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Strategic Readiness for Sustainable Transformation: A Capability-Based Benchmarking of OECD Countries with Evidence for Türkiye

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Abstract

Strategic readiness denotes the capability base that conditions a country's ability to absorb and capitalise on the transformations required for sustainable development. Drawing on the resource-based and dynamic capabilities views, this study conceptualises it as a stock of capabilities in seven domains linked to the Sustainable Development Goals and develops a scale-free benchmarking framework for the 38 OECD countries. Using 17 World Bank indicators averaged over the period of 2015–2023, principal component analysis identifies one dominant dimension of general capability, driven mainly by institutional quality, income and digital infrastructure, that represents the seven domains unequally. Ward's clustering on this dimension yields a descriptive classification into three segments of a capability continuum: an advanced core (21 countries), an intermediate group (14) and a capability-constrained group of Colombia, Mexico and Türkiye. The classification is stable under full-procedure resampling, equal domain weights and the addition of education indicators. Higher capability is associated with higher per capita CO_2 emissions but faster reductions, also when measured in 2015, although this association cannot be separated from income; no clear association with renewable electricity shares is detected. For Türkiye, a rule-based comparison identifies Hungary and the Slovak Republic as candidate benchmarks and inflation and institutional quality as priority gaps.

Keywords: strategic readiness; sustainable transformation; Sustainable Development Goals; national capabilities; dynamic capabilities; benchmarking; principal component analysis; hierarchical clustering; OECD; Türkiye

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1. Introduction

Since the mid-2010s, advanced and emerging economies have faced an unusually dense sequence of structural transformations and shocks: the acceleration of digitalisation, the commitments made under the 2030 Agenda and the Paris Agreement, the COVID-19 pandemic, the 2021–2023 energy price shock and the subsequent surge in

inflation. These events have exposed large differences in the ability of countries to anticipate change, absorb disruption and turn transformation into new sources of value. In the strategic management tradition, such differences are explained by the resources and capabilities an organisation controls and by its ability to reconfigure them as its environment changes [1,2]. The parallel literature in economics and international business has extended this capability logic to nations, arguing that the prosperity of countries depends on the quality of their business environment, human capital, technological base and institutions [3–5]. We use the term *strategic readiness* to describe the capability base of a country: the stock of economic, technological, human and institutional assets that conditions its ability to respond to such transformations.

Strategic readiness is especially relevant to sustainable development. The 2030 Agenda frames sustainable development as an integrated transformation of economic, social and environmental systems [6], and research on sustainability transitions shows that such transformations require coordinated change across technologies, infrastructures, skills, markets and institutions [7]. Innovation policy has accordingly shifted from supporting R&D alone towards enabling transformative change in whole socio-technical systems [8]. A country's ability to pursue the Sustainable Development Goals (SDGs) therefore depends not only on its current environmental performance but also on the broader capability base that allows it to finance, govern and implement transitions. Strategic readiness, as defined here, is this capability base, and an open question is whether, and how, it is related to environmental outcomes.

Strategic readiness is usually assessed with composite indicators and the league tables they produce. Composite indices condense complex phenomena into a single number, but their results depend on choices about normalisation, weighting and aggregation that are partly arbitrary and that can change country rankings substantially [9–11]. A single score also assumes that strengths in one domain can compensate for weaknesses in another, so two countries with the same rank may rest on very different capability mixes. Any data-driven score, including the principal component score used in this study, shares this compensatory property; it can be made transparent, but not removed. Krugman's warning that nations are not firms competing in a zero-sum market [12] is a further reason to be cautious about reading national rankings as competitive positions.

Classification offers a complementary perspective. Configurational theory holds that organisations, and by extension national systems, cluster into a limited number of coherent types whose elements reinforce one another [13,14]. The comparative capitalism literature has used this logic to identify distinct institutional models among OECD economies [15,16], and capability-based development research has used factor-analytic methods to uncover the latent dimensions of national capabilities [17]. Benchmarking research adds that benchmarks are useful only when the comparator is relevant and the gap is attainable [18]. Yet three weaknesses recur in applied country-benchmarking studies. First, they often combine level variables such as total GDP or the total number of subscriptions with ratio variables, so the resulting dimensions and clusters partly reflect country size rather than capability. Second, cluster solutions are seldomly tested for stability, even though cluster analysis always returns groups whether or not a real structure exists [19]. Third, typologies are rarely linked to environmental outcomes or translated into concrete, peer-based benchmarking guidance for individual countries. Whether national capabilities form distinct types or vary along a common continuum is therefore an empirical question rather than an assumption.

This study addresses these gaps. It examines the structure of strategic readiness among the 38 OECD member countries over the period of 2015–2023 using a theory-guided, scale-free and robustness-tested multivariate framework; describes how readiness evolved and how it is associated with emissions and renewable energy; and shows

how the resulting classification can support benchmarking, with Türkiye as an illustrative case. Four research questions guide the analysis. RQ1: Which latent dimensions structure cross-country differences in strategic readiness within the OECD? RQ2: Can readiness profiles be distinguished, and how robust is the resulting classification to methodological choices and to the time window? RQ3: How is strategic readiness associated with sustainability outcomes? RQ4: Where does Türkiye stand, and which peers and capability gaps are relevant for benchmarking?

The study makes three contributions. Conceptually, it defines national strategic readiness as a capability base by integrating the resource-based and dynamic capabilities views with the development literature on social and technological capabilities [20,21]; it distinguishes this base from the dynamic processes through which countries adapt, from competitiveness and from resilience, and it separates readiness from sustainability outcomes so that the relationship between the two can be examined empirically. Methodologically, it does not claim to remove the compensation inherent in composite scores. Instead, it estimates the weights from the data and reports how much each domain contributes; quantifies the uncertainty of the resulting classification by re-estimating the whole procedure; complements the score with indicator-level gap profiles; and shows, in a matched comparison, that replacing per capita indicators with totals produces a materially different typology. Practically, it proposes *stepping-stone benchmarking*, in which a country is compared first with its structural peers and then with candidate comparators in the adjacent profile that are selected by an explicit rule rather than with the global frontier. Türkiye is an informative case because it combines a large, dynamic economy with persistent macroeconomic volatility and was among the OECD members most exposed to the inflation and energy shocks of the study period.

Section 2 develops the theoretical background and the capability framework. Section 3 describes the data and the analytical procedure. Section 4 presents the results. Section 5 discusses their implications, and Section 6 concludes with limitations and directions for future research.

2. Theoretical Background

2.1. From Firm Capabilities to National Strategic Readiness

The resource-based view explains performance differences by the heterogeneous, imperfectly mobile resources that organisations control [1,22]. The dynamic capabilities view adds that in changing environments, advantage depends less on a static stock of resources than on the capacity to sense opportunities and threats, to seize them through investment, and to transform the resource base accordingly [2,23]. Capabilities also have life cycles: they are built, renewed or eroded over time [24]. These ideas are not limited to firms. Porter's analysis of national advantage locates the sources of firm competitiveness in national factor conditions, demand conditions, related industries and institutional settings [3], and later work shows that institutions, social infrastructure and the business environment explain a large share of cross-country differences in output per worker [4].

Development economics provides a complementary lens. Abramovitz argued that the potential for catching up is realised only when a country has sufficient *social capability*, meaning the education, institutions and organisational competence needed to absorb advanced technology [20]. Subsequent research operationalised related ideas as national technological capabilities [21,25] and showed, using factor analysis, that national capabilities consist of several partly independent dimensions, including technological capability, education, the quality of governance and the political system [17]. Together the literature suggests that national capacity for transformation is multidimensional; partly cumulative and path dependent; and conditioned by complementarities between economic, technological, human and institutional assets.

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Extending firm-level concepts to nations requires a distinction that the dynamic capabilities literature draws explicitly. Ordinary or 'zero-level' capabilities allow an organisation to perform its current activities, whereas dynamic capabilities are higher-order routines that change the resource base [23,26]. At the level of cities and regions, research on transformative capacity similarly distinguishes the agency and governance processes that drive change from the resources on which they draw [27]. Cross-national indicators can observe the second element much better than the first: income, infrastructure, health, innovation inputs and the quality of public institutions describe the asset positions and preconditions from which transformation can be organised, not the processes of sensing, seizing and transforming themselves. We therefore treat strategic readiness as a capability base rather than as a measure of national dynamic capabilities, and we observe the dynamic element only indirectly through changes in this base over time (Section 4.8).

Building on these foundations, we define *national strategic readiness* as the capability base of a country: the stock and configuration of economic, technological, human, environmental and institutional capabilities that condition its ability to sense, absorb and capitalise on structural transformations. Readiness differs from competitiveness, which usually refers to realised outcomes such as productivity or market share [4], and from economic resilience, which refers to the ability to withstand and recover from shocks [28,29]. Some indicators of readiness, such as income per capita and life expectancy, are themselves the cumulative result of past capabilities. We include them because accumulated income and health form part of the resource base available for future transformation, but we test whether the results depend on them (Section 4.5). Environmental outcomes, namely greenhouse gas emissions and the share of renewable electricity, are not treated as components of readiness; they are analysed separately as outcomes whose association with readiness is an empirical question (RQ3).

2.2. Capability Domains of Strategic Readiness

Drawing on the literature above, we specify seven capability domains (Table 1). *Economic capacity* reflects the resource base available for strategic investment: income per capita captures accumulated productive capacity, and gross capital formation captures the rate at which that capacity is renewed. *Macroeconomic stability* determines the planning horizon of firms and governments; high and volatile inflation and unemployment raise uncertainty, shorten investment horizons and divert attention from long-term capability building [30]. *Digital infrastructure* is an enabling platform for nearly all contemporary transformations. Broadband diffusion has a measurable effect on growth [31], and the distinction between basic mobile connectivity and deeper fixed and secure infrastructure separates access from capability.

Human capital and health determine a country's ability to adopt and generate knowledge [32] and its effective labour supply [33]. Because the available cross-national measures of education and skills either lack consistent validity across the OECD or do not cover all members in the study period (Section 3.2), the domain is measured here by its health component (life expectancy and health expenditure); the education and skills component of human capital is not part of the main indicator set, and its omission is examined in a sensitivity analysis (Section 4.5). *Innovation capacity*, captured by research and development (R&D) intensity and high-technology exports, reflects the generation of new knowledge and its commercialisation [25,34]. *Energy and environment* capture the material basis of the growth model: energy import dependence affects exposure to external price shocks and is a core element of energy security [35,36], and forest cover indicates natural capital. Finally, *institutional quality* (government effectiveness, regulatory quality and control of corruption) shapes the incentives for investment and the state's capacity to coordinate transformation [37–39]; it is measured with the Worldwide Governance Indicators

[40,41]. Each domain corresponds to one or more SDGs (Table 1): economic capacity and macroeconomic stability to SDG 8, digital infrastructure and innovation capacity to SDG 9, health to SDG 3, energy and environment to SDGs 7 and 15, and institutional quality to SDG 16 [6]. Climate outcomes (SDG 13) and the share of renewable electricity (SDG 7) are analysed separately as outcomes.

The domains are expected to be interdependent. Digital infrastructure creates value only when it is complemented by human capital and institutions, and decarbonisation is easier to finance under macroeconomic stability. Because of such complementarities, countries may differ in the combination of capabilities and not only in their individual levels; whether they do is an empirical question addressed in Section 4.

2.3. Readiness Indices, Classifications and Benchmarking

Several international indices already measure aspects of national readiness. The Global Competitiveness Index assessed the drivers of productivity across institutions, infrastructure, ICT adoption, macroeconomic stability, health, skills and innovation [42]; the Network Readiness Index measures countries' preparedness to benefit from digital technologies [43]. The Global Innovation Index benchmarks innovation inputs and outputs [44], and the Sustainable Development Report tracks progress towards the SDGs [45]. These indices are valuable for monitoring, but they share the limitations of composite indicators: their results depend on normalisation, weighting and aggregation choices, and methodological reviews recommend systematic uncertainty and sensitivity analysis [9–11]. They also impose a compensatory logic and a single ordering on what may be qualitatively different development paths. The framework proposed here does not escape compensation because a principal component score is also a weighted sum of indicators. It differs in three respects: The weights are estimated from the data and their domain composition is reported. The uncertainty of the resulting classification is quantified, and the score is complemented by indicator-level gaps that retain the non-compensatory information a single number hides.

The configurational approach starts from a different assumption: units of analysis form a limited number of internally coherent types [13,14], and comparative studies of OECD economies have shown that institutional complementarities produce distinct national models [15,16]. Cluster analysis is the main tool for identifying such types, but its use in strategic management has been criticised for atheoretical variable selection, inattention to multicollinearity and insufficient validation [19]. Recent country-level studies illustrate both the potential and the limitations of these approaches. Composite indices of country sustainability profiles and of sustainable transformation potential have been built with equal or PCA-based weights and tested for robustness [46,47]; OECD countries have been ranked on sustainable competitiveness with objective weighting and multi-criteria methods and grouped with k-means [48]. EU member states have been classified by innovation capacity and sustainability outcomes with grey clustering [49], and national SDG pathways have been classified with Bayesian and machine-learning methods [50,51]. Recent multidimensional analyses also report a dominant common factor: in the EU, a single factor dominated by digital variables explains most of the variation in digital transformation and sustainable orientation, and Ward clustering yields three groups [52]; globally, countries' positions in a multidimensional capability space have converged mildly since the mid-1990s [53]. Most of these studies focus on outcomes or rankings, and few combine scale-free capability indicators, formal cluster-stability testing and peer-based benchmarking for an individual country. These considerations translate into four design principles: indicators are selected according to an explicit capability framework; they are expressed in scale-free units. The dimensionality of the data is assessed before clustering, and the solution is subjected to validation and stability tests.

