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Mapping ICT Skills Polarisation: A Four-Regime Typology of Basic versus Above-Basic Competency Gaps Across 49 Countries

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ABSTRACT

Digital transformation has elevated ICT skills to a foundational capability for economic participation and social inclusion, yet existing frameworks rarely examine the internal structure of digital competencies. This study addresses that gap by constructing an empirically grounded four regime typology of ICT skills polarisation based on the relative prevalence of basic versus above basic communication and collaboration competencies across 49 countries. Drawing on the ITU ICT_SKLS_COM_CB indicator, the analysis integrates descriptive inequality metrics (Gini coefficient, median absolute deviation, interquartile range, and a composite inequality index), principal component analysis, and dual clustering algorithms (K-means and hierarchical Ward). Results reveal a pronounced structural polarisation: above basic skills are, on average, 4.63 times more prevalent than basic skills, with an absolute gap of approximately 53 percentage points. Principal component analysis confirms that this basic-versus-above-basic contrast constitutes the dominant axis of cross country variation, explaining 88.51% of total variance. The resulting four regime typology Low inequality (1 country), Moderate inequality (3 countries), High inequality (16 countries), and Very high inequality (29 countries) is robust across clustering algorithms (Adjusted Rand Index = 0.853) and multiple validation criteria. Critically, 91.8% of countries exhibit large positive gaps, indicating that structural polarisation rather than uniform skill scarcity is the prevailing global pattern. The typology offers policy-makers a regime specific diagnostic tool and informs higher education curriculum design by demonstrating the inadequacy of average attainment metrics for capturing digital skills inequality.

Keywords: ICT Skills, Digital Inequality, Skills Polarisation, Basic Versus Above basic Competency, Four-regime Typology, Principal Component Analysis, Cluster Analysis, Communication and Collaboration, Digital Transformation

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1. Introduction

The rapid advancements of digital technology, including automation, artificial intelligence (AI), big data, cloud computing, robotics, and the Internet of Things (IoT), have profoundly impacted organizations [1, 2, 3]. These technologies enable organizations to process, archive, and access information at an unprecedented scale, facilitate real time data analysis, and improve productivity, efficiency, and quality [2] [Ivaldi S]. Such advancements drive digital transformation (DT), defined as the process of improving organizations "by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies" [4]. Organizations across sectors undergo DT as they adopt new digital technologies to redefine value propositions for stakeholders and to optimize or develop digital strategies, structures, processes, and operations [1, 5].

The rapid adoption of the Internet has revolutionized many aspects of daily life, from patterns of social interaction to employment opportunities and the ways in which individuals search for information. This shift has produced a surge of online content, making it increasingly difficult to locate reliable facts [6, 7]. Concurrently, technological evolution has reshaped pedagogical and academic criteria, requiring curriculum designers to ensure that students acquire abilities aligned with labour market expectations [8, 9].

In the 21st century, digital literacy has emerged as a crucial competency for students, particularly in higher education, where it is essential for navigating complex digital environments. Many universities continue to struggle to establish technological solutions that effectively support the development of digital literacy an important enabler of academic success and future employability. Universities face mounting pressure to pursue digital transformation in order to strengthen internationalisation, competitiveness, digital culture, global mobility, and the democratisation of knowledge [10, 11, 12].

Digital competence is recognised as one of the basic key competences required for digital learning and employ ability. Consequently, its acquisition and systematic development should feature prominently on the agendas of higher education institutions (HEIs) that seek to prepare students for an ever faster evolving digital labour market. Nevertheless, a valid instrument capable of helping HEIs measure digital competence with sufficient precision and integrate it into pedagogical and organisational practices remains underdeveloped [13].

In response to this need, Lucas provided a valid and reliable instrument for measuring higher education students' digital competence, grounded in the European Digital Competence Framework for Citizens (DigComp) [13]. Parallel efforts in the professional domain have centred on the Skills Framework for the Information Age (SFIA). The SFIA framework is widely adopted by educational institutions and ICT industries because it supplies detailed ICT skills profiles that can serve as a valuable resource for student career planning. However, students currently lack practical methods for aligning the competencies they acquire during their education programmes with the skills defined in SFIA. V. Shankararaman [14] has proposed a solution model that generates a skills report based on an individual's competencies and experiences.

Despite these advances, there is still no consensus on the specific skill sets required for successful digital transformation. Although numerous scientific articles and models address the skills needed for DT, existing frameworks do not cover all essential competencies. This shortcoming arises largely because much of the extant research has focused narrowly on digital skills [15, 16] and has therefore overlooked other crucial capabilities necessary for exploiting the full potential of digital transformation [17, 18].

These measurement and conceptual gaps have tangible consequences. Rawal DM, for example, has examined critical issues within the Indian education system and contributed to efforts aimed at preventing the widening of the second and third digital divides in schools, thereby supporting progress toward UN Sustainable Development Goals 4 and 10 [19]. Collectively, the literature underscores both the urgency of developing robust approaches to assess and classify ICT competencies and the persistent challenge of understanding how basic and more advanced digital skills are distributed across populations and countries.

2. Research Problem and Statement

Digital transformation has elevated ICT skills from a specialised technical requirement to a foundational capability for economic participation, social inclusion and organisational competitiveness. While global discourse often emphasises overall digital skill shortages, far less attention has been paid to the internal structure of those skills specifically the relative prevalence of basic versus more advanced (above basic) competencies within and across countries.

Existing measurement frameworks (DigComp, SFIA and related instruments) and most cross country indicators treat digital skills as a single continuum or focus on average attainment. Consequently, they obscure a critical pattern: many countries exhibit a pronounced polarisation in which above basic ICT skills are widespread while basic skills remain scarce, or vice versa. This polarisation constitutes a distinct form of digital inequality that is not captured by conventional Gini coefficients of income or by simple mean skill scores.

The absence of a systematic, comparative typology of this basic versus above basic competency gap limits both academic understanding and policy design. Without such a typology, it remains unclear whether observed cross country differences reflect uniform skill deficits, structural polarisation, or heterogeneous regimes of digital skill distribution. The present study addresses this gap by analysing the ICT_SKLS_COM_CB indicator (communication and collaboration skills) for 49 countries and constructing an empirically grounded four-regime classification of ICT skills inequality.

Problem Statement: There is currently no robust, data driven typology that classifies countries according to the magnitude and direction of the gap between basic and above basic ICT skill prevalence. As a result, researchers and policymakers lack a clear analytical framework for understanding the structure of digital skills inequality and for designing targeted interventions that address polarisation rather than merely raising average skill levels.

This study conceptualises ICT skills inequality as a multidimensional phenomenon comprising cross country dispersion and within country polarisation between basic and above basic competency prevalence.

2.1 Research Gap

Prior work has advanced digital competence frameworks and has documented overall digital divides. However, three specific gaps remain:

• Conceptual: Most studies treat ICT skills as a unidimensional construct and therefore do not theorise or measure the internal disparity between basic and advanced competencies.

• Empirical: Cross country analyses rarely decompose skill prevalence into basic versus above basic categories or quantify the resulting gap with inequality metrics (Gini, MAD, IQR) and multivariate techniques.

• Typological: To the best of our knowledge, few cross country studies have systematically classified countries according to the joint distribution of basic and above basic ICT competencies.

This study fills these gaps by combining descriptive inequality metrics, principal component analysis, and dual clustering algorithms to produce a four regime typology of basic versus above basic ICT competency gaps.

2.2 Research Objectives and Questions

Primary Objective: To map and classify cross country patterns of polarisation between basic and above-basic ICT skill prevalence, and to derive a robust four regime typology of ICT skills inequality.

Specific Objectives

1. Quantify the absolute and relative prevalence of basic versus above basic ICT skills (communication and

collaboration) across 49 countries.

2. Measure cross country and within country inequality in these two competency levels using Gini coefficients, median absolute deviation (MAD), interquartile range (IQR) and a composite ICT Skills Inequality Index.

3. Reduce the two dimensional competency space via principal component analysis (PCA) and identify the dominant axis of variation.

