2 = 0.025$; (b) the required educational level was globally associated with skills gaps, $H(5) = 16.548$, $p = 0.005$, $\varepsilon^2 = 0.054$, the relationship with the largest effect size in the entire analysis; and (c) future hiring intention was globally associated with recruitment and selection, $H(2) = 11.271$, $p = 0.004$, $\varepsilon^2 = 0.043$. Because no global correction was applied to these 18 tests, the significant results are considered exploratory; Table IV reports, alongside the raw p-values, Holm- and FDR-adjusted values that confirm this caution empirically—none of the three relationships remains significant under the more conservative Holm adjustment, and only the required-educational-level/skills-gaps and future-hiring/recruitment relationships remain significant ($p = .049$ for each) under the less conservative FDR adjustment—even though the post hoc pairwise comparisons reported below were separately adjusted using the Holm procedure. For company size, these comparisons did not identify statistically distinct specific pairs. Table V summarizes the significant post hoc comparisons for required educational level and future hiring; the complete pairwise matrix for all three variables (24 comparisons) is reported in Appendix B.

TABLE V. DUNN POST HOC COMPARISONS WITH HOLM ADJUSTMENT

Variable	Significant comparison	Medians	Adj. p
Required educational level	Primary-Postgraduate	2.20-3.00	0.038
Required educational level	Secondary-Postgraduate	2.40-3.00	0.019
Required educational level	Postgraduate-Not applicable	3.00-2.40	0.038
Future hiring	Yes-No	2.80-2.40	0.018
Future hiring	Yes-Don't know	2.80-2.40	0.018

Md = median of each category compared; the sample size per future-hiring category, not disaggregated in Table I, was Yes = 121, No = 38, Don't know = 61 (N = 220). "Not applicable" is not a comparable educational level (Section V). Company size × Recruitment had no significant pairs; the complete 24-pair matrix is reported in Appendix B.

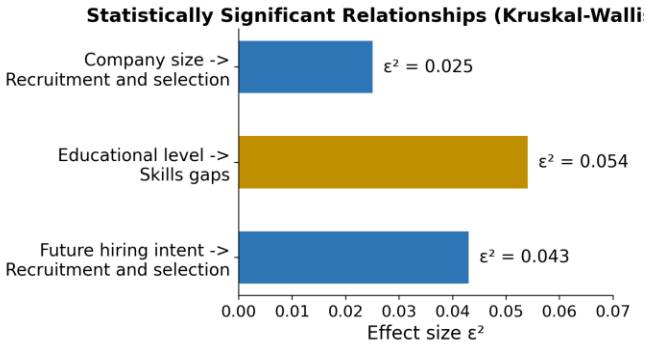


Fig. 8. Effect size (ε²) of statistically significant relationships.

D. Descriptive Evaluation of the Hypotheses

Hypotheses were evaluated using a descriptive high-agreement criterion, defined as an average equal to or greater than 60% on the items linked to each hypothesis; this procedure is not equivalent to an inferential statistical test. Table VI compares the observed value for each hypothesis against this threshold.

TABLE VI. DESCRIPTIVE EVALUATION OF THE HYPOTHESES (THRESHOLD ≥60%)

Hyp.	Dimension evaluated	Observed	Descriptive criterion
H1	Skills gaps	52.7%	Criterion not met
H2	Technological transformation	64.1%	Criterion met
H3	Digital recruitment	55.5%	Criterion not met

Single high-agreement threshold (≥60%), Section III.B.

H1 was evaluated using the average of items E02.1, E02.2, and E02.3 (52.7%); H2 using the average of items E07.2 and E07.4 (64.1%); and H3 using the average of items E03.1 (48.6%) and E03.2 (62.3%), with a result of 55.5%. Only H2 met the predefined high-agreement criterion; H1 and H3 did not, although in H3 the perceived usefulness of social media and digital portals (E03.2, 62.3%) individually reached a high level of agreement, unlike the use of multiple channels (E03.1, 48.6%), which fell within the medium-agreement range.

To assess how sensitive these conclusions are to the specific 60% cutoff, each hypothesis's composite percentage was bootstrapped (5,000 resamples) and reclassified at two alternative thresholds, 55% and 65%. H1's interval (47.3%-58.2%) stays below 60% throughout, confirming "not met." H2's interval (58.6%-69.3%) would no longer be classified as "met" at 65%. H3's interval (49.8%-61.1%) spans the 60% cutoff and flips to "met" at 55%, making it the most threshold-dependent of the three.