A classification also has value for benchmarking. Classic benchmarking emphasises learning from relevant comparators rather than from an abstract frontier [18], and Gerschenkron's analysis of relative backwardness implies that late developers follow paths shaped by their starting conditions [54]. A classification makes these ideas operational by identifying a country's structural peers and the nearest members of the next profile, whose capability mix may represent an attainable intermediate target. Whether such a comparator is useful in practice also depends on whether its policies can be transferred to a different economic and institutional context [55]. We call this approach *stepping-stone benchmarking* and apply it to Türkiye in Section 4.10.

3. Materials and Methods

3.1. Sample and Period

The sample consists of all 38 OECD member countries, including Colombia and Costa Rica, which acceded in 2020 and 2021, respectively, and are analysed for the whole period. The OECD is a suitable setting because its members share comparable statistical standards and policy frameworks while still differing considerably in their capabilities. The study period, 2015–2023, begins with the adoption of the 2030 Agenda and the Paris Agreement and covers a pre-pandemic expansion (2015–2019) and a period of overlapping shocks (2020–2023). Because structural capabilities change slowly and annual observations are affected by cyclical noise, the main analysis uses country-level averages over the period; sub-period averages and annual projections are used to examine robustness and change over time.

3.2. Indicators

Seventeen indicators were selected from the World Development Indicators and the Worldwide Governance Indicators [40,41,56] according to four criteria: (i) theoretical relevance to one of the seven capability domains; (ii) scale independence, meaning that every indicator is expressed per capita, per 100 or per million inhabitants, as a share, or as an index; (iii) public availability with adequate coverage; and (iv) meaningful and valid variation within the OECD. The fourth criterion led to the exclusion of three candidate indicators. Access to electricity is at or very close to 100% in almost all member countries. Gross secondary and tertiary enrolment ratios frequently exceed 100% and are inflated by distance and open-education enrolment in some countries; over the period of 2015–2023, the gross secondary ratio exceeds 100% in 34 of the 38 countries and the gross tertiary ratio reaches 147% in Greece and 113% in Türkiye, so these ratios do not measure human capital consistently across the OECD. Assessment-based measures were not used either: student assessments such as PISA measure the skills of 15 year olds rather than those of the workforce and are available only every three years, and adult skill surveys do not cover all members within the study period. Because the omission of education may still matter, the analysis was repeated with the enrolment ratios added (Section 4.5). Two indicators were excluded from the readiness set because they describe environmental outcomes rather than capabilities: CO_2 emissions per capita and the share of renewable electricity in total electricity output. Both are analysed separately as outcomes (Section 3.9); including the renewable share among the inputs would make the analysis of its association with readiness partly circular. Table 1 lists the indicators, their World Bank codes, transformations, the expected direction of their association with readiness and the related SDGs.

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Table 1. Capability domains, indicators and related Sustainable Development Goals.

Domain	Indicator	World Bank Code	Transf.	Sign	SDG
Economic capacity	GDP per capita, PPP (constant 2021 int. $)	NY.GDP.PCAP.PP.KD	log	+	SDG 8
	Gross capital formation (% of GDP)	NE.GDI.TOTL.ZS	–	+	SDG 8
Macroeconomic stability	Inflation, consumer prices (annual %)	FP.CPI.TOTL.ZG	signed log	−	SDG 8
	Unemployment (% of labour force)	SL.UEM.TOTL.ZS	–	−	SDG 8
Digital infrastructure	Individuals using the Internet (% of population)	IT.NET.USER.ZS	–	+	SDG 9
	Fixed broadband subscriptions (per 100 people)	IT.NET.BBND.P2	–	+	SDG 9
	Mobile cellular subscriptions (per 100 people)	IT.CEL.SETS.P2	–	+	SDG 9
	Secure Internet servers (per 1 million people)	IT.NET.SECR.P6	log	+	SDG 9
Human capital and health	Life expectancy at birth (years)	SP.DYN.LE00.IN	–	+	SDG 3
	Current health expenditure (% of GDP)	SH.XPD.CHEX.GD.ZS	–	+	SDG 3
Innovation capacity	Research and development expenditure (% of GDP)	GB.XPD.RSDV.GD.ZS	–	+	SDG 9
	High-technology exports (% of manufactured exports)	TX.VAL.TECH.MF.ZS	–	+	SDG 9
Energy and environment	Energy imports, net (% of energy use)	EG.IMP.CONS.ZS	rank	−	SDG 7
	Forest area (% of land area)	AG.LND.FRST.ZS	–	+	SDG 15
Institutional quality	Government effectiveness (estimate)	GE.EST	–	+	SDG 16
	Regulatory quality (estimate)	RQ.EST	–	+	SDG 16
	Control of corruption (estimate)	CC.EST	–	+	SDG 16

Note: Data from the World Development Indicators [56] and the Worldwide Governance Indicators, 2025 revision [41]. Transf. = transformation (rank = rank-based normal scores). "+"/"−" indicate the expected direction of association with strategic readiness; signs are used for interpretation only and indicators are not re-oriented before PCA. CO_2 emissions per capita (EN.GHG.CO2.PC.CE.AR5) and renewable electricity output (EG.ELC.RNEW.ZS) are analysed as outcomes and are not part of the readiness set.

3.3. Data Preparation and Coverage

For each country and indicator, the arithmetic mean of all available annual observations in 2015–2023 was computed. Coverage is close to complete (Table S2): 15 of the 17 indicators are observed for all 38 countries in all nine years. The exceptions are R&D expenditure, for which six countries have between four and eight annual observations (Australia, Switzerland, Chile, Colombia, Costa Rica and New Zealand), and net energy imports, which are not reported for Iceland; in total, 99.5% of country-year cells are observed, and the annual share of missing cells never exceeds 1%. Mobile subscriptions per 100 inhabitants were computed from total subscriptions and population. The governance indicators were taken from the 2025 revision of the Worldwide Governance Indicators, in which all historical estimates were recalculated with a revised methodology [41]; the version used (downloaded on 9 November 2026) is archived with the raw data in the Supplementary Materials. GDP per capita and secure Internet servers, which are strongly right-skewed, were log-transformed. Inflation was transformed with a signed logarithm, $\text{sign}(x)\cdot\ln(1 + |x|)$, which preserves the ordering of countries while limiting the leverage

of the extreme rates observed in a few members during the period of 2021–2023. Net energy imports, which range from −657% of energy use for Norway, a large net exporter, to 109%, were converted to rank-based normal scores so that a single extreme exporter does not dominate the standardised values. The single missing period mean (energy imports for Iceland; 0.2% of the data matrix) was imputed with regularised iterative PCA [57]. All indicators were then standardised to z-scores.

3.4. Principal Component Analysis

The suitability of the correlation matrix for dimension reduction was assessed with the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy [58] and Bartlett's test of sphericity. PCA was performed on the correlation matrix [59]. The number of components was determined with Horn's parallel analysis [60], which retains components whose eigenvalues exceed the 95th percentile of eigenvalues from 1000 random data sets of the same dimensions; the Kaiser criterion is reported for comparison. The first unrotated principal component (PC1) is the general capability score used throughout the analysis: it defines the clustering space, and its loadings are used to project annual data (Section 3.8). A country's PC1 score is the sum of its standardised indicator values weighted by the elements of the first eigenvector; a score of zero corresponds to the OECD average profile. Positive scores indicate above-average general capability, and the standard deviation of the score across countries equals the square root of the first eigenvalue. Because PC1 is largely a combination of income and governance, we also examined what it adds beyond these two elements by comparing it with a classification based only on GDP per capita and the governance indicators and by examining the part of PC1 that they do not explain. To describe secondary structure, the first two components were also rotated with the varimax criterion [61]. The rotated components (RC1 and RC2) and the unrotated second component (PC2) are used only for description and visualisation.

3.5. Clustering and the Number of Profiles

Countries were clustered with Ward's minimum-variance method [62] in its Ward.D2 implementation [63]. Because parallel analysis retained a single component, the main clustering space is PC1. Clustering in a single dimension amounts to dividing the capability continuum into segments: Ward's method places the boundaries between profiles at the largest gaps in the ordered PC1 scores, and we report the resulting cut-points. The profiles are therefore interpreted as a descriptive classification of countries by their level of general capability rather than as natural types. To show how this choice affects the results, the same procedure was applied in the space of the first two components, in the space of the Kaiser-retained components and on all standardised indicators (Section 4.6). The number of profiles k was evaluated for $k = 2, \ldots, 8$ using the average silhouette width [64] and the gap statistic with 500 reference data sets [65]; the majority rule across the validity indices in NbClust [66] is reported in Table S4 for the two-component space. Solutions containing a cluster with fewer than three countries were treated as inadmissible for benchmarking, and the final k was the admissible solution with the largest average silhouette width. Because the gap statistic tests whether any clustering is preferable to none, its result is reported alongside the chosen solution and taken into account in the interpretation.

3.6. Validation and Robustness

Eight sets of checks were performed. (i) *Stability*: In each of 1000 bootstrap resamples of countries, the indicators were re-standardised. PCA was re-estimated, and the countries were re-clustered so that the uncertainty of every step of the procedure is reflected; the same was performed for 1000 subsamples containing 80% of the countries. Cluster-wise

stability was measured with the mean Jaccard similarity between each original cluster and its most similar resampled cluster; values above 0.75 indicate stable clusters, values between 0.60 and 0.75 patterns, and values below 0.50 dissolved clusters [67]. For each country, we also report the share of resamples in which it was assigned to the same cluster as the other members of its profile and, for the smallest profile, the share of resamples in which it re-formed with exactly the same members. The conventional bootstrap with component scores held fixed is reported for comparison. (ii) *Algorithm*: The partition was compared with those from k-means (100 starts), partitioning around medoids [68], and average and complete linkage. (iii) *Clustering space*: The clustering space is as described in Section 3.5. (iv) *Indicators and domains*: The procedure was repeated after removing each indicator and each domain in turn [10]. (v) *Outcome-type indicators and transformations*: The procedure was repeated without GDP per capita and life expectancy, with untransformed inflation and energy imports, with the renewable share added back to the inputs, with gross tertiary and secondary enrolment ratios added, and with an earlier 20-indicator specification. (vi) *Time window and coverage*: The procedure was repeated for 2015–2019 and 2020–2023, for the common period 2015–2021, using 2015 data only, and after setting period means based on fewer than five annual observations to missing and re-imputing them. (vii) *Domain weighting*: See Section 3.7. (viii) *Scale*: See Section 4.7. Agreement between partitions was measured with the adjusted Rand index (ARI) [69], which equals 1 for identical partitions and has an expected value of 0 under random labelling.

3.7. Domain Weighting

Any procedure that combines indicators implies weights. In PCA, the weight of each indicator in PC1 is determined by its correlations with the other indicators, so domains whose indicators are strongly intercorrelated, or measured by more indicators, contribute more to the score; PC1 is therefore independent of *predetermined* weights but not of weighting *choices*. To make this explicit, we report the share of each domain's variance that is captured by PC1, and we repeated the clustering under three alternatives that give the seven domains equal total weight: (a) Ward clustering of the z-scores after multiplying each indicator by $1/\sqrt{n_a}$, where n_a is the number of indicators in its domain, so that each domain contributes the same total variance; (b) Ward clustering of seven direction-adjusted domain scores, each the mean z-score of the domain's indicators; and (c) Ward clustering of an equal-weight composite of the seven standardised domain scores. Memberships and Türkiye's nearest neighbours were compared with those of the main solution.

3.8. Profile Characterisation and Change over Time

Profiles were characterised by their mean z-scores and by their means in original units. Because the profiles were formed from the same indicators, conventional significance tests of differences between them would be circular and their p-values would be invalid. Differences are therefore reported descriptively using the Kruskal–Wallis ε^2 effect size; for the same reason, the random forest classifier [70] (2000 trees) is used only to rank indicators by their contribution to separating the profiles. To examine change over time, each country's annual observations for 2015–2023 were transformed with the same transformations, standardised with the cross-country means and standard deviations of the 2015–2023 period averages, and multiplied by the PC1 weights estimated for the period. The annual score of country i in year t is thus $\Sigma_j\, w_j\, (x_{ijt} - \bar{x}_j)/s_j$, where w_j is the PC1 weight of indicator j and $\bar{x}_j$ and s_j are its period mean and standard deviation. Because the weights and standardisation parameters are held fixed, changes in a country's score reflect changes in its indicators relative to a common benchmark rather than changes in the weights. Gaps in the annual series were filled with the country's period mean; because this can flatten trends and uses information from later years, the results were also

computed with linear interpolation, with the last observation carried forward and for complete cases only. Change was summarised with σ-convergence, the change in the cross-country standard deviation of the scores, which is the primary measure. β-convergence, the rank correlation between initial level and subsequent change, is reported as a secondary measure because it is biased towards convergence by measurement error and regression to the mean [71]. To reduce this bias, the initial level (mean of 2015–2016) and the change (from the mean of 2017–2018 to the mean of 2022–2023) were measured in non-overlapping years, and the observed correlation was compared with its distribution in 2000 simulated panels without true convergence, in which each country's mean score was held constant and noise with the observed within-country standard deviation was added.