4. Cluster countries into four interpretable inequality regimes using K-means and hierarchical (Ward) clustering, and validate the solution with multiple internal criteria and the Adjusted Rand Index.

5. Characterise each regime by its mean basic prevalence, above basic prevalence and competency gap, thereby providing an actionable typology for research and policy.

Research Questions

- RQ1. What is the magnitude and distribution of the gap between basic and above basic ICT skill prevalence across the 49 countries

- RQ2. Do basic and above basic skills exhibit different patterns of relative and absolute cross country inequality

- RQ3. What is the dominant source of variation in the two dimensional competency space, and how many distinct inequality regimes emerge from unsupervised clustering

- RQ4. How robust is the resulting four regime typology across alternative clustering algorithms and validation metrics

2.3 Conceptual Framework

The study is guided by an integrated conceptual framework that links three theoretical strands:

2.3.1 Digital Competence Continuum Drawing on DigComp and related frameworks, ICT skills are conceptualised as a continuum ranging from basic operational and communicative activities to more advanced, collaborative and creative uses. The present analysis operationalises this continuum as two discrete prevalence measures Basic and Above basic derived from the ITU activity based indicator ICT_SKLS_COM_CB.

2.3.2 Skills Polarisation and Inequality Building on literature on digital divides and skills polarisation, the framework posits that the absolute difference (gap) between above basic and basic prevalence constitutes a meaningful dimension of digital inequality. This gap may be large and positive (high above basic, low basic), large and negative (high basic, low above basic), or near zero. Inequality metrics (Gini, MAD, IQR) and a composite index are used to quantify both the cross-country dispersion of each skill level and the within country polarisation.

2.3.3 Typological Approach to Cross-Country Variation Rather than treating countries as points on a single continuum, the framework adopts a configurational logic: countries can be grouped into distinct regimes characterised by similar combinations of basic prevalence, above basic prevalence and gap size. Principal component analysis identifies the dominant axis of this configuration space; unsupervised clustering (K-means and hierarchical Ward) recovers discrete regimes. The resulting typology is interpreted as a set of ideal typical patterns of ICT skills polarisation.

2.4 Significance of the Study

The study contributes to theory by demonstrating that digital skills inequality is not solely a matter of overall scarcity but also of structural polarisation between competency levels. Methodologically, it illustrates the value of combining inequality metrics with PCA and dual clustering for typological research in comparative digital skills studies. Practically, the four regime typology offers policymakers a concise diagnostic tool:

countries in the Very high inequality regime require strategies that address the scarcity of basic skills even when advanced skills appear abundant, whereas countries in the Low or Moderate regimes face different developmental priorities. The findings also inform higher-education and curriculum design debates by highlighting that raising average digital competence is insufficient if the distribution between basic and above basic skills remains highly skewed**.**

3. Dataset Description: ICT Skills in Communication and Collaboration

This dataset, sourced from the International Telecommunication Union (ITU) and accessible via the World Bank Data360 platform, provides cross-country comparative data on the proportion of individuals possessing specific information and communication technology (ICT) skills related to communication and collaboration. The indicator, identified as ICT_SKLS_COM_CB, is a critical metric for assessing digital literacy and participation in the digital economy.

3.1 Definition and Measurement:
The core variable measures the percentage of individuals within a given population who have undertaken activities related to "Communication and collaboration" within the last three months preceding the survey. The measurement is activity based rather than skill based, capturing practical application. Importantly, the definition is device agnostic, meaning it includes activities performed on any device (e.g., personal computers, smartphones, tablets) capable of performing the function.

The dataset captures a composite skill, as individuals may have performed multiple activities. Consequently, an individual who engaged in several of the defined collaborative activities is considered to possess multiple related ICT skills. The precise set of activities defining this indicator (e.g., sending emails, participating in video conferences, using collaborative work platforms) would be detailed in the original ITU methodology documentation referenced by the source.

3.2 Geographic and Temporal Coverage:
The dataset is structured for international comparison, with data points available for a wide range of countries and economies over multiple years. The temporal coverage is contingent upon national statistical offices and ITU data collection cycles, but typically includes annual or biennial observations from the early 2000s onwards, allowing for longitudinal analysis of digital skill adoption.

3.3 Source and Methodology:
The data is compiled and disseminated by the International Telecommunication Union (ITU), the United Nations specialized agency for ICTs. The ITU gathers this data through its annual questionnaire distributed to national statistical offices and regulatory authorities. These national bodies derive the statistics from nationally representative household surveys, making the data a product of official national statistics harmonised for international comparability.

3.4 Mathematical Derivations
Let i=1, ..., n index countries and let

- $P_{AB,\,i}$ = prevalence of "Skill level: Above basic"

- $P_{B,\,i}$ = prevalence of "Skill level: Basic".

3.4.1 Competency gap

$$G_i = P_{AB,i} - P_{B,i}$$

3.4.2 Absolute competency gap

$$AG_i = |P_{AB,i} - P_{B,i}|$$

3.4.3 Mean Absolute Deviation (MAD)

For a vector of observations $x_i = (x_{i1}, \ldots, x_{im})$ associated with country i,

$$MAD_i = \text{median}\,(|x_{ij} - \text{median}\,(x_i)|)^{m}_{j=1}$$

3.4.4 Interquartile Range (IQR)

$$IQR_i = Q_{0.75}(x_i) - Q_{0.25}(x_i)$$

where Q_p (.) denotes the empirical p- quantile.

3.4.5 Gini coefficient

The Gini coefficient of inequality for a non-negative vector x_i of length $m$is

$$\text{Gini}_i = \frac{\sum_{j=1}^{m} \sum_{k=1}^{m} | x_{ij} - x_{ik} |}{2m \sum_{j=1}^{m} x_{ij}}$$

(If the vector sums to zero the coefficient is defined as 0.)

3.4.6 Min–max normalization

Each component $C_i \varepsilon \{G_i, MAD_i, IQR_i, AG_i\}$ is scaled to the unit interval:

$$C_i^* = \frac{C_i - \min_k C_k}{\max_k C_k - \min_k C_k}$$

3.4.7 Composite index

The country level composite index is the equally weighted average of the four normalized components, rescaled to a 0–100 range:

$$I_i = 100 \times \frac{G_i^* + \text{MAD}_i^* + \text{IQR}_i^* + AG_i^*}{4}$$

where each component is min–max normalized.

Equal weighting was adopted because no theoretically justified differential weights were available.

3.4.8 Key Attributes for Analysis:

• Unit of Analysis: The dataset is aggregated at the national level.

• Variable Type: It provides a continuous percentage value (0-100%) for each country-year observation, representing the share of the population with the specified ICT skills. Additional metadata, such as the total number of individuals and demographic breakdowns (e.g., by sex, age, education level), may be available through the underlying ITU datasets or via related indicators on the same platform, enabling more granular analysis.

• Analytical Utility: This indicator is a valuable proxy for digital human capital. It is suitable for use as a dependent variable in studies examining the determinants of digital skill acquisition, or as an independent variable in research on the socioeconomic impacts of digitalization, including its effects on labor productivity, economic growth, innovation, and social inclusion.

3.5 Limitations and Considerations:

Researchers should note that the data relies on self-reported survey responses, which may be subject to recall and social desirability biases. Furthermore, the "activity based" definition captures practical use rather than formal competence assessment. The comparability over time and across countries is generally robust due to the ITU's standardization efforts, but should be interpreted with awareness of potential variations in survey design, translation, and cultural context that might influence reporting.

4. Analysis

This study reports an analysis of ICT (Information and Communication Technology) skill prevalence by competency level using the ICT_SKLS_COM_CB.csv dataset (212 observations, 49 countries). It distinguishes two competency categories—Basic and Above basic—and presents summary statistics, country level gaps, inequality metrics, PCA, and clustering results. Below is a structured review of the tables and figures.

