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Tackling Skills Shortages & Mismatch

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Name	Institution	Date
Sara Gysen	IPSOS	Month 02, 2026
Vincenzo Pezone	TiU	Month 02, 2026

Quality Manager Revision

Name	Institution	Date
Kyriaki Kosmidou	AUTH	Month 02, 2026
Dimitrios Kousenidis	AUTH	Month 02, 2026

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ACRONYMS

Acronym	Definition
AI	Artificial Intelligence
DigComp	European Digital Competence Framework
EC	European Commission
ESCO	European Skills, Competences, Qualifications and Occupations
EU	European Union
EQF	European Qualifications Framework
GreenComp	European Sustainability Competence Framework
GISCO	Geographical Information System of the Commission
ISCO	International Standard Classification of Occupations
ISCO-ESCO Linkage	Mapping of ISCO occupational codes to ESCO skill profiles
NACE	Statistical Classification of Economic Activities in the European Community
NUTS	Nomenclature of Territorial Units for Statistics
RPL	Recognition of Prior Learning
SME	Small and Medium-sized Enterprise
VET	Vocational Education and Training
WP	Work Package

EXECUTIVE SUMMARY

Deliverable D5.2 presents the outcomes of Task 5.2 of the TRAILS project, which advances a new classification and measurement of basic and transferable skills in the context of the green and digital transitions and the rapid diffusion of artificial intelligence. Building on the conceptual foundations established in WP1 and the survey infrastructure developed in WP2, this deliverable proposes an updated understanding of "basic" skills that extends beyond literacy and numeracy to encompass decision-relevant competences required in technologically advanced and sustainability-oriented societies.

The deliverable introduces and empirically validates a multidimensional literacy framework covering financial, health and medical, digital financial, media and information, artificial intelligence, data and programming, political, environmental, sustainable finance, and human and cultural literacies. Using harmonised data from TRAILS Survey I, it documents substantial cross-country and demographic disparities in these domains and highlights patterns of cumulative skill deficits. The analysis shows that literacy domains are interrelated and often cluster, reinforcing structural inequalities across education, age, income, gender, and regional lines.

Beyond descriptive evidence, Deliverable D5.2 examines how these literacies relate to labour market and financial resilience. The findings indicate that technical digital literacies are associated with adaptability, upskilling behaviour, and lower automation exposure, while financial literacy is linked to reduced financial strain and stronger household resilience. Sustainability-related literacies align with greener occupational skill structures, and interpersonal literacies contribute to adaptability and social skill intensity. These results underscore the importance of viewing basic and transferable skills as structurally relevant for both employment outcomes and economic security.

A central methodological innovation is the operationalisation of the ISCO–ESCO linkage. By mapping 4-digit ISCO occupations from the TRAILS survey to ESCO skill profiles, the analysis situates individual literacy profiles within occupational skill architectures. This enables the construction of indicators of cognitive, digital, green, social, and automation-related skill intensity, as well as measures of skill breadth and transferability. In Task 5.2, the ISCO–ESCO framework is used to anchor and validate the proposed literacy classification within real occupational environments, rather than to analyse mobility or occupational distance directly.

Overall, Deliverable D5.2 provides a structured empirical foundation for understanding how multidimensional literacies relate to resilience and occupational skill structures across Europe. By offering a coherent classification framework and harmonised measurement approach, it contributes to more informed discussion on curriculum development, adult learning strategies, and skill-based labour market analysis in the era of digital and green transformation.

Purpose of the Deliverable

The purpose of this deliverable is to propose and empirically substantiate an updated classification of basic and transferable skills that reflects the structural transformations associated with digitalisation, automation, and the green transition. It responds to the need for a more comprehensive understanding of "basic" skills, moving beyond narrow definitions centred on

literacy and numeracy toward a multidimensional framework of decision-relevant literacies that shape individuals' economic resilience, employability, and social participation.

To this end, the deliverable develops a coherent conceptual framework and applies harmonised measurement instruments through TRAILS Survey I to capture competences across multiple domains, including financial, digital, sustainability-related, civic, and interpersonal literacies. It documents how these skills are distributed across European populations, examines patterns of clustering and cumulative deficits, and identifies key socio-demographic and regional disparities associated with skill gaps. In addition, it anchors the proposed literacy framework within occupational structures through the ISCO–ESCO linkage, situating individual skill profiles within broader skill architectures.

At the same time, the deliverable maintains a clearly defined scope. Its focus is on skill classification, measurement, and structural association analysis. It does not directly analyse labour market transitions, occupational mobility, or the causal effectiveness of specific skill portfolios. Rather, it provides the analytical and measurement foundation upon which subsequent TRAILS tasks build, ensuring that later work on behavioural barriers, skills diversification, platform work, and labour market mobility is grounded in a coherent and empirically validated understanding of basic and transferable skills.

Relation with Other Deliverables and Tasks

Deliverable D5.2 is a core component of Work Package 5 and is closely linked to several tasks across the TRAILS project. It builds on the conceptual foundations developed in WP1 and the survey infrastructure established in WP2, which provide the analytical and data framework for the measurement of multidimensional literacies.

Within WP5, D5.2 establishes the classification and measurement architecture for basic and transferable skills. Task 5.3 builds on this foundation by analysing skills diversification and the profiles of workers in new forms of employment, including platform work, using the ESCO taxonomy. Task 5.4 further extends the analysis to skills portfolios, occupational distance, and labour market mobility pathways, merging TRAILS data with European Labour Force Survey data and the updated ESCO classification.

D5.2 also informs Task 3.4, which examines behavioural and social barriers to participation in adult learning and VET programmes through experimental approaches. The literacy framework developed in D5.2 provides the basis for identifying skill gaps and target groups relevant to such interventions. In parallel, Task 4.4 utilises ESCO-based AI tools to analyse skills matching and transferability across occupations and sectors. The operationalisation of ISCO–ESCO linkages in D5.2 ensures conceptual consistency between survey-based measurement and AI-enabled skills analytics.

Overall, Deliverable D5.2 provides the conceptual and empirical foundation upon which subsequent measurement refinement, skills diversification analysis, mobility modelling, and matching tools within TRAILS are built.

Structure of the Document

The remainder of this document is organised into eight sections: Section 1 outlines the policy and analytical motivation for revisiting the concept of basic and transferable skills in the context of the green and digital transitions. It situates the deliverable within the broader objectives of the TRAILS project. Section 2 develops the conceptual framework, redefining basic and transferable skills as multidimensional, decision-relevant literacies and discussing their inter-relationships and behavioural underpinnings. Section 3 presents the data and measurement strategy based on TRAILS Survey I, including the construction and validation of the literacy indices and the operationalisation of the ISCO–ESCO linkage. Section 4 introduces the proposed classification of basic and transferable skills and provides descriptive evidence on cross-country, regional, and demographic patterns, as well as skill clustering and cumulative deficits. Section 5 analyses the associations between the literacy domains and labour market and financial resilience outcomes. Section 6 extends the analysis to occupational skill intensity and skill architecture, linking literacy profiles to cognitive, digital, green, and automation-related task environments and to indicators of skill breadth and transferability. Section 7 discusses the policy implications for skills measurement, education systems, VET, lifelong learning, and skills intelligence. Section 8 concludes by summarising the main contributions, clarifying scope limits, and outlining how the findings inform subsequent TRAILS tasks, including Task 3.4, Task 5.3, and Task 5.4.

1. Introduction and policy motivation

This deliverable addresses a critical gap in current skills policy: the systematic under-recognition of basic and transferable skills in education, training, and labour market policy, despite their growing importance in the context of the green and digital transitions and the rapid diffusion of artificial intelligence (AI). While skills agendas across Europe have increasingly focused on technical, job-specific, and advanced digital competencies, much less attention has been paid to the foundational skills and literacies that enable individuals to adapt to structural change, make informed decisions, and remain resilient in both labour markets and everyday life.

Existing skills taxonomies and policy frameworks, including ESCO, DigComp, GreenComp, and established financial literacy frameworks, have made important contributions to harmonising skill definitions and supporting policy coordination. However, these frameworks often remain fragmented, domain-specific, or narrowly oriented toward occupational requirements. As a result, they tend to prioritise technical competencies while underestimating the role of basic and transferable skills such as financial, digital, environmental, political, health, media, and AI literacy, as well as human and social skills. These skills are not only essential for effective job performance but also for navigating increasingly complex economic, technological, and institutional environments.

Green and digital transitions, together with the rapid diffusion of AI, represent systemic shocks that simultaneously affect labour markets, production processes, and households. These transformations are reshaping job tasks, altering skill requirements, and increasing uncertainty around employment trajectories, while also placing greater responsibility on individuals to manage financial risks, health information, digital security, and civic engagement. In this context, deficiencies in basic and transferable skills can amplify vulnerability, particularly among population groups that are already disadvantaged, such as young people, women, migrants, and workers in routine or transition-exposed occupations.

Against this background, Task 5.2 positions basic and transferable skills as a central pillar of robot-proof education and training. Rather than treating these skills as secondary or complementary to technical expertise, this task proposes a departure from the current state of the art by developing a new classification that reflects their cross-domain relevance, internal coherence, and role in supporting adaptability and resilience. The task builds on novel measurement instruments developed within the TRAILS project and provides new empirical evidence on the distribution, clustering, and determinants of these skills across European populations.

Task 5.2 is closely linked to the broader objectives of the TRAILS project and draws on insights from earlier work packages addressing labour market transformation, skill demand, and task change. At the same time, it provides a distinct contribution by focusing on the conceptualisation and measurement of skills rather than on labour market outcomes or mobility pathways. A key innovation of this task is the integration of individual-level skill profiles with detailed occupational classifications using 4-digit ESCO groups. This linkage allows basic and transferable skills to be analysed within concrete occupational and task contexts, enabling a more granular understanding of how such skills relate to job characteristics and exposure to technological change, without conflating classification with mobility analysis.

The empirical foundation of this deliverable is the TRAILS-I European survey, which covers a wide range of countries and population groups and includes harmonised measures of multiple skill domains. The survey's scope and design allow for cross-country comparability, detailed socio-demographic analysis, and the contextualisation of skills within occupational structures. By combining innovative measurement with occupational anchoring, this deliverable lays the groundwork for a more coherent and policy-relevant understanding of basic and transferable skills in times of rapid economic and technological change.

2. Conceptual framework: From fragmented literacies to skill ecosystems

Traditional understandings of basic skills have centred on foundational literacy and numeracy, reflecting the requirements of earlier stages of economic development and more stable labour market structures. While these skills remain necessary, they are no longer sufficient for effective participation in contemporary economies characterised by rapid technological change, complex institutional environments, and heightened individual responsibility for managing economic and social risks. As work tasks, consumption choices, and civic interactions become more knowledge-intensive and digitally mediated, individuals are increasingly required to interpret information, evaluate trade-offs, and make decisions across multiple domains (OECD, 2019; OECD, 2021).

In this context, basic skills extend beyond reading, writing, and arithmetic to encompass a broader set of functional literacies related to finance, health and medical information, environmental and climate issues, digital technologies, media and information, artificial intelligence, and civic and political processes. A growing body of evidence shows that such literacies are closely linked to labour market outcomes, social inclusion, and economic resilience, particularly in environments marked by uncertainty and rapid change (Lusardi and Mitchell, 2014; Nutbeam, 2000; van Deursen and van Dijk, 2014). Deficits in these skills can constrain employability, reduce adaptability, and increase vulnerability to misinformation, financial stress, and exclusion from key economic and social institutions.

This deliverable conceptualises basic skills as decision-relevant literacies rather than narrow cognitive competencies. From this perspective, basic skills are understood as multidimensional constructs that combine factual knowledge with the capacity to apply that knowledge in real-life situations. Crucially, they also incorporate behavioural and confidence-related components, which influence how individuals interpret information, assess uncertainty, and act upon available options. Research in behavioural economics and psychology has shown that knowledge alone is often insufficient to ensure effective decision-making, as confidence, risk perception, and cognitive biases play a central role in shaping behaviour (Kahneman, 2011; Thaler and Sunstein, 2008).

For example, understanding financial concepts or digital security principles does not automatically translate into sound financial choices or safe online behaviour when individuals face time constraints, incomplete information, or complex trade-offs. Similarly, awareness of environmental or health-related information does not guarantee that such information is consistently incorporated into everyday decisions. These gaps between knowledge and action highlight the importance of integrating behavioural and applied dimensions into the measurement of basic skills.

By adopting this broader and more integrated understanding, Task 5.2 moves beyond fragmented and domain-specific approaches to skills. It recognises that effective functioning in the 21st century depends not only on what individuals know, but also on how they use that knowledge in practice and how behavioural traits shape decision-making across different contexts. This reconceptualisation provides the conceptual foundation for the new classification of basic and transferable skills developed in this deliverable and informs the empirical analysis presented in subsequent sections.

2.1 Transferable skills as cross-domain capabilities

Transferable skills are commonly understood as capabilities that retain their value across different occupations, economic sectors, and stages of the life course. Unlike job-specific or technical skills, which are closely tied to particular tasks or technologies, transferable skills support individuals' ability to adapt to changing work environments, learn new tasks, and remain productive as job requirements evolve. In the context of structural change driven by digitalisation, automation, and the green transition, such skills play a central role in sustaining employability and supporting long-term labour market participation (Autor, 2015; OECD, 2019).

However, transferable skills should not be interpreted as abstract or context-free attributes that operate independently of work settings. While their value extends across domains, their acquisition, deployment, and recognition are shaped by occupational contexts, task structures, and institutional arrangements. Skills such as problem-solving, communication, digital competence, or judgement under uncertainty are developed and exercised through concrete work activities, organisational practices, and interactions with technologies and institutions. As a result, the same transferable skill may manifest differently across occupations and sectors, even though its underlying function remains similar.

This deliverable adopts a cross-domain perspective on transferable skills, emphasising their role in linking different areas of knowledge and practice rather than treating them as generic add-ons to technical expertise. From this perspective, transferable skills enable individuals to mobilise basic and domain-specific knowledge in new situations, integrate information from multiple sources, and respond effectively to unfamiliar challenges. They also facilitate learning-to-learn processes, supporting continuous skill development over the life course (Heckman and Kautz, 2012; OECD, 2021).

Importantly, transferable skills are activated at the intersection of individual capacities and institutional environments. Their effective use depends not only on individual endowments but also on how work is organised, how tasks are designed, and how skills are valued and rewarded in labour markets. This interaction between individual skills and occupational contexts underscores the need to analyse transferable skills in relation to real-world job structures, rather than in isolation. In Task 5.2, this is addressed by linking individual-level measures of transferable skills to detailed occupational classifications, allowing these skills to be examined within the task environments in which they are applied.

By conceptualising transferable skills as cross-domain capabilities that are contextually activated, this framework moves beyond static and overly general definitions. It provides a basis for understanding how basic and transferable skills jointly support adaptability, resilience, and effective functioning in times of rapid economic and technological change, and sets the stage for the empirical analysis of skill patterns and complementarities presented in later sections of this deliverable.

2.2 Inter-relationships and confounding factors

A central question underlying the proposed classification of basic and transferable skills is whether different literacies operate largely independently of one another or whether they are shaped by common underlying factors. Existing skills frameworks often treat literacies such as financial, digital, health, environmental, or political literacy as distinct and separable domains. However, both theoretical and empirical work suggest that these skills may co-move systematically, reflecting shared cognitive, behavioural, and socio-cultural influences rather than purely domain-specific knowledge.

This deliverable adopts the view that observed correlations between different literacies may be influenced by common confounding factors, even when such factors are not directly elicited through dedicated behavioural experiments. Behavioural traits such as overconfidence and underconfidence, for example, have been shown to affect how individuals process information, assess their own capabilities, and act upon available knowledge across a wide range of contexts. These traits can influence performance in knowledge-based and scenario-based questions, as well as self-assessed competence, potentially generating correlated outcomes across multiple skill domains (Kahneman, 2011; Heckman and Kautz, 2012).

Similarly, time preferences and present-biased decision-making are known to affect investment in education and skills, preventive health behaviours, financial planning, and engagement with long-term environmental or civic issues. While TRAILS-I does not include direct experimental measures of time preferences or present bias, these behavioural tendencies provide an important interpretative framework for understanding why deficits in different literacies may cluster within individuals or population groups (Thaler and Sunstein, 2008; Guiso, Sapienza and Zingales, 2006).

Beyond individual behavioural traits, broader social and cultural factors are also likely to contribute to inter-relationships between skills. Educational trajectories, early-life socio-economic conditions, family background, and institutional trust can jointly shape multiple literacies over the life course. Such factors may give rise to cumulative advantages or disadvantages, leading to patterns of multi-literacy strength or deprivation that are not easily explained by domain-specific exposure alone.

In the empirical analysis of Task 5.2, these behavioural and socio-cultural influences are therefore treated as underlying and potentially confounding factors that help interpret observed patterns of skill clustering, co-deficits, and polarisation, rather than as directly estimated causal mechanisms. The explicit measurement and experimental identification of behavioural traits is undertaken in subsequent stages of the TRAILS project, notably in the TRAILS-II survey. In this sense, Task 5.2 provides the conceptual and descriptive foundation for a more granular behavioural analysis in later deliverables, while remaining firmly grounded in the data and measurement scope of TRAILS-I survey.

3. Rethinking Basic and Transferable Skills: A Multidimensional Framework

Using the TRAILS-I survey responses, we apply the conceptual framework developed in Section 2 by measuring decision-relevant literacies and human/social transferable skills at the individual level. Rather than relying on traditional "basic skills" proxies alone, TRAILS-I constructs a set of short, comparable indices that capture the practical knowledge, critical thinking, and behavioural orientation individuals draw upon in everyday contexts, e.g., at work, in markets, in institutions, and in households. These measures, described in more detail in Section 4, cover twelve domains grouped into four broad skill dimensions (Foundational Decision Skills; Digital-Era Functional Skills; Civic and Green Skills; Human and Social Transferable Skills). While Section 4 documents each index and its conceptual coverage, this subsection explains the common measurement approach used to design the survey items and to convert responses into comparable individual-level skill scores.

Across domains, sparing but well-targeted measures are used: most indices are built from three questions that capture key elements of the intended skill, and the index is calculated as a simple additive score (with different weights when needed). In practice, each item is recoded into a binary indicator that equals one when the respondent demonstrates the intended competence (e.g., correct knowledge, recognition of best practice, or a response consistent with effective decision-making), and zero otherwise. The index then sums these components, yielding the familiar 0-3 interpretation ("how many of the core elements does the respondent demonstrate?"). This design is applied even when questions allow multiple selections: the scoring is structured so that each question contributes at most one point, preserving comparability and keeping the index interpretable as a count-style measure (for example, in Media and Information Literacy, respondents can select up to two roles of the media, but the scoring still caps the contribution of that item at one point, keeping the overall index on a 0-3 scale).

Two indices intentionally depart from the 0-3 scale because the underlying concepts require a slightly different measurement. First, Data and Programming Literacy index is based on a single question that asks respondents to rate their confidence (0-10) across five distinct data and programming related tasks; each task is then converted into a binary "moderate confidence" indicator using a common cut-off, and the index sums across the five elements to produce a 0-5 score. Second, Artificial Intelligence (AI) Literacy combines multiple knowledge and judgement components (including multi-select items) to capture a broader competency set and this yields a wider index range (0-7).

Finally, some indices also use specific coding rules so that questions with "select all that apply" answers do not mechanically dominate the final score. A clear example is the Political Literacy index. Although political participation is asked through a multiple-selection list, it is coded as a single indicator, equal to one if the respondent reports any participation, so the index reflects engagement rather than the number of activities selected. The two knowledge components are then added to this participation indicator to keep the index on a transparent 0-3 scale. In addition, the EU-institutions

item is weighted differently for EU and non-EU countries: in EU member states it enters as a standard knowledge component, while in non-EU countries it receives a much smaller weight to preserve cross-country comparability. The same general principles, short instruments, binary competence coding, and additive scoring, are used across the domains where appropriate, ensuring that the measures remain conceptually coherent and comparable across countries.

Building on the conceptual framework developed in Section 2, this deliverable organises the TRAILS-I skill measures into a set of decision-relevant literacy indices and human/social transferable skill indices that reflect the realities of the green and digital transitions and the rapid diffusion of Artificial Intelligence (AI). Rather than treating "basic skills" as synonymous with traditional literacy and numeracy, the TRAILS framework interprets basic skills as functional literacies that support effective decision making in everyday settings, e.g., at work, in markets, in institutions, and in households. In practice, this means focusing on the knowledge and practical reasoning that individuals rely on when making decision under uncertainty: managing finances, navigating digital services, interpreting media information, understanding climate risks, participating in political processes, and interacting constructively in diverse social and cultural contexts.

The twelve indices constructed from the TRAILS-I survey are therefore grouped into four distinct skill dimensions. These dimensions are designed to be conceptually coherent and empirically applicable. Each dimension bundles skill indices that tend to be used in similar decision contexts and rely on related cognitive and behavioural mechanisms (e.g., information processing, risk assessment, trust and credibility evaluation, or social interaction). The proposed skill dimensions are not assumed to be independent; rather, they are presented as an organising structure to clarify the conceptual scope of the newly constructed skill indices. Some indices overlap across domains (for instance, sustainability and finance, or digitalisation and finance), and skills may cluster across dimensions.

The following structure organises the twelve proposed skills into broad dimensions for presentation and comparison:

a) Foundational Decision Skills: Financial Literacy, Retirement Literacy, Health and Medical Literacy
b) Digital-Era Functional Skills: Digital Financial Literacy, Media and Information Literacy, Artificial Intelligence (AI) Literacy, Data and Programming Literacy
c) Civic and Green Skills: Political Literacy, Environmental Literacy, Sustainable Financial Literacy
d) Human and Social Transferable Skills: Human Literacy, Cultural Agility

3.1 Foundational Decision Skills

3.1.1 Financial Literacy

The Financial Literacy index captures a set of foundational competencies that underpin individuals' ability to make informed financial decisions over the life course. Households across Europe are increasingly required to choose among complex financial products (credit, savings, pensions, insurance, and investment vehicles) while bearing greater responsibility for retirement security and risk management. As highlighted in the existing literature, limited financial knowledge can translate into systematic decision errors with long-run welfare consequences, particularly for lower-income and less-educated groups who face tighter constraints and higher exposure to costly mistakes (Lusardi and Mitchell, 2014; Safari et al., 2021).

The Financial Literacy index is constructed using three widely adopted items which assess knowledge of (i) compound interest, (ii) inflation (real vs nominal values), and (iii) risk diversification. These concepts represent minimum building blocks for everyday financial decision-making understanding how savings and debts grow over time, how purchasing power changes with inflation, and why diversification reduces risk in investment decisions. In addition, this measurement approach is widely use in the literature that examines financial knowledge gaps, linking them to household behaviour and outcomes (e.g., Lusardi and Mitchell, 2011; Lusardi and Mitchell, 2023).