3.9. Sustainability Outcomes

To address RQ3, the general capability score (PC1) was related to two outcomes that are not part of the readiness set. Emissions are measured with the World Bank series EN.GHG.CO2.PC.CE.AR5, *carbon dioxide (CO_2) emissions excluding land use, land-use change and forestry (LULUCF) per capita*, reported in tonnes of CO_2 equivalent per person and taken from the EDGAR Community GHG Database of the European Commission's Joint Research Centre [72]; the series covers fossil and industrial CO_2 only, and other greenhouse gases are not included. It is available for all countries for 2015–2023, and we used its period mean and its percentage change between 2015 and 2023. The renewable share is measured as renewable electricity output in percent of total electricity output (EG.ELC.RNEW.ZS); its period mean is based on 2015–2021 for 37 countries and on 2015–2016 for Iceland, and its change is measured in percentage points between the first and last available years. Because Iceland's shorter series reduces comparability, the renewable analysis was repeated without Iceland and with a common window of 2015–2016 for all countries. Associations were measured with Spearman rank correlations, with 95% bootstrap confidence intervals (2000 resamples) and the range of estimates when each country was left out in turn. Because emission change may reflect initial emission levels, income, the energy mix and the economic structure rather than capability, the percentage change in emissions was also regressed on PC1 with parsimonious sets of controls: the logarithm of initial emissions, the logarithm of GDP per capita, the initial renewable share and the initial industry share of GDP (NV.IND.TOTL.ZS). All predictors were standardised, and we report heteroskedasticity-consistent (HC3) standard errors, bootstrap confidence intervals and leave-one-country-out ranges for the PC1 coefficient. Because the main capability score averages the same years over which emission change is measured, the correlations and models were also estimated with capability measured in 2015, the first year of the period, both by projecting the 2015 values onto the period loadings and by estimating a separate PCA on 2015 data. With 38 observations, these models describe conditional associations and do not identify causal effects.

3.10. Benchmarking Türkiye

Three tools translate the classification into benchmarking information for Türkiye. First, Türkiye's nearest neighbours identify its structural peers. Second, the nearest countries in the adjacent higher profile are candidate stepping-stone benchmarks. Because distances, and therefore neighbours, depend on the space in which they are measured, neighbours were computed in six spaces: PC1, the first two components, the Kaiser-retained components, all standardised indicators, the domain-weighted indicators and the seven domain scores. To make the choice reproducible, the members of the adjacent profile were ranked by their mean distance rank across the six spaces, and the two countries with the lowest mean rank were selected as candidate benchmarks. Third, Türkiye's capability gaps are computed indicator by indicator as the difference between the comparator's

value and Türkiye's, with the sign reversed for indicators for which lower values are favourable. An indicator is classified as a priority gap if Türkiye is at least one standard deviation behind the mean of the adjacent profile, behind both candidate benchmarks, and the indicator carries a substantial weight in the general capability score (absolute PC1 loading of at least 0.40). For each priority gap, we report whether Türkiye's position improved, remained stable or deteriorated between 2015 and 2023 (a change of at least 0.25 standard deviations). These gaps identify where Türkiye differs from its comparators in the data, not which policies would close them.

3.11. Software and Reproducibility

All analyses were conducted in R version 4.6.0 using the packages WDI, FactoMineR [73], factoextra, psych, missMDA, cluster, NbClust, fpc, mclust and randomForest, with the random seed fixed at 2026. The complete R code, which reproduces all tables and figures, and the raw data, including the archived governance data, are provided as Supplementary Materials. Figure 1 summarises the analytical framework.

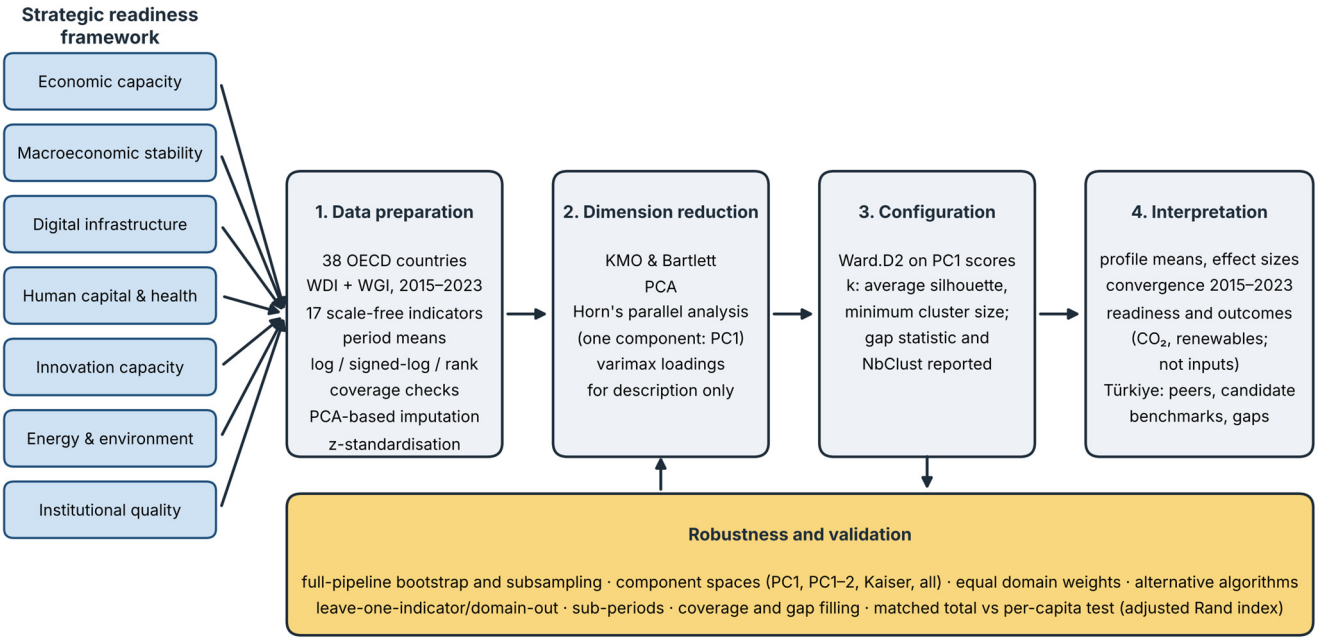


Figure 1. The analytical framework of the study.

4. Results

4.1. Data Structure and Sampling Adequacy

Descriptive statistics, including the values for Türkiye, are reported in Table S1. Türkiye records the highest average inflation (24.0%) and the highest gross capital formation (32.6% of GDP) in the OECD and the lowest current health expenditure (4.3% of GDP) and share of high-technology exports (3.3% of manufactured exports). Figure S1 shows the correlation structure. The three governance indicators, GDP per capita; Internet use, fixed broadband, and secure servers; and life expectancy, form a strongly correlated block; government effectiveness, for example, correlates at r = 0.94 with control of corruption, 0.88 with Internet use and 0.84 with GDP per capita. Inflation is negatively associated with this block (r = −0.53 with government effectiveness and −0.68 with life expectancy), whereas forest area, energy imports and mobile subscriptions are only weakly related to it. The overall KMO value was 0.758, and Bartlett's test rejected the hypothesis of an identity

correlation matrix (χ^2 = 545.9, df = 136, $p < 0.001$). Four indicators had individual MSA values below 0.50 (gross capital formation, mobile subscriptions, energy imports and forest area); they were retained for theoretical reasons, and removing any of them leaves the partition unchanged (Section 4.5).

4.2. Latent Dimensions of Strategic Readiness (RQ1)

The first principal component has an eigenvalue of 7.60 and explains 44.7% of the total variance; the second explains a further 12.0% (Figure 2; Table 2). Parallel analysis retains only the first component, whereas the Kaiser criterion would retain five. A single general dimension therefore dominates cross-country differences, and the secondary components cannot be distinguished from those expected in random data of the same size.

PC1 loads most strongly on government effectiveness (0.97), regulatory quality (0.92), control of corruption (0.91), Internet use (0.89), GDP per capita (0.87), fixed broadband (0.83), secure servers (0.77) and life expectancy (0.73), with further positive loadings for R&D intensity (0.67) and health expenditure (0.60) and negative loadings for inflation (−0.59) and unemployment (−0.47). We interpret PC1 as *general strategic capability*: institutional quality, income, digital infrastructure, health and innovation vary together, as the complementarity argument in Section 2 anticipates. After varimax rotation of the first two components, RC1 is very close to PC1 (the correlation between the two scores is 0.985). RC2 (12.9% of the variance) contrasts gross capital formation (0.61), high-technology exports (0.49) and inflation (0.45) with unemployment (−0.60), mobile subscriptions (−0.53), energy imports (−0.48) and forest area (−0.43); it can be read as an investment- and manufacturing-oriented growth model, but because it is not retained by parallel analysis, we use it only descriptively.

PC1 does not represent the seven domains equally (Table 2 and Table S5). It captures 87% of the variance of the institutional quality indicators, 52% of digital infrastructure and 45% of health, but only 39% of economic capacity, 32% of innovation, 28% of macroeconomic stability and 2% of energy and environment. Communalities in the two-component solution range from 0.19 (forest area) and 0.23 (energy imports) to 0.94 (government effectiveness). The general capability score is therefore driven mainly by institutional quality, income, digital infrastructure and health and says little about the energy and environment domain.

Because PC1 is so closely related to income and institutions, we examined what it adds beyond them. GDP per capita and the mean of the three governance indicators together explain 92% of the cross-country variance of PC1 (adjusted R^2 = 0.92), and a Ward classification based only on GDP per capita and the governance indicators reproduces the main solution only partly (ARI = 0.72), moving Estonia, Israel and Korea (Table S10). The part of PC1 not explained by income and governance is most strongly associated with R&D intensity (ϱ = 0.64), fixed broadband (0.51), health expenditure (0.45) and high-technology exports (0.44). The general capability score thus combines income and institutional quality with digital, innovation and health depth, and it is this additional depth that distinguishes countries such as Korea and Israel from others with similar income and governance. Its added value lies less in the scalar score itself than in the classification and indicator-level comparisons built on it.

Table 2. Principal component loadings, varimax-rotated loadings and communalities (h^2).

Indicator	PC1	RC1	RC2	h^2
GDP per capita (PPP)	0.87	0.85	0.21	0.77
Gross capital formation	0.16	0.06	0.61	0.38
Inflation	−0.59	−0.68	0.45	0.66
Unemployment	−0.47	−0.37	−0.60	0.50

Internet users	0.89	0.86	0.26	0.80
Fixed broadband	0.83	0.84	0.06	0.70
Mobile subscriptions	−0.01	0.08	−0.53	0.29
Secure internet servers	0.77	0.74	0.22	0.60
Life expectancy	0.73	0.79	−0.27	0.70
Health expenditure	0.60	0.61	−0.05	0.38
R&D expenditure	0.67	0.66	0.12	0.45
High-tech exports	0.43	0.35	0.49	0.37
Energy imports	−0.01	0.07	−0.48	0.23
Forest area	−0.18	−0.10	−0.43	0.19
Government effectiveness	0.97	0.96	0.14	0.94
Regulatory quality	0.92	0.90	0.19	0.84
Control of corruption	0.91	0.91	0.10	0.83
Eigenvalue (unrotated)	7.60	–	–	
Variance explained (%)	44.7	43.8	12.9	

Note: PC1 = first unrotated principal component (general strategic capability), used for clustering and for the annual projections. RC1 and RC2 = varimax-rotated components of the two-component solution, reported for description only; h^2 = communality in the two-component solution. KMO = 0.758; Bartlett's $\chi^2 = 545.9$, df = 136, $p < 0.001$. Parallel analysis retains one component.