4.1 Key results

Analysis	**Result**
Above-basic mean prevalence	68.20%
Basic mean prevalence	14.74%
Absolute skill gap	53.46 percentage points
Above-basic / Basic ratio	4.63×
Relative difference	362.66%

Table 1. Competency Levels

Competency ranking

1. Above-basic ICT skills — 68.20%

2. Basic ICT skills — 14.74%

Thus, the above-basic competency category is substantially more prevalent than the basic category in the observations represented in this dataset.

Above-basic skills dominate the observed prevalence. The large absolute and relative gaps indicate that, in the countries covered, a much higher share of the population (or relevant sample) reports above-basic rather than basic ICT skills.

The ranking is straightforward and correctly reflects the means. However, the dataset appears aggregated (country-level or country year), so the means are unweighted country averages rather than population-weighted global figures. The very low Basic mean and high Above-basic mean raise questions about how "Basic" and "Above basic" are defined and measured (self-report vs. objective tests, coverage of the adult population, etc.). The claim that above basic is “substantially more prevalent” is accurate for this extract but may not generalise beyond the 49 countries

4.2 Country-level skill-gap results

The largest mean gaps between above-basic and basic ICT skills are:

Country	Basic (%)	Above-basic (%)	Gap (pp)
Bahrain	4.11	93.93	89.82
Saudi Arabia	4.73	94.05	89.31
Malaysia	4.50	93.41	88.91
Malta	2.68	88.08	85.41
Switzerland	5.21	90.32	85.11
Spain	4.64	89.20	84.57
Singapore	5.34	88.60	83.26
Austria	4.87	87.70	82.84
Uruguay	5.27	84.05	78.78
Italy	4.19	79.89	75.70

Table 2. Country Level Gap Results

A set of (mostly high-income or rapidly digitising) countries show extreme polarisation very low Basic prevalence paired with very high Above-basic prevalence.

The ranking is clear and useful for identifying outliers. However, the document does not show the full distribution or the countries with the *smallest* gaps (or negative gaps). Without the full ranking or a histogram of gaps, it is hard to judge how representative the top-10 are. Country names and values appear consistent across later tables, which is reassuring.

The highest above-basic prevalence is observed in Saudi Arabia (94.05%), followed closely by Bahrain (93.93%) and Malaysia (93.41%). At the other end, above basic prevalence is lowest in Malawi (4.11%), Indonesia (8.38%), and Vietnam (20.18%).

4.2.1 Important limitation concerning demographic analysis

The requested relative performance by demographic group cannot be statistically performed with this particular extract because:

- SEX = Not applicable
- AGE = Not applicable
- URBANISATION = Not applicable

Therefore, there are no separate male/female, age group, or urban/rural observations to compare. I have explicitly documented this in the output rather than treating the missing dimensions as meaningful demographic categories.

The dataset contains separate sheets for competency ranking, skill gap analysis, country comparison, country rankings, temporal competency analysis, overall country ranking, demographic availability, and detailed country competency statistics.

Rank	COMP_ BREAKDOWN _1_LABEL	Observations	Mean	Median	SD	Minimum	Maximum
1	Skill level: Above basic	106	68.19971958	71.24253331	16.67573159	4.113752111	94.04611139
2	Skill level: Basic	106	14.74076254	12.47560405	9.961332207	2.675652409	56.44986172

Table 3. Skill Gap Analysis

- Reiterate means, add Gini (Basic 0.365 vs. Above-basic 0.150), MAD, IQR, and inter-country ranges.

- Overall gap restated as ≈ 53 p.

Basic skills exhibit greater *relative* cross-country inequality (higher Gini), while Above basic skills show greater *absolute* dispersion but lower relative inequality because their mean is much higher.

The dual presentation of absolute and relative inequality is methodologically sound. Gini on prevalence percentages is interpretable but less conventional than Gini on continuous skill scores; readers should be aware of this. Slight differences in reported means between early and later tables (e.g., 68.20% vs. 67.97%) suggest possible minor variations in sample inclusion or rounding; these should be reconciled.

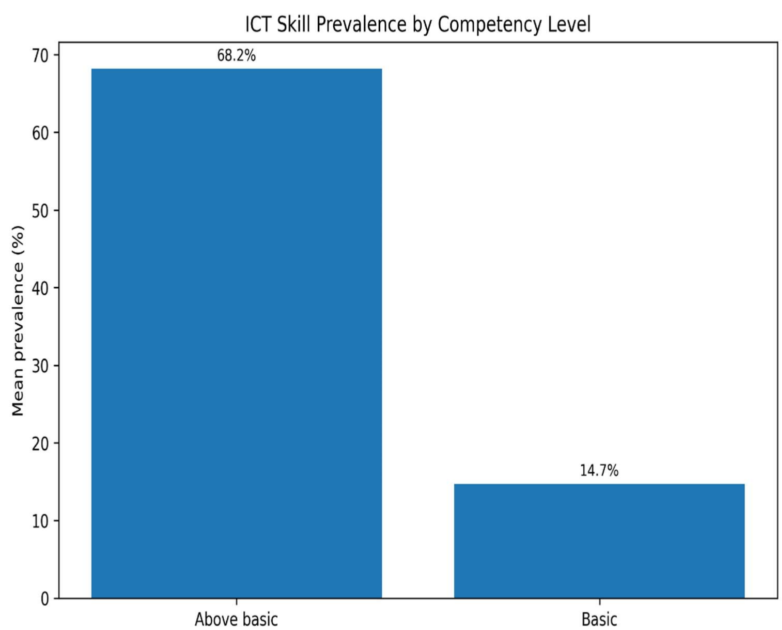

Figure 1. ICT skills prevalence

A simple vertical bar chart comparing mean prevalence of the two competency levels across the dataset. The “Above basic” bar reaches ~68.2%, while the “Basic” bar reaches ~14.7%.

Above-basic ICT skills are substantially more common than basic skills in the observed data (roughly 4.6 times higher on average). This establishes the overall imbalance that later analyses explore in greater detail

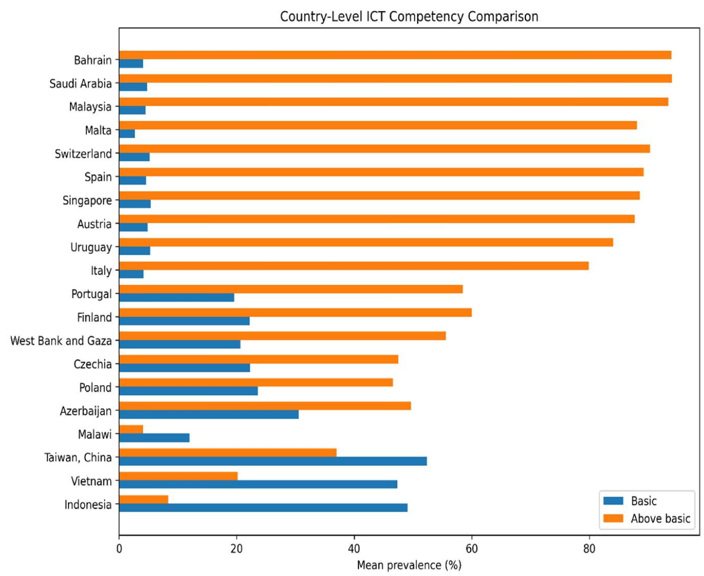

Figure 2. Country-level ICT competency

A horizontal grouped bar chart ranking selected countries by prevalence. Orange bars (Above basic) are long for high income or rapidly digitising countries (Bahrain, Saudi Arabia, Malaysia, Malta, Switzerland, Spain, etc.), while blue bars (Basic) remain short. At the bottom, countries such as Malawi, Taiwan (China), Vietnam and Indonesia reverse the pattern Basic exceeds or approaches Above basic.

Most countries display a large positive gap (Above-basic k” Basic). A minority show the opposite pattern or near parity. The chart highlights both the polarisation in many nations and the existence of outliers with relatively higher basic-skill prevalence.