Specifically, the Financial Literacy index (range 0-3) is constructed from the following three TRAILS-I survey questions:

Q11. Suppose you have €100 in a savings account earning 5% interest per year, compounded annually. After 2 years, how much do you think you will have in the account?
1. More than €110
2. Exactly €110
3. Less than €110
98. I don't know

Q12. Imagine that the annual inflation rate is 5%, and your savings account earns 3% interest per year. After one year, will the money in your savings account buy:
1. More than it does today
2. The same as it does today
3. Less than it does today
98. I don't know

Q13. Suppose you want to invest €10,000. Is it safer to:
1. Invest the money in a single company's stock
2. Invest the money in a range of different stocks
98. I don't know

Conceptually, these items provide strong coverage of what the index is intended to measure. Q11 captures whether respondents understand how money grows when returns compound, which is fundamental for evaluating both savings and debts over time. Q12 tests whether respondents

understand that inflation erodes purchasing power, a key insight for assessing the real value of savings and returns. Q13 assesses whether respondents recognise that spreading investments across different assets generally reduces risk. Taken together, these questions capture financial reasoning that is widely relevant across countries and socio-economic groups, while remaining simple enough to support harmonised measurement in a cross-country survey context (Lusardi & Streeter, 2023). Finally, the "I don't know" response helps to reduce random error by minimizing guessing.

This measurement approach is also well validated by prior research. Using closely related financial literacy questions, studies show that financial literacy is related to stock market participation, consistent with the idea that basic knowledge lowers barriers to engaging with more complex financial products (van Rooij et al., 2011). In addition, evidence on financial education suggests that exposure to financial courses tend to be linked with saving and wealth accumulation, reinforcing the policy relevance of monitoring financial literacy in a comparable way across populations.

Figure 3-1 maps the weighted country average of the Financial Literacy index (0-3) based on the TRAILS-I survey. Results are grouped using a quintile classification, which divides the distribution into seven classes of an equal number of values, ensuring a balanced comparison across categories (cut-offs shown in the legend). The map indicates higher average financial literacy in several Northern and Western European countries (e.g., Finland and the Netherlands), while lower averages are concentrated in parts of Southern and Eastern Europe (e.g., Spain, Italy, Greece, Romania and Bulgaria), with several countries falling in intermediate categories across Central Europe. Grey shading denotes countries for which data are not available.

Figure 3-2 shows the weighted regional average of the Financial Literacy index (0-3) at the NUTS-2 level for most countries and at NUTS-1 for the UK, Germany, and Turkey. As in the country-level map, results are grouped using a quantile (equal-count) classification. The map highlights within-country variation in financial literacy. Higher-scoring regions are concentrated in parts of Northern and Western/Central Europe, while lower-scoring regions are more common in Southern and Eastern Europe, with many countries showing a mix of high- and low-performing regions. Grey areas indicate regions with no available data.

Table 3-1 presents the pairwise correlations between the Financial Literacy Index and its three constituent items: compound interest, inflation, and risk diversification. Each item is strongly and positively correlated with the overall index ($r = 0.665–0.696$, $p < 0.01$), indicating that all three components contribute meaningfully and relatively evenly to the composite measure. The similarity in the magnitude of these correlations suggests that the index is not disproportionately driven by a single question, but instead reflects a balanced aggregation of different financial knowledge domains. This pattern provides evidence of convergent validity, as each individual literacy dimension aligns closely with the broader construct the index is intended to capture.

At the same time, the correlations among the three individual items are positive but modest in size ($r = 0.152–0.264$, $p < 0.01$). These moderate inter-item associations indicate that while the items are related, they are not redundant and appear to capture distinct aspects of financial literacy-namely numeracy and compound growth, understanding of inflation and purchasing power, and risk diversification principles. The relatively low-to-moderate correlations are consistent with the conceptual multidimensionality of financial literacy and suggest that the index combines complementary competencies rather than overlapping measures of the same skill. Overall, the

correlation structure supports the statistical validity of the Financial Literacy Index as a coherent yet multifaceted construct.

Table 3-1: Financial Literacy index correlation matrix

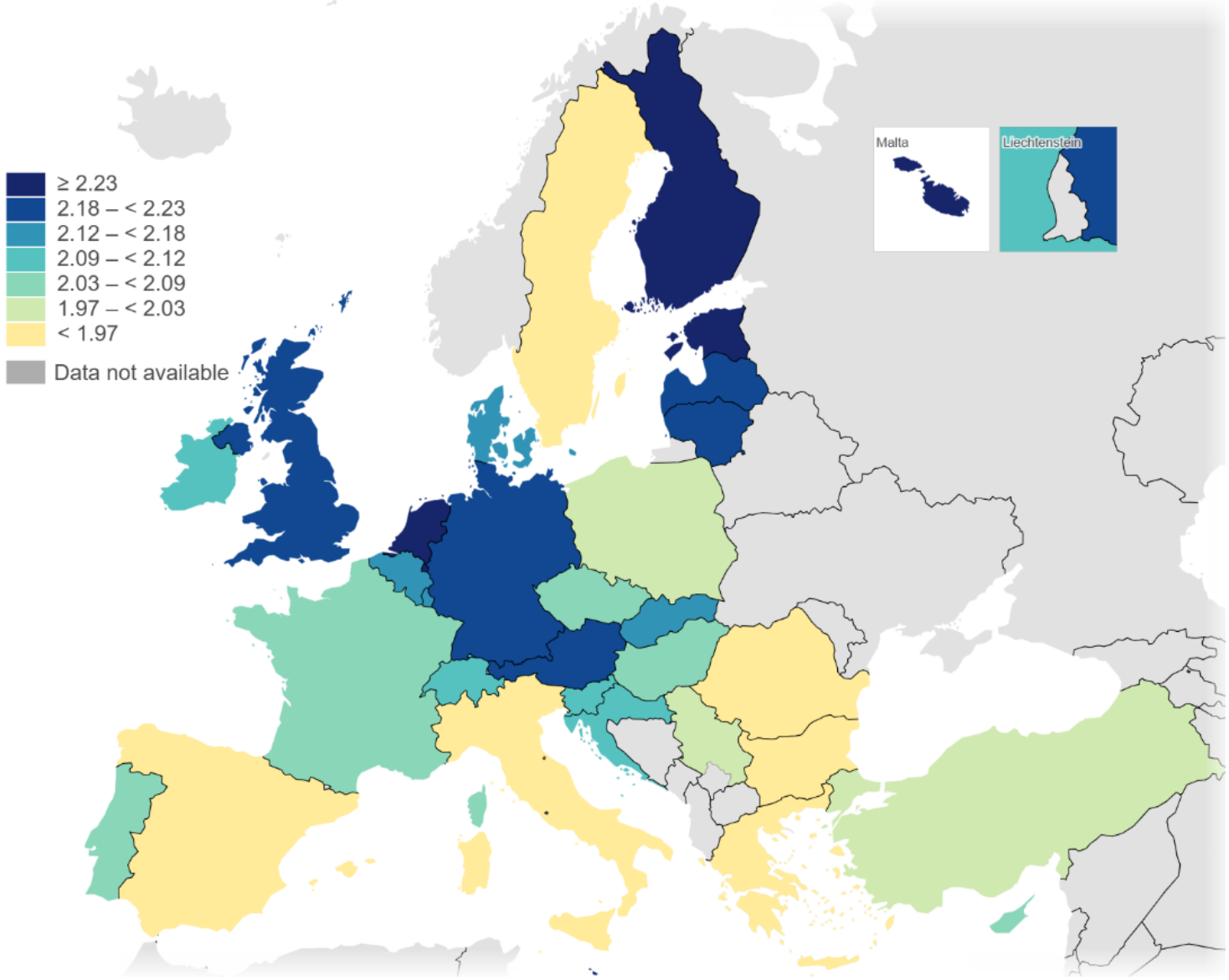
	Financial Literacy Index	Compound interest	Inflation	Risk diversification
Financial Literacy Index	1.000			
Q11: Compound interest	0.696**	1.000		
Q12: Inflation	0.676**	0.152**	1.000	
Q13: Risk diversification	0.665**	0.169**	0.264**	1.000

Figures 3-3 to 3-8 provide a systematic descriptive profile of the financial literacy index across key socio-demographic and labour-market groups. Each figure reports weighted average scores separately for each country and for the pooled sample ("All Countries"), enabling comparisons both within and across national contexts. This structure makes it possible to examine how financial literacy differs across population subgroups inside each country, and to assess whether common patterns, such as gaps by gender, age, education, income, wealth, or employment characteristics, are consistently observed across countries or instead vary with institutional and socioeconomic conditions.

Figure 3-3 presents the gender breakdown in Financial Literacy index, reporting weighted average scores for women and men. Across the sample, the figure shows a general pattern of higher average financial literacy among men. Overall, in All Countries, men score 2.298 compared to 1.918 for women, implying an average gender gap of about 0.38 index points. While the direction of the gap is broadly uniform, its magnitude varies across countries. The largest gender gaps appear in Luxembourg (+0.59), Italy (+0.56) and Ireland (+0.56). While the smallest gaps, though still favouring men, are in Malta (+0.18), the Netherlands (+0.23) and Slovenia (+0.24). Levels are highest for both genders in the Netherlands, while women's averages are comparatively lowest in Italy, Greece and Spain. The figure also highlights variation in overall levels by country for both genders. Financial literacy is highest for both women and men in the Netherlands, while women's average scores are comparatively lowest in Italy, Greece, and Spain.

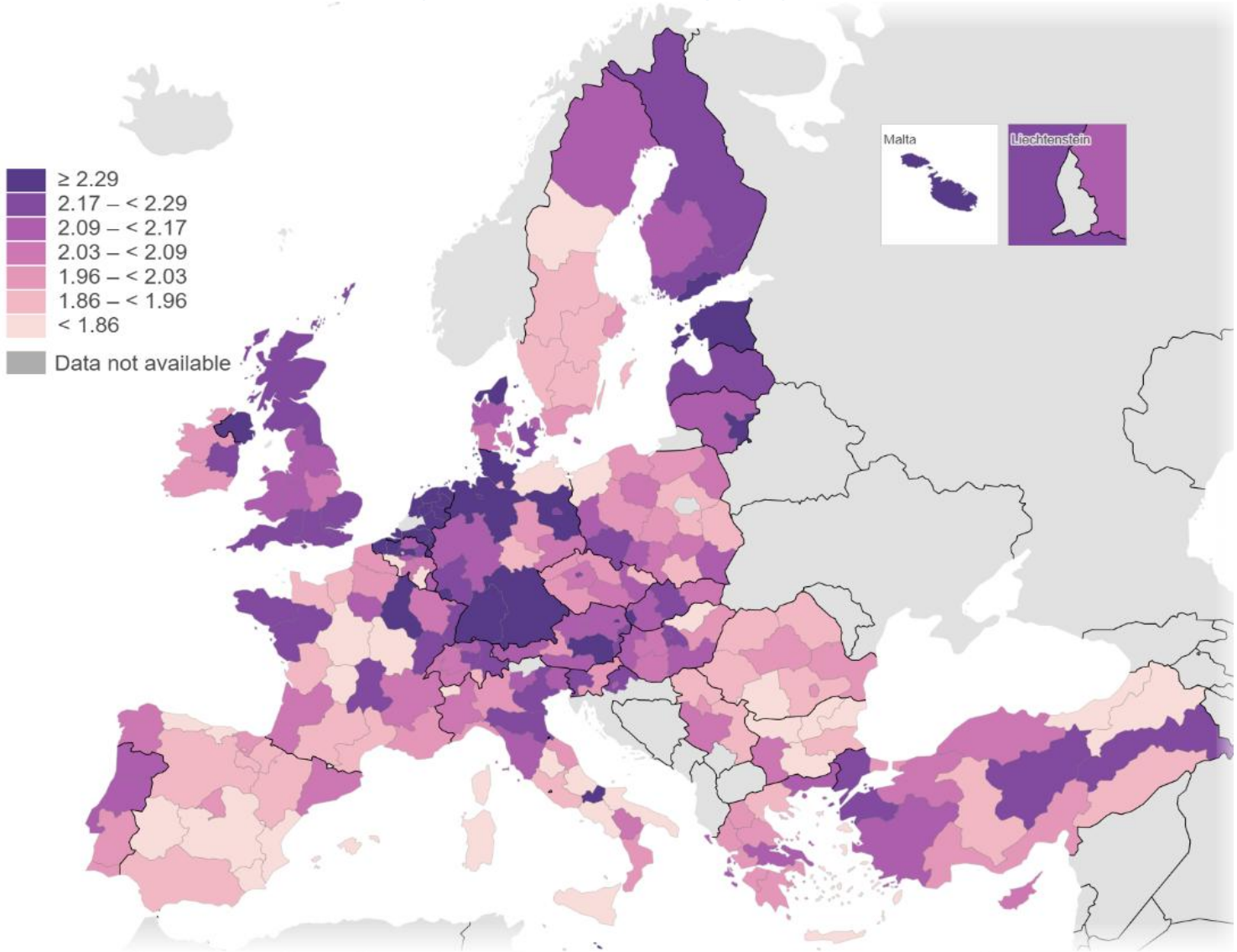
Figure 3-4 presents the age breakdown in Financial Literacy index, reporting weighted average scores across six age groups. Overall, in All Countries, financial literacy rises steadily with age, increasing from 1.988 among those aged 18-24 to 2.187 among those aged 65-80. This pattern is consistent with the notion that financial knowledge accumulates through life-cycle experience, repeated exposure to financial decisions, and learning-by-doing in areas such as saving, borrowing, and investment. Most countries exhibit the same upward pattern, although the magnitude of age differences varies across national contexts. In particular, Cyprus, Ireland, and Greece display especially large gaps between younger and older respondents. In terms of overall levels, the Netherlands, Estonia, and Malta stand out with comparatively high scores across most age groups, while Sweden, Greece, and Spain record the lowest averages.

Figure 3-1: Financial Literacy by country



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 3-2: Financial Literacy by region



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 3-5 reports weighted average Financial Literacy scores by education level, distinguishing three categories: low (early childhood to lower secondary), medium (upper secondary to short-cycle tertiary), and high (tertiary education, from short-cycle programmes to doctoral studies). Overall, in All Countries, financial literacy increases with educational attainment level (Low 1.699, Medium 1.971, High 2.265). This pattern is expected, as higher education is typically associated with stronger numeracy and reading skills, greater exposure to formal economic and financial concepts, and more frequent engagement with complex financial decisions (e.g., saving, borrowing, investment). The similar gradient holds in almost all countries, except Bulgaria which is the only case where average score in Medium-level category is marginally lower than that in the Low-level educational category. Among the high-educated, the highest average scores are in the Netherlands (2.631), Estonia (2.518) and Germany (2.503), while the lowest are in Bulgaria (2.008), Romania (2.070) and Spain (2.084). The education gap between High and Low categories is especially large in Cyprus (1.38), Hungary (1.01) and Ireland (0.91), whereas it is relatively small in Bulgaria (0.27).

Figure 3-6 shows the weighted average scores of the Financial Literacy index across income deciles, based on respondents' self-reported annual net disposable income (including wages, self-employment income, property income and government benefits) ranked from the 1st (lowest) to the 10th (highest) decile. Overall, in All Countries, scores rise from 1.90 in the 1st decile to 2.41 in the 10th decile (gap +0.51). The steepest upward gradients, across all deciles, are observed in France (+0.91), Greece (+0.81) and Czechia (+0.80), while the flattest patterns are in Denmark (+0.13), the Netherlands (+0.30) and Austria (+0.31). At the top of the distribution, the highest 10th-decile average score is in Estonia (2.74), whereas the lowest 1st-decile value is in Romania (1.56).

Figure 3-7 reports the weighted average scores of the Financial Literacy index across wealth deciles, based on respondents' self-reported net household wealth (defined as the total value of all assets owned by the household, after deducting liabilities such as debts or loans) ranked from the 1st (lowest) to the 10th (highest) decile. In All Countries average scores increase from 1.86 in the 1st (lowest-wealth) decile to 2.47 in the 10th (top-wealth) decile (gap +0.61), with a broadly upward pattern. Wealth gradients are particularly steep in Belgium (+1.14), Malta (+0.95) and Czechia (+0.91). By contrast, gradient is comparatively flat in Poland (+0.13) and Hungary (+0.25), while the Netherlands shows a non-monotonic pattern with a lower 10th-decile average score than that in the 1st-decile, a gap of -0.36. The highest 10th-decile average score is observed in Belgium (2.88), while the lowest 1st-decile average score is in Bulgaria (1.60).

Figure 3-8 reports weighted average Financial Literacy scores by skills-matching status, linking individual skill profiles to respondents' perceived fit between their qualifications and the demands of their main job. Skills matching is based on self-assessed alignment of education and training with job requirements and distinguishes three groups: matched (align well), overqualified (qualifications exceed job needs), and underqualified (qualifications are lower of job requirements). In All Countries, overqualified (2.17) and matched (2.16) respondents have almost identical average scores, while underqualified respondents score clearly lower (1.94). Comparing matched to the mismatched average (the mean of overqualified and underqualified), the matched score (2.16) exceeds the mismatched score (2.06), implying a match premium of 0.11. This pattern, underqualified workers scoring lowest, holds in most countries, with notable exceptions such as Malta and Portugal, where underqualified respondents perform comparatively well. The largest gaps between the two mismatched groups (overqualified vs underqualified) are observed in Romania (0.76) and Luxembourg (0.70).