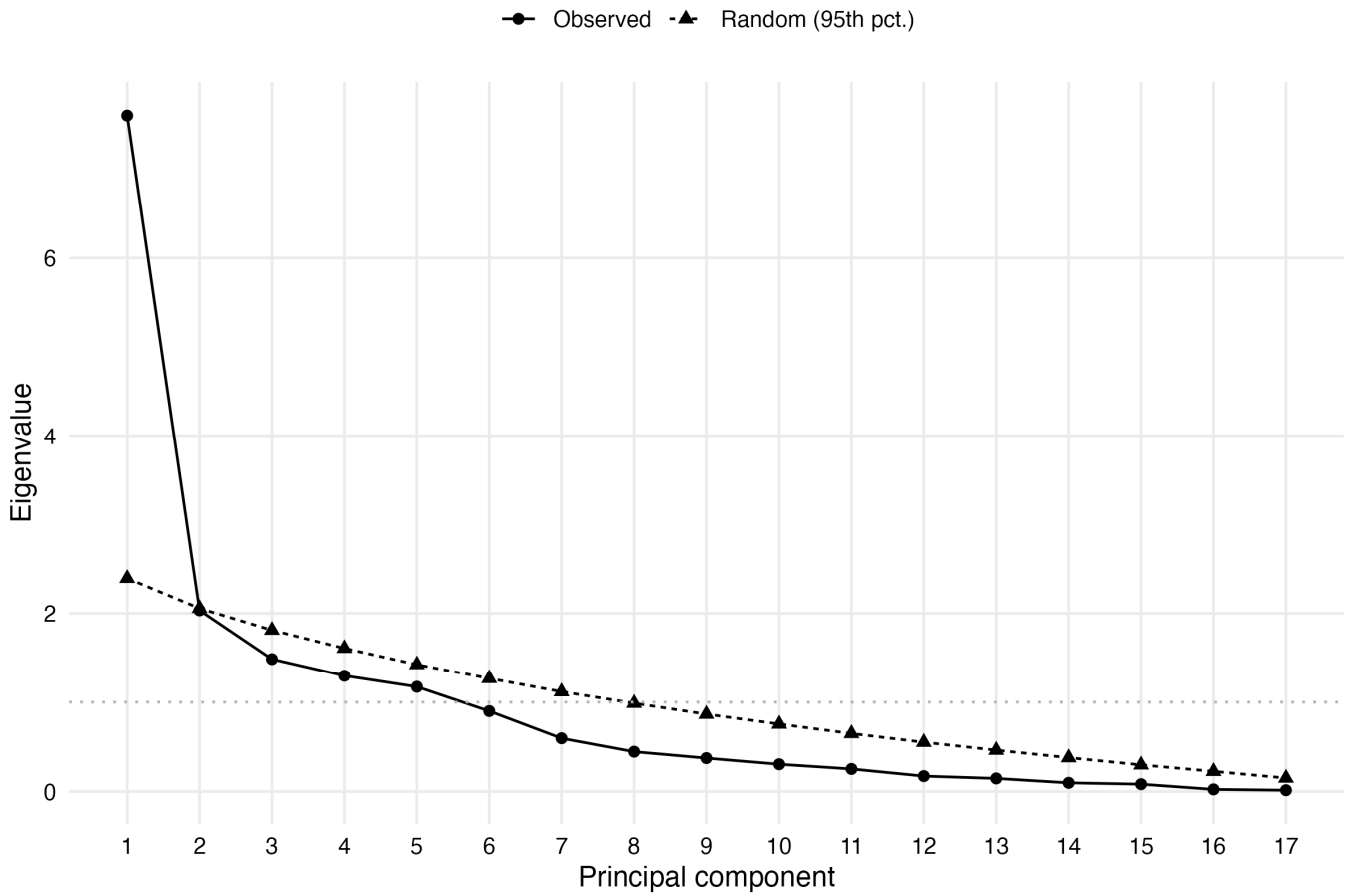


Figure 2. The scree plot with Horn's parallel analysis (95th percentile of 1000 random data sets); the dotted line marks an eigenvalue of 1.

4.3. Number of Profiles

Table 3 and Figure 3 summarise the evidence on the number of profiles in the PC1 space. The average silhouette width is highest for three profiles (0.724), followed by four

(0.697) and two (0.673), and the three-profile solution was therefore retained; in the two-component space, the NbClust majority rule also favours three profiles (nine indices, against five for two). A silhouette width above 0.70 indicates a strong structure [68], but in one dimension it mainly reflects how well the continuum is divided at its largest gaps. The gap statistic does not support a departure from a single group: under the first-SE-maximum rule it selects $k = 1$ because the gap at $k = 2$ (0.217; SE 0.095) does not exceed the gap at $k = 1$ (0.145) by more than one standard error. Together with the dominance of a single component, this shows that the OECD countries do not form sharply separated natural groups. The profiles reported below are best understood as a descriptive classification of a capability continuum into segments whose boundaries lie at the largest gaps in the distribution of PC1. The boundary between the third and second profiles lies between Türkiye (PC1 = −5.85), the highest-scoring member of the third profile, and Costa Rica (−3.89), the lowest-scoring member of the second; the boundary between the second profile and the core lies between Estonia (0.01) and Israel (1.04) (Table S3). The two-profile solution differs from the three-profile solution only in that it merges the second and third profiles.

Table 3. Evidence on the number of strategic readiness profiles.

k	Cluster sizes	Avg. Silhouette	Gap (SE)	NbClust Votes (PC1–PC2)	Admissible
2	21/17	0.673	0.217 (0.095)	5	Yes
3	21/14/3	0.724	0.195 (0.093)	9	Yes
4	21/9/5/3	0.697	0.161 (0.086)	3	Yes
5	17/9/5/4/3	0.663	0.209 (0.089)	2	Yes
6	11/9/6/5/4/3	0.679	0.277 (0.094)	1	Yes
7	11/8/6/5/4/3/1	0.674	0.287 (0.101)	0	No
8	11/8/6/5/3/3/1/1	0.663	0.246 (0.104)	3	No

Note: Admissible solutions contain no cluster with fewer than three countries. Cluster sizes, silhouette widths and gap statistics refer to the PC1 space. The gap statistic for k = 1 is 0.141 (SE 0.080); the first-SE-maximum rule therefore selects k = 1. NbClust votes are the number of indices for which k is optimal in the space of the first two components, reported descriptively. The retained solution is k = 3, the admissible solution with the largest average silhouette width.

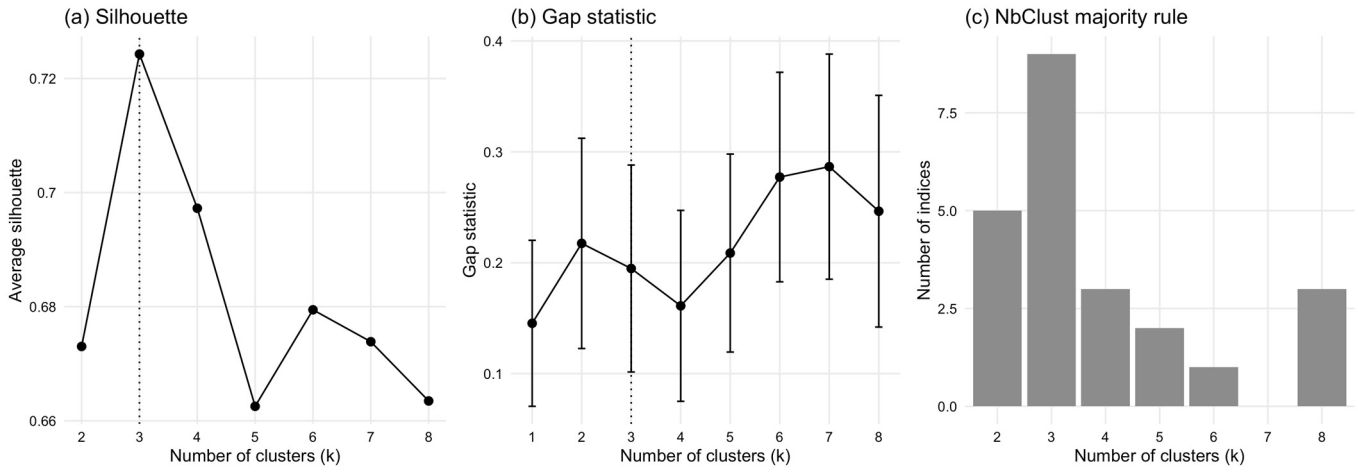


Figure 3. The selection of the number of profiles in the PC1 space: (**a**) average silhouette width; (**b**) gap statistic with simulation standard errors; (**c**) number of NbClust indices supporting each k in the space of the first two components.

4.4. Strategic Readiness Profiles (RQ2)

Figure 4 places the countries in the space of the first two components. Table 4 and Figure 5 report the profile means, and the Ward dendrogram is shown in Figure S2.

Profile 1—Advanced capability core (n = 21: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Iceland, Ireland, Israel, Japan, Korea, Luxembourg, the Netherlands, New Zealand, Norway, Sweden, Switzerland, the United Kingdom and the United States). These countries are above the OECD mean on almost every capability indicator. Their average GDP per capita is 65,600 international dollars (PPP, constant 2021 prices), and their government effectiveness, regulatory quality and control of corruption estimates average 1.70, 1.58 and 1.71. Their R&D intensity is 2.7% of GDP, and inflation and unemployment average 2.3% and 5.2%.

Profile 2—Intermediate group (n = 14: Chile, Costa Rica, Czechia, Estonia, Greece, Hungary, Italy, Latvia, Lithuania, Poland, Portugal, the Slovak Republic, Slovenia and Spain). This group combines Southern European, Central and Eastern European and two Latin American members. It lies below the core on institutional quality (estimates of 0.84, 0.87 and 0.68), income (38,200 international dollars), digital depth and innovation (R&D intensity 1.2% of GDP), and it has higher unemployment (8.3%). Its inflation (3.5%) is only slightly above that of the core.

Profile 3—Capability-constrained group (n = 3: Colombia, Mexico and Türkiye). These countries are furthest from the core on almost every indicator: GDP per capita of 22,800 international dollars, governance estimates close to zero (0.06, 0.10 and −0.49), an average of only 2077 secure Internet servers per million inhabitants, 16.1 fixed broadband subscriptions per 100 inhabitants and average inflation of 11.5%. Their gross capital formation (25.3% of GDP), by contrast, is the highest of the three profiles.

The effect sizes in Table 4 show that the profiles differ most in government effectiveness ($\varepsilon^2 = 0.78$), GDP per capita (0.73), regulatory quality (0.69), control of corruption (0.67), Internet use (0.65) and R&D intensity (0.55) and least in forest area, mobile subscriptions, energy imports and gross capital formation ($\varepsilon^2 \leq 0.09$). The random forest ranks government effectiveness, regulatory quality, GDP per capita and control of corruption as the four indicators that best separate the profiles (Figure S4). Because the profiles are segments of PC1, these differences largely mirror the PC1 loadings. Costa Rica and Estonia (silhouette widths of 0.05 and 0.06) lie on the boundary between profiles, and Czechia (0.43) is less clearly assigned than the other members of the intermediate group.

Table 4. Mean standardised indicator values by strategic readiness profile.

Indicator	P1 (n = 21)	P2 (n = 14)	P3 (n = 3)	ε^2	RF Rank
GDP per capita (PPP)	0.66	−0.59	−1.86	0.73	3
Gross capital formation	0.20	−0.41	0.48	0.09	13
Inflation	−0.41	0.18	2.03	0.30	9
Unemployment	−0.42	0.51	0.58	0.18	14
Internet users	0.66	−0.55	−2.09	0.65	5
Fixed broadband	0.58	−0.44	−1.99	0.51	8
Mobile subscriptions	−0.12	0.33	−0.76	0.06	17
Secure internet servers	0.41	−0.12	−2.27	0.31	12
Life expectancy	0.57	−0.48	−1.76	0.42	7
Health expenditure	0.48	−0.44	−1.32	0.38	10
R&D expenditure	0.62	−0.67	−1.18	0.55	6
High-tech exports	0.44	−0.50	−0.76	0.25	11
Energy imports	−0.06	0.23	−0.64	0.06	16
Forest area	−0.17	0.22	0.16	0.05	15
Government effectiveness	0.75	−0.70	−2.01	0.78	1
Regulatory quality	0.70	−0.62	−2.04	0.69	2

Control of corruption	0.69	−0.60	−2.05	0.67	4

Note: Values are profile means of z-scores (OECD mean = 0, SD = 1) before direction adjustment. P1 = advanced capability core; P2 = intermediate group; P3 = capability-constrained group. ε^2 is the Kruskal–Wallis effect size, reported descriptively because the profiles were formed from the same indicators. RF rank = rank by random-forest permutation importance (mean decrease in accuracy; out-of-bag error = 7.9%).