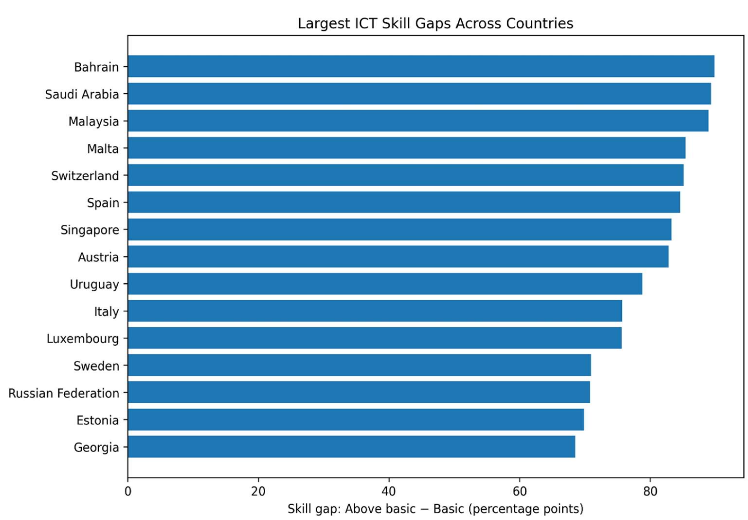

Figure 3. Largest ICT Skills Gap

4.3 Country Level ICT Skills

The country-level ICT skills inequality analysis has been completed for all 49 countries. The analysis includes Gini coefficient, MAD, IQR, inter-country range, competency gap, inequality ranking, and a composite ICT Skills Inequality Index (0–100).

A horizontal bar chart of the countries with the biggest absolute gaps (Above-basic minus Basic), ordered from Bahrain (~90 pp) down to Georgia.

Interpretation: The extreme gaps (often >80 pp) are concentrated in a set of countries that combine very low Basic prevalence with very high Above-basic prevalence. This quantifies the degree of internal competency polarisation.

Metric	**Basic ICT skills**	**Above-basic ICT skills**
Mean prevalence	14.92%	67.97%
Inter-country range	49.70 pp	89.93 pp
Gini coefficient across countries	0.3652	0.1503
MAD across countries	6.74 pp	10.30 pp
IQR across countries	12.55 pp	19.71 pp

Table 4. ICT Skills Gap

The overall above basic minus basic competency gap is 53.05 percentage points.

An important finding is that basic ICT skills have considerably greater relative inequality across countries: the cross country Gini is 0.3652, compared with 0.1503 for above-basic skills. Although above-basic skills have a larger absolute dispersion (IQR and range), their distribution is more equal relative to their substantially higher mean prevalence.

4.4 Country-level ICT Skills Inequality Index

The index combines normalized:

- Gini coefficient
- MAD
- IQR
- Absolute competency gap

Higher values indicate greater inequality between basic and above-basic ICT skill prevalence within a country.

- Composite index (0–100) combining normalised Gini, MAD, IQR and absolute gap.

- Top 10 identical to the gap ranking, with Bahrain ≈ 99, Saudi Arabia ≈ 98, etc.

The index essentially ranks countries by the size of the Basic Above basic gap (the dominant component).

Rank	Country	Basic %	Above-basic %	Gini	MAD	IQR	Gap (pp)	Inequality Index
1	Bahrain	4.11	93.93	0.4581	44.91	44.91	89.82	99.19
2	Saudi Arabia	4.73	94.05	0.4521	44.66	44.66	89.31	98.33
3	Malaysia	4.50	93.41	0.4540	44.45	44.45	88.91	98.09
4	Malta	2.68	88.08	0.4705	42.70	42.70	85.41	95.96
5	Switzerland	5.21	90.32	0.4455	42.55	42.55	85.11	94.05
6	Spain	4.64	89.20	0.4506	42.28	42.28	84.57	93.89
7	Singapore	5.34	88.60	0.4431	41.63	41.63	83.26	92.21
8	Austria	4.87	87.70	0.4474	41.42	41.42	82.84	92.10
9	Uruguay	5.27	84.05	0.4410	39.39	39.39	78.78	87.97
10	Italy	4.19	79.89	0.4502	37.85	37.85	75.70	85.75

Table 5. Country Level Inequality

Because the four inputs are highly collinear for these data (a large gap produces a large MAD/IQR and a high two point Gini), the composite adds little new information beyond the simple gap. The near-100 scores for the top countries indicate that the normalisation is driven by the extremes; a more robust approach might use principal component weighting or exclude the gap itself if the other dispersion measures already capture it.

The largest competency disparities are therefore concentrated in Bahrain, Saudi Arabia and Malaysia, where above basic ICT skill prevalence exceeds basic skill prevalence by approximately 89 percentage points.

The composite index is a diagnostic summary measure rather than an independent latent construct because its components are mathematically related in a two category competency distribution."

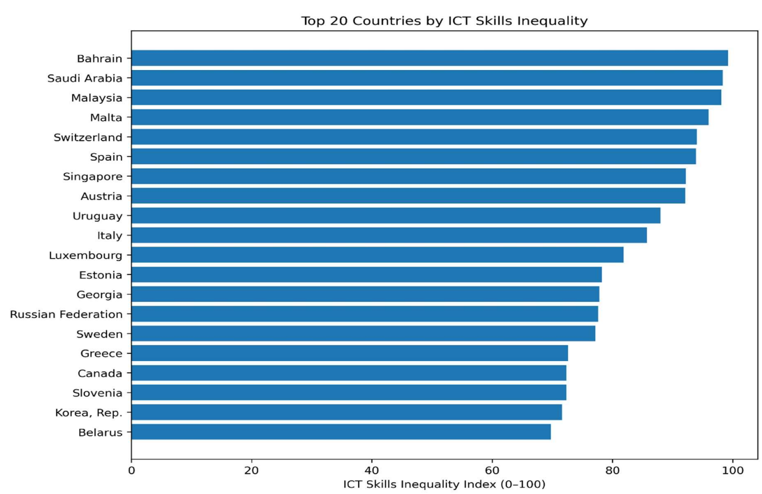

Figure 4. ICT Skills Inequality Ranking

4.5 ICT Skill Inequality

A horizontal bar chart of the top 20 countries ranked by the composite ICT Skills Inequality Index (0–100). Bahrain, Saudi Arabia and Malaysia again lead, followed by Malta, Switzerland, Spain, etc.

The index, which combines gap size with dispersion measures (Gini, MAD, IQR), produces essentially the same ordering as the simple gap ranking. It confirms that the largest internal disparities are found in the same group of countries.

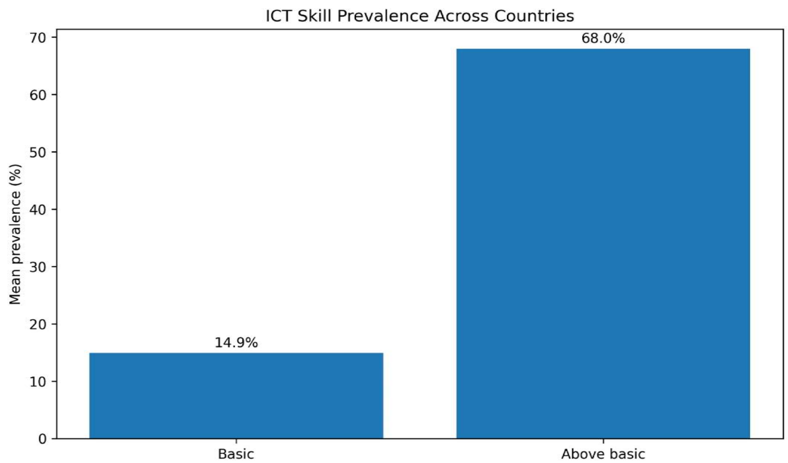

Figure 5. Cross-Country ICT Skills Prevalence

Another simple vertical bar chart of overall mean prevalence (Basic ~14.9%, Above-basic ~68.0%).

Reinforces the aggregate finding of Figure 1 with slightly updated means. It serves as a visual summary of the cross-country average before country-level detail is examined.