Figure 3-3: Gender breakdown in Financial Literacy by country

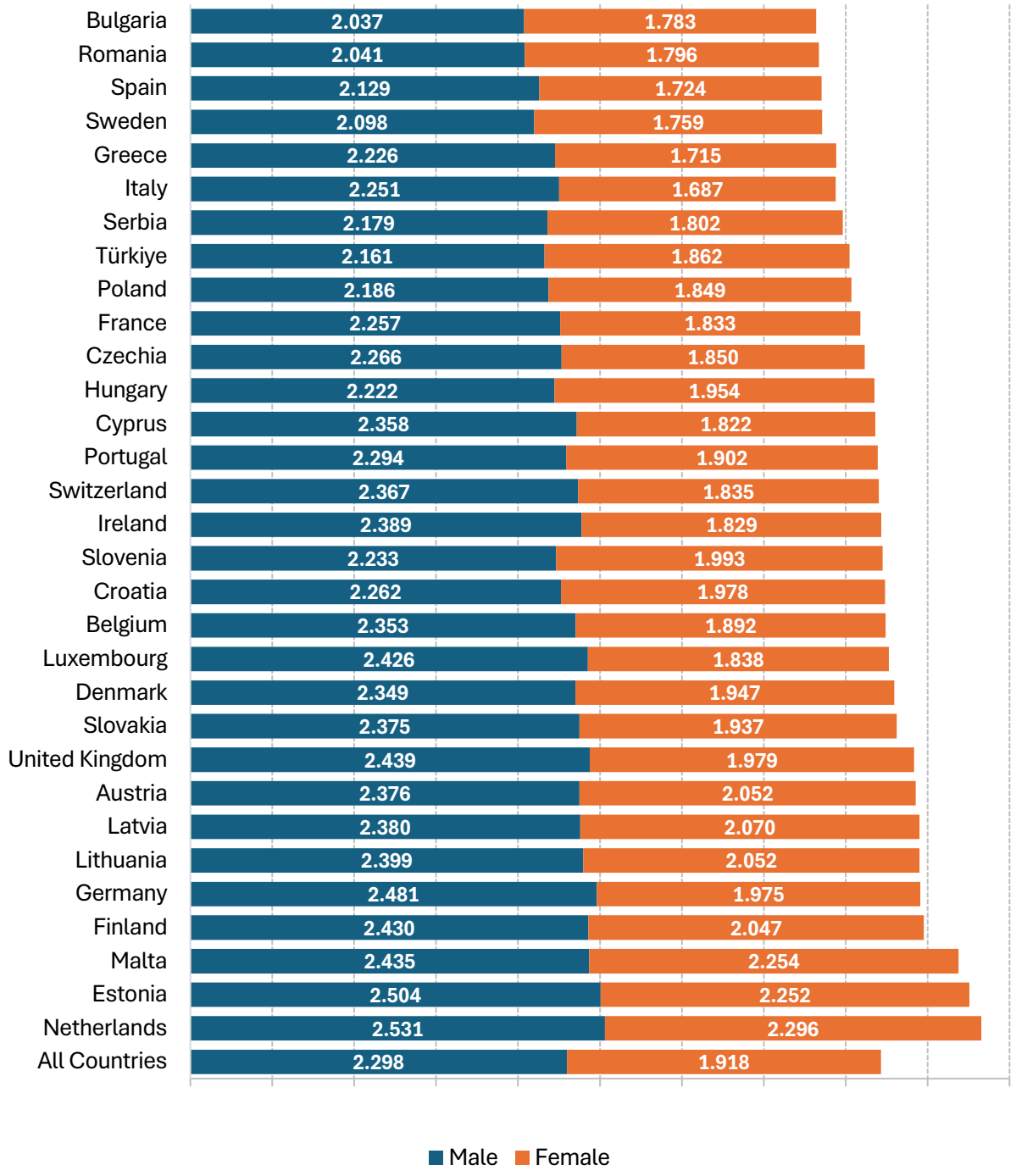


Figure 3-4: Age breakdown in Financial Literacy by country

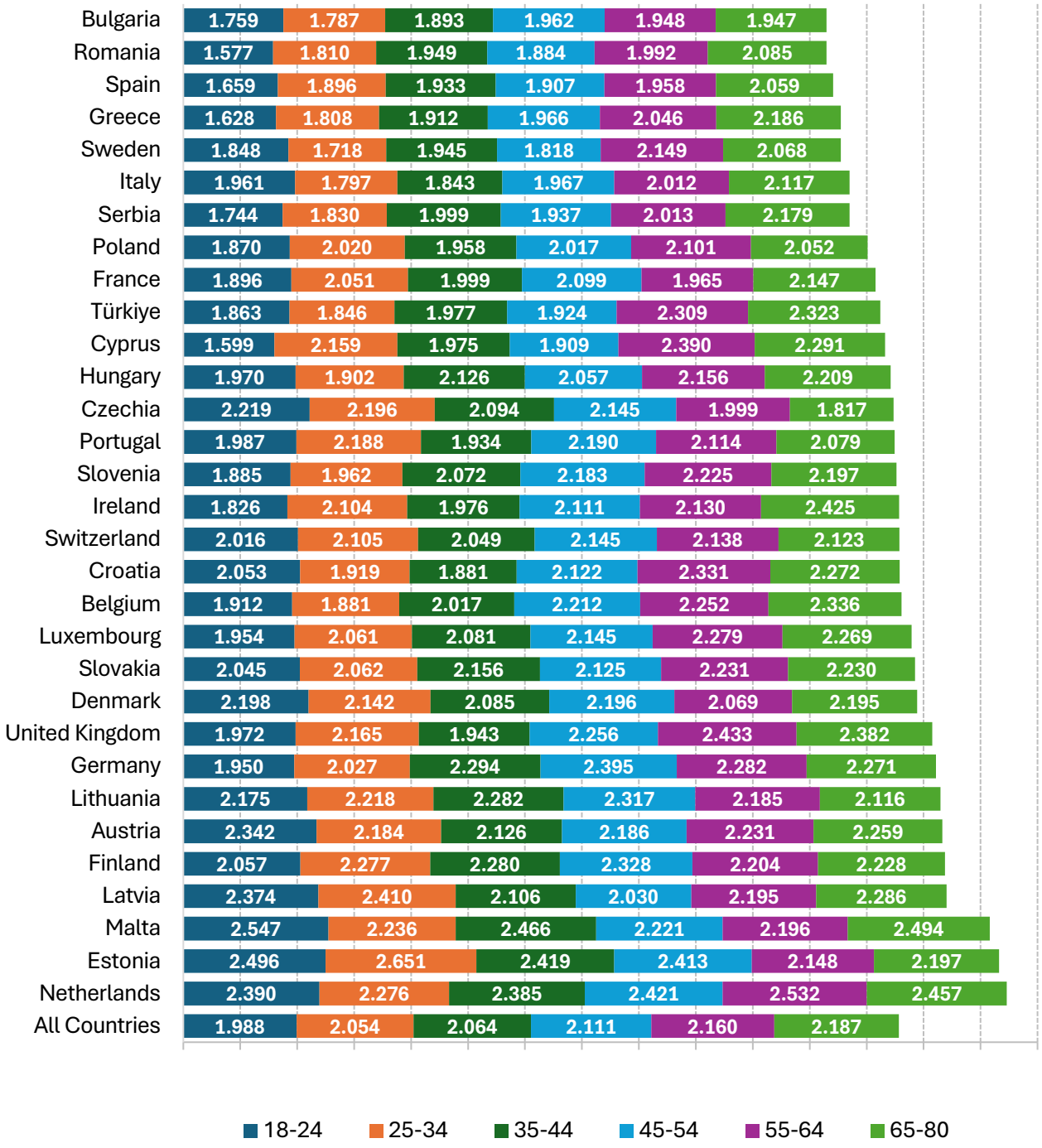


Figure 3-5: Educational breakdown in Financial Literacy by country

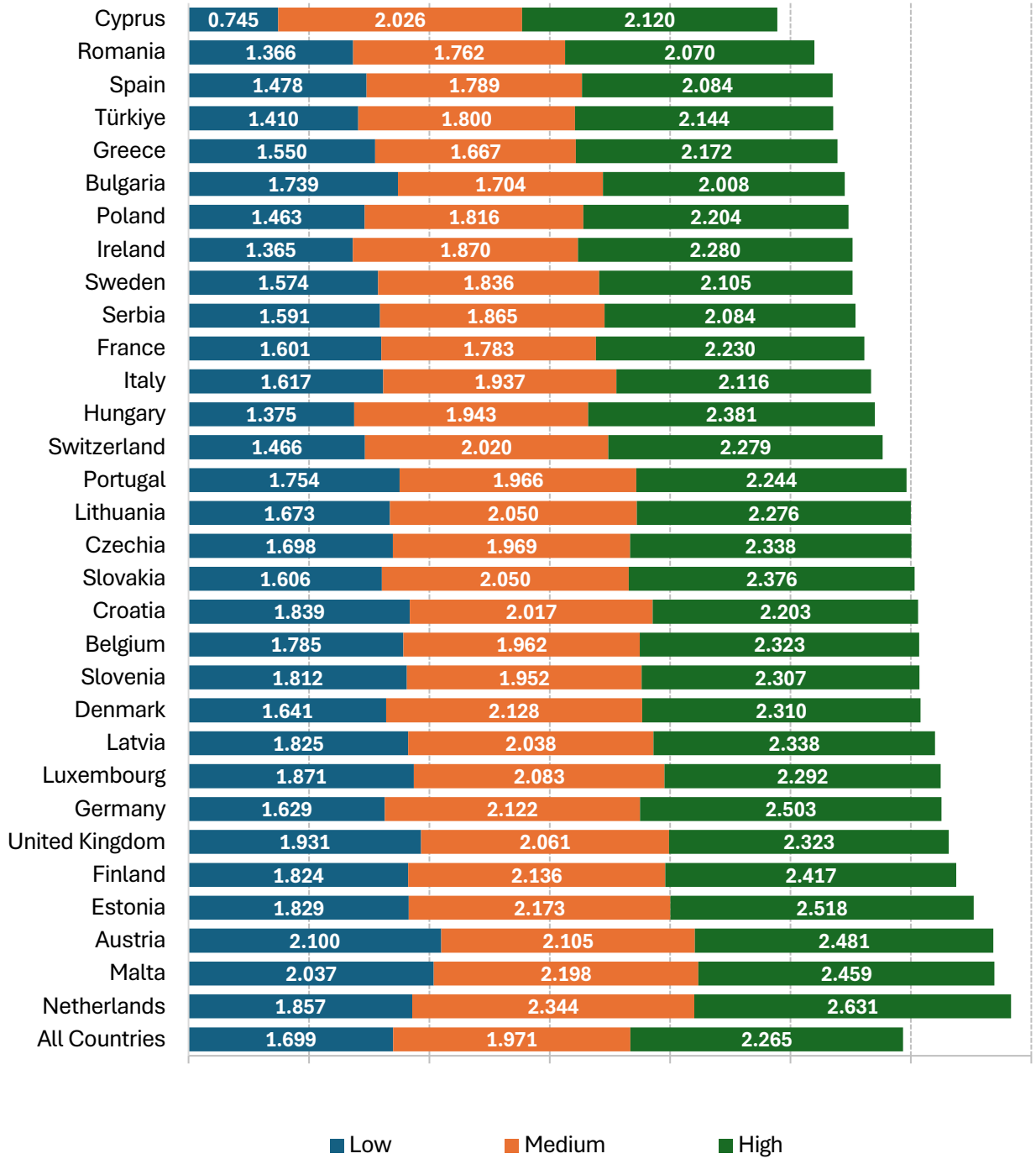


Figure 3-6: Income Composition in Financial Literacy by country

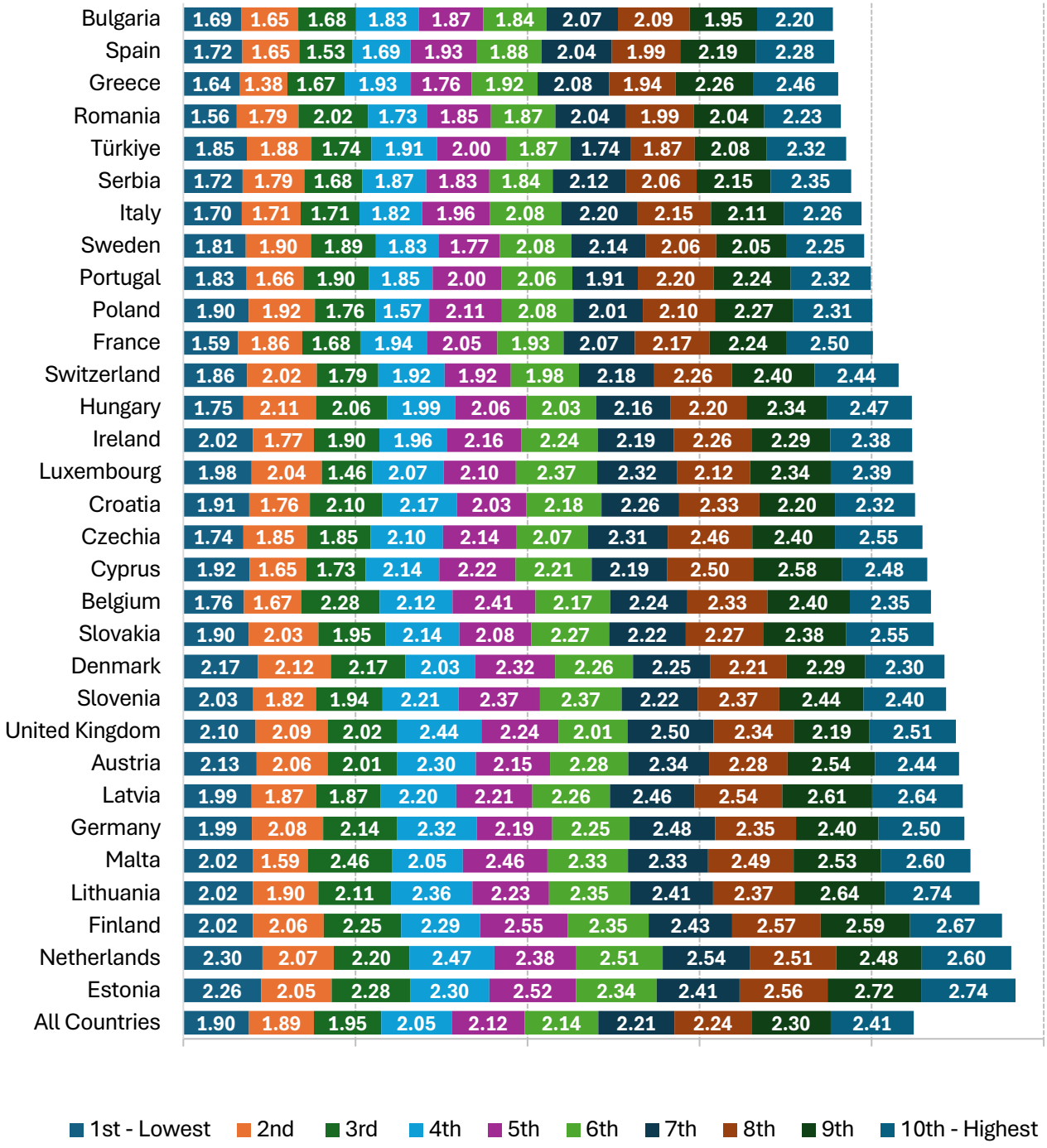


Figure 3-7: Wealth Composition in Financial Literacy by country

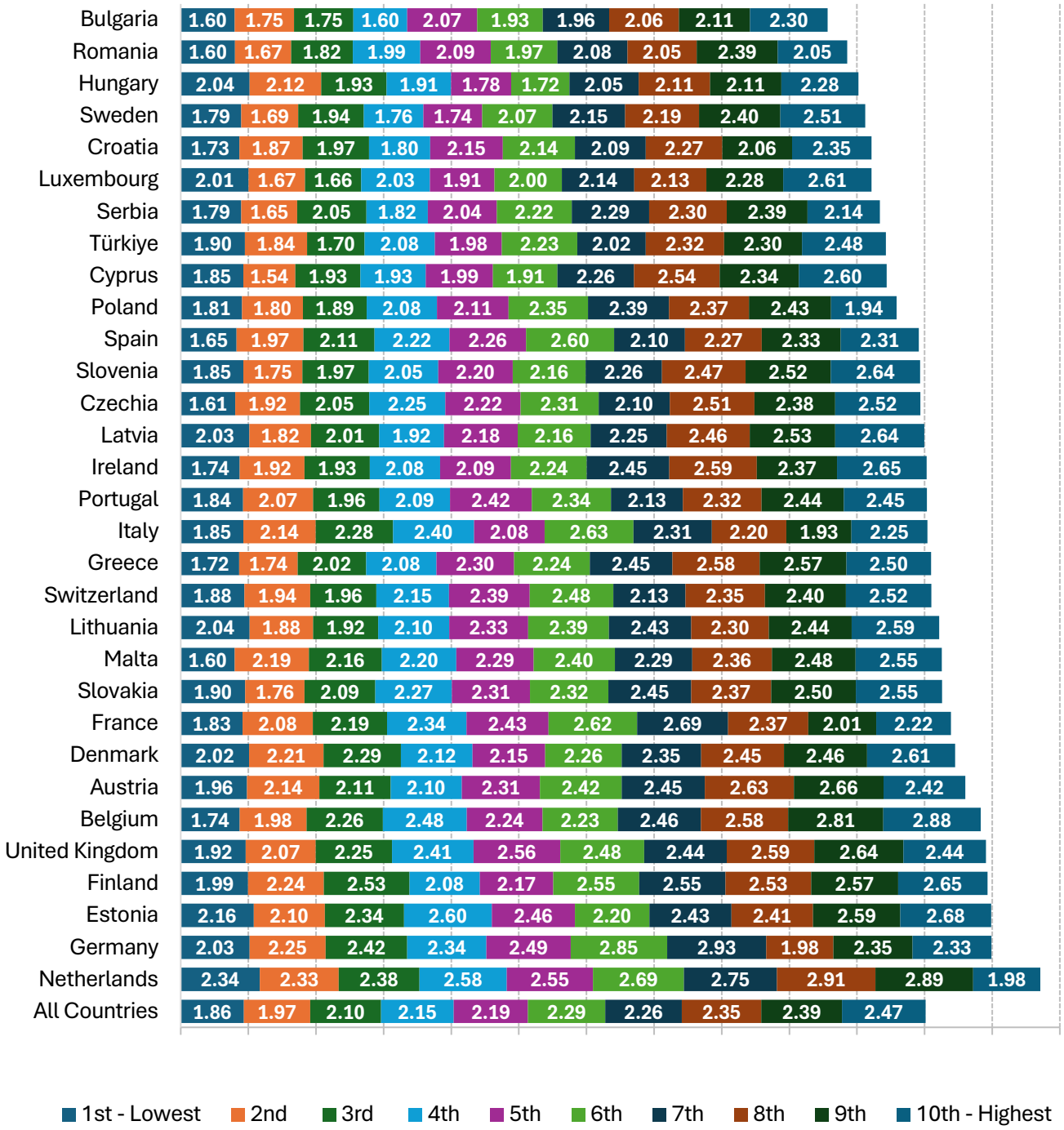
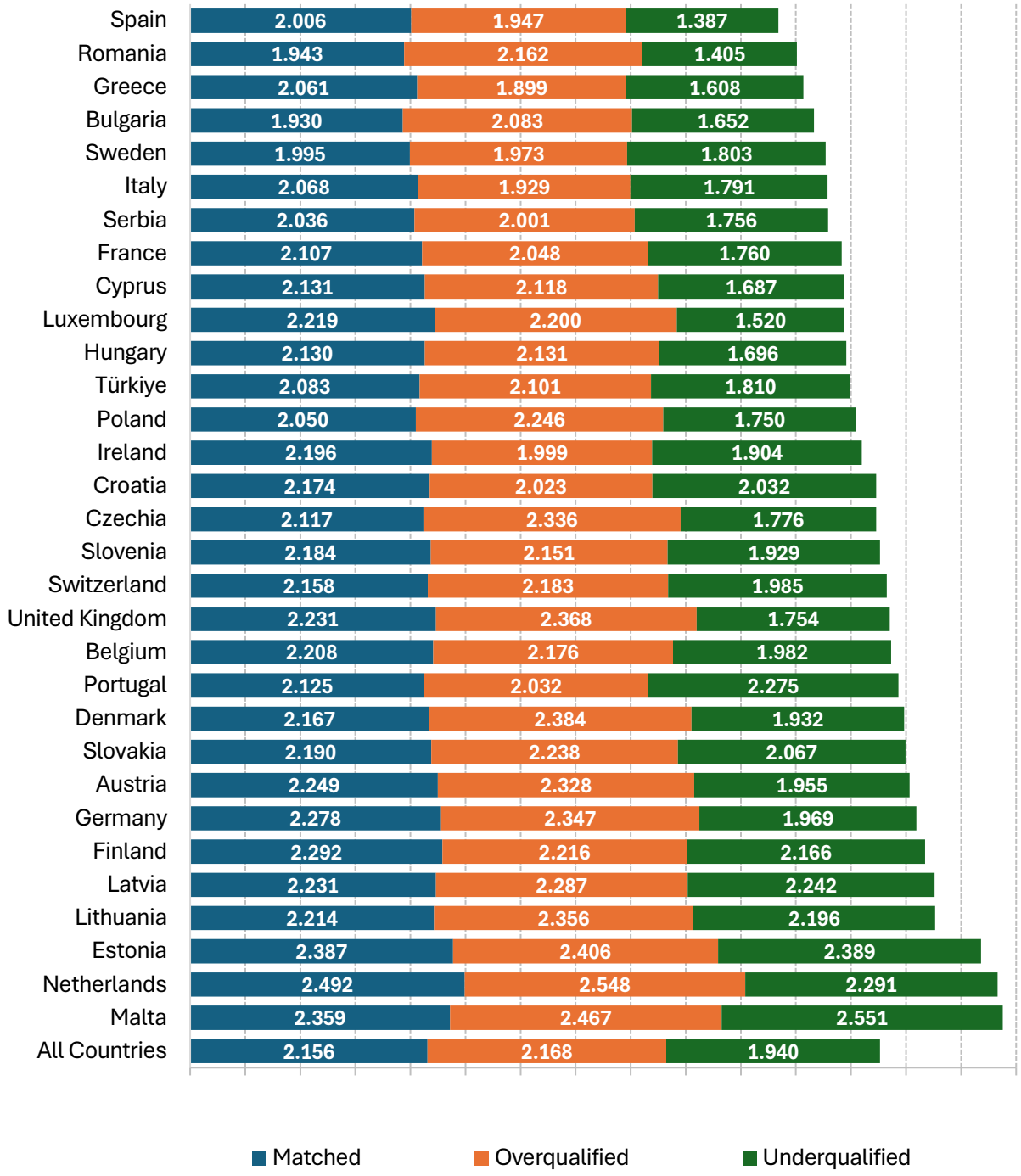


Figure 3-8: Skills Mismatch in Financial Literacy by country



3.1.2 Retirement Literacy

The Retirement Literacy index captures individuals' understanding of key concepts that shape long-term financial security and the capacity to plan for life after work. Across Europe, population ageing, pension reforms, and the gradual shift in many systems towards defined contribution (DC) arrangements have increased the extent to which retirement outcomes depend on individuals' decisions, e.g., how much to contribute, how to allocate savings, and when to retire. In this context, limited knowledge about pension institutions and responsibilities can lead to under-saving, weak retirement literacy, and higher vulnerability to shocks later in life. In addition, literature in economics consistently emphasises that retirement literacy is closely linked to financial preparedness and wellbeing in older age (Lusardi and Mitchell, 2008; van Rooij et al., 2012; Safari et al., 2021).

The index is constructed using items designed to capture three core components of retirement decision-making: (i) understanding what DC pension scheme is, (ii) recognising the multi-pillar structure of retirement income in European systems, and (iii) knowing who has the primary responsibility for adequate retirement income under a DC framework. Together, these concepts go beyond generic financial literacy and directly reflect the institutional setting in which retirement decisions are made in Europe. This approach is consistent with the broader literature showing that knowledge and planning related to pensions and retirement are key channels through which financial literacy translates into household outcomes (see Ingale & Paluri, 2024, for a review).

Specifically, the Retirement Literacy index (range 0-3) is constructed from the following three TRAILS-I survey questions:

Q22. Which of the following statements best describes a defined contribution (DC) pension scheme?
1. *A pension that guarantees a fixed amount of income based on your salary and years worked*
2. *A pension where your contributions are invested, and your retirement income depends on investment performance*
3. *A pension provided by the government to all citizens regardless of employment history*

98. *I don't know*

Q23. Which of the following are typically considered the three pillars of retirement income in many European systems? You can select up to three answer options.
1. *State/public pension (e.g., social security)*
2. *Employer-sponsored occupational pension*
3. *Personal savings or private pension plans*
4. *Inheritance from family*
5. *Public healthcare benefits*
6. *Rental income from real estate*

98. *I don't know*

Q24. Who is primarily responsible for ensuring an adequate retirement income under a defined contribution pension system?
1. *The state*
2. *The employer*

3. *The individual*
4. *The pension fund manager*
   98. I don't know

Conceptually, these items provide strong coverage of what the index is intended to measure. Q22 tests whether respondents understand the defining feature of DC pensions, investment-based accumulation and outcome uncertainty, which is crucial for anticipating risk and evaluating long-run trade-offs. Q23 captures whether respondents recognise that retirement income commonly comes from multiple pillars (public, occupational, and private), a basic institutional insight that shapes realistic expectations and planning strategies. Q24 addresses a central implication of DC systems: greater individual responsibility for achieving adequate retirement income, reinforcing the role of active decision-making and long-term planning in determining outcomes. Finally, the explicit "I don't know" response option helps reduce random error by limiting guessing.

This measurement approach is well supported by prior research. Studies using closely related measures show that higher financial and retirement-related literacy is associated with greater retirement literacy, which is an important predictor of retirement preparedness and later-life financial outcomes (Lusardi and Mitchell, 2011; Lusardi and Mitchell, 2014). Evidence further indicates that knowledge relevant to pensions and the retirement system is closely associated with retirement literacy and household wealth accumulation, consistent with the view that better-informed individuals face lower barriers to engaging with long-horizon financial decisions (van Rooij et al., 2012).

Table 3-2 reports the pairwise correlations between the Retirement Literacy Index and its three component items: knowledge of defined contribution (DC) pension schemes, understanding of the multi-pillar pension system, and responsibility within a DC pension framework. Each item shows a strong and statistically significant correlation with the overall index ($r = 0.601–0.673$, $p < 0.01$). The highest association is observed for knowledge of DC pension schemes ($r = 0.673$), followed closely by understanding of the multi-pillar system ($r = 0.658$), while responsibility in the DC framework shows a slightly lower but still substantial correlation ($r = 0.601$). The similarity in these magnitudes suggests that all three items contribute meaningfully to the composite index, with no single question disproportionately driving the construct. This provides evidence of convergent validity, indicating that the index coherently captures a broader underlying dimension of retirement literacy.

Figure 3-10 maps the weighted average of the Retirement Literacy index (0-3) across countries. Results are displayed using a quintile (equal-count) classification, which splits the distribution into classes with an equal number of values (legend cut-offs shown). The map points to marked cross-country differences, with higher average scores in parts of Northern/Western Europe and several Central-Eastern European countries, and lower averages more common in Southern Europe. Grey shading indicates countries with no available data.

Figure 3-11 shows the same indicator at the regional level, reported at NUTS-2 for most countries and at NUTS-1 for the UK, Germany, and Turkey due to data availability. The classification method is consistent with the country map (quintiles with equal numbers of values per class). The regional view highlights substantial within-country heterogeneity, with several countries displaying a mix of higher- and lower-scoring regions rather than a uniform national pattern. As above, grey areas denote missing data.

At the same time, the inter-item correlations are relatively modest ($r = 0.087–0.143$, $p < 0.01$), with particularly low association between knowledge of the multi-pillar system and responsibility within the DC framework ($r = 0.087$). This pattern suggests that the items measure related but conceptually distinct aspects of retirement knowledge: structural understanding of pension design, system-level architecture, and the allocation of responsibility within DC schemes. The absence of high inter-item correlations indicates that the scale does not suffer from redundancy, but instead combines complementary components of retirement literacy. Overall, the correlation structure supports the statistical validity of the Retirement Literacy Index as a coherent yet multidimensional measure of pension-related knowledge.