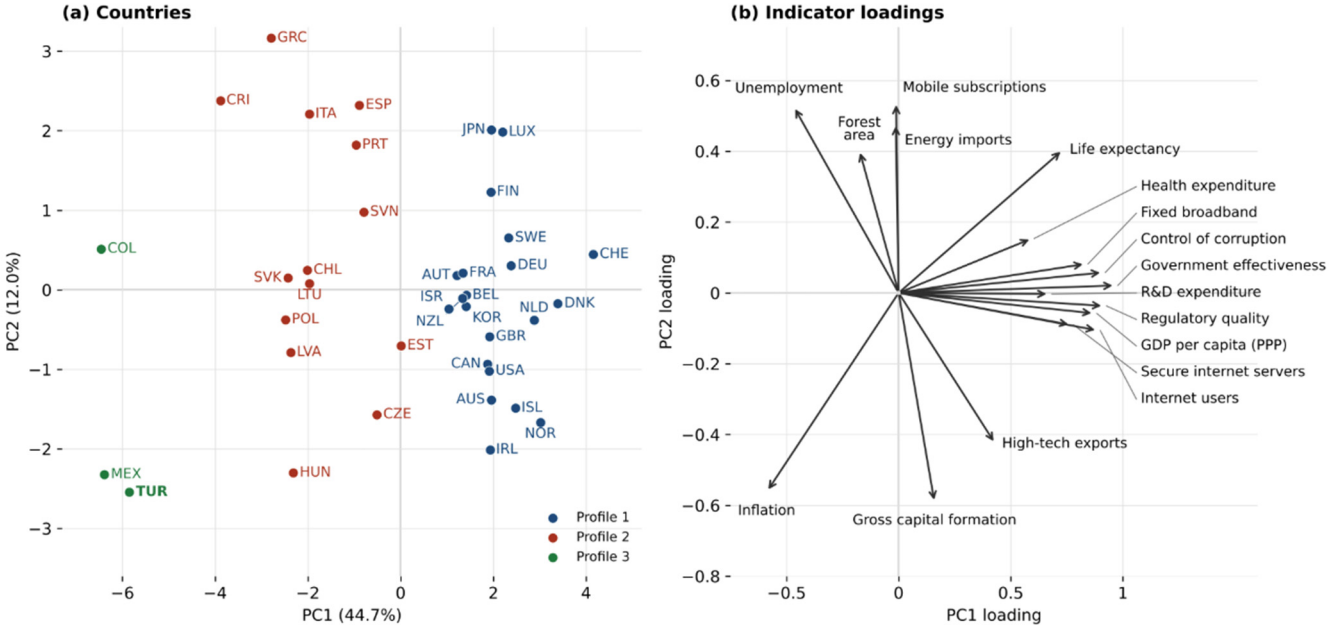


Figure 4. Countries and indicators in the space of the first two principal components: (a) country scores, coloured by profile; (b) indicator loadings. The profiles were formed on PC1 only; PC2 is shown for description. Türkiye is shown in bold.

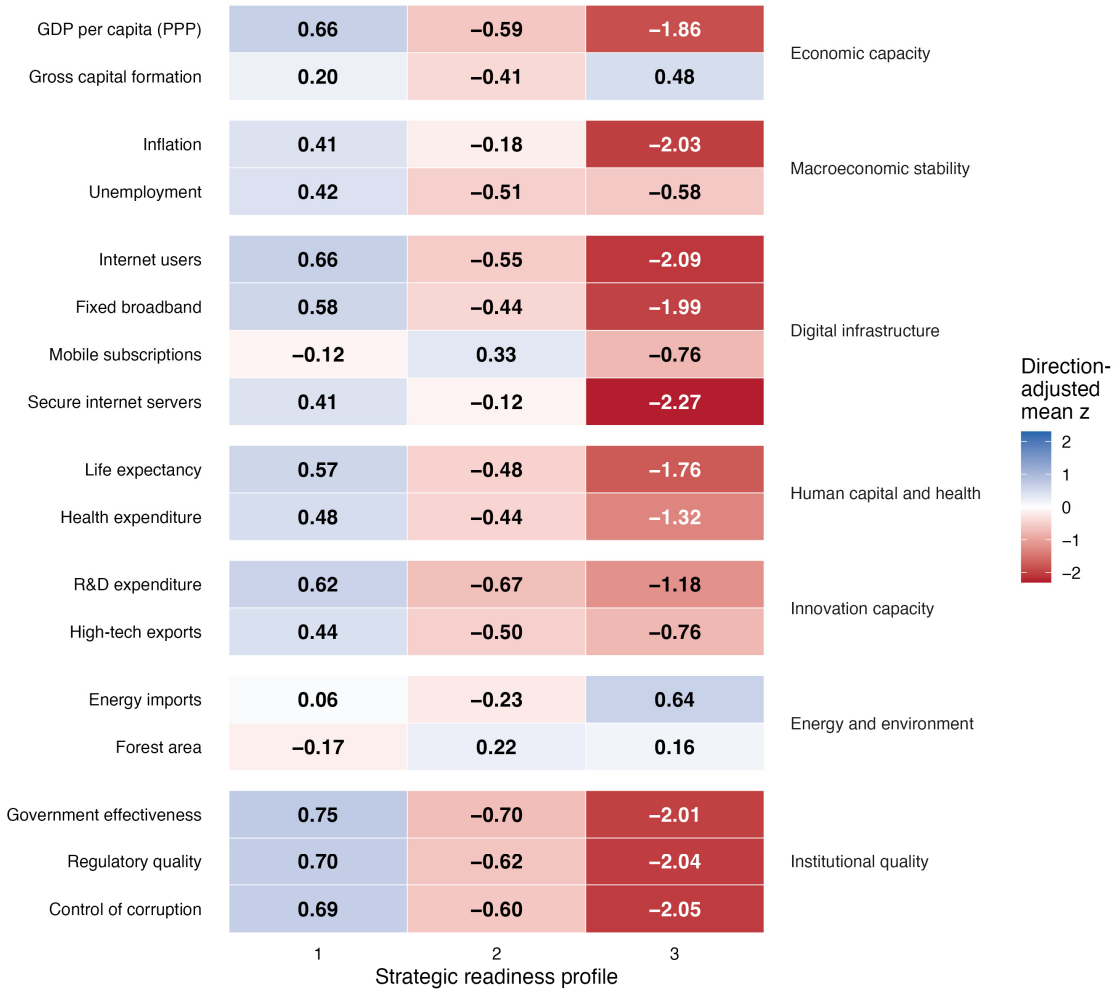


Figure 5. Direction-adjusted mean standardised indicator values by profile. For inflation, unemployment and energy imports the sign is reversed so that positive (blue) values always indicate a favourable position.

4.5. Stability and Robustness

Table 5 summarises the robustness checks. When the whole procedure, including standardisation and PCA, is re-estimated in each bootstrap resample, the mean Jaccard coefficients of the three profiles are 0.97, 0.93 and 0.89, and in 80% subsamples they are 1.00, 0.99 and 0.97; the conventional bootstrap with fixed scores gives slightly higher values (1.00, 0.97 and 0.91). The capability-constrained group re-forms with exactly the same three members in 94% of the bootstrap resamples that contain all three countries and in 99.8% of such subsamples; when it does not, it is usually because Costa Rica joins it. At the country level, every member of the core and of the third profile is co-assigned with the other members of its profile in at least 95% of resamples, whereas Costa Rica (69%) and Estonia (74%) are the least stable members of the intermediate group (Table S4; Figure S6). The partition is reproduced exactly by average and complete linkage and closely by k-means (ARI = 0.95) and partitioning around medoids (0.90). Removing any single indicator yields ARI values between 0.90 and 1.00, and removing any single domain yields values between 0.81 and 1.00; the partition is most sensitive to the removal of the innovation and the human capital and health domains (0.81). Excluding GDP per capita and life expectancy together gives an ARI of 0.81; leaving inflation or energy imports untransformed, adding the renewable share back to the inputs, using the common period 2015–2021 or re-imputing period means based on fewer than five observations leaves the

partition unchanged. Adding the gross tertiary enrolment ratio, with or without capping it at 100%, or both the tertiary and secondary ratios also leaves the partition unchanged (ARI = 1.00), so the omission of education indicators does not drive the classification (Table S11). The 2015–2019 and 2020–2023 partitions are identical to the full-period solution, and a PCA estimated on 2015 data alone yields a nearly identical score (ϱ = 0.98) and partition (ARI = 0.90).

Table 5. The stability and robustness of the strategic readiness profiles.

Check	Result	Interpretation
Full-procedure bootstrap, mean Jaccard, P1/P2/P3 (1000 resamples)	0.97/0.93/0.89	All profiles stable
Full-procedure 80% subsampling, mean Jaccard, P1/P2/P3	1.00/0.99/0.97	All profiles stable
Bootstrap with fixed PC1 scores, mean Jaccard, P1/P2/P3	1.00/0.97/0.91	For comparison
Profile 3 re-formed with identical members (bootstrap/subsampling)	94%/99.8%	Costa Rica occasionally joins
Lowest country-level co-assignment with own profile	CRI 0.69; EST 0.74	Boundary countries
Average linkage/complete linkage, ARI	1.00/1.00	Identical partition
k-means (100 starts)/partitioning around medoids, ARI	0.95/0.90	High agreement
Leave-one-indicator-out, ARI (min–max)	0.90–1.00	Most sensitive: R&D expenditure
Leave-one-domain-out, ARI (min–max)	0.81–1.00	Most sensitive: innovation; health
Without GDP per capita and life expectancy, ARI	0.81	Boundary countries reallocated
Inflation/energy imports untransformed, ARI	1.00/1.00	Identical partition
Renewable electricity added to the inputs (18 indicators), ARI	1.00	Identical partition
Earlier 20-indicator specification, ARI	0.90	High agreement
Sub-periods 2015–2019/2020–2023, ARI	1.00/1.00	Identical partitions
Common period 2015–2021, ARI	1.00	Identical partition
Period means based on <5 annual observations re-imputed, ARI	1.00	Identical partition

Note: In the full-procedure resamples, the indicators are re-standardised, PCA is re-estimated and the countries are re-clustered in each resample. Jaccard > 0.75 indicates a stable cluster, 0.60–0.75 a pattern and < 0.50 a dissolved cluster [67]. ARI = adjusted Rand index with the main solution (1 = identical partitions; 0 = agreement expected by chance).

4.6. Clustering Space and Domain Weighting

Table 6 compares the main solution with solutions obtained in other spaces and under equal domain weights. Clustering on the first two components reproduces the main solution exactly, and clustering on the five Kaiser-retained components or on all standardised indicators changes only the assignment of Costa Rica (ARI = 0.95). Because PC2 has a variance of only 2.05, the partition is identical when PC2 is given any weight between 0 and 1.25 times its variance-based weight; giving the two components equal weight or clustering on standardised varimax scores (ARI = 0.59 in both cases) enlarges the core to 24 countries and forms the lowest group of eight countries along the second dimension (Figure S5). That the main solution does not depend on PC2 confirms that the profiles are level groups along the general capability dimension rather than configurations that differ in their capability mix.

Equal domain weighting gives a more differentiated picture. Ward clustering of the seven domain scores and clustering on PC1 of the domain-weighted indicators (whose correlation with the main PC1 is ϱ = 0.98) reproduce the main solution exactly. Ward clustering of the domain-weighted indicators keeps the core unchanged but splits the remaining countries differently (ARI = 0.79): Greece, Italy, Portugal, Slovenia and Spain form a

separate group, and Türkiye, Mexico and Colombia are joined by Chile, Costa Rica, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland and the Slovak Republic. An equal-weight composite of the seven domains moves Czechia, Estonia and Slovenia into the core and Greece into the third group (ARI = 0.69). The core is thus robust to domain weighting, whereas the boundary between the intermediate and constrained groups depends partly on how much weight is given to the institutional and digital domains, which dominate PC1. Türkiye's nearest neighbours also depend on the space: in the PC1 space they are Mexico, Colombia and Costa Rica, whereas under equal domain weights they are Hungary and the Slovak Republic (Section 4.10).

Table 6. Profiles under alternative clustering spaces and domain weights.

Specification	Sizes	ARI	Lowest Group	Türkiye's Nearest Three
Main: Ward on PC1	21/14/3	1.00	COL, MEX, TUR	MEX, COL, CRI
Ward on PC1 and PC2	21/14/3	1.00	COL, MEX, TUR	MEX, COL, HUN
Ward on five Kaiser-retained components	21/13/4	0.95	COL, CRI, MEX, TUR	HUN, MEX, POL
Ward on all standardised indicators	21/13/4	0.95	COL, CRI, MEX, TUR	HUN, SVK, MEX
Ward on PC1 and PC2 with equal weight	24/8/6	0.59	CHL, COL, LTU, LVA, MEX, POL, SVK, TUR	MEX, HUN, LVA
Ward on standardised varimax scores	24/8/6	0.59	CHL, COL, LTU, LVA, MEX, POL, SVK, TUR	MEX, HUN, LVA
Ward on domain-weighted indicators	21/12/5	0.79	CHL, COL, CRI, CZE, EST, HUN, LTU, LVA, MEX, POL, SVK, TUR	HUN, SVK, CHL
Ward on PC1 of domain-weighted indicators	21/14/3	1.00	COL, MEX, TUR	MEX, COL, CRI
Ward on seven domain scores	21/14/3	1.00	COL, MEX, TUR	HUN, SVK, LTU
Ward on equal-weight composite of seven domains	24/10/4	0.69	COL, GRC, MEX, TUR	MEX, COL, GRC

Note: ARI = adjusted Rand index with the main solution. Equal weight of PC1 and PC2 corresponds to a weight of 1.93 for PC2. Domain-weighted indicators: z-scores multiplied by $1/\sqrt{n_a}$, where n_a is the number of indicators in the domain so that each domain contributes the same total variance. Domain scores are direction-adjusted mean z-scores of each domain's indicators. Country codes are ISO 3166-1 alpha-3 codes.