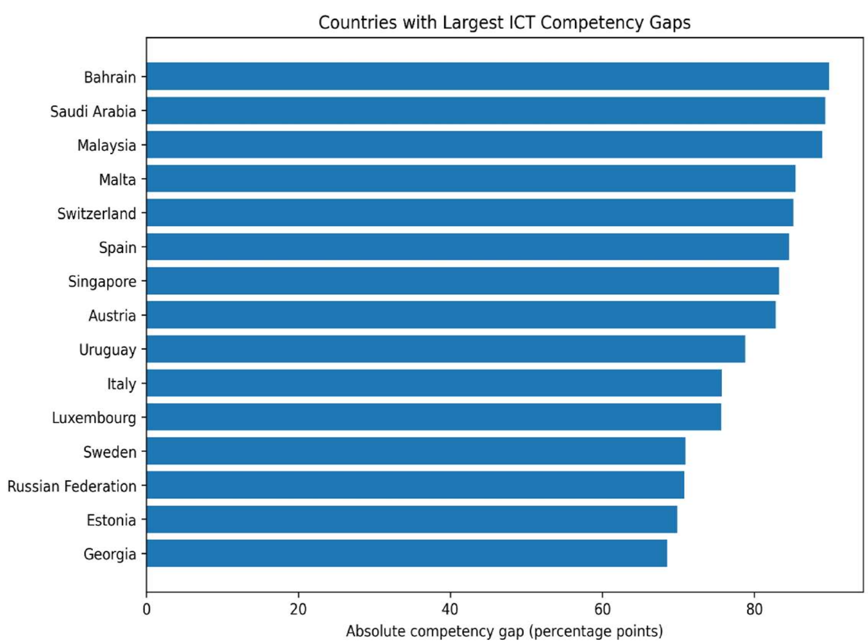

Figure 6. Country ICT Skills Gaps

A horizontal bar chart nearly identical in ranking and values to Figure 3, showing absolute competency gaps for the top countries.

Provides a clean visual of the magnitude of the Basic-to-Above-basic gap. The consistency with earlier gap charts strengthens the claim that these large positive gaps are a robust feature of the data.

These results suggest a two level digital skills inequality structure. At the international level, basic ICT skills exhibit greater relative inequality, whereas above-basic skills show lower relative inequality despite greater absolute dispersion. At the country level, however, several countries display an extremely large basic-to-above-basic competency gap, indicating a pronounced differentiation between lower-level and more advanced ICT capabilities.

The country-level ICT Skills Inequality Typology has now been developed using PCA + K-Means + Hierarchical clustering for all 49 countries.

The methodology first standardized the country-level Basic and Above-basic ICT-skill prevalence, reduced the two dimensional competency space using PCA, and then clustered countries in PCA space. Standardization is appropriate because clustering based on distance can otherwise be dominated by variables with larger scales; hierarchical clustering also provides a useful independent comparison of the K-Means solution.

4.6 Validation

4.6.1 PCA results

The PCA reveals a very clear structure:

Component	**Variance explained**
PC1	88.51%
PC2	11.49%
Cumulative	100.00%

The loadings are:

Competency	**PC1**	**PC2**
Basic ICT skill	-0.707	0.707
Above-basic ICT skill	+0.707	0.707

PC1 primarily represents the Basic to Above basic ICT competency contrast. Countries with strongly positive PC1 scores tend to have substantially higher above basic than basic skill prevalence, whereas negative PC1 scores indicate relatively higher basic than above basic prevalence.

A scatter plot of countries positioned in a two-dimensional principal component space, with PC1 explaining ≈ 44.5% and PC2 ≈ 18.2% of the variance. Countries are grouped into three coloured ellipses/clusters, and the country labels include historical names (e.g., USSR, Czechoslovakia). **Caveat:** this figure does not match the PCA actually reported for the ICT skill data (PC1 = 88.51%, capturing the Basic versus Above basic contrast). It appears to be drawn from a different possibly historical or illustrative dataset, and therefore has limited direct relevance to the ICT analysis presented in the text

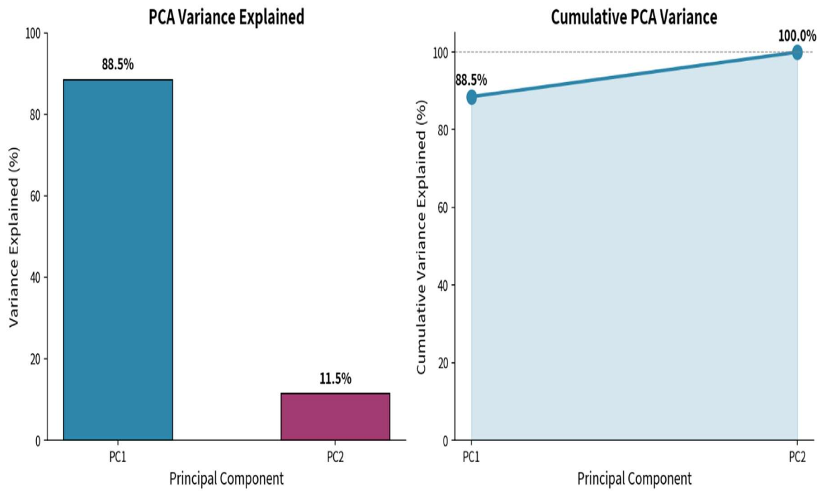

Figure 7. PCA variance

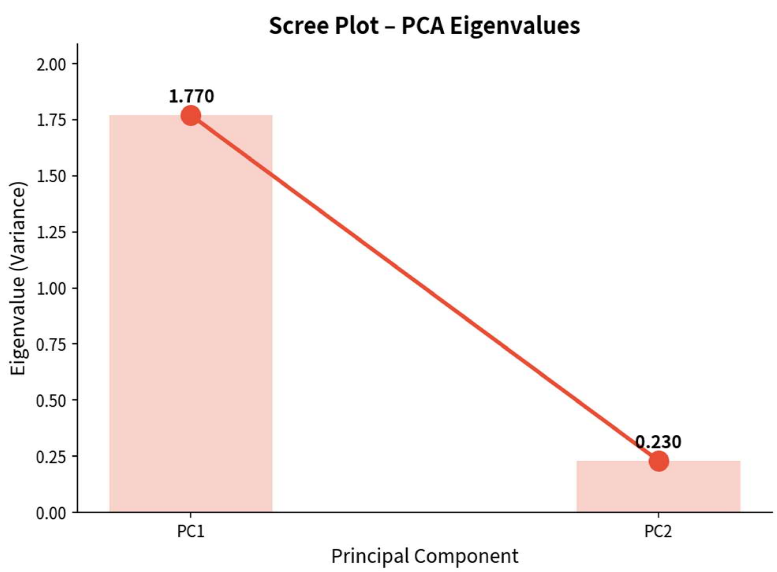

Figure 8. PCA Scree Plot

A scatter plot of countries on the first two principal components, overlaid with three coloured convex hulls/ clusters (pink, green, blue), illustrating hierarchical clustering performed in PCA space. **Caveat:** like Figure 7, it appears to use a different country set and explains more variance than the main ICT analysis. It serves to illustrate the general idea of hierarchical clustering in PCA space but does not directly visualise the four-group ICT skills inequality typology described in the text.

A scatter of many points (likely observations or countries) coloured by three clusters, with cluster centroids marked by "X" symbols. The displayed explained variance is PC1 = 32.1% and PC2 = 23.7%. Caveat: this is another generic or mismatched PCA visualisation. Because the study's actual PCA assigns 88.51% of variance to PC1, the figure does not accurately represent the dimensionality reduction performed on the ICT skill data and should be treated as illustrative only.