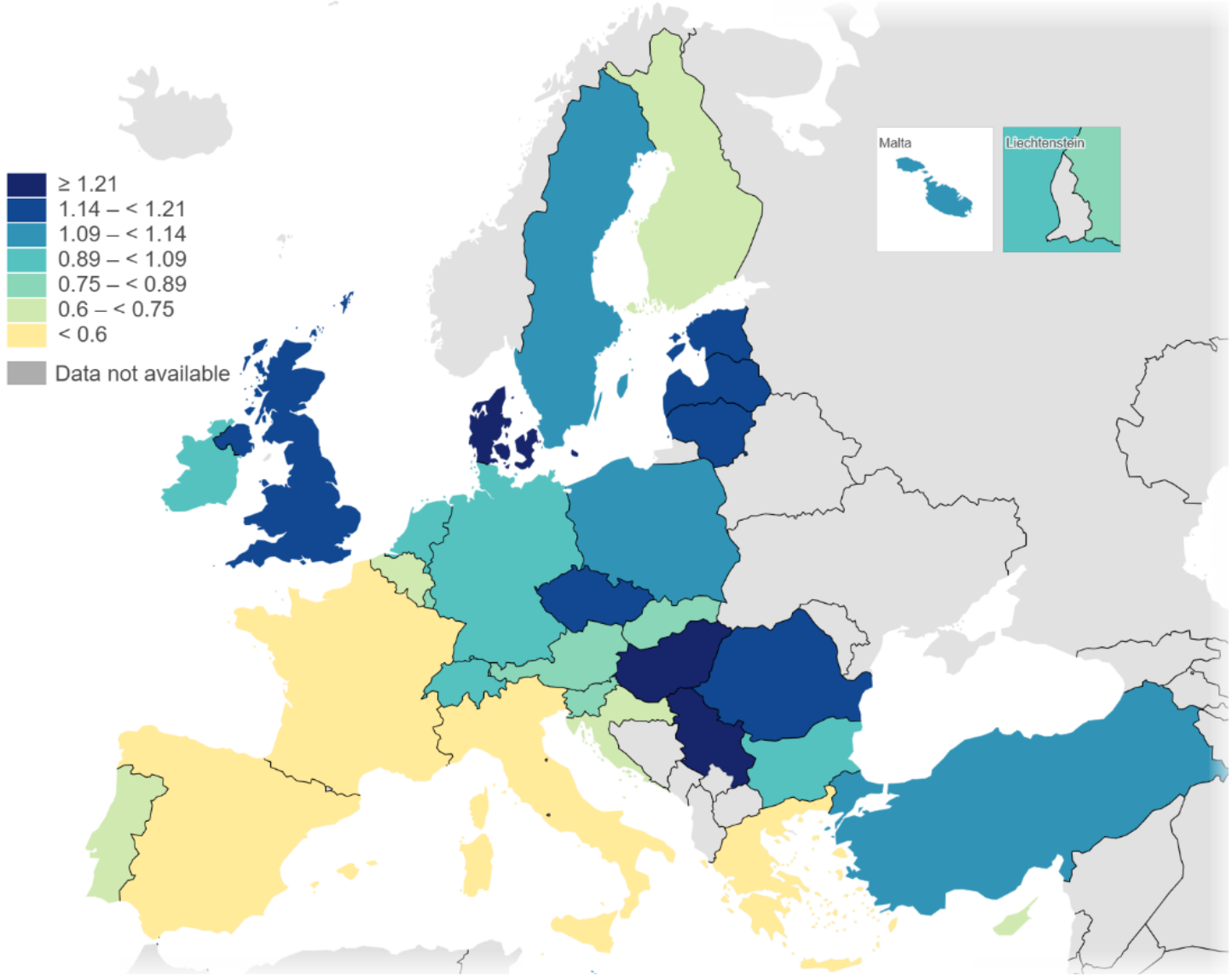
Table 3-2: Retirement Literacy index correlation matrix

	Retirement Literacy Index	Defined contribution (DC) pension scheme	Multi-pillar pension system	Responsibility in DC pension framework
Retirement Literacy Index	1.000			
Q22: Defined contribution (DC) pension scheme	0.673**	1.000		
Q23: Multi-pillar pension system	0.658**	0.138**	1.000	
Q24: Responsibility in DC pension framework	0.601**	0.143**	0.087**	1.000

Figures 3-11 to 3-16 provide a systematic descriptive profile of the Retirement Literacy index across key socio-demographic and labour-market groups. For each subgroup breakdown, weighted averages are reported both by country and for the pooled sample ("All Countries"). This structure allows to identify both within-country disparities and cross-country differences in overall levels. It also allows an assessment of whether the same subgroup patterns, including differences by gender, age, or education, income, wealth and employment status, are broadly shared across national contexts or whether they vary depending on country's institutional factors, such as pension system complexity, labour-market structures, etc.

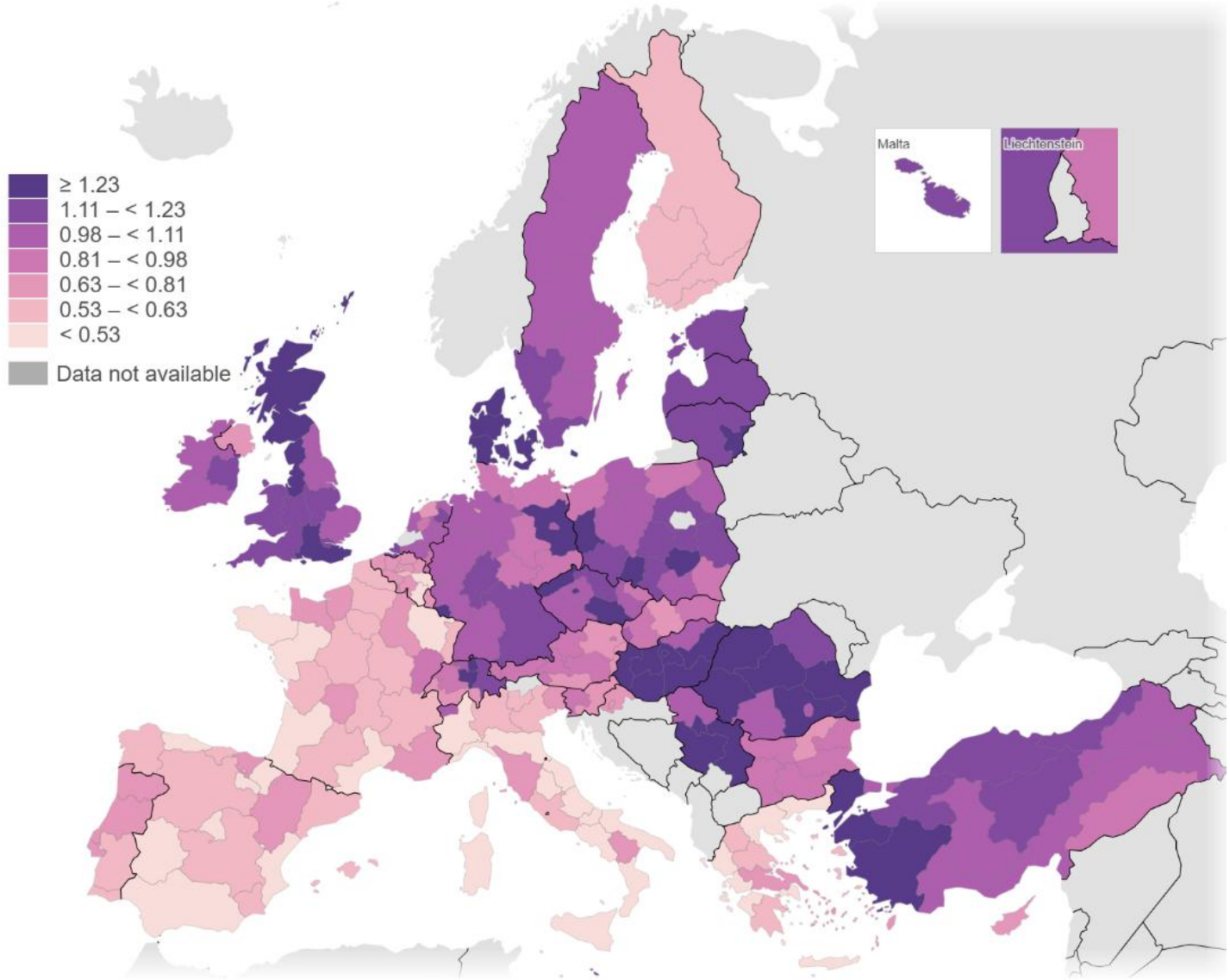
Figure 3-11 shows the gender breakdown in Retirement Literacy index, reporting weighted average scores for women and men. Across all countries men score higher than women, indicating a gender disparity in retirement-related knowledge and understanding. However, the pooled gap, in All Countries, is modest in magnitude: 1.024 for men versus 0.881 for women (a difference of about +0.14). The size of this gap varies across countries, with the largest differences in Denmark (+0.35), the United Kingdom (+0.31), and Ireland (+0.25), suggesting that gender disparities are more pronounced in some contexts than others. Nearly equal scores are observed in Hungary and Estonia (both gaps are almost zero) and Finland (very small gap). While average levels are lowest for both genders in Italy, Greece and Spain.

Figure 3-9: Retirement Literacy by country



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 3-10: Retirement Literacy by region



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 3-12 depicts the age breakdown in Retirement Literacy index, reporting weighted average scores across six age groups. Overall, in All Countries, the life-cycle pattern is reverse U-shaped: the weighted average score increases from 0.767 (18-24) to a peak around 45-54 (1.022), then declines to 0.900 (65-80). This profile is consistent with retirement literacy being shaped by proximity to retirement decision-making, individuals in midlife may have stronger incentives to acquire information about pensions, eligibility, and retirement planning, while younger cohorts may not yet engage with these topics and older cohorts may be further removed from active planning. Cross-country patterns show meaningful variation in the steepness of this age profile. Several countries show large life-cycle differences, most notably Türkiye showing a sharp increase into late working ages and then decreases again. By contrast, both Denmark and Ireland show a more monotonic increase with age, suggesting more continuous accumulation of retirement-related knowledge over the life course. Cross-country levels are generally highest in Denmark, and relatively high in Hungary and Serbia, while Spain, France, and Finland are among the lowest on average.

Figure 3-13 reports weighted average Retirement Literacy scores by education level, distinguishing three categories: low (early childhood to lower secondary), medium (upper secondary to short-cycle tertiary), and high (tertiary education, from short-cycle programmes to doctoral studies). The overall pattern, in All Countries, show that retirement literacy increases systematically with education (Low 0.611, Medium 0.862, High 1.067), indicating that educational attainment is strongly associated with individuals' ability to understand and navigate retirement-related concept. This is a plausible and widely observed pattern, given that education is linked to stronger cognitive and information-processing skills and to greater access to formal and informal learning opportunities. The magnitude of the education gap (High minus Low) is particularly pronounced in Hungary (about 1.20), Denmark (0.79), and Türkiye (0.75), but much smaller in Serbia (0.14). In addition, cross-country variation is substantial even within the high-education group: the highest averages among High-educated respondents are observed in Hungary (1.648), Denmark (1.639) and Czechia (1.459), whereas Greece (0.580), Spain (0.591), and Italy (0.607) record the lowest high-education scores.

Figure 3-14 shows the weighted average scores of the Retirement Literacy index across income deciles, based on respondents' self-reported annual net disposable income (including wages, self-employment income, property income and government benefits) ranked from the 1st (lowest) to the 10th (highest) decile. Overall, in All Countries, the index increases from 0.78 (1st decile) to 1.25 (10th decile), implying a sizeable gap of +0.46. The strongest upward gradients appear in Serbia (+0.79), Hungary (+0.76) and Latvia (+0.72), while Italy (+0.05), Finland (+0.11) and Luxembourg (+0.17) display comparatively small income differences. The highest 10th-decile level is recorded in Hungary (1.77), and the lowest 1st-decile level in France (0.34).

Figure 3-15 reports the weighted average scores of the Retirement Literacy index across wealth deciles, based on respondents' self-reported net household wealth (defined as the total value of all assets owned by the household, after deducting liabilities such as debts or loans) ranked from the 1st (lowest) to the 10th (highest) decile. Overall, in All Countries, the index rises from 0.71 (1st decile) to 1.33 (10th decile), implying an upward wealth gradient (+0.62). The strongest increases are present in Switzerland (+1.09), Ireland (+0.99) and Denmark (+0.82). In a few countries, however, the gradient is weak or reversed at the top, most notably Italy (-0.10) and Poland (-0.07), suggesting non-monotonic wealth patterns in those countries. The highest 10th-decile average score is in Denmark (2.03), while the lowest 1st-decile average score is in Cyprus (0.37).