4.7. The Consequences of Scale-Dependent Indicators

To isolate the effect of scale, we compared specifications that differ only in whether four indicators (GDP, fixed broadband subscriptions, mobile subscriptions and secure servers) are measured as totals or per capita, keeping countries, years and all other indicators fixed (Table S8). In the 14-indicator specification of the earlier conference version of this study, in which these four indicators enter as log totals, PC1 is almost entirely a size factor (its rank correlation with log total GDP is $|\varrho| = 0.95$), and the resulting partition is unrelated to the main solution (ARI = 0.01): its lowest group consists of small economies (Costa Rica, Estonia, Iceland, Latvia, Lithuania, Luxembourg and Slovenia). Replacing only the four totals with their per capita counterparts in the same specification lowers the correlation with total GDP to $|\varrho| = 0.31$ and yields a partition close to the main solution (ARI = 0.90), with Colombia, Mexico and Türkiye again forming the lowest group. The remaining difference (ARI = 0.90 rather than 1.00) is the effect of the different indicator set. Conversely, replacing the four per capita indicators of the main specification with totals raises the correlation with total GDP from 0.29 to 0.49 and changes the two-component

partition (ARI = 0.59), although the PC1 partition is preserved because PC1 remains dominated by the governance indicators. Scale, rather than the choice of indicators, thus explains why the conference specification produced a typology driven by economic mass.

4.8. Change in General Capability, 2015–2023

Figure 6 shows the annual projections. The cross-country standard deviation of the general capability score fell from 2.85 in 2015 to 2.57 in 2023 (σ-convergence), and the gap between the mean scores of the core and the intermediate group narrowed from 4.11 to 3.52, whereas the gap between the intermediate and constrained groups remained almost unchanged (4.31 and 4.39). General capability rose in 36 of the 38 countries; the exceptions were the United Kingdom and Sweden. The largest improvements were recorded by Italy (2.22), Greece (2.13), Costa Rica (1.89), Portugal (1.87) and Korea (1.80), and all members of the intermediate group improved. The rank correlation between the 2015 score and the change to 2023 is ϱ = −0.66; when level and change are measured in non-overlapping years, it is ϱ = −0.57 ($p < 0.001$), well outside the range expected from measurement noise and regression to the mean alone (95% interval of the simulated null distribution for this measure: −0.30 to 0.31; for the overlapping measure, −0.42 to 0.20). These results do not depend on how gaps in the annual series are filled: linear interpolation and carrying the last observation forward give the same values to two decimals, and the complete-case analysis (34 countries) gives σ-convergence from 2.86 to 2.41 and a non-overlapping β-correlation of −0.71 (Table S5). The members of the third profile also improved (Türkiye 1.33, Colombia 1.18 and Mexico 1.00), but from much lower levels, so they remained clearly separated from the intermediate group. The convergence is modest: the cross-country dispersion fell by about one tenth, and it reflects mainly the narrowing of the gap between the core and the intermediate group.

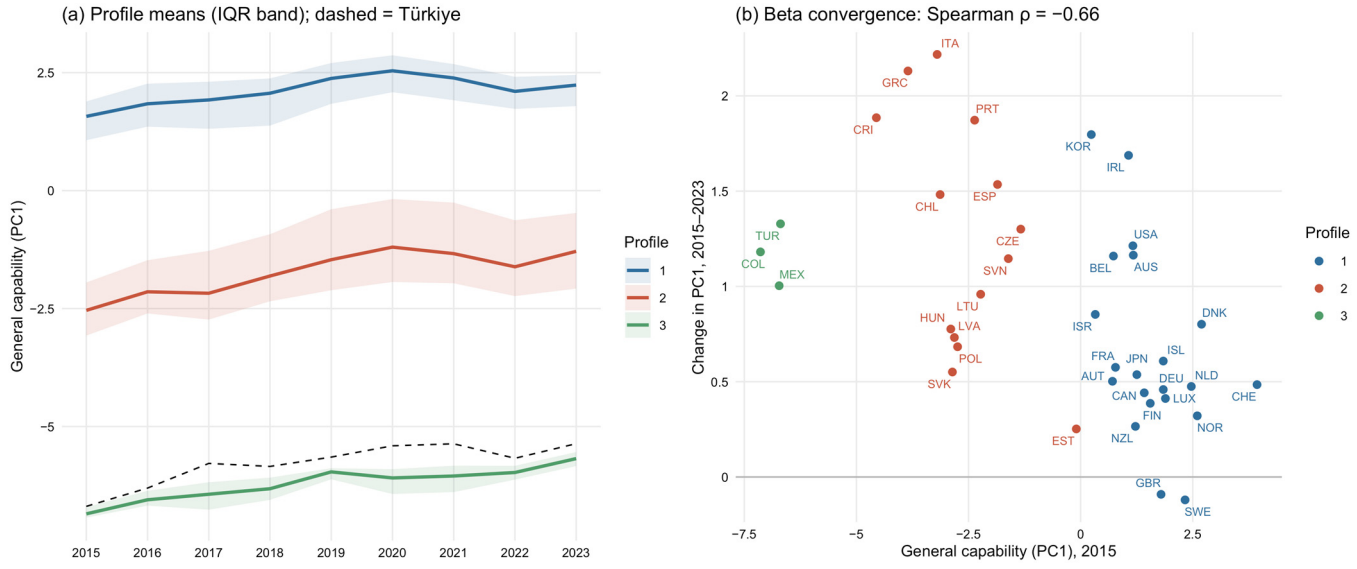


Figure 6. Change in general strategic capability (PC1), 2015–2023: (a) Annual mean PC1 score of each profile (solid lines); the shaded areas show the interquartile range (25th to 75th percentile) of the annual scores of the countries in each profile, and the dashed line shows Türkiye's annual score. (b) PC1 score in 2015 and its change between 2015 and 2023 for each country; the negative rank correlation (ϱ = −0.66) indicates β-convergence.

4.9. Strategic Readiness and Sustainability Outcomes (RQ3)

Table 7 and Figure 7 relate general capability to the sustainability outcomes. Higher capability is associated with higher average CO_2 emissions per capita (ϱ = 0.49; 95% CI

0.16 to 0.74): the core emits 8.8 t CO_2e per capita on average, the intermediate group 6.1 t and the third profile 3.6 t. Higher capability is also associated with larger reductions in per capita emissions between 2015 and 2023 (ϱ = −0.62; 95% CI −0.80 to −0.35), which fell by 21.7% on average in the core and by 15.8% in the intermediate group but remained almost unchanged in the third profile (−0.5%). Both associations hold when any single country is left out. Among the 38 countries, per capita emissions rose only in Türkiye (+11.3%, from 4.70 to 5.23 t); the next-highest changes were those of Costa Rica (−1.5%) and Colombia (−3.4%) (Table S6). For the share of renewable electricity, no clear association with this capability score is detected, either for its level (ϱ = 0.18; 95% CI −0.17 to 0.48) or for its change (ϱ = 0.06; 95% CI −0.28 to 0.39). The confidence intervals include both zero and moderate positive associations, and the result does not depend on the different observation periods: excluding Iceland gives ϱ = 0.12 (p = 0.49) for the level and 0.13 (p = 0.45) for the change, and a common window of 2015–2016 for all countries gives ϱ = 0.14 (p = 0.42) (Table S12). Because PC1 captures only 2% of the variance of the energy and environment indicators, the absence of an association should be read as a property of this particular score rather than as evidence about energy-related capabilities. Renewable shares range from below 5% in Israel and Korea to almost 100% in Iceland, Norway and Costa Rica; this pattern is consistent with the role of natural endowments such as hydropower and geothermal resources, but the present data do not test that explanation.

Table 8 examines whether the association between capability and emission change survives alternative explanations. Without controls, a one-standard-deviation higher PC1 is associated with a 6.9-percentage-point larger reduction in per capita emissions. Controlling for initial emissions reduces the coefficient to −5.6 (HC3 SE 2.2), and controlling for initial emissions and the initial industry share reduces it to −4.7 (2.2; bootstrap 95% CI −9.0 to −0.6). A higher initial industry share is associated with smaller reductions (3.1 points per standard deviation). When income is added, the PC1 coefficient remains negative (−7.0) but becomes imprecise (HC3 SE 4.7) because PC1 and log GDP per capita are almost collinear (ϱ = 0.91), so the data cannot separate capability from income. The PC1 coefficient is negative in every leave-one-country-out estimate and remains negative when Türkiye is excluded (−3.2 to −5.6, depending on the model). Measuring capability in 2015, the first year of the period, leaves these results essentially unchanged (Table S9). The 2015 score, obtained by projecting 2015 values onto the period loadings, correlates at ϱ = 0.97 with the main score and at ϱ = −0.63 with the subsequent change in emissions; a PCA estimated on 2015 data alone gives ϱ = 0.98 and −0.63. With the 2015 score, the PC1 coefficient is −5.6 (HC3 SE 2.0) when initial emissions are controlled and −4.7 (2.0) when the initial industry share is added. Finally, the part of PC1 not explained by income and governance (Section 4.2) is not associated with emission change (ϱ = −0.19, p = 0.25), so the association with decarbonisation is carried by the income and institutional component of the score. These models describe conditional associations in a cross-section of 38 countries; they do not establish that capability causes decarbonisation.

Table 7. General strategic capability and sustainability outcomes.

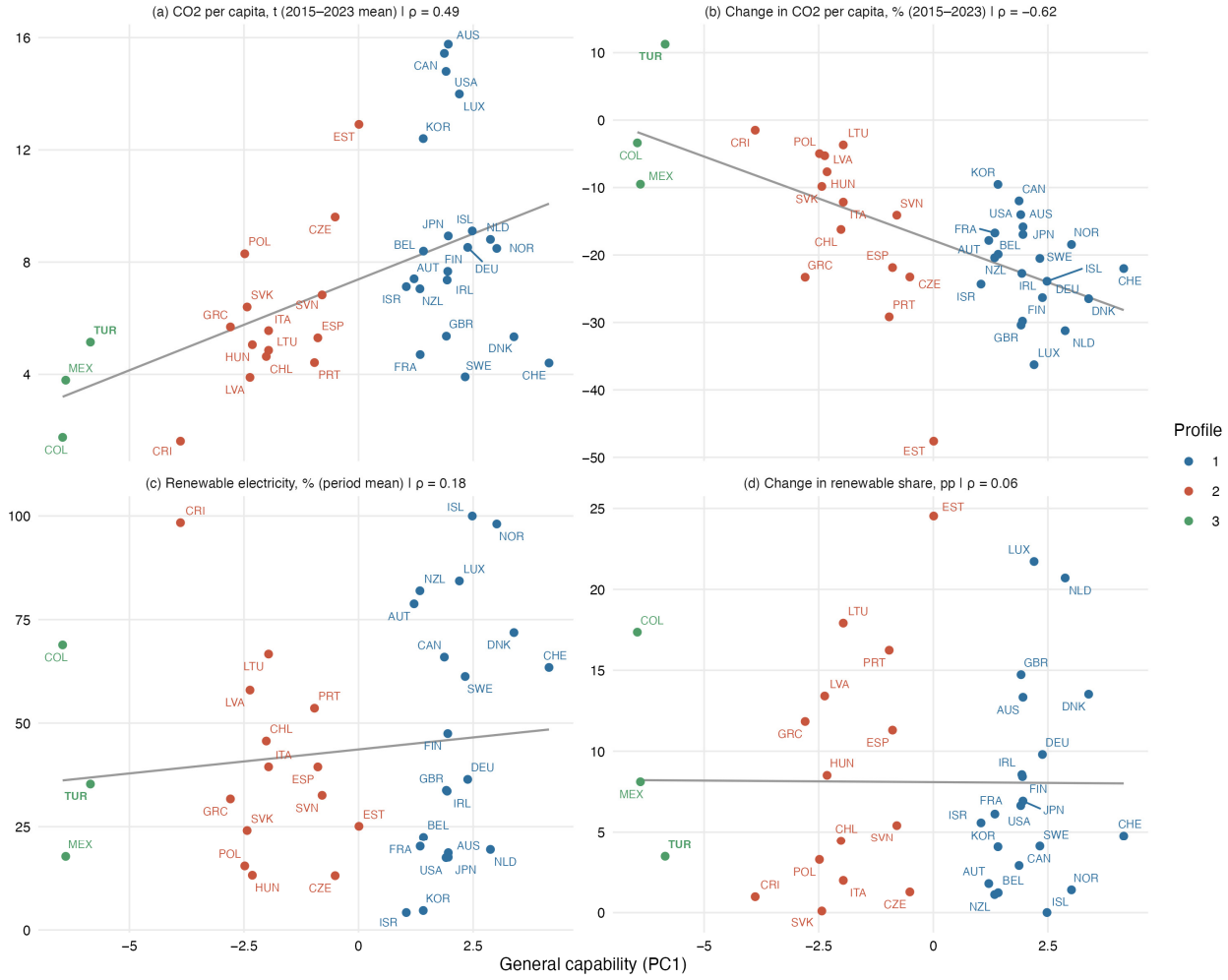
Outcome	ϱ	p	95% CI	Leave-One-Out	P1	P2	P3	TUR
CO_2 per capita, t (2015–2023 mean)	0.49	0.002	0.15, 0.75	0.45, 0.58	8.81	6.08	3.57	5.15
Change in CO_2 per capita, % (2015–2023)	−0.62	<0.001	−0.81, −0.34	−0.67, −0.59	−21.69	−15.76	−0.54	11.26
Renewable electricity, % (period mean)	0.18	0.293	−0.19, 0.48	0.12, 0.25	46.71	39.72	40.60	35.29
Change in renewable share, pp	0.06	0.715	−0.30, 0.38	0.00, 0.13	7.49	8.66	9.64	3.46

Note: ϱ = Spearman rank correlation between the general capability score (PC1) and the outcome across the 38 countries; 95% CI from 2000 bootstrap resamples; leave-one-out = range of ϱ when each country is excluded in turn. P1–P3 and TUR = profile means and the value for Türkiye. CO_2 = CO_2 emissions excluding LULUCF per capita (t CO_2e), EDGAR [72]. Renewable share = renewable electricity output (% of total), 2015–2021 for 37 countries and 2015–2016 for Iceland.