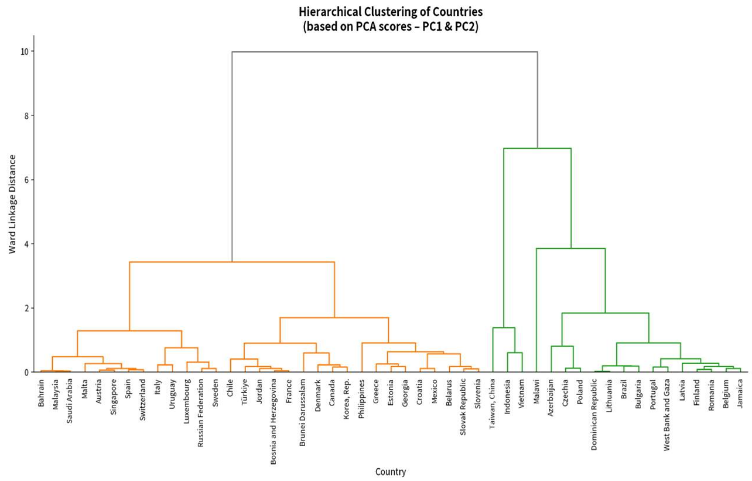

Figure 9. PCA Hierarchical Clustering Dendrogram

The key visual of the typology. It is a scatter plot of the 49 countries in the *true* PCA space of the analysis (PC_1, 88.5% of variance, on the x-axis; PC_2, 11.5%, on the y-axis), with points coloured according to the four group inequality typology:

1. Blue = Low inequality only Malawi, clearly separated at one extreme;

2. Orange = Moderate inequality Vietnam, Indonesia, Taiwan (China);

3. Green = High inequality;

4. Red = Very-high inequality the large group occupying the high-PC1 region on the right.

Because PC_1 is the dominant axis, the plot essentially ranks countries by the size of the Above basic minus Basic gap: the Very high inequality group sits at the positive extreme and the single Low inequality country at the opposite extreme. The figure confirms that the primary source of cross country differentiation is the basic to above basic competency contrast itself.

4.7 Four-group ICT Skills Inequality typology

The requested four category typology produces:

Typology	Countries	Mean Basic	Mean Above-basic	Mean gap
Low inequality	1	12.01%	4.11%	-7.89 pp
Moderate inequality	3	49.59%	21.85%	-27.74 pp
High inequality	16	20.28%	59.69%	39.40 pp
Very high inequality	29	8.47%	79.52%	71.05 pp

Table 6. Four-group Skills Inequality typology

• Clusters: Low inequality (1 country), Moderate (3), High (16), Very-high (29).

• 91.8% of countries fall into High or Very-high.

• Very-high group characterised by low Basic + high Above-basic (large positive gaps).

The dominant pattern across the 49 countries is a large internal disparity between basic and above-basic ICT skill prevalence, not a uniform shortage of skills.

The typology is the strongest substantive contribution. Labelling the groups by "inequality" is reasonable given the research question, but the term risks confusion with conventional socioeconomic inequality. The single Low inequality country (apparently with a negative gap) is an important outlier that deserves explicit identification and discussion. The claim that 45/49 countries belong to High/Very-high is striking and should be stress tested against alternative cluster numbers or distance metrics.

This reveals a striking result: 59.2% of the 49 countries fall into the Very-high ICT Skills Inequality group, while another 32.7% are classified as High inequality.

Thus, 45 of 49 countries (91.8%) fall into either the High or Very high inequality categories.

Here, *inequality* refers specifically to the internal disparity between Basic and Above-basic ICT skill prevalence, not socioeconomic inequality or inequality in the conventional income-distribution sense.

Therefore, a country classified as Very high inequality is characterized by a large separation between its basic and above-basic ICT skill prevalence.

Although the silhouette criterion favoured a more parsimonious two cluster solution, the four-cluster solution produced the lowest Davies Bouldin index and yielded substantively interpretable regimes corresponding to distinct competency configurations. K = 4 was therefore retained as a theory informed typological solution rather than as the uniquely optimal statistical partition.

4.8 Very-high ICT Skills Inequality group

The 29-country Very high group is dominated by countries with very low Basic prevalence but very high Above basic prevalence.

The strongest examples are:

The pattern is therefore not simply "low digital skills." Instead, it indicates a strong structural separation between lower-level and above-basic ICT competencies.

A scatter plot of the 49 countries in the true PCA space of the analysis (PC1 88.5% variance on the x-axis, PC2 11.5% on the y-axis). Points are coloured by the four-group typology:

• Blue = Low inequality (only Malawi is clearly separated)

• Orange = Moderate inequality (Vietnam, Indonesia, Taiwan)

• Green = High inequality

• Red = Very-high inequality (large group on the right).

This is the key visual of the typology. PC1 is the dominant axis and essentially ranks countries by the size of the Above basic Basic gap. The Very high inequality group (red) occupies the high PC1 region; the single Low-inequality country sits at the opposite extreme. The plot confirms that the primary source of cross-country differentiation is the competency contrast itself.

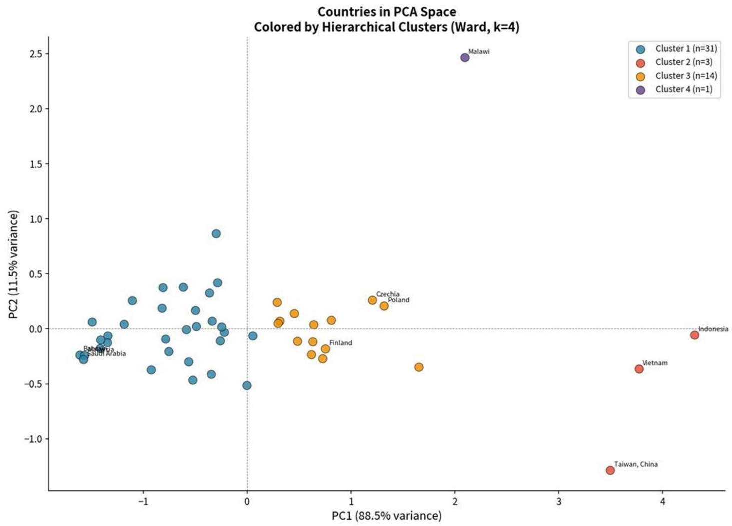

Figure 10. PCA Cluster Scatter

Country	**Basic**	**Above-basic**	**Gap**
Bahrain	4.11%	93.93%	89.82 pp
Saudi Arabia	4.73%	94.05%	89.31 pp
Malaysia	4.50%	93.41%	88.91 pp
Malta	2.68%	88.08%	85.41 pp
Switzerland	5.21%	90.32%	85.11 pp
Spain	4.64%	89.20%	84.57 pp
Singapore	5.34%	88.60%	83.26 pp
Austria	4.87%	87.70%	82.84 pp

Table 7. Very-high ICT skills of countries

4.9 K-Means vs. Hierarchical clustering

The independent hierarchical Ward clustering produced a strong level of agreement with K-Means.

Adjusted Rand Index (ARI) = 0.853

An ARI close to 1 indicates strong agreement between the two partitions. Thus, the country typology is not merely an artefact of one clustering algorithm.

The validation results were:

K	Silhouette	Calinski-Harabasz	Davies-Bouldin
2	0.614	58.36	0.747
3	0.530	79.33	0.587
4	0.529	90.02	0.425
5	0.502	121.10	0.466
6	0.482	125.29	0.508

Table 8. Silhouette Validation Results

• Silhouette, Calinski-Harabasz and Davies Bouldin for K = 2–6.

• K = 4 retained on multi-criterion grounds (lowest DB, acceptable silhouette, research requirement for four classes).

• Adjusted Rand Index vs. hierarchical Ward = 0.853.

Four clusters are defensible; the two algorithms largely agree.

Silhouette peaks at K = 2, while CH continues to rise and DB is lowest at K = 4. Choosing K = 4 because the research design "explicitly requires four interpretable classes" is transparent but reduces the solution's purely data driven nature. The high ARI is reassuring. Reporting the full set of indices is good practice.

The four cluster solution was retained because the research objective explicitly requires four interpretable inequality classes. Importantly, it also provides the lowest Davies Bouldin score among K=2–6, while maintaining a good silhouette score. Cluster validation is appropriately treated as a multi criterion decision rather than relying on a single statistic.