Figure 3-11: Gender breakdown in Retirement Literacy by country

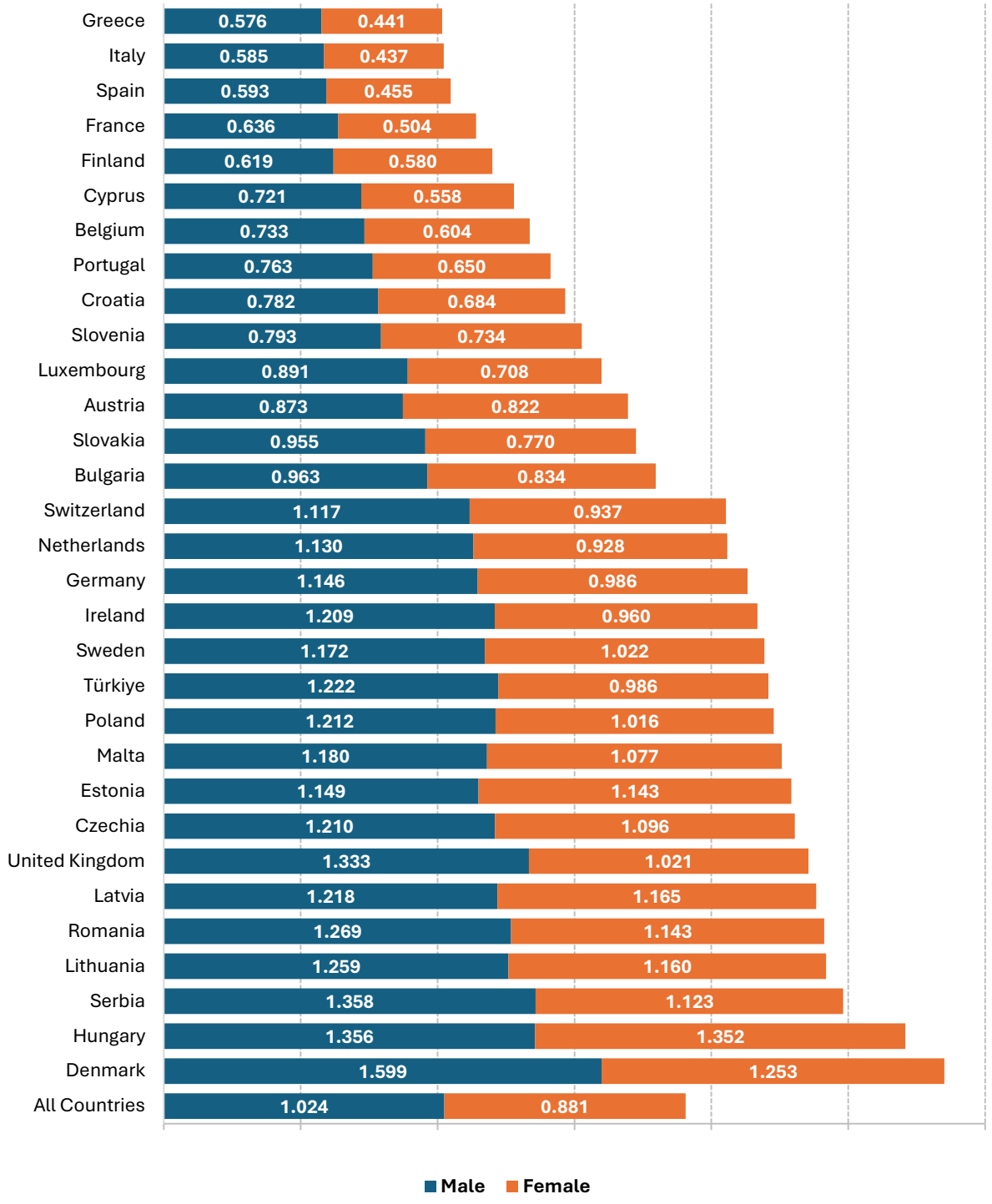


Figure 3-12: Age breakdown in Retirement Literacy by country

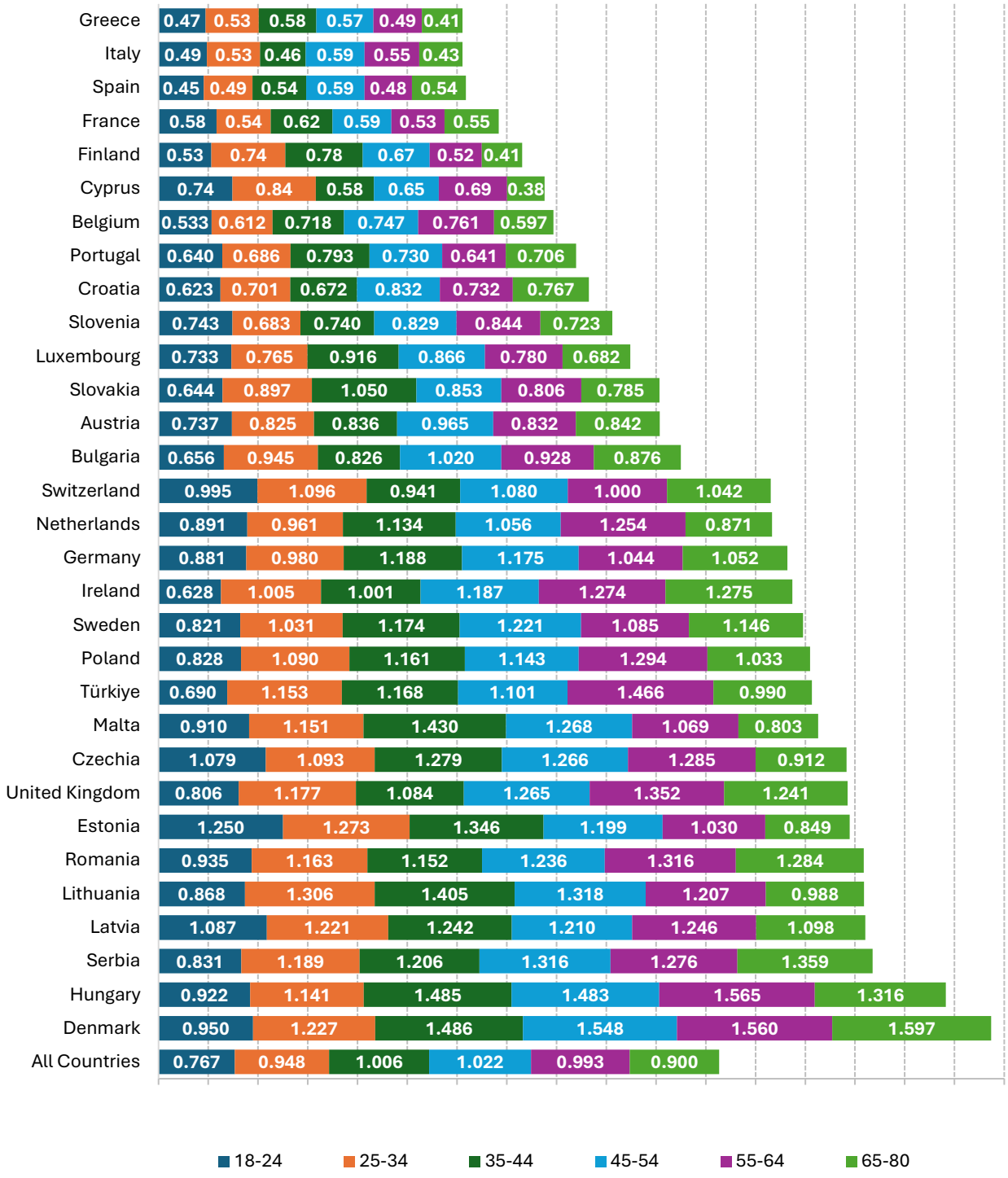


Figure 3-13: Educational breakdown in Retirement Literacy by country

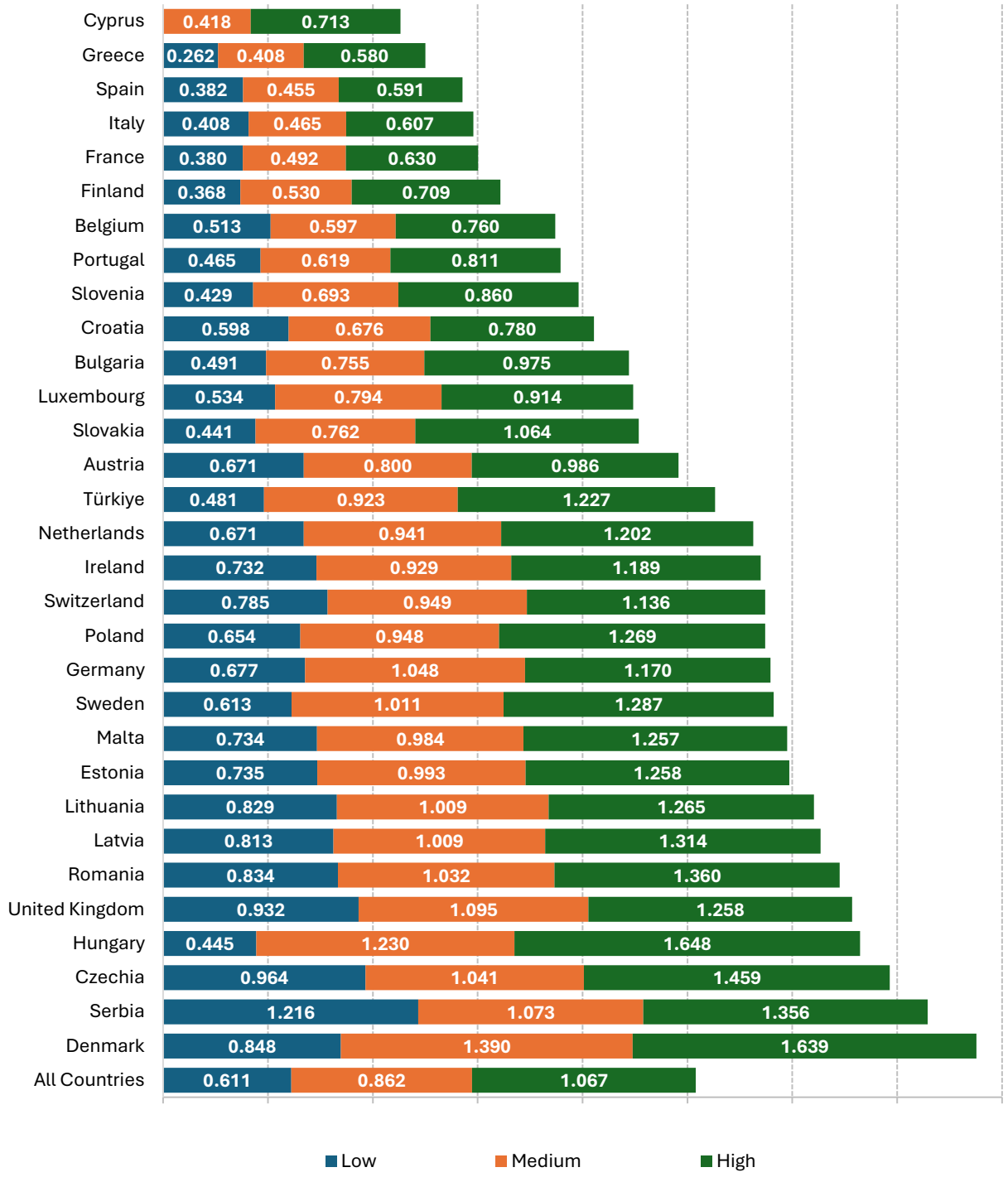


Figure 3-14: Income Composition in Retirement Literacy by country

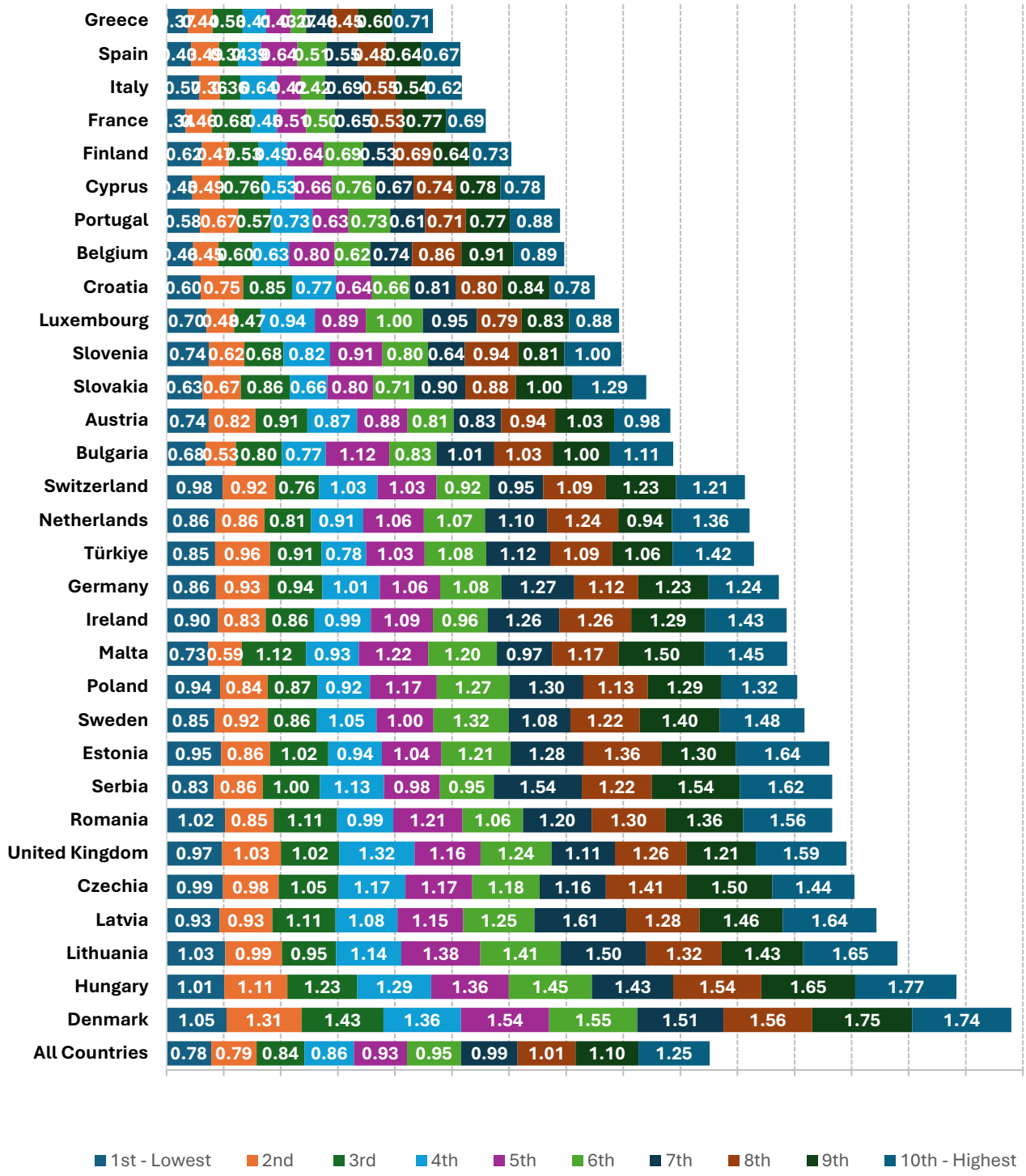


Figure 3-15: Wealth Composition in Retirement Literacy by country

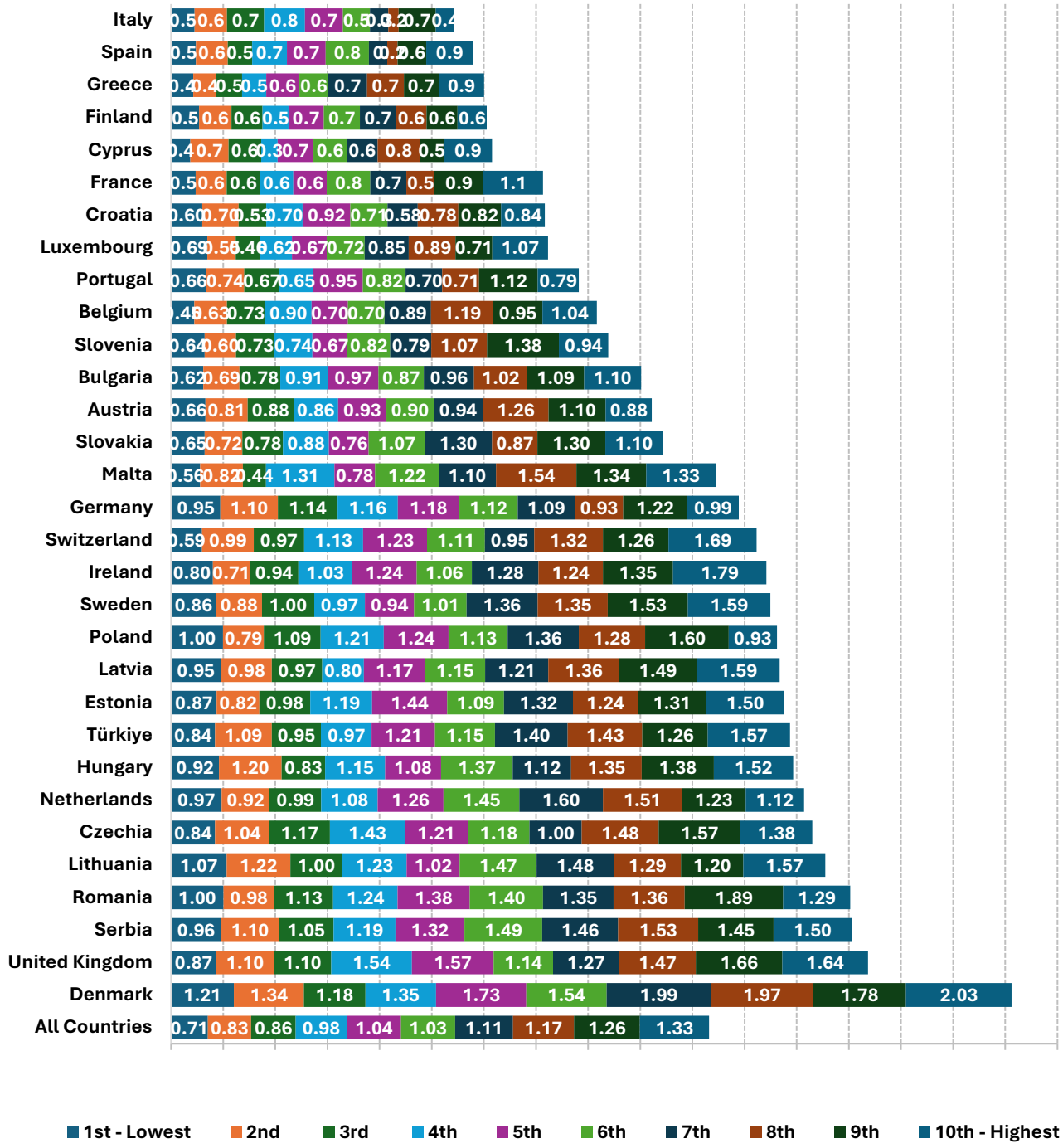
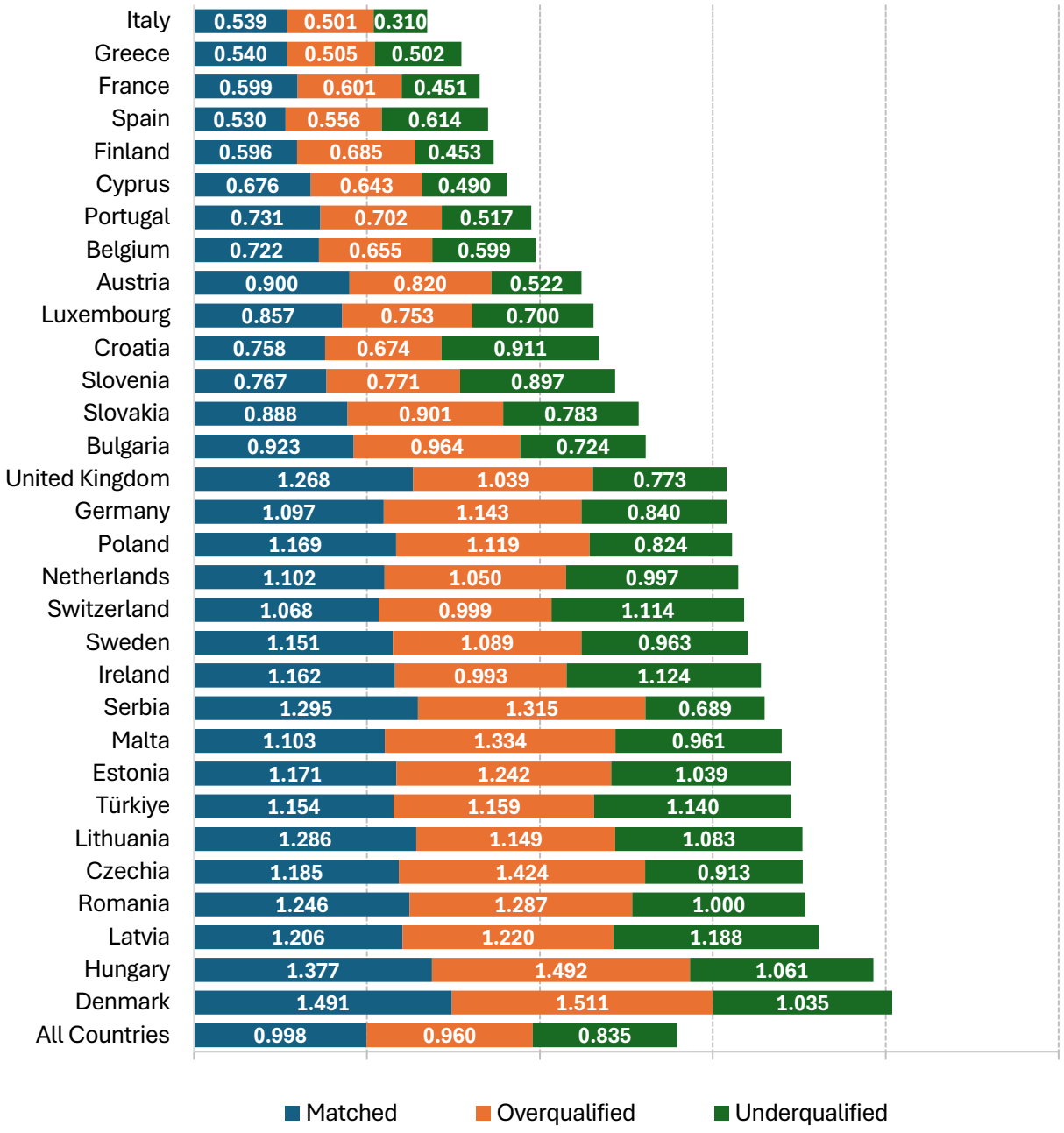


Figure 3-16 reports weighted average Retirement Literacy scores by skills-matching status, linking individual skill profiles to respondents' perceived fit between their qualifications and the demands of their main job. In All Countries, the average score is highest among matched respondents (1.00), slightly lower for overqualified (0.96), and lowest for underqualified (0.83). Comparing matched to the mismatched average (mean of overqualified and underqualified), matched score (1.00) slightly

exceeds the mismatched score (0.90), implying a match premium of 0.11. This pattern is broadly consistent across countries, although there are exceptions where underqualified respondents score highest (notably Switzerland, Slovenia, Croatia, and Spain), which reduces the matched-mismatched gap. The largest differences between the two mismatched groups (overqualified vs underqualified) are observed in Serbia (0.63) and Czechia (0.51), while some countries show near-parity across groups (e.g., Türkiye).

Figure 3-16: Skills Mismatch in Retirement Literacy by country



3.1.3 Health and Medical Literacy

The Health and Medical Literacy index captures a set of basic competencies that help individuals make informed choices about healthcare access, prevention, and treatment in everyday life. These skills matter in contexts where people must interpret health information, follow medical guidance, and navigate institutional rules for accessing care, often under uncertainty and time pressure. In health economics, health is commonly modelled as a form of human capital, and differences in individuals' ability to produce and maintain health can translate into differences in wellbeing and economic outcomes (Grossman, 1972).

The index is constructed using items that cover three core elements of functional health and medical literacy: (i) knowledge of institutional access rights, (ii) understanding of effective prevention measures for infectious diseases, and (iii) basic medical knowledge related to appropriate antibiotic use. Together, these dimensions reflect practical, decision-relevant knowledge that individuals draw on when engaging with health systems and managing common health risks. This approach is consistent with existing studies showing that health knowledge is one channel through which education and other forms of human capital shape health behaviours (Kenkel, 1991; Sørensen et a. (2012),).

Specifically, the Health and Medical Literacy index (range 0-3) is constructed from the following three TRAILS-I survey questions:

Q32. Which document enables EU citizens to access medically necessary healthcare services when temporarily visiting another EU member state?
1. *European Health Insurance Card (EHIC)*
2. *European Social Security Number Card*
3. *European Health Passport*
98. *I don't know*

Q33. Which of the following is the most effective way to prevent the spread of infectious diseases like COVID-19?
1. *Taking antibiotics for every illness*
2. *Regular handwashing and vaccination*
3. *Avoiding outdoor activities*
98. *I don't know*

Q34. If a doctor prescribes antibiotics, which type of illness are they most likely intended to treat?
1. *Viral infections like colds*
2. *Fungal infections*
3. *Bacterial infections*
98. *I don't know*

Conceptually, these items provide strong coverage of what the index is intended to measure. Q32 captures whether respondents know a key instrument (the EHIC) that enables access to medically necessary care during temporary stays abroad, an important aspect of practical system navigation in a mobile Europe. Q33 measures understanding of basic prevention, distinguishing effective public-health measures (handwashing and vaccination) from ineffective strategies. Q34 tests

essential medical knowledge about antibiotics (i.e., that they are primarily used to treat bacterial infections), relevant for appropriate treatment expectations, compliance, and avoiding misconceptions that contribute to misuse. Again, the explicit "I don't know" response option helps reduce random error by discouraging guessing.

This measurement approach is consistent with a broad literature showing that health knowledge and health literacy are closely linked to health behaviours, and can help explain differences in prevention, treatment adherence, and lifestyle choices. Sørensen et al. (2012), for example, propose an integrated health literacy framework that explicitly combines public-health and medical knowledge and emphasises individuals' ability to access, understand, appraise, and apply health information, supporting the view that knowledge improves the quality and efficiency of health-related decision-making. In addition, the systematic review by Urstad et al. (2022) documents substantial variation in how health literacy is defined and measured across studies, reinforcing the value of using clear, decision-relevant items that capture practical competencies in navigation, prevention, and basic medical understanding.

Table 3-3 presents the pairwise correlations between the Health and Medical Literacy Index and its three component items: healthcare access rights, infectious disease prevention, and antibiotic stewardship. Each item is strongly and positively correlated with the overall index ($r = 0.593–0.689$, $p < 0.01$). Knowledge of healthcare access rights shows the highest correlation with the index ($r = 0.689$), followed by antibiotic stewardship ($r = 0.658$) and infectious disease prevention ($r = 0.593$). The relatively balanced magnitude of these correlations indicates that all three items contribute meaningfully to the composite measure, with no single question dominating the index. This pattern provides evidence of convergent validity, suggesting that the index captures a coherent underlying construct of health and medical literacy.

Table 3-3: Health and Medical Literacy index correlation matrix

	Health and Medical Literacy Index	Healthcare access rights	Infectious disease prevention	Antibiotic stewardship
Health and Medical Literacy Index	1.000			
Q32: Healthcare access rights	0.689**	1.000		
Q33: Infectious disease prevention	0.593**	0.132**	1.000	
Q34: Antibiotic stewardship	0.658**	0.100**	0.170**	1.000

In contrast, the inter-item correlations are modest ($r = 0.100–0.170$, $p < 0.01$), indicating that the three items measure related but distinct domains of health knowledge. The low correlations between healthcare access rights and both infectious disease prevention ($r = 0.132$) and antibiotic stewardship ($r = 0.100$) suggest that understanding institutional entitlements is conceptually different from knowledge of disease prevention or appropriate antibiotic use. The somewhat stronger association between infectious disease prevention and antibiotic stewardship ($r = 0.170$) is theoretically consistent, as both concern clinical and public health practices. Overall, the

correlation structure supports the statistical validity of the Health and Medical Literacy Index as a coherent yet multidimensional construct that combines complementary aspects of medical knowledge without redundancy.

Figure 3-17 presents the weighted average of the Health and Medical Literacy index (0–3) across countries. Results are displayed using a quintile (equal-count) classification, which splits the distribution into seven classes with an equal number of values (legend cut-offs shown). The map suggests higher average health and medical literacy in parts of North-Western Europe (e.g., the UK, Ireland and Denmark) and selected Western countries (e.g., France), while lower averages are more common in Southern Europe and Turkey. Grey shading denotes countries with no available data.

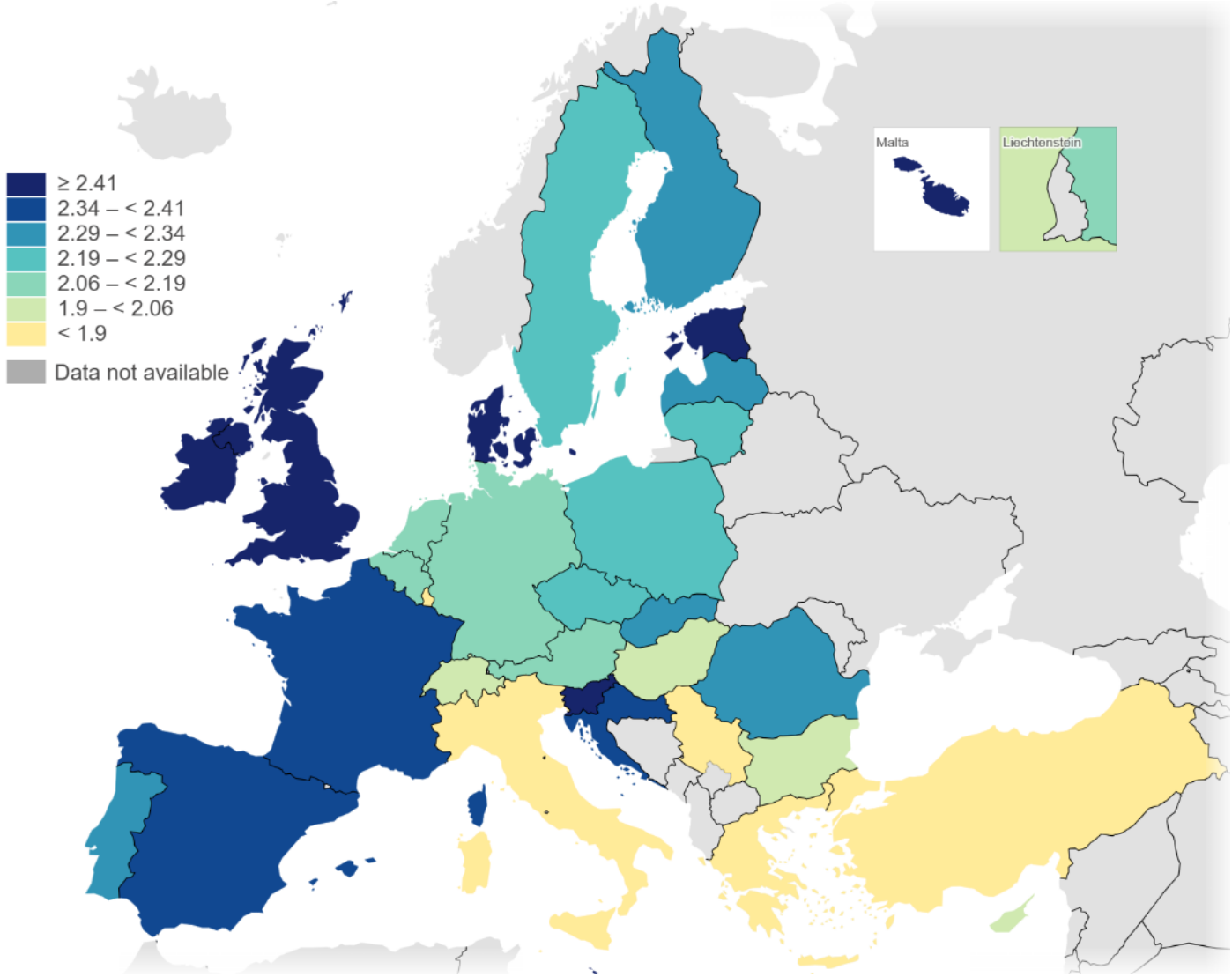
Figure 3-18 shows the same indicator at the regional level (NUTS-2 for most countries and NUTS-1 for the UK, Germany, and Turkey). The classification approach is consistent with the country map (equal-count classes). The regional view highlights substantial within-country variation, with several countries displaying a mix of higher- and lower-scoring regions rather than a uniform national pattern; in contrast, some areas (notably Turkey and parts of Southern Europe) show broader concentrations of lower-scoring regions. As above, grey areas indicate missing regional data.

Figures 3-19 to 3-24 provide a systematic descriptive profile of the Health and Medical Literacy index across key socio-demographic and labour-market groups. For each subgroup breakdown, the figures report the weighted averages both by country and for the pooled sample ("All Countries"), enabling comparisons both within and across national contexts. This structure helps identify which population groups systematically display higher or lower health-related knowledge and decision capacity, and whether these differences are consistent across countries or vary with institutional features such as health-system organisation, the availability of preventive care, and exposure to health information.