Table 8. Change in CO_2 emissions per capita (%, 2015–2023) and general strategic capability: ordinary least squares models.

Predictor/Statistic	M1	M2	M3	M4	M5	M6
PC1 (general capability)	−6.86 (1.44)	−5.63 (2.22)	−6.98 (4.66)	−7.01 (4.83)	−4.68 (2.24)	−6.14 (4.14)
Log initial CO_2 per capita		−1.97 (2.62)	−2.27 (3.06)	−2.07 (3.54)	−2.47 (2.61)	−2.28 (3.62)
Log GDP per capita			1.76 (5.58)	1.61 (5.65)		1.45 (5.45)
Initial renewable share				0.30 (1.49)		0.79 (1.45)
Initial industry share of GDP					3.09 (1.43)	3.20 (1.99)
PC1: bootstrap 95% CI	−9.60, −3.94	−9.96, −1.41	−15.87, −0.90	−16.86, −0.89	−9.02, −0.61	−14.99, −1.13
PC1: leave-one-out range	−7.21, −5.57	−7.02, −4.03	−10.58, −4.35	−10.82, −4.37	−6.11, −3.18	−8.98, −3.64
PC1: without Türkiye	−5.57	−4.03	−4.35	−4.37	−3.18	−3.64
Adjusted R^2	0.37	0.38	0.36	0.35	0.44	0.42

Note: n = 38 in all models. Coefficients are percentage-point changes per standard deviation of the predictor; heteroskedasticity-consistent (HC3) standard errors in parentheses. Bootstrap confidence intervals are based on 2000 resamples of countries. Initial values refer to 2015. Spearman ϱ between PC1 and log GDP per capita = 0.91. The models describe conditional associations and do not identify causal effects.



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Figure 7. The general strategic capability (PC1) and sustainability outcomes: (**a**) CO_2 emissions per capita, 2015–2023 mean; (**b**) the change in CO_2 emissions per capita, 2015–2023; (**c**) the share of renewable electricity, period mean; (**d**) the change in the renewable share, first to last available year. Grey lines are least-squares fits; ϱ = Spearman rank correlation.

4.10. Türkiye's Position and Candidate Benchmarks (RQ4)

Türkiye belongs to the third profile with a silhouette width of 0.86 in the PC1 space, which indicates a clear assignment. Its nearest neighbour on general capability is Mexico (distance 0.54), followed by Colombia (0.61) and Costa Rica (1.96). The ranking of comparators in the adjacent profile, however, depends on the space in which distances are measured (Table 9). On PC1 alone, the nearest members of the intermediate group are Costa Rica, Greece and Poland, whereas Hungary is Türkiye's nearest neighbour overall in the Kaiser space, in the full indicator space, under domain weighting and in the space of the domain scores. Applying the selection rule of Section 3.10, Hungary has the lowest mean rank across the six spaces (2.5), followed by the Slovak Republic (3.7), Latvia (4.8) and Poland (6.2). Hungary and the Slovak Republic are therefore selected as candidate benchmarks; Poland, which is close to Türkiye on PC1 but not in the multidimensional spaces, is not. Mexico is Türkiye's closest peer in the *level* of general capability, but its mean rank (4.0) reflects a different capability mix. Hungary's own assignment to the intermediate group is clear on PC1 (silhouette width 0.77) but weaker in the two-component space (0.21). The nearest member of the core is Israel in the PC1 and two-component spaces but Ireland, Austria or Belgium in the other spaces, so we do not single out a long-term benchmark.

Table 10 and Figure 8 report Türkiye's direction-adjusted gaps and apply the priority rule of Section 3.10. Relative to the intermediate group, the largest gap concerns inflation (3.88 standard deviations), followed by mobile subscriptions (2.02), regulatory quality (1.62), health expenditure (1.59), fixed broadband (1.41), high-technology exports (1.28), control of corruption (1.17), government effectiveness (1.15) and Internet use (1.10). Mobile subscriptions do not qualify as a priority gap: Their loading on PC1 is close to zero. Subscription rates above 100 per 100 inhabitants are common across the OECD, and Türkiye is close to Hungary on this indicator. The remaining eight indicators meet all three criteria, but they differ in their trends. Inflation and the three governance indicators deteriorated between 2015 and 2023. Health expenditure and high-technology exports remained broadly stable, and fixed broadband and Internet use improved strongly. Türkiye's R&D intensity is at the level of both benchmarks. Its gross capital formation is well above both, and its life expectancy is slightly above Hungary's. The emphasis on inflation and institutional quality in the discussion below therefore follows from the combination of gap size, weight in the general capability score and deterioration over time, not from gap size alone.

The trajectory analysis (Figure 9) shows that Türkiye's general capability score rose from −6.69 in 2015 to −5.36 in 2023, the ninth-largest improvement in the OECD and larger than those of Mexico (1.00), Hungary (0.78) and the Slovak Republic (0.55). This improvement reflected digital diffusion in particular: Internet use rose from 53.7% to 86.0% of the population. At the same time, Türkiye moved along the second component from −1.24 in 2015 to −4.14 in 2022 and −3.62 in 2023, reflecting the surge in inflation to 72.3% in 2022 and 53.9% in 2023, and its governance estimates deteriorated: government effectiveness fell from 0.39 to −0.09, regulatory quality from 0.20 to −0.17 and control of corruption from −0.13 to −0.43. Türkiye's improvement in digital infrastructure has therefore been accompanied by deterioration in the domains that weigh most heavily in PC1.

Table 9. Selection of candidate benchmarks: rank of distance from Türkiye in six spaces.

Country	Profile	PC1	PC1–PC2	Kaiser	All ind.	Domain-wt.	Domains	Mean rank
Hungary	2	8	3	1	1	1	1	2.5
Slovak Republic	2	6	6	4	2	2	2	3.7
Latvia	2	7	4	5	4	4	5	4.8
Poland	2	5	5	3	7	7	10	6.2
Chile	2	9	8	7	5	3	6	6.3
Lithuania	2	10	7	6	8	5	4	6.7
Mexico	3	1	1	2	3	8	9	4.0
Nearest member of Profile 1	1	Israel	Israel	Ireland	Austria	Austria	Belgium	–

Note: Ranks among the 37 other OECD countries by Euclidean distance from Türkiye. Kaiser = five Kaiser-retained components; All ind. = 17 standardised indicators; Domain-wt. = domain-weighted indicators; Domains = seven domain scores. Selection rule: the two members of the adjacent profile (Profile 2) with the lowest mean rank are the candidate benchmarks. The six Profile 2 countries with the lowest mean rank and Mexico (Profile 3) are shown; ranks of all Profile 2 members are given in Table S7. Silhouette widths: Türkiye 0.86 (PC1) and 0.65 (PC1–PC2); Hungary 0.77 and 0.21.

Table 10. Türkiye's direction-adjusted capability gaps and priority classification.

Indicator	Profile 2 Mean	Hungary	Slovak Republic	PC1 Loading	Change 2015–2023	Priority Gap
Inflation	3.88	2.96	3.62	−0.59	−4.03	Yes (deteriorated)
Mobile subscriptions	2.02	0.46	2.38	−0.01	0.90	No
Regulatory quality	1.62	0.91	1.43	0.92	−0.69	Yes (deteriorated)
Health expenditure	1.59	1.08	1.21	0.60	0.07	Yes (stable)
Fixed broadband	1.41	1.78	1.38	0.83	1.25	Yes (improved)
High-tech exports	1.28	1.92	0.92	0.43	0.15	Yes (stable)
Control of corruption	1.17	0.48	0.69	0.91	−0.37	Yes (deteriorated)
Government effectiveness	1.15	0.80	0.85	0.97	−0.81	Yes (deteriorated)
Internet users	1.10	1.18	1.43	0.89	3.84	Yes (improved)
Unemployment	0.91	2.10	1.16	−0.47	0.28	No
Secure internet servers	0.86	1.19	0.95	0.77	2.42	No
Life expectancy	0.75	−0.42	0.00	0.73	0.22	No
Forest area	0.64	−0.34	0.63	−0.18	0.07	No
GDP per capita (PPP)	0.56	0.48	0.50	0.87	0.73	No
Energy imports	0.38	0.46	0.39	−0.01	0.55	No
R&D expenditure	−0.05	0.14	−0.30	0.67	0.40	No
Gross capital formation	−2.72	−1.39	−2.39	0.16	1.14	No

Note: Gaps are differences in z-units between the comparator and Türkiye, with the sign reversed for inflation, unemployment and energy imports; positive values indicate that Türkiye is behind. Change 2015–2023 is the change in Türkiye's own value in units of the cross-country standard deviation, with the sign adjusted so that positive values indicate improvement. Priority gap: gap to the Profile 2 mean of at least 1, positive gaps to both benchmarks and an absolute PC1 loading of at least 0.40; trends are classified as deteriorated or improved when the change is at least 0.25 in absolute value.