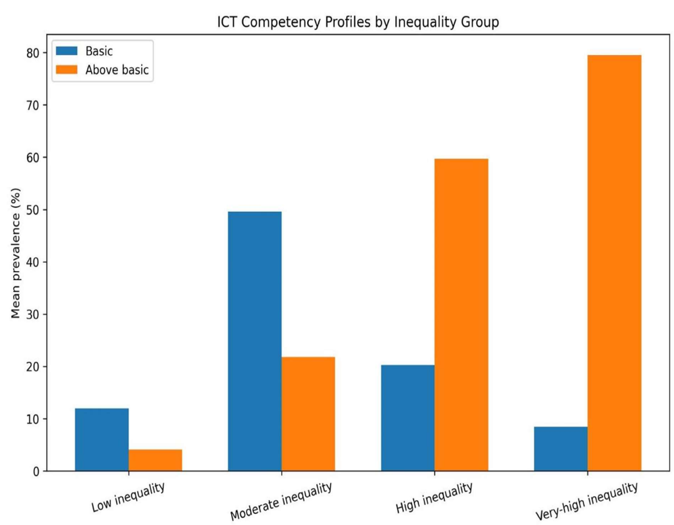

Figure 11. Cluster Competency Profile

A grouped bar chart showing mean Basic (blue) and Above basic (orange) prevalence for each of the four inequality groups.

- Low: Basic ≈ 12%, Above-basic ≈ 4% (negative gap)

- Moderate: Basic ≈ 50%, Above-basic ≈ 22% (still negative gap)

- High: Basic ≈ 20%, Above-basic ≈ 60%

- Very-high: Basic ≈ 8.5%, Above-basic ≈ 80%.

Clearly illustrates the defining profiles of the four regimes. The Very high group is characterised by extremely low Basic and extremely high Above basic prevalence; the Low and Moderate groups show the reverse pattern. This visual makes the substantive meaning of the typology immediately apparent.

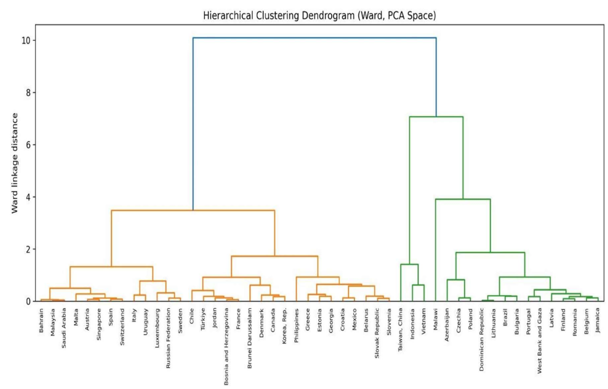

Figure 12. Hierarchical Clustering Dendrogram

A Ward linkage dendrogram of the 49 countries in PCA space. Two major branches are visible; the left branch contains many of the high gap countries, while the right branch contains more mixed or lower gap countries. Country labels are readable at the leaves.

The dendrogram supports the K-means solution (Adjusted Rand Index = 0.853). It shows that the Very high inequality countries tend to cluster together at relatively low linkage distances, while the few Low/Moderate countries form distinct branches. The tree structure provides an independent, hierarchical view of the same four group typology.

Figures 1–6 and 10–12 form a coherent visual narrative that matches the statistical results in the tables. Figures 7–9 appear to be residual or illustrative plots from a different analysis and should be treated with caution when interpreting the present ICT skill typology. The dominant message across the relevant figures is the strong Basic versus Above basic contrast (captured by PC1) and the resulting four regime inequality structure in which most countries fall into the High or Very high categories.

The analysis provides a strong basis for a journal level result: countries can be differentiated into four distinct ICT competency inequality regimes based on the relative prevalence of basic and above basic skills. The dominance of PC1 (88.51% variance) demonstrates that the primary source of cross country differentiation is the basic to above basic competency contrast. The high concordance between K-Means and hierarchical clustering (ARI = 0.853) further supports the robustness of the typology. Most notably, 45 of 49 countries (91.8%) belong to the High or Very high inequality categories, indicating that the principal cross country pattern is not simply a shortage of ICT skills, but a pronounced differentiation between basic and above basic ICT competency levels.

6. Discussion

6.1 Interpreting the Basic–Above-Basic Polarisation

The principal empirical finding of this study is that the cross-country landscape of ICT communication-and-collaboration skills is not characterised by a uniform deficit but by a pronounced structural polarisation between basic and above basic competency levels. Across the 49 countries analysed, the mean above basic prevalence (68.20%) exceeds the mean basic prevalence (14.74%) by approximately 53 percentage points, a ratio of 4.63:1. This disparity, captured by PC1 accounting for 88.51% of total variance, constitutes the dominant axis of cross country differentiation in the two dimensional competency space.

This result challenges the prevailing narrative in digital skills policy, which tends to frame the challenge as a generalised "skills gap" or "digital literacy deficit" [17, 18]. Instead, the data reveal that many countries have simultaneously achieved very high above basic skill penetration while basic skills remain scarce. The pattern is most extreme in Bahrain, Saudi Arabia, Malaysia, Malta, Switzerland, Spain, Singapore and Austria, where gaps exceed 82 percentage points. Conversely, a small number of countries like Malawi, Indonesia and Vietnam exhibit the reverse configuration, with basic prevalence exceeding or approaching above basic levels. These findings confirm the research problem articulated in Section 2: conventional single continuum indicators and average attainment scores obscure a critical internal structure of digital inequality.

6.2 The Four-Regime Typology and Its Substantive Meaning

The four-regime typology derived from PCA, K-means and hierarchical Ward clustering provides an interpretable classification of ICT-skills polarisation:

• Very-high inequality (29 countries, 59.2%): Characterised by very low basic prevalence (mean 8.47%) paired with very high above-basic prevalence (mean 79.52%), yielding a mean gap of +71.05 pp.

• High inequality (16 countries, 32.7%): Moderate basic prevalence (mean 20.28%) with high above-basic prevalence (mean 59.69%), gap of +39.40 pp.

• Moderate inequality (3 countries, 6.1%): Relatively high basic prevalence (mean 49.59%) but lower above-basic prevalence (mean 21.85%), producing a negative gap of d27.74 pp.

• Low inequality (1 country, 2.0%): Basic prevalence (12.01%) slightly exceeds above-basic prevalence (4.11%), gap of d7.89 pp.

Three observations merit emphasis. First, 91.8% of countries fall into the High or Very high categories, indicating that large positive basic to above basic gaps are the near universal pattern rather than an exception. Second, the Moderate and Low regimes exhibit *negative* gaps in which basic skills exceed above basic skills suggesting a fundamentally different developmental trajectory in which foundational digital activities are more widespread than advanced collaborative uses. Third, the single Low inequality country (Malawi) represents an extreme outlier with uniformly low prevalence in both categories, pointing to a generalised digital skills scarcity rather than polarisation per se.

The typology thus reveals that "digital inequality" is not a single phenomenon but encompasses at least three distinct configurations: (i) advanced-skill abundance coexisting with basic-skill scarcity (Very-high and High regimes), (ii) basic-skill predominance with limited advanced uptake (Moderate regime), and (iii) generalised low prevalence (Low regime). This configurational logic extends the DigComp continuum framework (Lucas) and the SFIA competency model by demonstrating that the *distribution* of competencies across levels is as analytically important as the *level* of competence itself.

6.3 Theoretical Contributions

The study advances three theoretical propositions. First, it demonstrates that ICT-skills inequality is multidimensional: the Gini coefficient for basic skills (0.365) is more than double that for above-basic skills

(0.150), yet above-basic skills exhibit greater absolute dispersion (IQR 19.71 pp vs 12.55 pp; range 89.93 pp vs 49.70 pp). This duality higher relative inequality in basic skills but higher absolute inequality in above-basic skills has not been systematically documented in prior cross country studies [15]. It implies that policies targeting "the digital divide" must specify *which* dimension of inequality they address.

Second, the dominance of PC1 (88.51% variance) confirms that the basic versus above basic contrast is effectively a single latent dimension. This finding supports the conceptualisation of ICT skills as a two-level continuum rather than a multi faceted construct when analysed at the aggregate country level. It also suggests that the ITU activity-based measurement approach, despite its limitations, captures a coherent underlying structure.