V. DISCUSSION

The results show that participating companies recognize technological changes in job profiles and recruitment processes, although the intensity of these perceptions varies across dimensions and organizational characteristics. Given the non-probabilistic sampling used, these conclusions refer to the

sample analyzed and should not be generalized to the country's companies as a whole. Likewise, although statistically significant differences were identified for three firm characteristics, effect sizes were small in all cases ($\varepsilon^2 < 0.06$), so their practical relevance should be interpreted with caution throughout this discussion.

First, technological transformation was the dimension with the highest score and the greatest reliability ($\alpha = 0.851$), consistent with international literature linking corporate digitalization to employment and job perception [1], [2] and to improvements in innovation and organizational performance [5], [4]. The need for retraining—the item with the highest agreement in the entire instrument (66.4%)—coincides with automation studies documenting how it transforms the evolution of jobs without necessarily eliminating them [7], [8], [9], although it can displace lower-skilled employment if not accompanied by retraining [11], [6].

Second, the combination of soft, technical, and digital skills as the main gaps is consistent with the skills mismatch documented in local labor markets and transition economies [13], [14], and with digital gaps in customer-service-intensive sectors [15], [16]. Skills shortages have been associated with lower productivity in affected firms [17] and with more limited adaptation among traditional industries [18], reinforcing the importance of addressing the hardest-to-fill positions, in line with the value of training when job content changes [22]. Unlike other contexts where English is often a significant gap, here it was the indicator with the lowest agreement, suggesting it was perceived as less cross-cutting than soft and digital skills.

Third, the predominance of social media and job portals, together with evidence that selection slows when candidates do not meet the required profile, is consistent with the literature on the digitalization of talent management [3] and with Ibero-American studies on online job portals [27]. Emerging proposals—natural-language-based recommendation [28] and graph-based recommendation [29], and AI in selection [30], [31]—point to a more advanced digitalization of recruitment than that reported here. Strengthening profile definition, in line with what hiring managers look for [32], could reduce hiring times.

One of the findings with the greatest potential contribution is that only 1.8% of participating companies reported university links as a recruitment channel, far below social media (34.5%) and job portals (25.9%). This limited use suggests that university-industry recruitment mechanisms remain underdeveloped among the participating companies, and opens a concrete opportunity to strengthen university-industry linkages through actions such as university job boards, employability fairs, labor observatories, internship programs, short courses and microcredentials, business participation in curriculum design, and digital labor-intermediation systems that directly connect the academic offer with corporate demand for competencies.

Fourth, company size showed a global difference without identifiable specific pairs (Table IV); moreover, this global difference itself does not survive a Holm correction across the 18 comparisons tested (Table IV), so it should not be treated as a robust finding independent of the specific comparisons examined here. Differences in skills gaps by educational level were indeed located in specific pairs, concentrated among companies requiring staff with postgraduate education (Md = 3.00; n = 10) versus primary or secondary education. The comparison with "not applicable" is reported for statistical completeness but is not interpreted as a difference between comparable educational levels. This result may relate to the greater specialization of the required profiles, although the small number of companies in the postgraduate category (n = 10) calls for additional caution. This relationship remains significant under FDR but not Holm correction ($p = .093$; Table IV).

Fifth, the differences observed by future hiring intention indicate that companies planning to add staff show a higher valuation of their recruitment and selection processes, distinguishing themselves both from those that do not plan to hire and from those that have not yet decided (with no difference between these last two). This result may reflect that such organizations are more actively engaged in candidate search, use of digital channels, and application management; however, given the small effect size, it should be interpreted as an exploratory trend within the sample analyzed; like the educational-level result, it survives FDR but not Holm correction ($p = .064$; Table IV).

Sixth, the fact that administrative, sales, and managerial positions concentrate the greatest filling difficulties—although technological positions, with a lower frequency (5.0%), may require more specialized profiles—without sufficient statistical evidence of differences across economic sectors, suggests that the mismatch between training and corporate demand is not limited to a particular sector in the sample analyzed, as has been documented in other transition economies [14], [19], [21]. This absence of significant differences should, however, be interpreted with caution: several sectors had very small subsamples (financial, 7.3%; technology, 5.5%; agriculture, 3.6%; tourism and construction, 3.2% each; livestock, 2.3%), so the null result may partly reflect low statistical power rather than genuine homogeneity across economic sectors.