Figure 3-19 depicts the gender breakdown in Health and Medical Literacy index, reporting weighted average scores for women and men by country and overall. In contrast to the financial literacy domain, the overall pattern, in All Countries, shows a modest female advantage: women score 2.260 compared to 2.147 for men (gap -0.11). This pattern is observed in most countries, suggesting that women tend to score higher on health and medical knowledge and decision-relevant understanding, potentially reflecting greater engagement with healthcare systems, preventive behaviours, and health-related information. The largest female advantages are recorded in Estonia (around -0.25), Croatia (-0.24), and Finland (-0.23), indicating sizeable gender differentials in these contexts. Only a small number of countries show a male advantage, and even there the gaps are limited in size, most notably in Switzerland (+0.08), Luxembourg (+0.04), and Italy (+0.02). In terms of overall levels, both women and men reach their highest average values in Denmark, whereas the lowest averages for both genders appear in Greece and Türkiye.

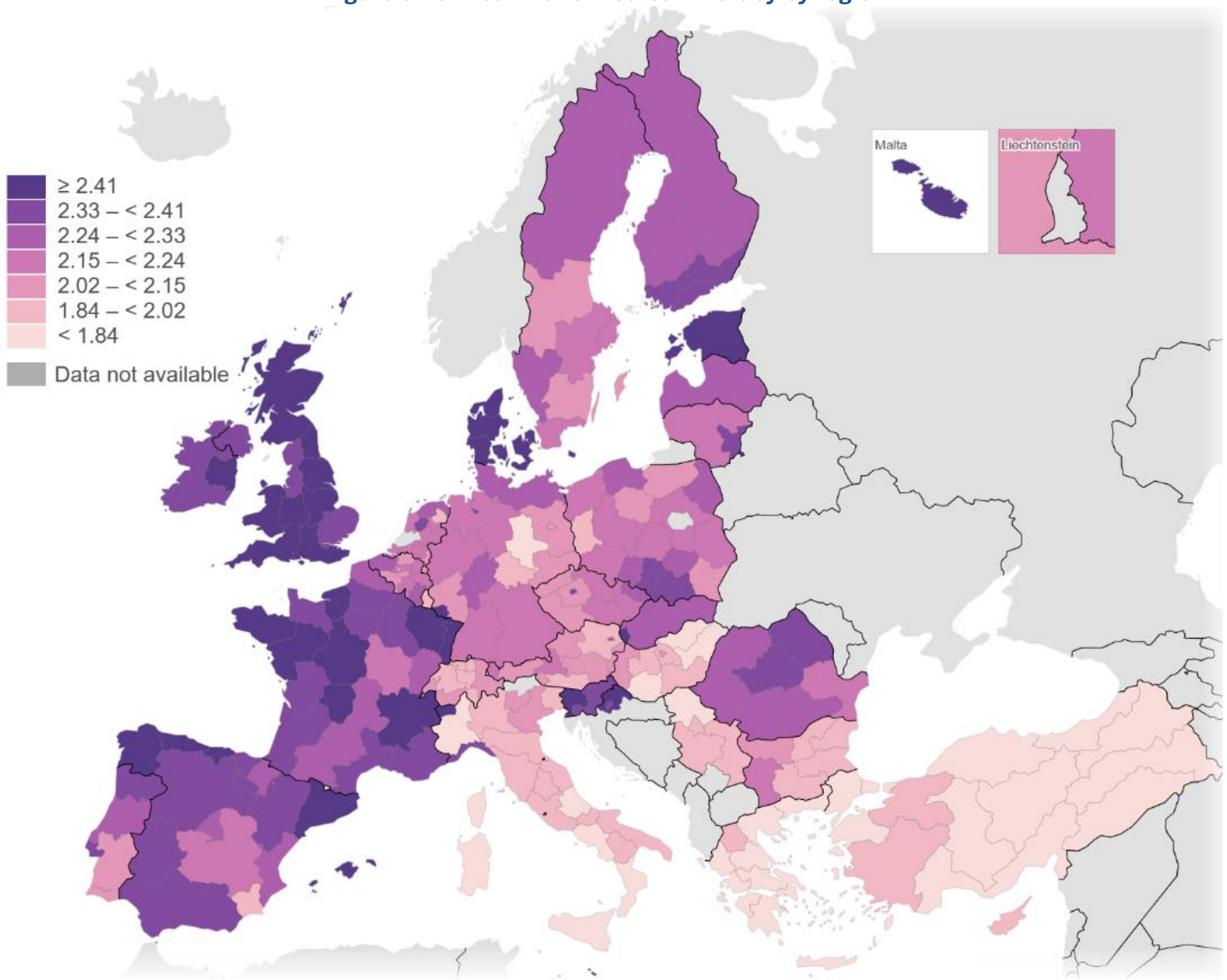
Figure 3-20 reports the age breakdown in Health and Medical Literacy index, reporting weighted average scores across six age groups. Overall, in All Countries, this index increases monotonically with age: average scores increase steadily from 2.038 among those aged 18-24 to 2.287 among those aged 65-80. This age profile is consistent with cumulative exposure to health-related experiences over the life course, including interactions with healthcare providers, medication use, and experience managing chronic conditions, which may contribute to learning and familiarity with medical concepts. However, the magnitude of age differences varies across countries. The most

Figure 3-17: Health and Medical Literacy by country



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 3-18: Health and Medical Literacy by region



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

pronounced age-related increases appear in Sweden, Romania, and Hungary, while other countries show more moderate gradients. Across age groups, Denmark, Estonia, and Malta tend to report among the highest scores across all age groups, whereas Luxembourg, Italy, and Serbia more often report the lowest scores.

Figure 3-21 reports weighted average Health and Medical Literacy scores by education level, distinguishing three categories: low (early childhood to lower secondary), medium (upper secondary to short-cycle tertiary), and high (tertiary education, from short-cycle programmes to doctoral studies). Overall, in All Countries, the index rises steadily with education (Low 1.938, Medium 2.122, High 2.304), indicating that education is strongly associated with health-related knowledge and the capacity to interpret medical information. This pattern is expected given the role of general skills, such as reading comprehension, numeracy, and information processing, in understanding health guidance, risk information, and treatment options. Cross-country dispersion remains substantial even among the highly educated: the highest High-education averages are found in Denmark (2.720), Estonia (2.593), and Slovenia (2.538), while the lowest are in Greece (1.797), Türkiye (1.844), and Italy (1.913). The education gap (High minus Low) is particularly large in Hungary (0.85), Portugal (0.59), and Latvia (0.57), suggesting that education translates into markedly higher health and medical literacy in these countries. By contrast, the education gradient is comparatively small in Italy (0.11), Malta (0.13), and the United Kingdom (0.13), indicating weaker differentiation by education. Finally, Sweden shows a minor non-monotonicity, with the medium-education category scoring slightly below the low-education group.

Figure 3-22 shows the weighted average scores of the Health and Medical Literacy index across income deciles, based on respondents' self-reported annual net disposable income (including wages, self-employment income, property income and government benefits) ranked from the 1st (lowest) to the 10th (highest) decile. The overall pattern, in All Countries, shows a modest income upward gradient, from 2.09 (1st) to 2.30 (10th), a gap of +0.21. The most pronounced income increases are in Hungary (+0.51), Lithuania (+0.43) and Portugal (+0.41), whereas gradients are very small in Spain (+0.05), Switzerland (+0.05) and Cyprus (+0.06). The highest 10th-decile level is in Denmark (2.74), while the lowest 1st-decile level is in Greece (1.50).

Figure 3-23 reports the weighted average scores of the Health and Medical Literacy index across wealth deciles, based on respondents' self-reported net household wealth (defined as the total value of all assets owned by the household, after deducting liabilities such as debts or loans) ranked from the 1st (lowest) to the 10th (highest) decile. Overall, in All Countries, the gradient is modest: 2.09 in the 1st-decile versus 2.39 in the 10th-decile (gap +0.31). Wealth differences are largest in Malta (+0.64), Latvia (+0.63) and Hungary (+0.59), while they are close to zero in Luxembourg (+0.02). A small number of countries show a reversed pattern at the top compared to the bottom, such as the Netherlands (-0.43) and Switzerland (-0.19). The highest 10th-decile average score is in Denmark (2.84), and the lowest 1st-decile average score is in Hungary (1.48).

Figure 3-24 reports weighted average Health and Medical Literacy scores by skills-matching status, linking individual skill profiles to respondents' perceived fit between their qualifications and the demands of their main job. Overall, in All Countries, matched respondents score highest (2.25), followed by overqualified (2.21), with underqualified lowest (2.07). Comparing the mismatched average (2.14) with the matched score (2.25) suggests a match premium of 0.11. In most countries, matched respondents have the highest scores, while underqualified have the lowest scores, keeping the mismatched average score below that in matched. A few countries show the opposite ordering,

underqualified average score is highest in the Netherlands, Switzerland, and Cyprus, which reduces the matched-mismatched difference. The widest gaps between overqualified and underqualified are in Hungary (0.64) and Czechia (0.49), while differences are very small in the Netherlands, where the three categories are close.