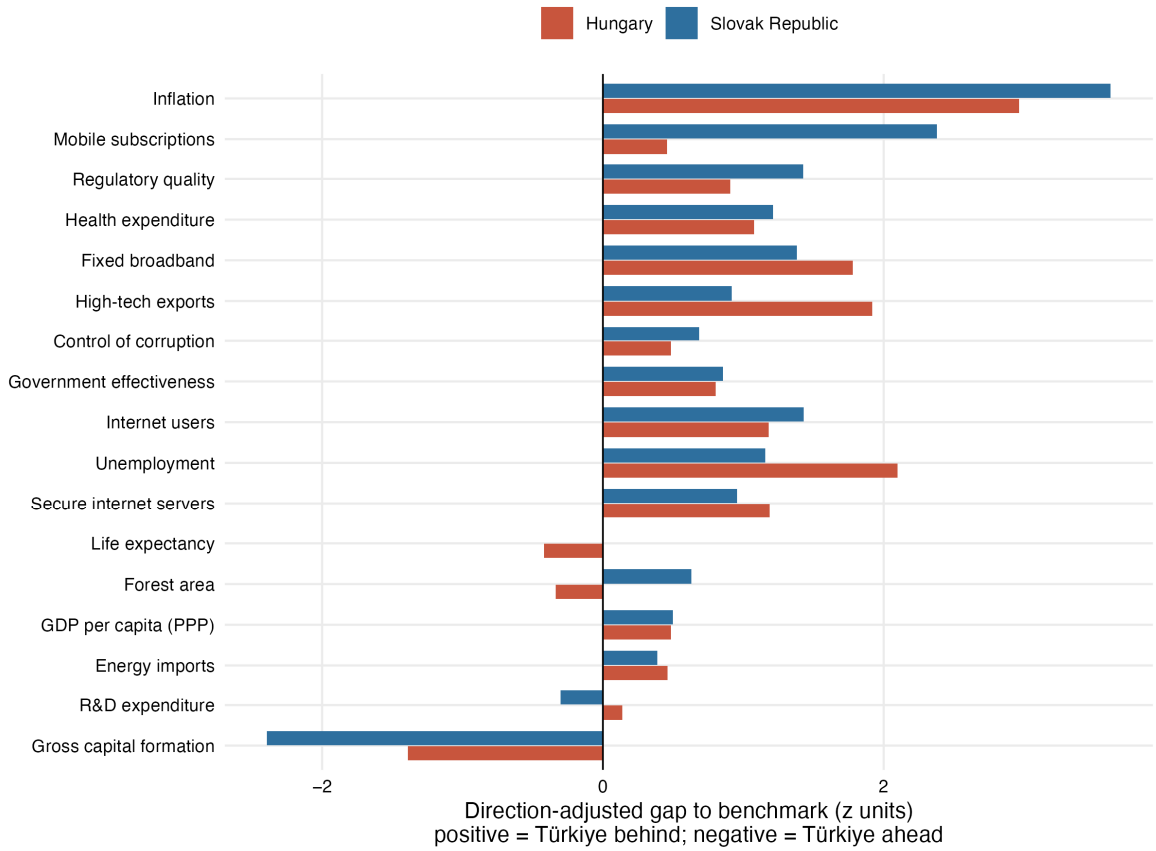
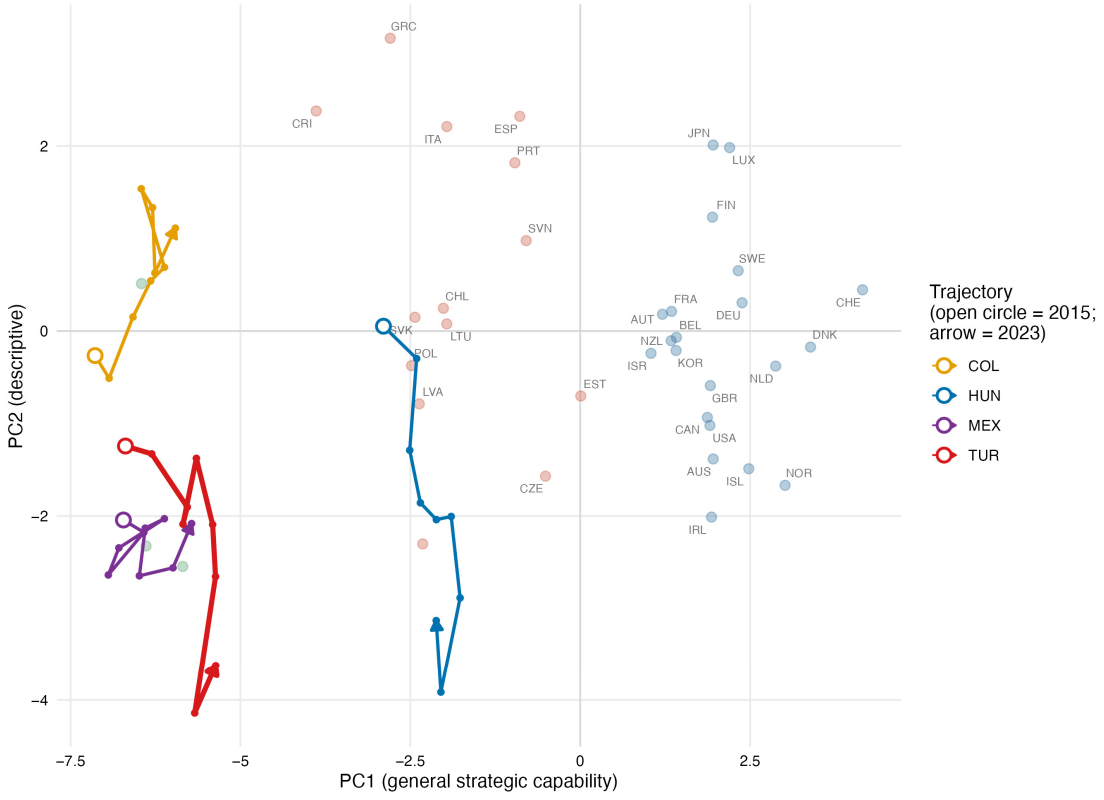


Figure 8. Türkiye's direction-adjusted capability gaps relative to the two candidate benchmarks, Hungary and the Slovak Republic, in standardised units. Positive values indicate that Türkiye is behind; negative values indicate that it is ahead.



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Figure 9. Annual trajectories of Türkiye and its three nearest neighbours in the two-component space (Mexico, Colombia and Hungary), 2015–2023, projected onto the period PCA, against the period averages of all OECD countries. PC2 is shown for description only.

5. Discussion

5.1. Principal Findings

Four findings summarise the evidence. First, cross-country differences in the 17 indicators are dominated by a single dimension of general capability, which is driven mainly by institutional quality, income, digital infrastructure and health and captures little of the energy and environment domain. Second, the OECD countries do not form sharply separated groups; along this dimension they can be described by three segments of a continuum, and this classification is stable under full-procedure resampling; alternative clustering spaces; sub-periods; the addition of education indicators; and, for the core, equal domain weighting. Third, higher capability is associated with higher per capita emissions but faster reductions, also when capability is measured at the start of the period, whereas no clear association with the renewable share is detected; the association with emission reductions cannot be separated from income. Fourth, Türkiye is clearly assigned to the capability-constrained group, Hungary and the Slovak Republic are its candidate benchmarks under an explicit selection rule, and its priority gaps concern inflation and institutional quality, where its position deteriorated over the period.

5.2. Theoretical Implications

The results support the conceptualisation of strategic readiness as a set of interdependent capabilities, but they do not support the stronger configurational premise that OECD countries form qualitatively distinct types. The dominance of a single general capability dimension (RQ1) shows that institutional quality, income, digital infrastructure and health vary together across OECD countries. This is consistent with the complementarity argument of the capabilities literature, according to which digital infrastructure and R&D create value where effective institutions and human capital are present [17,20], and with recent evidence of a dominant common factor in digital and sustainability indicators in the EU [52]. Readiness is therefore better described as a coherent capability syndrome than as a set of independent strengths that can be traded off against one another, which is the implicit assumption of compensatory composite indices [9,11].

Three qualifications define the scope of this conclusion. First, the general capability score does not represent the seven domains equally. It is dominated by institutional quality and, to a lesser extent, by digital infrastructure and health, and captures only a small part of macroeconomic stability and innovation and almost none of the energy and environment domain. The finding that institutional quality separates the profiles most sharply is therefore partly a consequence of how PC1 weights the domains, although it remains consistent with institutional explanations of development [37–39]. Second, because the profiles were formed on a single dimension and the gap statistic does not reject a single group, they are a descriptive classification of a continuum, not evidence of distinct national models; differences in the capability mix appear only at a secondary level that cannot be distinguished from noise with 38 countries. Third, the indicators describe a capability base, not the dynamic processes through which countries sense, seize and transform [23,26,27]. The modest convergence of this base over the period of 2015–2023, with larger gains in initially weaker countries, is consistent with Abramovitz's argument that catching up is possible where social capabilities are sufficient [20] and with evidence of mild global convergence in capability spaces [53], but it does not show how, or how quickly, countries reconfigure their capabilities. Measuring these processes directly would require indicators

of policy learning, coordination and implementation that are not available in harmonised form.

5.3. Methodological Implications for Country Benchmarking

The matched comparison in Section 4.7 shows that when aggregate quantities are combined with ratio indicators, the leading component captures country size, and clusters are formed by economic mass rather than by capability; this is an effect of scale and not of the particular indicators chosen. Recent benchmarking studies have addressed weighting sensitivity in depth [46,49]; our results show that the choice between level and ratio indicators deserves the same scrutiny. Three further points follow. Cluster-validity statistics should be read together: the silhouette width supported three profiles, whereas the gap statistic and the parallel analysis indicated a single continuum. Stability should be assessed by re-estimating the whole procedure, not only the final clustering step. PCA-based scores are free of predetermined weights but neither of weighting choices nor of compensation because the data determine how much each domain contributes; this should be reported rather than presented as neutrality, and the score should be complemented by indicator-level comparisons. The three-profile structure is compatible with recent evidence of a small number of sustainable-competitiveness clusters among OECD countries [48].

5.4. Readiness and Sustainability

More capable countries emit more CO_2 per capita, which is consistent with their higher incomes and consumption, but they also reduced their emissions faster between 2015 and 2023. This association holds when capability is measured in 2015, when any single country is excluded and when initial emissions and industrial structure are controlled, but it cannot be distinguished from the association between income and emission reductions, and it is carried by the income and institutional component of the score. The finding is consistent with the view that institutional, financial and technological capabilities facilitate the transformation of energy and production systems [7,8] and with evidence that income and digital specialisation are associated with sustainable transformation potential in the EU [47]. The cross-sectional design does not, however, allow us to conclude that these capabilities are preconditions for, or causes of, decarbonisation; reverse causation and omitted factors, such as climate policy stringency, energy prices, economic structure and the composition of electricity generation, are plausible alternatives. For the renewable share, the analysis detects no clear association with this particular capability score, which captures little of the energy and environment domain; it does not show that renewable deployment is unrelated to national capabilities more broadly.

5.5. Practical Implications

For Türkiye, the analysis suggests a benchmarking approach that differs from league-table comparisons. Comparisons with frontier economies reveal large gaps on almost every indicator but offer little guidance on priorities. The rule-based approach instead identifies Mexico as Türkiye's closest peer in the level of general capability and Hungary and the Slovak Republic as candidate stepping-stone benchmarks in the adjacent profile. Both benchmarks combine an investment- and manufacturing-oriented growth model with lower inflation, stronger institutions and deeper digital infrastructure than Türkiye. They should nevertheless be treated as reference points for comparison rather than as models to copy. Both operate within the institutional, fiscal and regulatory framework of the European Union, including the single market, cohesion funding and the external anchor of EU rules, and their economic structures and implementation capacities differ from Türkiye's; these differences limit how far their policies could be transferred [55].

The priority gaps identify where Türkiye differs most from its comparators and where its position worsened: inflation and the three governance indicators. Health expenditure and high-technology exports are persistent gaps, whereas the digital gaps narrowed rapidly during the period. These are priorities in a descriptive sense; the analysis does not show which policy measures would close the gaps, whether closing them would move Türkiye into the intermediate group, or whether practices from the benchmark countries would be effective in the Turkish context. Türkiye's position on emissions is also distinctive: it is the only OECD member whose per capita emissions rose over the period, which indicates that the composition of its high investment matters for whether catching up in capability is compatible with its climate commitments. For other OECD members, the same procedure can be applied: structural peers indicate feasible comparisons, and rule-based benchmarks in the adjacent profile indicate intermediate reference points whose relevance must be checked against the country's context. For international managers, the profiles summarise the strategic environment of host countries because countries in the same profile offer broadly similar levels of infrastructure, macroeconomic risk and institutional quality even when their headline rankings differ.

6. Conclusions

This study conceptualised national strategic readiness as a capability base in seven domains linked to the SDGs and developed a scale-free, robustness-tested framework to classify the 38 OECD members. Its main conclusion is that readiness within the OECD is best described as a single general capability continuum, dominated by institutional quality, income, digital infrastructure and health, rather than as a set of distinct national configurations. Classifying countries along this continuum and complementing the score with indicator-level gaps and rule-based comparators yields benchmarking information that is more transparent and more realistic than league-table comparisons, provided that its descriptive nature and its unequal representation of the capability domains are kept in view.

The study has limitations that suggest directions for future research. First, the indicators measure a capability base rather than the dynamic processes through which countries adapt, and the main analysis uses period averages; longitudinal methods, such as latent transition models, and indicators of policy learning and implementation could capture these processes more directly. Second, the indicator set is constrained by harmonised public data. Education and skills are not part of the main indicator set, although adding enrolment ratios does not change the classification; governance measures are perception-based and were revised in 2025 [40,41]. The emission series covers CO_2 only, and renewable electricity data end in 2021. Third, the analysis is restricted to OECD members, so the classification describes readiness *within* a relatively advanced group. Fourth, the profiles are segments of a continuum. The assignment of boundary countries such as Costa Rica, Estonia and Czechia should be interpreted with caution, and the composition of the lower groups depends on domain weighting. Fifth, the analysis is descriptive: with 38 countries, it identifies associations between readiness and sustainability outcomes but cannot establish causality or separate capability from income. Future studies could use panel models with policy variables or fuzzy-set qualitative comparative analysis [14] to examine whether, and through which combinations of capabilities, readiness contributes to decarbonisation and progress towards the SDGs.

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Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/sustainability-4730138/s1. Table S1: Descriptive statistics of the indicators; Table S2: Data coverage by indicator, country and year; Table S3: Profile membership, component scores, silhouette widths and cut-points; Table S4: Number of profiles, stability and full robustness results, including country-level co-assignment rates; Table S5: Domain shares in PC1, annual capability scores, gap-filling alternatives and convergence by country; Table S6: CO_2 emissions per capita in the first and last year for all countries, correlations with sustainability outcomes and emission models; Table S7: Türkiye's indicator-level gaps, benchmark selection rule, domain scores and nearest neighbours in alternative spaces and sub-periods; Table S8: Matched comparison of total and per capita specifications; Table S9: Capability measured in 2015 and emission models; Table S10: Classification based on income and governance only and correlates of the PC1 residual; Table S11: Sensitivity to education indicators; Table S12: The sensitivity of the renewable analysis to observation periods; Figure S1: The correlation matrix of the indicators; Figure S2: Ward dendrogram; Figure S3: The silhouette plot of the three-profile solution; Figure S4: Random forest importance; Figure S5: The sensitivity of the partition to the weight of the second component; Figure S6: Bootstrap co-assignment matrix; Script S1: R code reproducing all analyses; Data S1: Raw indicator data, including the archived governance data.

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Conflicts of Interest: The authors declare no conflicts of interest.

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