Finally, the fact that only H2 met the descriptive high-agreement criterion, in contrast to the fact that H1 and H3 did not meet this predefined criterion, suggests that participating companies recognize the need for technological transformation and employee reskilling—consistent with the upskilling and reskilling programs documented in the literature [11], [24]—more clearly than the specific magnitude of their own skills gaps or the robustness of their digital recruitment processes overall. In the case of H3, the result combines a medium-agreement level in the use of multiple channels (E03.1, 48.6%) with a high-agreement level in the perceived usefulness of social media and digital portals (E03.2, 62.3%), suggesting that companies value these channels once they are already using them, but have not yet broadly diversified their recruitment mechanisms. This pattern, together with the greater dispersion of responses on skills-gap items (experience, technical competencies, soft skills) compared with the other two

dimensions, is consistent with what has been reported on job performance in the digital era [12] and with the role of artificial intelligence in reducing the talent supply-demand mismatch [26].

A. Implications for Universities, Companies, and Public Policies

For universities, the results suggest it would be worthwhile to update academic programs with an emphasis on soft skills, data analysis, and digital competencies, and to actively expand the university-industry linkage channels described above, given their currently very low use (1.8%) [20], [25], [21].

Although the post hoc analysis did not identify specific differences by company size, the literature indicates that micro and small enterprises face greater resource constraints [36] and could benefit from shared programs and low-cost certifications, while medium and large companies could implement formal diagnostics and more structured digital recruitment systems [23], [34], [33], [35].

For government and technical-training bodies, the findings support the relevance of promoting accessible technical certifications for MSMEs, as well as public information systems on the competencies demanded by the business sector, which can facilitate evidence-based employability policy design.

As limitations, the sample was non-probabilistic, concentrated in urban companies in the western region, so the results describe the sample analyzed and should not be generalized. The information came from a single informant per company (possible perception bias, e.g., over-rating channels the company already uses)—and the uneven distribution across sectors limits sectoral comparison. The dataset does not record respondent role, so its distribution cannot be reported; likewise, duplicate submissions were identified by consulting the surveyors rather than through a company identifier (Section III.A) and could not be independently re-verified from the data. The data are self-reported and cross-sectional, precluding causal relationships; the significant effect sizes were always small, and the 18 uncorrected global tests call for interpretive caution. Finally, the post hoc exploratory factor analysis reported in Section III.D offers only partial support for the three-dimension structure, so a confirmatory factor analysis on an independent, larger sample is still needed.

VI. CONCLUSIONS

In the sample analyzed, companies perceive that technological transformation is closely linked to changes in job profiles and to a greater need for employee reskilling. The most frequently reported gaps involved soft skills and digital and data-analysis competencies, while administrative, sales, and managerial positions presented the greatest hiring difficulties; technological positions, though less frequently mentioned, may require more specialized profiles that merit further study. Digital channels—particularly social media and job portals—play a prominent role in attracting candidates, whereas university linkage remains marginal. Because of the non-probabilistic sampling and the territorial and urban concentration of the sample, these results describe the participating companies and should not be generalized to Honduran companies as a whole.

Technological transformation was the most highly rated and most reliable dimension in the study, and the hypothesis related to profile modification and employee reskilling (H2, 64.1%) met the predefined high-agreement criterion. By contrast, neither the skills gaps assessed in H1 (52.7%) nor the use of digital recruitment channels assessed in H3 (55.5%) met this criterion, although in H3 the perceived usefulness of social media and digital portals individually reached a high level of agreement (62.3%). This pattern suggests that, while companies recognize the need for technological transformation, their perceptions of their own talent gaps and the diversification of their recruitment channels remain more moderate and heterogeneous.

Overall, the findings suggest that the participating Honduran companies recognize the effects of technological transformation on job profiles and employee reskilling needs; however, perceptions of skills gaps and the diversification of digital recruitment channels remain moderate and heterogeneous. Strengthening university-industry collaboration, competency observatories, microcredential programs, and accessible reskilling initiatives may improve firms' capacity to adapt to technological change and participate more effectively in regional innovation and entrepreneurship ecosystems. Future research should extend the sample to other regions and sectors, incorporate multiple informants per company, employ probabilistic sampling, assess the factorial validity of the instrument, and adopt longitudinal designs capable of tracking the evolution of competencies and recruitment processes over time.