Figure 3-19: Gender breakdown in Health and Medical Literacy by country

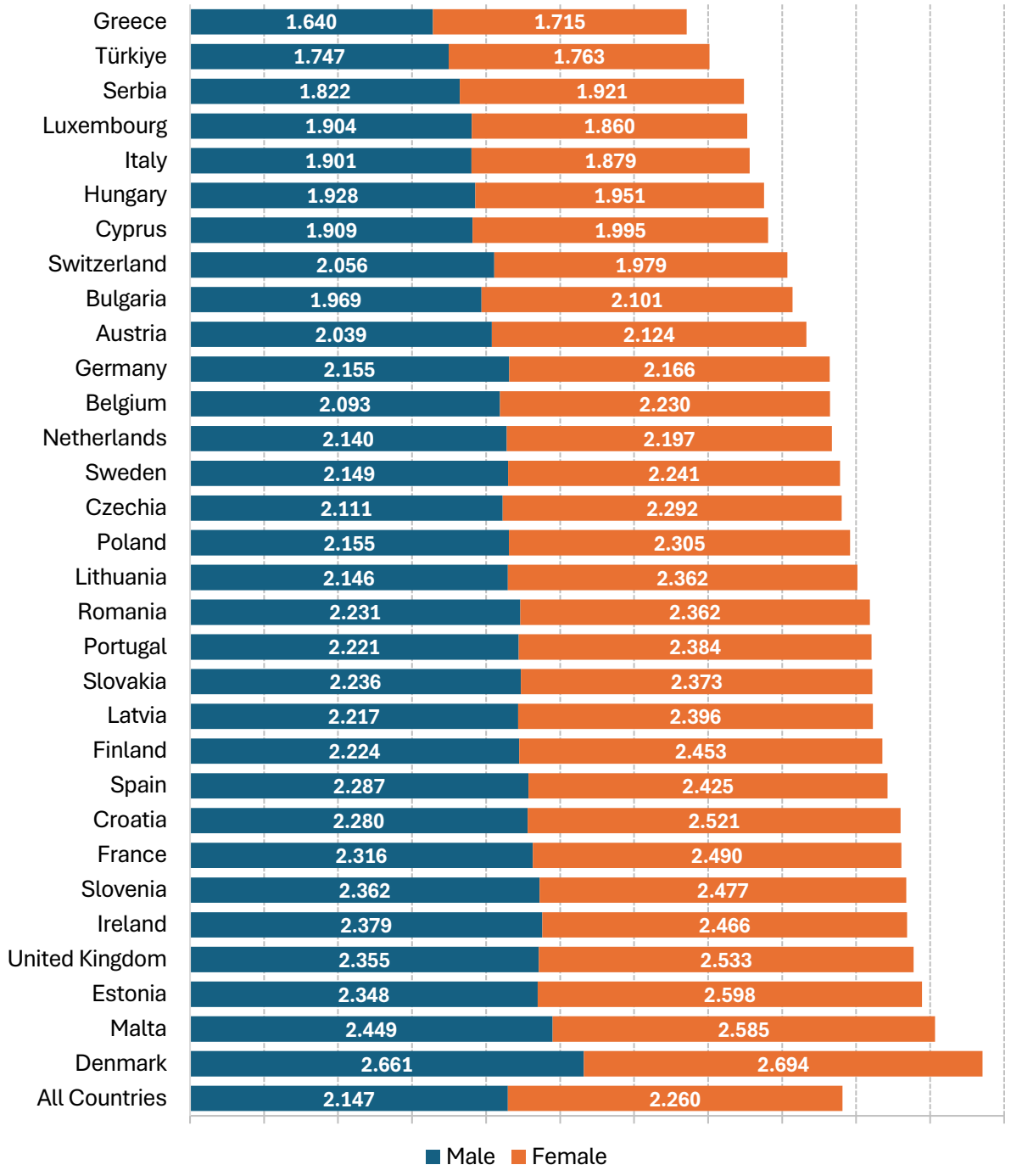


Figure 3-20: Age breakdown in Health and Medical Literacy by country

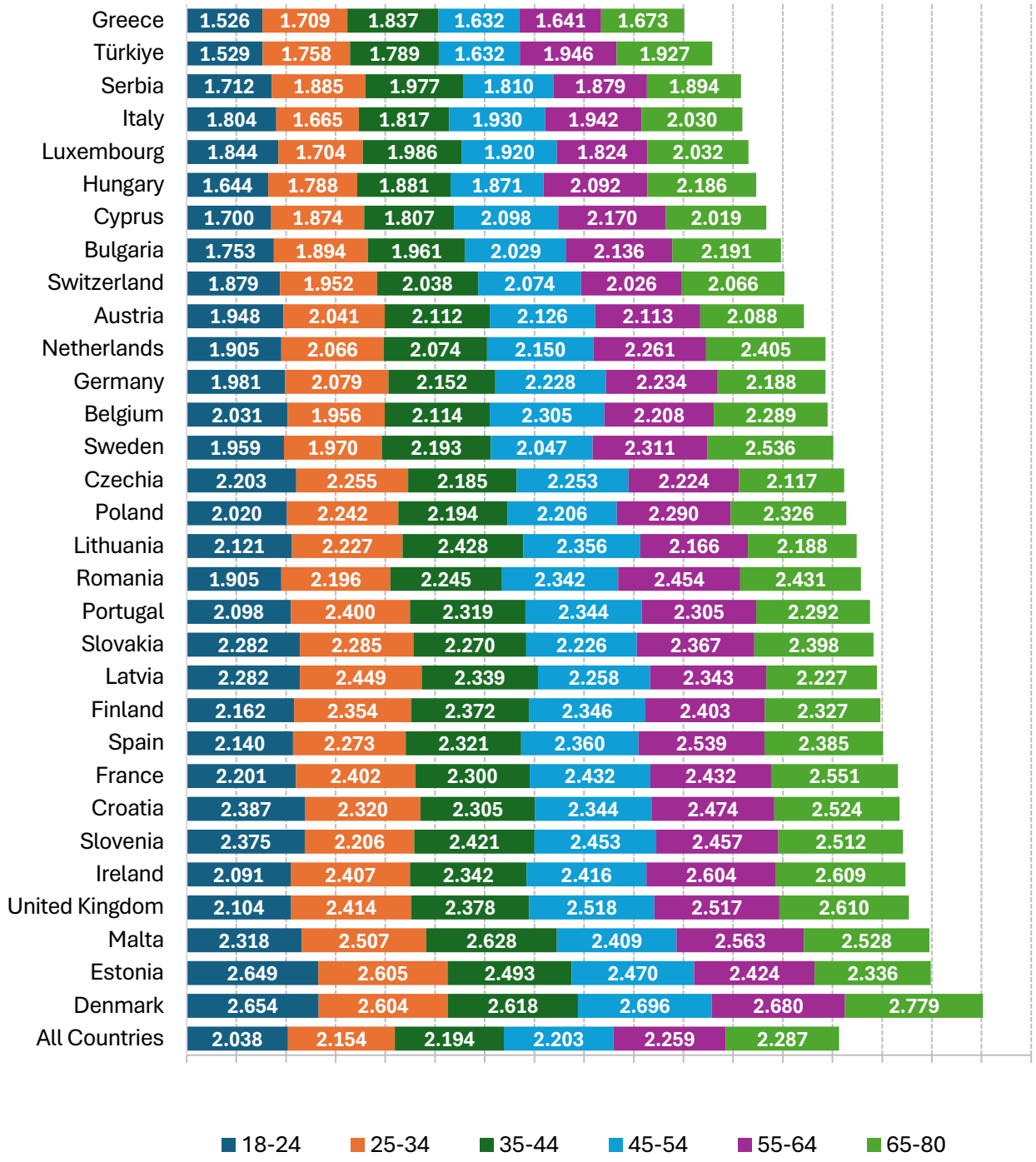


Figure 3-21: Educational breakdown in Health and Medical Literacy by country

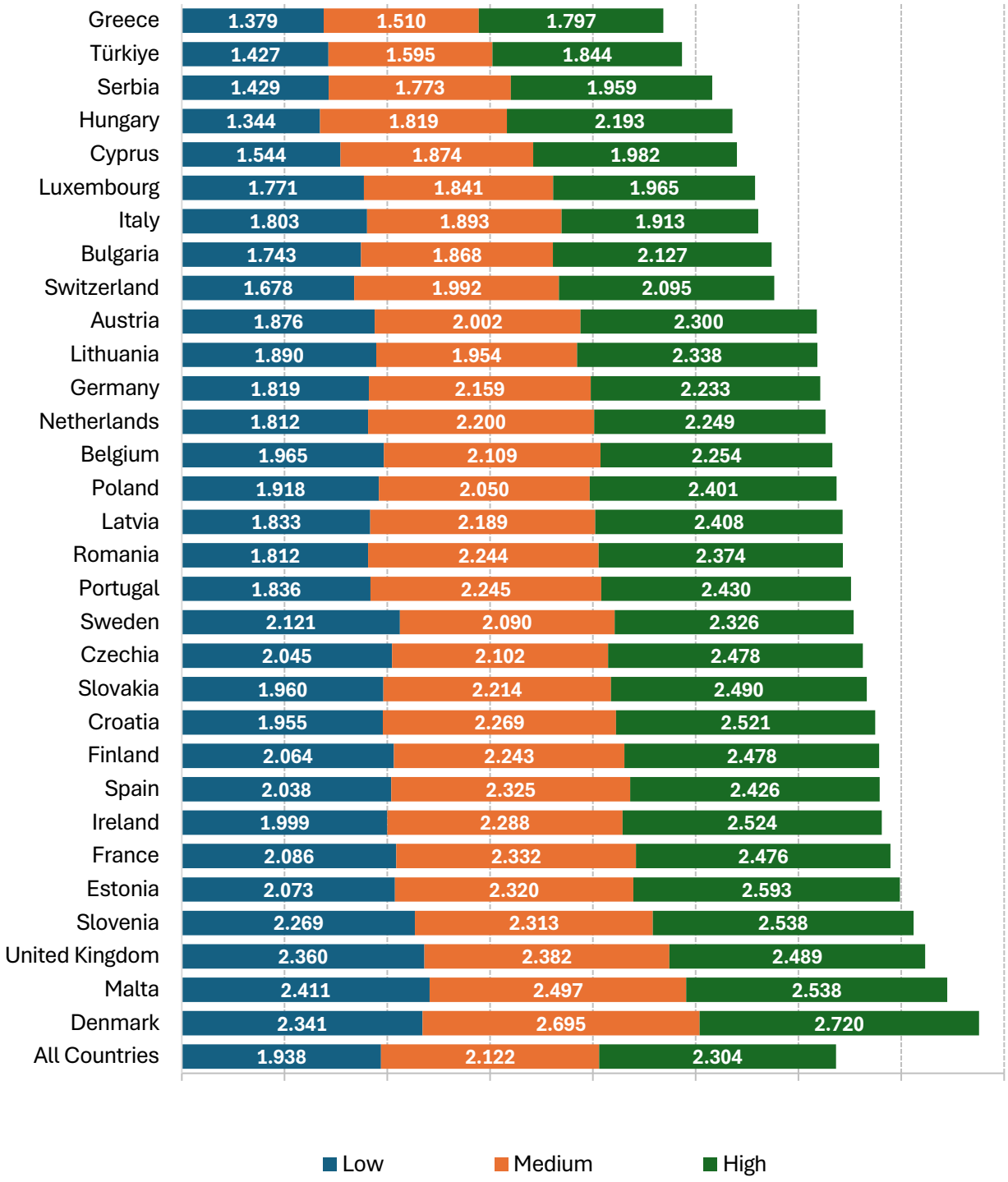


Figure 3-22: Income Composition in Health and Medical Literacy by country

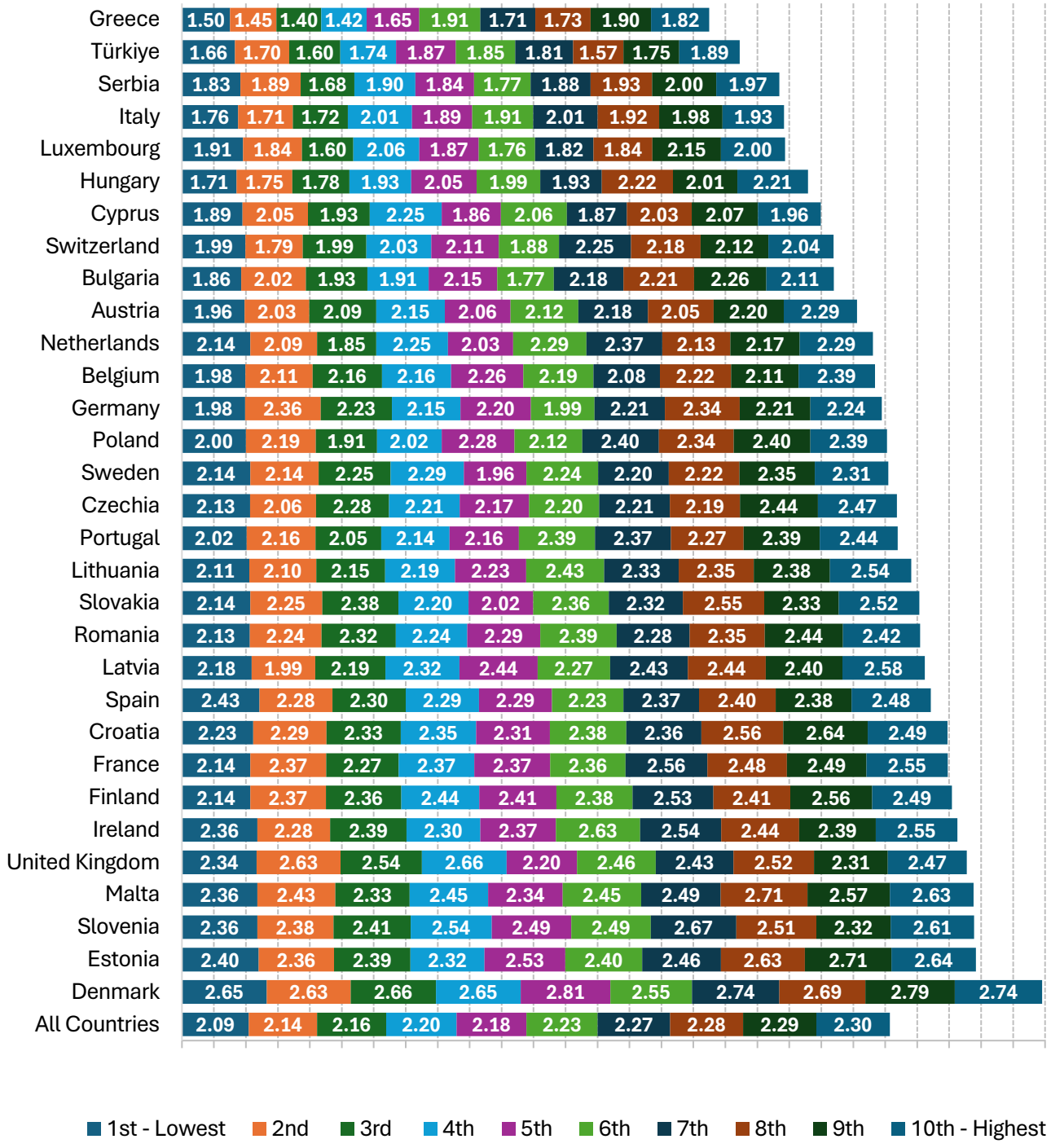


Figure 3-23: Wealth Composition in Health and Medical Literacy by country

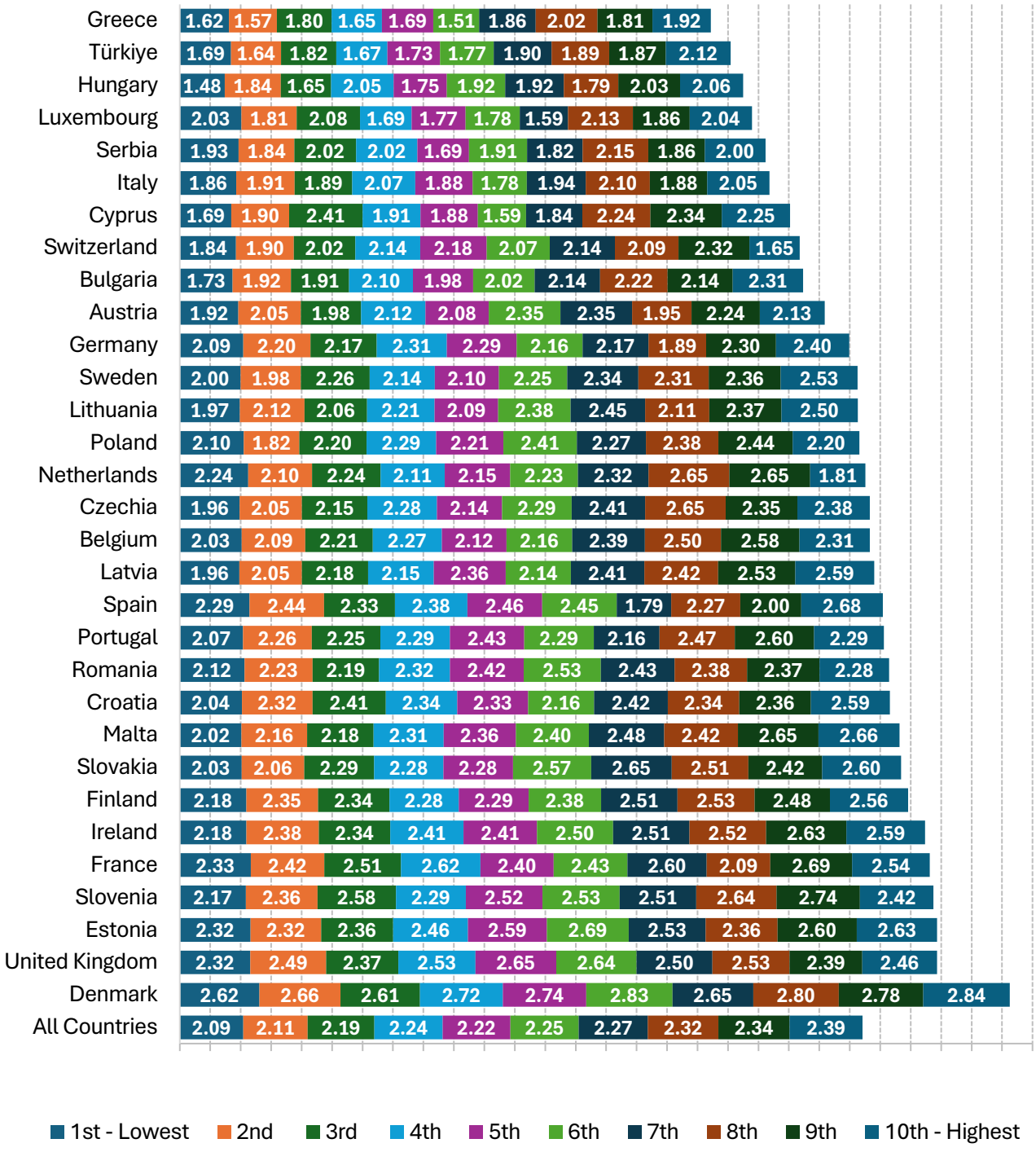
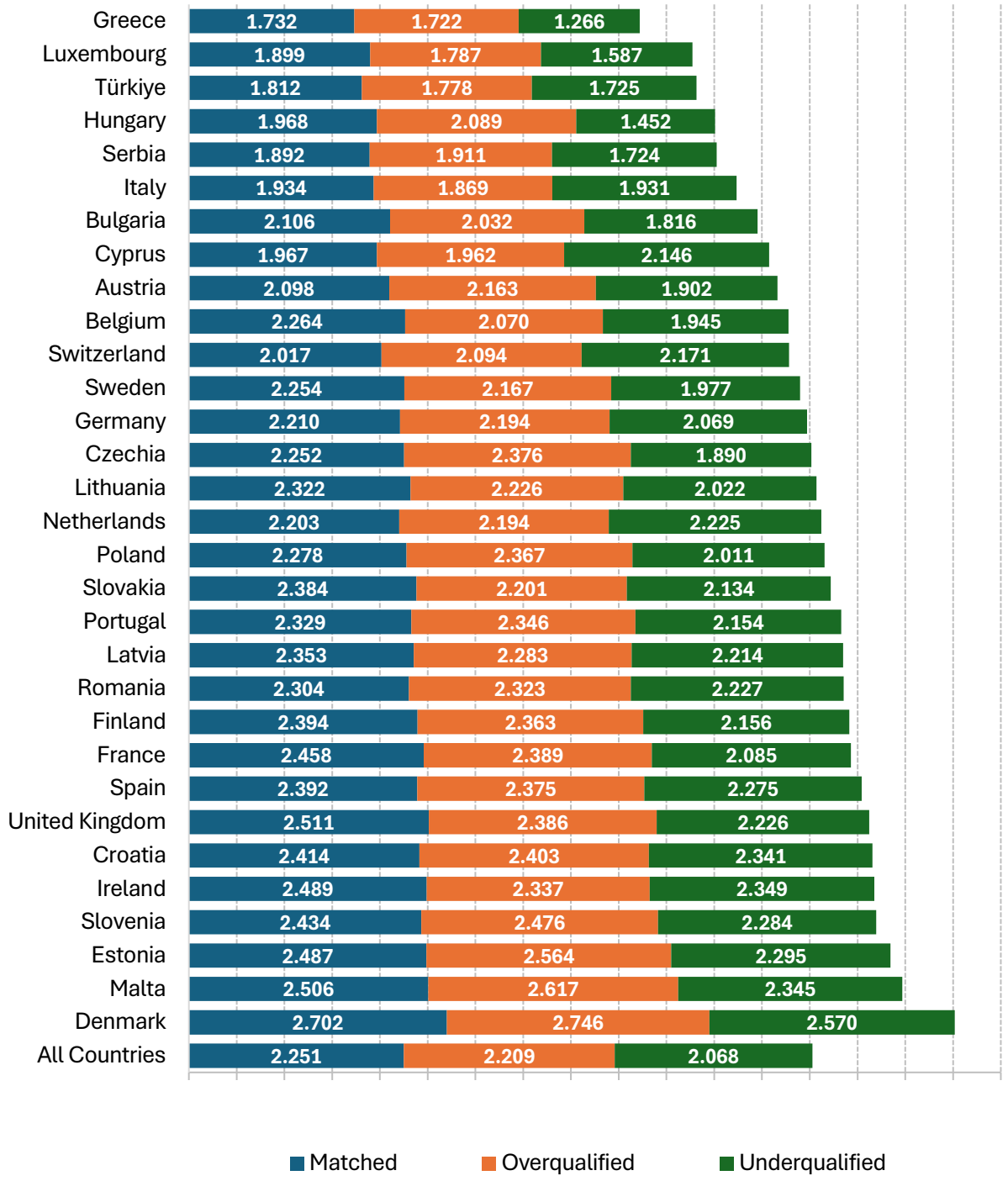


Figure 3-24: Skills Mismatch in Health and Medical Literacy by country



3.2 Digital-Era Functional Skills

3.2.1 Digital Financial Literacy

The Digital Financial Literacy index captures the set of competencies that individuals need to use digital financial services safely and effectively. As banking, payments, and personal financial management increasingly move online, households are expected not only to understand basic financial concepts, but also to navigate digital interfaces, data risks, and online fraud. This is particularly relevant in a context where financial intermediation and consumer-facing financial services are being reshaped by digital technologies and fintech, changing how people access credit, manage accounts, and transact in everyday life (Bollaert et al., 2021).

The index is constructed using three items that reflect three core building blocks of decision-making in digital finance: (i) recognising and responding appropriately to phishing and impersonation attempts, (ii) understanding the practical value of digital tools for monitoring spending and budgeting, and (iii) applying basic online payment safety practices. This approach aligns with the growing literature emphasising that "digital" financial literacy should reflect both financial decision skills and the digital competences needed to use financial services responsibly and securely (Lyons and Kass-Hanna, 2021). It is also consistent with studies highlighting that online environments create both new opportunities and new vulnerabilities, especially because phishing, spam, and other forms of online crime exploit information frictions and behavioural responses (e.g., Moore et al., 2009).

Specifically, the Digital Financial Literacy index (range 0-3) is constructed from the following three TRAILS-I survey questions:

Q19. You receive an email from your bank asking you to verify your account by clicking a link. What do you do?
1. *Click the link immediately and follow the instructions.*
2. *Ignore the email and delete it.*
3. *Verify the email sender's address and contact the bank directly using their official website or phone number.*

98. I don't know

Q20. Which of the following is a key advantage of using digital financial tools, such as mobile banking apps or online budgeting tools?
1. *They help track spending and manage budgets in real-time.*
2. *They automatically guarantee higher savings.*
3. *They eliminate the need to monitor your finances.*

98 I don't know

Q21. When making an online purchase, which method is the safest for protecting your financial information?
1. *Using a bank transfer for convenience.*
2. *Saving your card details directly on the website for future purchases.*

3. *Using a secure payment method, such as a credit card or PayPal, and verifying the website's SSL certificate (look for "https").*
98. I don't know

Conceptually, these items provide strong coverage of what the index is intended to measure. Q19 captures a central digital-finance risk, phishing and impersonation, and tests whether respondents follow a verification strategy that reduces exposure to fraud. Q20 measures whether respondents understand that digital tools can support active financial control (real-time tracking and budgeting), rather than replacing attention and monitoring. Q21 assesses awareness of basic online transaction protections, using secure payment methods and checking for encrypted connections ("https"), which are practical steps for protecting personal financial information in everyday e-commerce. As above, the "I don't know" response option helps to reduce random error by minimizing guessing.

This measurement approach is supported by recent empirical evidence linking literacy to digital finance engagement. For example, Yang, Wu, and Huang (2023) show that higher financial literacy is associated with greater use of digital financial services among Chinese households, with stronger effects for more complex services, consistent with the idea that competence becomes increasingly important as digital products grow more sophisticated. More broadly, digital capability and inclusion have been shown to matter for wider welfare outcomes: Naveenan, Liew, and Kijkasiwat (2024) document systematic links between digital inclusion, financial inclusion, and health outcomes in developing economies, reinforcing the relevance of digital financial skills as part of a broader set of functional literacies.

Table 3-4 reports the correlations between the Digital Financial Literacy Index and its three components: phishing awareness, knowledge of digital budgeting tools, and online payment safety. Each item is positively and significantly correlated with the overall index ($r = 0.592–0.678$, $p < 0.01$), indicating that all three dimensions contribute meaningfully to the composite construct. The strongest association is observed for digital budgeting tools ($r = 0.678$), followed by phishing awareness ($r = 0.643$), while online payment safety shows a slightly lower but still substantial correlation ($r = 0.592$). The relatively similar magnitude of these coefficients suggests a balanced contribution of items, supporting the convergent validity of the index as a coherent measure of digital financial literacy.

Table 3-4: Digital Financial Literacy index correlation matrix

	Digital Financial Literacy Index	Phishing awareness	Digital budgeting tools	Online payment safety
Digital Financial Literacy Index	1.000			
Q19: Phishing awareness	0.643**	1.000		
Q20: Digital budgeting tools	0.678**	0.090**	1.000	
Q21: Online payment safety	0.592**	0.084**	0.168**	1.000

At the same time, the correlations among the individual items are modest ($r = 0.084–0.168$, $p < 0.01$). The very low associations between phishing awareness and digital budgeting tools ($r = 0.090$), and

between phishing awareness and online payment safety (r = 0.084), indicate that these competencies capture distinct aspects of digital financial capability-namely cybersecurity awareness, digital financial management, and secure transaction practices. The somewhat stronger relationship between digital budgeting tools and online payment safety (r = 0.168) is theoretically plausible, as both relate to active engagement with digital financial platforms. Overall, the correlation structure supports the statistical validity of the Digital Financial Literacy Index as a coherent yet multidimensional construct, combining complementary but non-redundant domains of digital financial knowledge.

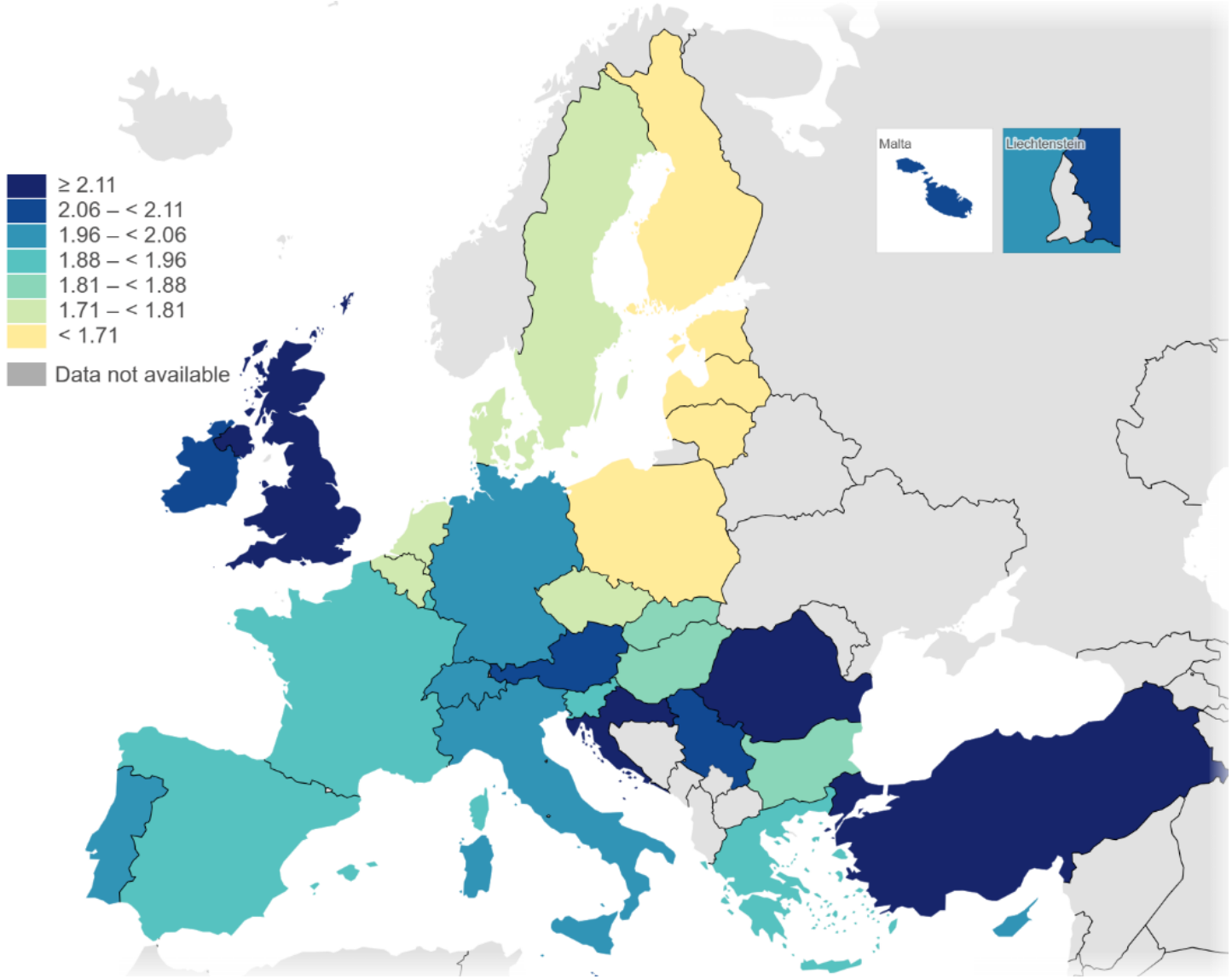
Figure 3-25 reports the weighted average of the Digital Financial Literacy index (0–3) across countries. Results are shown using a quintile (equal-count) classification, which splits the distribution into seven classes with an equal number of values, ensuring a balanced distribution across categories (legend cut-offs shown). The map points to marked cross-country differences, with higher averages in the UK and Ireland and in parts of South-Eastern Europe (notably Romania and Turkey), while lower averages are more common in parts of the Nordic/Baltic area and selected countries in Central-Eastern Europe. Grey shading denotes countries with no available data.

Figure 3-26 presents the same indicator at the regional level (NUTS-2 for most countries and NUTS-1 for the UK, Germany, and Turkey). The classification approach is consistent with the country map (equal-count classes). The regional view highlights substantial within-country variation, with several countries showing a mix of higher- and lower-scoring regions rather than a uniform national pattern; at the same time, some areas, such as Turkey and parts of Romania, display broader concentrations of higher-scoring regions, while lower-scoring regions are more visible in parts of the Nordic/Baltic area. Grey areas indicate missing data.

Figures 3-27 to 3-32 provide a systematic descriptive profile of the Digital Financial Literacy index across key socio-demographic and labour-market groups. For each breakdown, weighted averages are reported both by country and for the pooled sample ("All Countries"), enabling comparisons of within-country subgroup differences alongside cross-country variation in overall levels. This structure helps to identify whether digital financial skills, understood as the capacity to navigate financial decisions in digital environments, are concentrated among particular population groups and whether the same patterns appear consistently across Europe. It also helps distinguish broad regularities (e.g., age-related digital divides) from country-specific configurations that may reflect differences in digital infrastructure, payment technologies, financial inclusion, and the diffusion of online banking and fintech services.

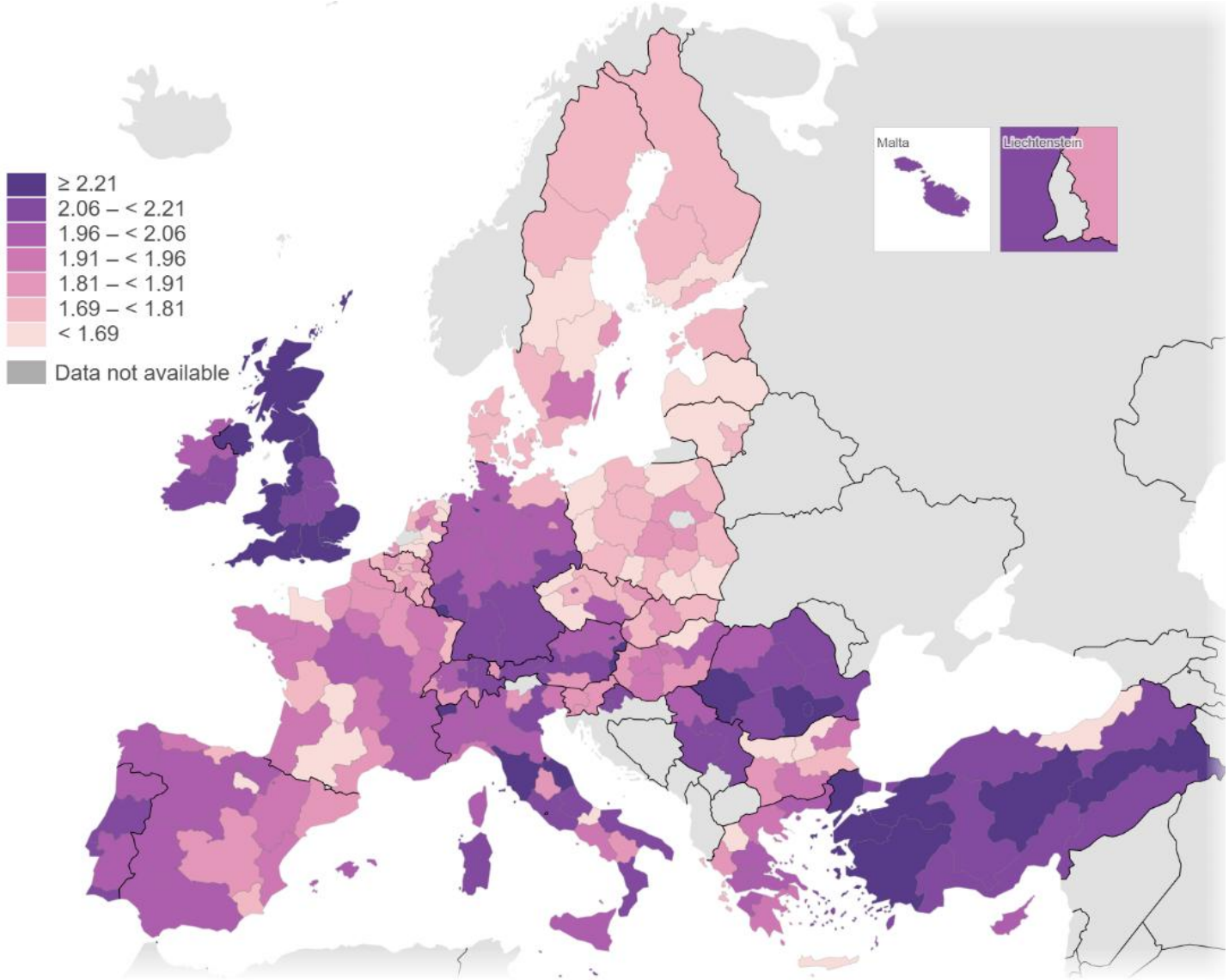
Figure 3-27 presents the gender breakdown in Digital Financial Literacy index, reporting weighted average scores for women and men. In contrast to some other literacy domains, gender differences in digital financial literacy are generally modest and do not display a uniform direction across countries. Overall, in All Countries, men score 1.949 and women 1.902, implying a small average gap of about +0.047. However, the direction of the gap varies by country, indicating that gender disparities in these skills are context-dependent rather than systematic. The largest male advantages are observed in Serbia (+0.19), Luxembourg (+0.19), and Denmark (+0.13), suggesting that gender differences may be more pronounced in certain institutional or cultural settings. Conversely, women score higher in Estonia (−0.14), the Netherlands (−0.11), and Malta (−0.08), and slightly in Cyprus, pointing to cases where women's digital financial capabilities are at least on par with, or exceed, those of men. In terms of overall country levels, the United Kingdom ranks at the top for both genders, indicating strong digital financial literacy performance across the population, while the lowest male average is recorded in Estonia.