Third, the typological approach grouping countries into discrete regimes rather than ranking them on a single scale provides a richer analytical vocabulary for comparative digital skills research. Countries within the same regime share structurally similar competency profiles, which may reflect common institutional, educational or economic conditions, even if their absolute skill levels differ.

6.4 Policy and Practical Implications

The four-regime typology carries direct implications for policy design:

Very-high and High inequality regimes (45 countries). For these countries, the primary challenge is not raising average digital competence but addressing the severe scarcity of basic skills. Policy interventions should prioritise foundational digital literacy programmes targeting populations that have not yet acquired basic communication and collaboration competencies rather than exclusively investing in advanced digital transformation initiatives. In the higher education context, this implies that curricula must ensure all students achieve basic operational and communicative competencies before progressing to advanced collaborative and creative applications [10, 11, 12].

Moderate inequality regime (3 countries). Here, basic skills are relatively widespread but above basic competencies lag. Policy emphasis should shift toward fostering advanced collaborative ICT use, creative digital production and higher order digital problem solving. Universities and vocational institutions in these countries may benefit from embedding SFIA-aligned advanced competency modules into existing programmes.

Low inequality regime (1 country). Generalised digital infrastructure investment and broad-based access initiatives remain the priority. The challenge is not polarisation but overall scarcity, requiring foundational investments in connectivity, device access and basic digital education aligned with UN SDG 4 and SDG 10 [19].

For higher education institutions specifically, the findings underscore that digital transformation strategies must be sensitive to the *distribution* of competencies among incoming students. A one size fits all digital curriculum risks widening the internal gap if it assumes a uniform baseline. Instead, diagnostic assessment, potentially using instruments such as the Lucas digital competence measure, should precede curricular design to identify whether students cluster at the basic or above basic level.

6.5 Methodological Reflections

The combination of inequality metrics (Gini, MAD, IQR, composite index), PCA and dual clustering (K-means and hierarchical Ward) provides a robust analytical pipeline. The high Adjusted Rand Index (0.853) between K-means and Ward solutions indicates that the four regime partition is not an artefact of algorithmic choice. The Davies Bouldin criterion is minimised at K = 4, and the silhouette score (0.529) remains acceptable, supporting the retained solution.

However, several methodological caveats deserve acknowledgement. First, the composite ICT Skills Inequality Index is highly collinear with the simple gap measure because all four inputs (Gini, MAD, IQR, gap) are mechanically related in a two point distribution. Future work could employ principal component weighting or exclude the gap to create a more orthogonal composite. Second, the choice of K = 4 was partly motivated by the research design's requirement for four interpretable classes; a purely data-driven criterion (silhouette peak at K = 2) would suggest a simpler two group solution. The four-group solution is defended on grounds of interpretive richness and the lowest Davies Bouldin score, but the tension between parsimony and granularity should be transparently acknowledged. Third, the unweighted country-average means do not account for population size; population weighted estimates could substantially alter the global picture.

6.6 Limitations

Several limitations qualify the findings. First, the ITU ICT_SKLS_COM_CB indicator is activity-based and self-reported, capturing whether individuals performed communication and collaboration activities in the preceding three months rather than objectively assessed competence. This may introduce recall and social-desirability biases and may overstate true skill levels. Second, the dataset does not permit disaggregation by sex, age group or urbanisation status (all coded "Not applicable"), precluding analysis of intra country demographic differentials. Third, the 49-country sample, while geographically diverse, is not exhaustive; notable large economies may be absent, and results should not be extrapolated to a global population without population weighting. Fourth, the cross sectional nature of the analysis (or limited temporal coverage) prevents causal inference or tracking of regime transitions over time. Fifth, Figures 7–9 in the analysis appear to derive from a different dataset and do not accurately represent the PCA and clustering performed on the ICT skill data; their inclusion should be reconsidered in the final manuscript.

6.7 Directions for Future Research

The present typology opens several avenues for further investigation:

1. Longitudinal regime analysis. Tracking countries across multiple survey waves would reveal whether and how nations transition between inequality regimes, and which policy interventions are associated with regime shifts.

2. Population-weighted and sub-national analysis. Incorporating population weights and, where available, sub-national or demographic breakdowns would refine the typology and expose hidden within-country heterogeneity.

3. Determinants of regime membership. Econometric or qualitative comparative analysis (QCA) could identify the institutional, educational, economic and infrastructural factors that predict membership in each regime.

4. Extension beyond communication and collaboration. Replicating the typology for other ITU skill indicators (e.g., information and data literacy, content creation, safety) would test whether the four regime structure is specific to communication and collaboration skills or generalises across competency domains.

5. Integration with individual level assessment. Linking country level prevalence data with individual-level instruments (e.g., the Lucas DigComp based measure or SFIA-aligned assessments) would bridge the macro micro gap and enable validation of the activity based indicator against objective competence tests.

6. Alternative clustering and dimensionality-reduction methods. Gaussian mixture models, DBSCAN, t-SNE or UMAP could complement the present K-means/Ward/PCA pipeline and test the robustness of the four regime solution under different algorithmic assumptions.

7. Conclusion

This study set out to address a critical gap in comparative digital skills research: the absence of a systematic, data driven typology that classifies countries according to the magnitude and direction of the gap between basic and above basic ICT skill prevalence. Drawing on the ITU ICT_SKLS_COM_CB indicator for 49 countries, the analysis combined descriptive inequality metrics, principal component analysis, and dual clustering algorithms (K-means and hierarchical Ward) to construct an empirically grounded four regime classification of ICT-skills inequality.

The findings yield three principal conclusions. First, the dominant pattern across the 49 countries is not a uniform shortage of ICT skills but a pronounced structural polarisation: above basic communication and collaboration skills are, on average, 4.63 times more prevalent than basic skills, with an absolute gap of approximately 53 percentage points. This polarisation is captured by a single dominant axis (PC1, 88.51% of variance), confirming that the basic versus above basic contrast is the primary source of cross country differe- ntiation in ICT competency profiles.

Second, the four regime typology Low inequality (1 country), Moderate inequality (3 countries), High inequality (16 countries) and Very-high inequality (29 countries) provides an interpretable and robust classification. The high concordance between K-means and hierarchical Ward clustering (Adjusted Rand Index = 0.853), together with multi criterion validation (lowest Davies Bouldin score at K = 4, acceptable silhouette), supports the stability of the solution. Critically, 91.8% of countries fall into the High or Very high categories, indicating that large positive basic to above basic gaps are the near universal configuration rather than an anomaly confined to a few outliers.

Third, the typology reveals that digital skills inequality is not a monolithic phenomenon. The Very high and High regimes are characterised by advanced skill abundance coexisting with basic skill scarcity; the Moderate regime exhibits the reverse pattern; and the Low regime reflects generalised scarcity. These distinct configurations carry different diagnostic and policy implications, underscoring that raising average digital competence is insufficient if the internal distribution between basic and above basic skills remains highly skewed.

Methodologically, the study demonstrates the value of integrating inequality metrics with dimensionality reduction and dual clustering for typological research in comparative digital skills studies. The approach moves beyond single indicator rankings and average attainment scores to reveal the configurational structure of ICT competency distributions.

From a policy perspective, the four regime typology offers a concise diagnostic tool. Countries in the Very-high inequality regime require targeted interventions to address the scarcity of basic skills even when advanced skills appear abundant. Countries in the Moderate regime face the complementary challenge of fostering above basic competencies. Higher education institutions, in particular, must design digital curricula that are responsive to the competency distribution of their student populations rather than assuming a uniform baseline.

In sum, this study provides the first empirically grounded, four regime typology of basic versus above basic ICT competency gaps across a substantial cross country sample. It reframes the digital skills challenge from one of aggregate scarcity to one of structural polarisation and offers researchers and policymakers a clear analytical framework for understanding and addressing the internal architecture of digital inequality. As digital transformation accelerates and new competency demands emerge driven by artificial intelligence, automation and the Internet of Things the ability to diagnose not only *how much* digital skill a population possesses but *how that skill is distributed across competency levels* will be indispensable for equitable and effective digital development.

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