APPENDIX

A. Complete Factor Loading Matrix and Item-Total Correlations

Table VII reports the full three-factor promax-rotated loading matrix underlying the exploratory factor analysis summarized in Section III.D (N = 220, KMO = 0.893, Bartlett's $\chi^2(105) = 1628.8$, $p < .001$, 63.6% cumulative variance), with each item's communality and corrected item-total correlation.

TABLE VII. THREE-FACTOR PROMAX-ROTATED LOADING MATRIX (N = 220)

Item	F1 (Recruit.)	F2 (Gaps)	F3 (Transf.)	Communality	Item-total r
E02.1	-0.050	0.955	-0.081	0.921	0.733
E02.2	-0.043	0.956	-0.093	0.925	0.715
E02.3	-0.113	0.852	0.062	0.742	0.615
E02.4	0.117	0.410	0.253	0.245	0.513
E02.5	0.288	0.241	-0.030	0.142	0.302
E03.1	0.730	0.029	0.070	0.538	0.650
E03.2	0.810	0.114	-0.158	0.694	0.624
E03.3	0.712	-0.017	-0.023	0.508	0.518
E03.4	0.891	-0.085	-0.126	0.816	0.637
E03.5	0.347	0.310	0.244	0.276	0.559
E07.1	0.760	-0.253	0.210	0.685	0.525
E07.2	0.366	-0.132	0.647	0.569	0.754
E07.3	-0.016	-0.124	0.930	0.880	0.721
E07.4	-0.023	-0.029	0.895	0.803	0.732
E07.5	-0.228	0.215	0.831	0.789	0.600

F1, F2, F3 = extracted factors, labeled post hoc by dominant intended dimension. Salient loadings ($|\lambda| \geq 0.40$, Section III.D): E02.1–E02.3 and E07.3–E07.4 load cleanly on their intended factors; E07.1 loads on the recruitment factor (F1) instead; E02.4/E02.5 show low

communalities without a salient loading; E03.5 splits across F1/F2. Item-total r = corrected item-total correlation within the item's intended dimension.

B. Complete Pairwise Post Hoc Comparisons (Dunn's Test, Holm Adjustment)

Table VIII reports all 24 pairwise post hoc comparisons (Dunn's test, Holm-adjusted p, within each variable's family) for the three firm characteristics with a significant global Kruskal-Wallis test (Table IV). The five significant pairs from Table V are reproduced here with the nineteen non-significant pairs.

TABLE VIII. COMPLETE PAIRWISE COMPARISONS ACROSS THREE VARIABLES (24 PAIRS)

Variable / Dimension (n pairs)	Comparison: adj. p (Holm)
Company size × Recruitment (6)	Large-Medium: 1.000; Large-Micro: 0.226; Large-Small: 0.064; Medium-Micro: 0.527; Medium-Small: 0.333; Micro-Small: 1.000
Educ. level × Gaps (15)	Prim-Sec: 1.000; Prim-Tech: 0.635; Prim-Undergrad: 0.996; Prim-Postgrad: 0.038; Prim-N/A: 1.000; Sec-Tech: 0.299; Sec-Undergrad: 0.996; Sec-Postgrad: 0.019; Sec-N/A: 1.000; Tech-Undergrad: 1.000; Tech-Postgrad: 0.635; Tech-N/A: 0.635; Undergrad-Postgrad: 0.377; Undergrad-N/A: 0.996; Postgrad-N/A: 0.038
Future hiring × Recruitment (3)	No-Don't know: 0.783; No-Yes: 0.018; Don't know-Yes: 0.018

Adj. p = Holm-adjusted p (Dunn's test). Abbreviations: Prim = Primary, Sec = Secondary, Tech = Technical, Undergrad = Undergraduate, Postgrad = Postgraduate, N/A = Not applicable (not a comparable educational level, Section V). Significant pairs (adj. p < .05, Table V): Prim-Postgrad (.038), Sec-Postgrad (.019), Postgrad-N/A (.038); No-Yes (.018), Don't know-Yes (.018). Category ns: company size — Micro 44, Small 66, Medium 39, Large 71; future hiring — Yes 121, No 38, Don't know 61 (N = 220).

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