Figure 3-25: Digital Financial Literacy by country



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 3-26: Digital Financial Literacy by region



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 3-28 shows the age breakdown in Digital Financial Literacy index, reporting weighted average scores across six age groups. The overall scores, in All countries, show a clear decline with age, from 2.080 from 2.080 among those aged 18-24 to 1.841 among those aged 65-80. This age profile is consistent with a digital divide in financial contexts with younger cohorts to have greater familiarity with digital interfaces, online authentication, and app-based financial services, while older cohorts may face higher barriers to adopting or confidently using such tools. The magnitude of the age-related decline varies substantially across countries, with particularly pronounced drops in the Baltic states, such as Estonia, Latvia, and Lithuania, where younger respondents score much higher than older respondents. This suggests that cohort differences in exposure to digital technologies and online financial services are especially strong in these settings. Across age groups, the United Kingdom consistently records among the highest scores, pointing to relatively widespread digital financial competencies across the life course. By contrast, Estonia, Latvia, and Poland more frequently appear among the lowest-scoring countries, particularly at older ages.

Figure 3-29 reports weighted average Digital Financial Literacy scores by education level, distinguishing three categories: low (early childhood to lower secondary), medium (upper secondary to short-cycle tertiary), and high (tertiary education, from short-cycle programmes to doctoral studies). Overall, in All Countries, this index increases with education (Low 1.686, Medium 1.880, High 1.991), indicating that educational attainment is positively associated with digital financial capabilities. This is plausible given the links between education, cognitive skills, and access to information and training environments that facilitate digital engagement. Nevertheless, several countries show small deviations from a strictly monotonic pattern, suggesting that formal education is not the only pathway through which digital financial skills are acquired. Among the highly educated, the highest average scores are observed in the United Kingdom (2.316), Türkiye (2.260), and Romania (2.215), while the lowest high-education averages are found in Lithuania (1.646), Latvia (1.681), and Estonia (1.752). The education gap (High minus Low) is particularly large in Cyprus (0.89), Türkiye (0.57), and Romania (0.57), indicating strong stratification by education in these countries. In contrast, the gradient is very small in Luxembourg (0.04), implying relatively weak differentiation by educational attainment. In some countries, such as Croatia and Malta, the Medium-education group slightly exceeds the High-education group, which may reflect compositional factors within education categories, differences in occupational exposure to digital financial tools, or the role of informal learning and on-the-job experience in shaping digital financial literacy.

Figure 3-30 shows the weighted average scores of the Digital Financial Literacy index across income deciles, based on respondents' self-reported annual net disposable income (including wages, self-employment income, property income and government benefits) ranked from the 1st (lowest) to the 10th (highest) decile. Overall, in All Countries, the index rises from 1.87 (1st) to 2.07 (10th), a gap of +0.20, but cross-country patterns are less uniform than in the foundational decision indices. The strongest positive gradients are in Lithuania (+0.35), Finland (+0.33) and Romania (+0.30), while a small set of countries shows a reversed pattern, most notably Denmark (-0.27), Malta (-0.20) and Luxembourg slightly negative gap (-0.03). The highest 10th-decile average score is in the United Kingdom (2.38), and the lowest 1st-decile average score in Lithuania (1.47).

Figure 3-27: Gender breakdown in Digital Financial Literacy by country

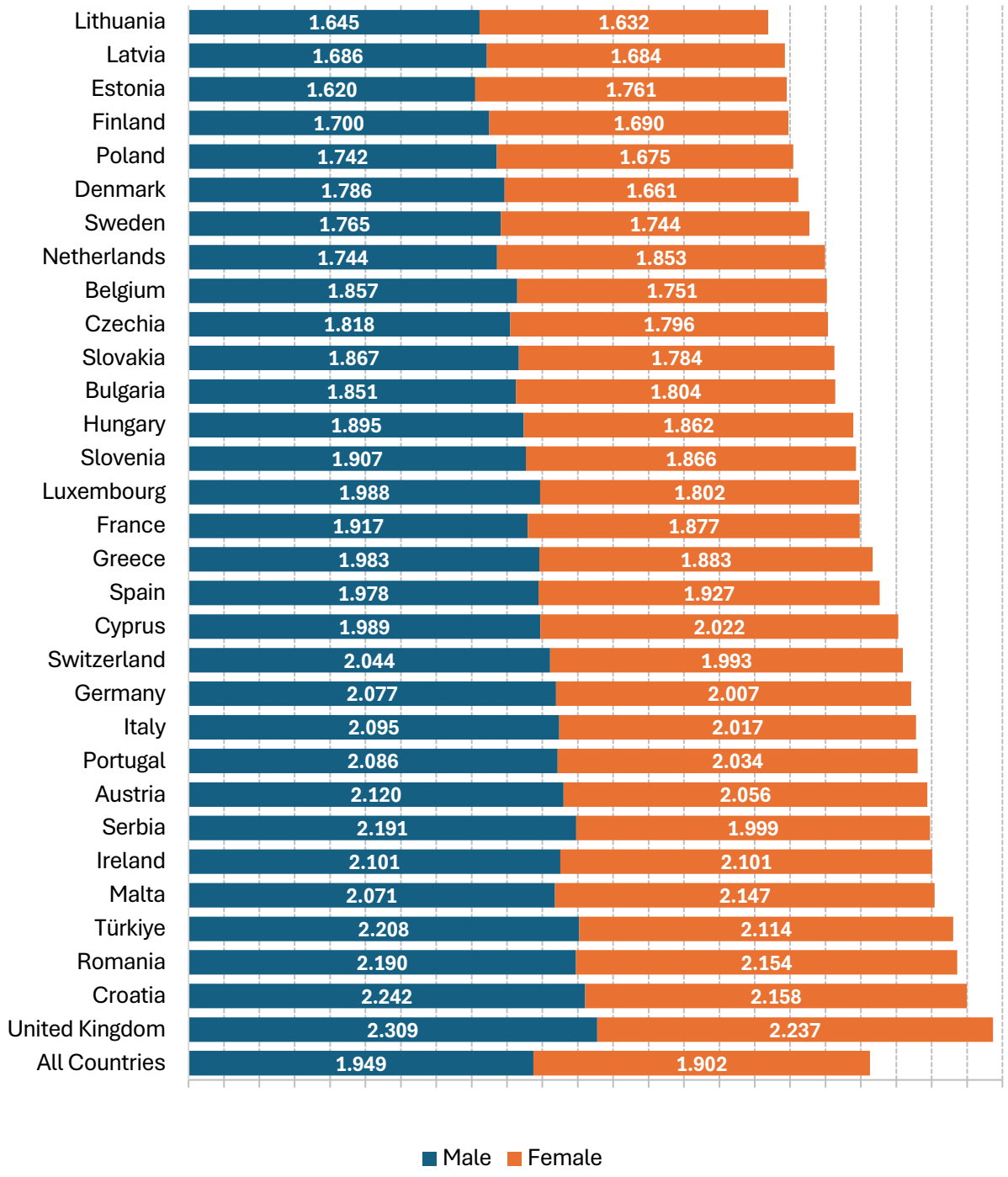


Figure 3-28: Age breakdown in Digital Financial Literacy by country

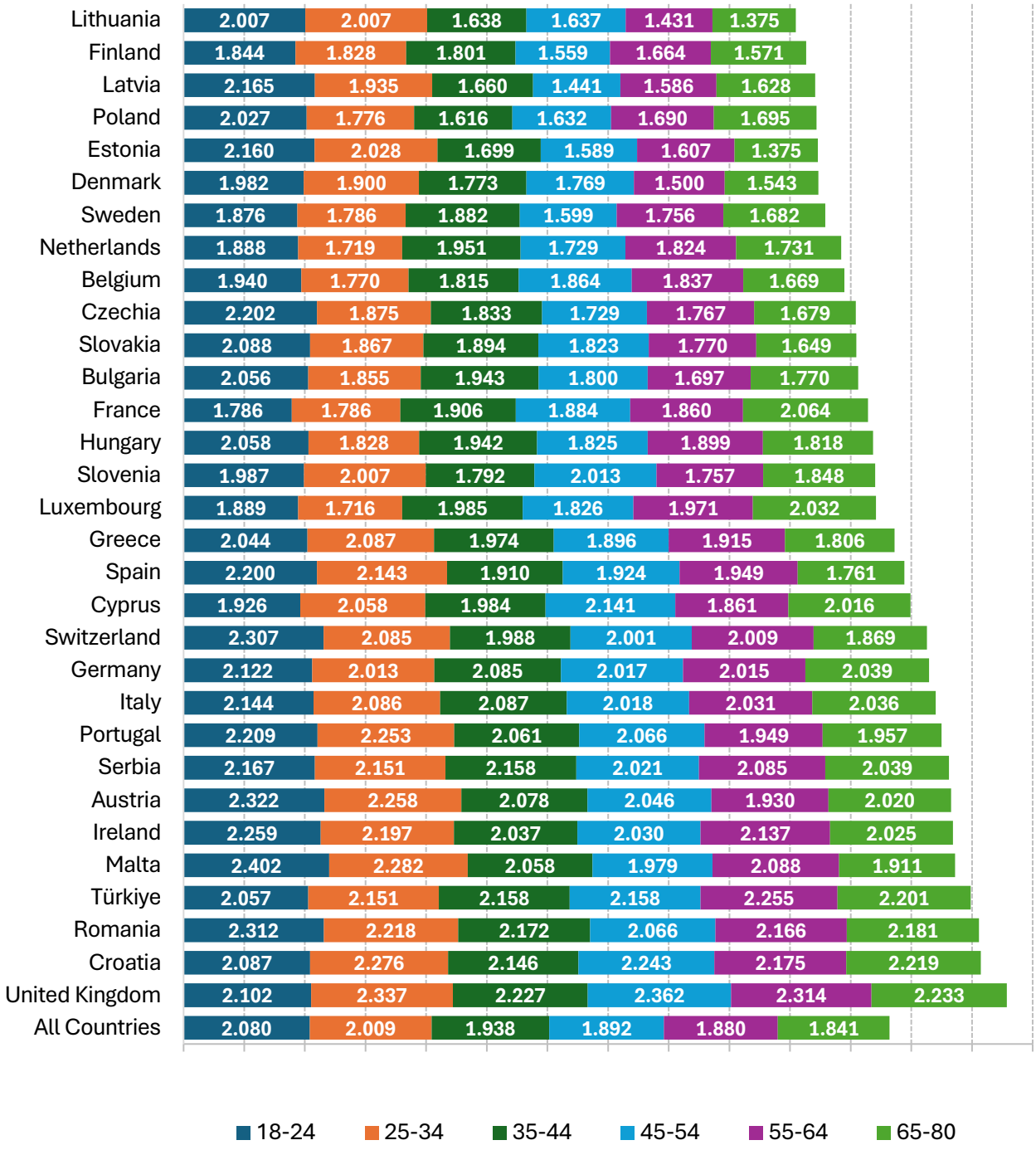


Figure 3-29: Educational breakdown in Digital Financial Literacy by country

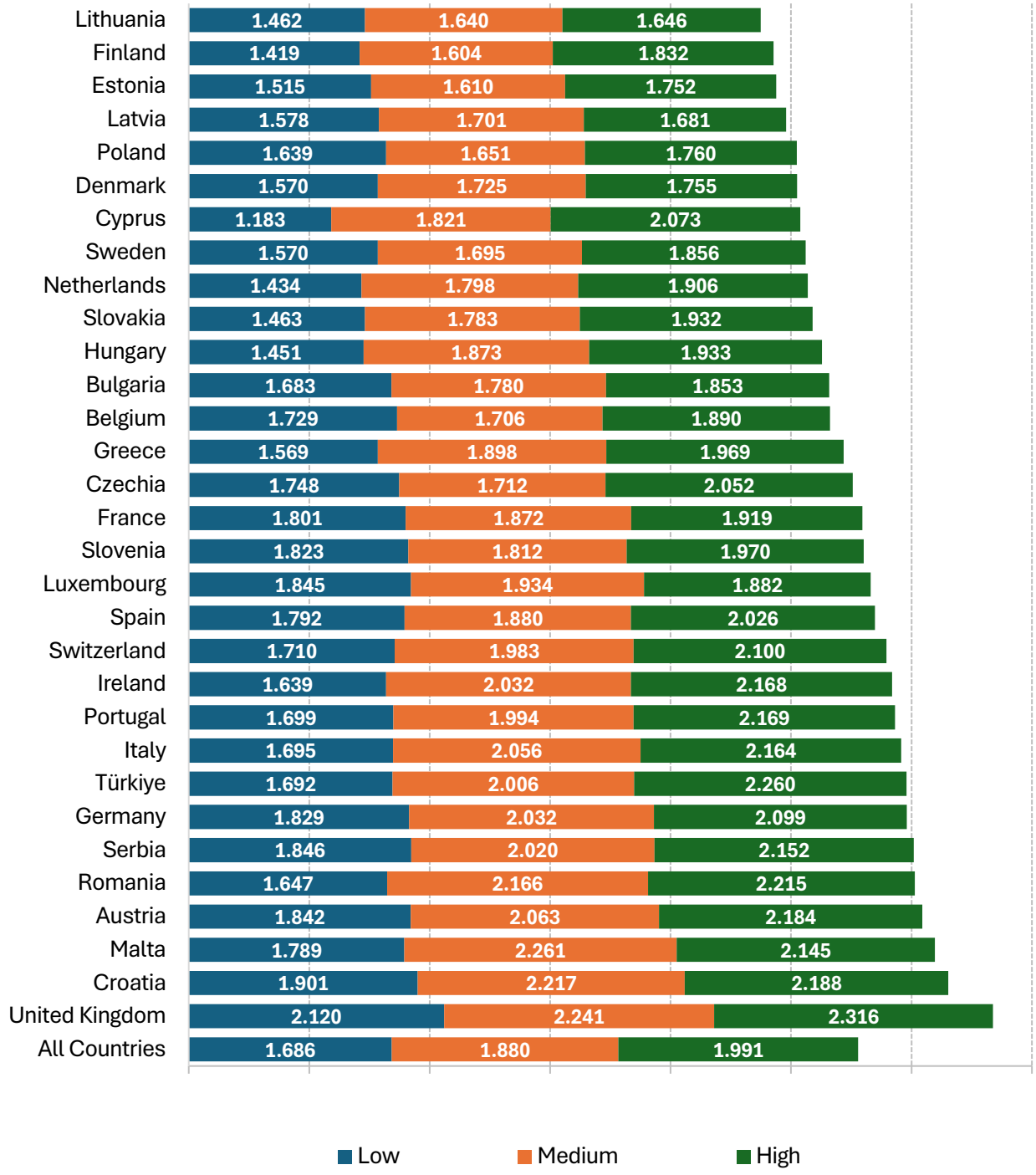


Figure 3-30: Income Composition in Digital Financial Literacy by country

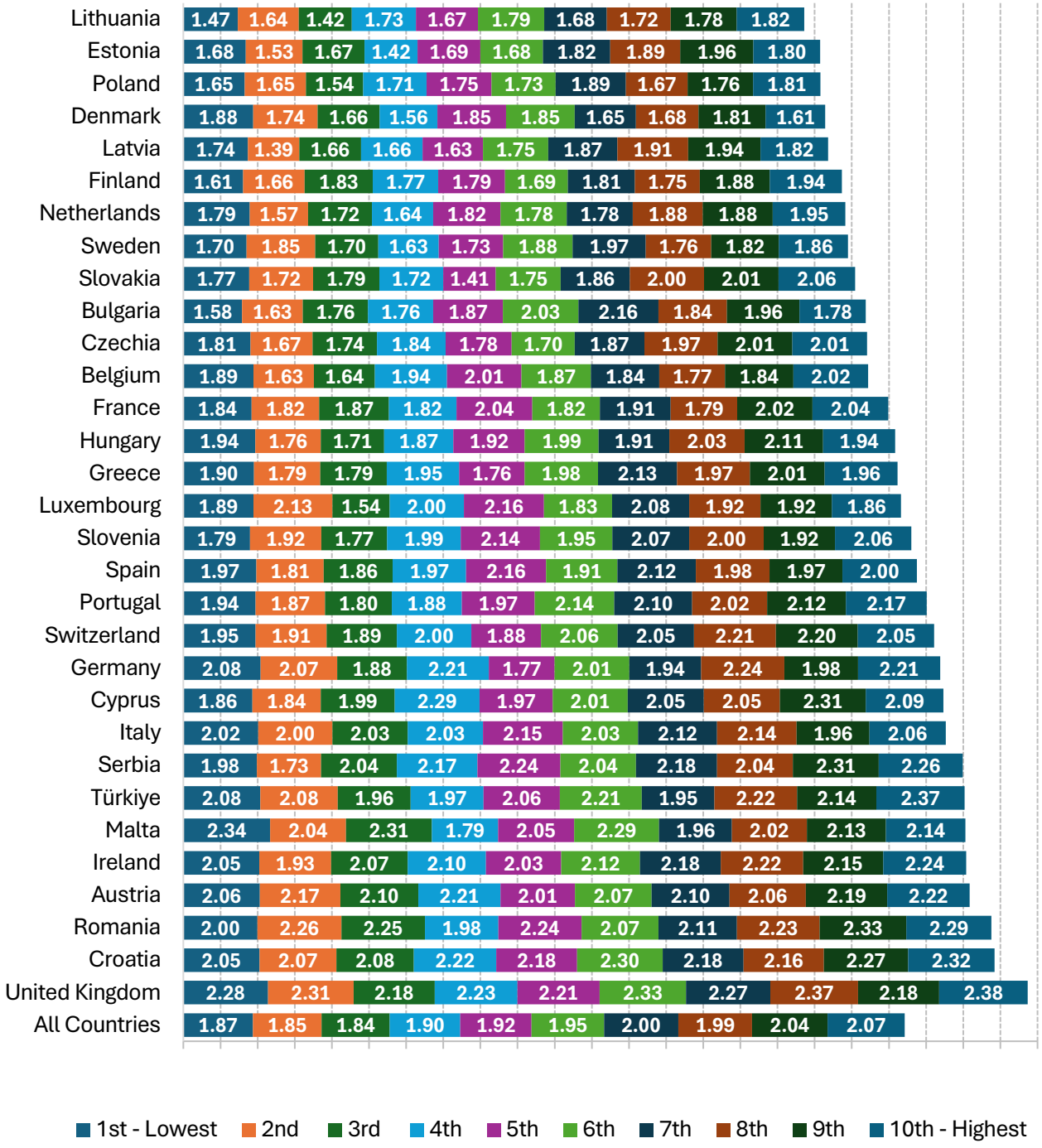


Figure 3-31: Wealth Composition in Digital Financial Literacy by country

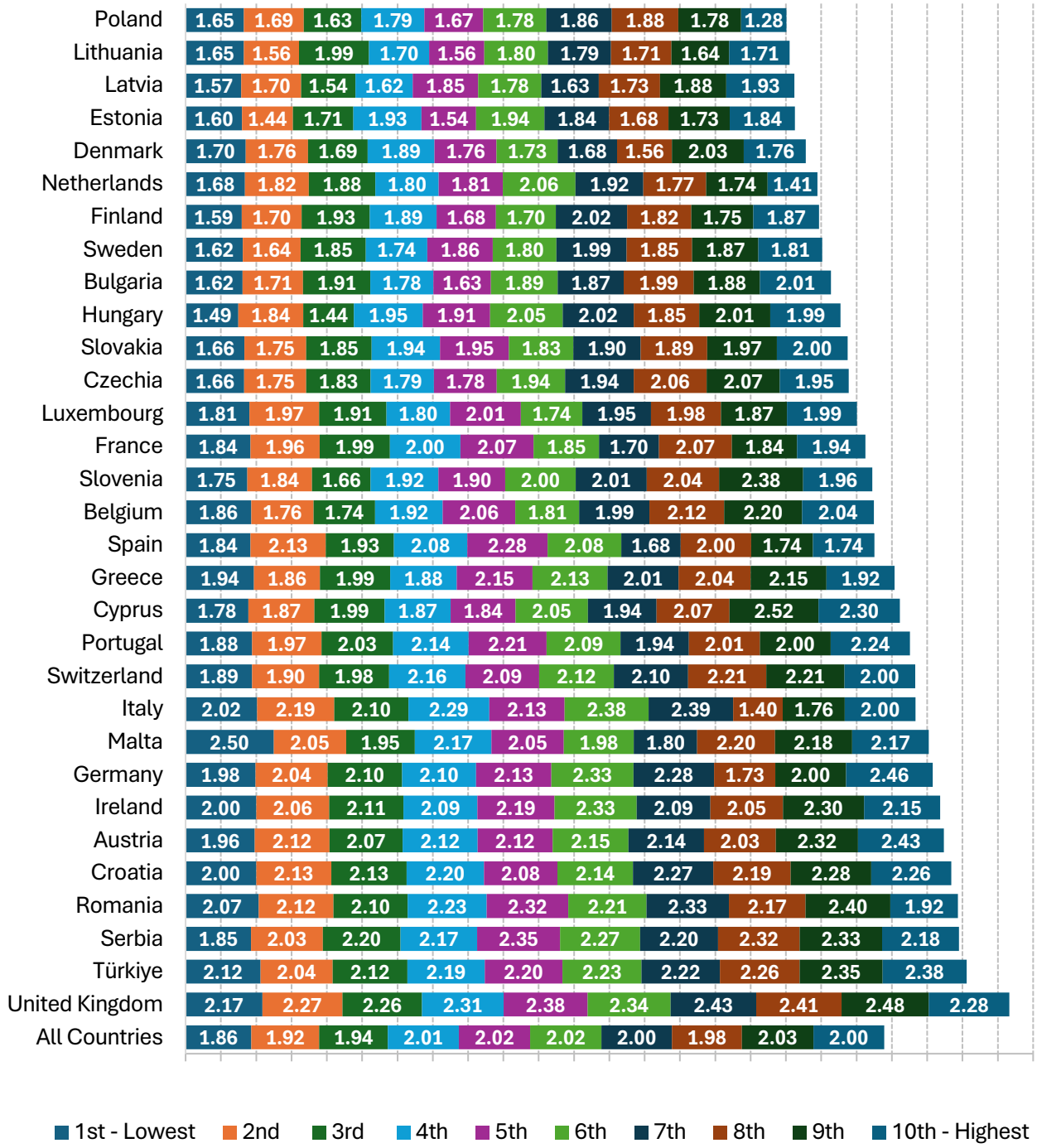


Figure 3-32: Skills Mismatch in Digital Financial Literacy by country

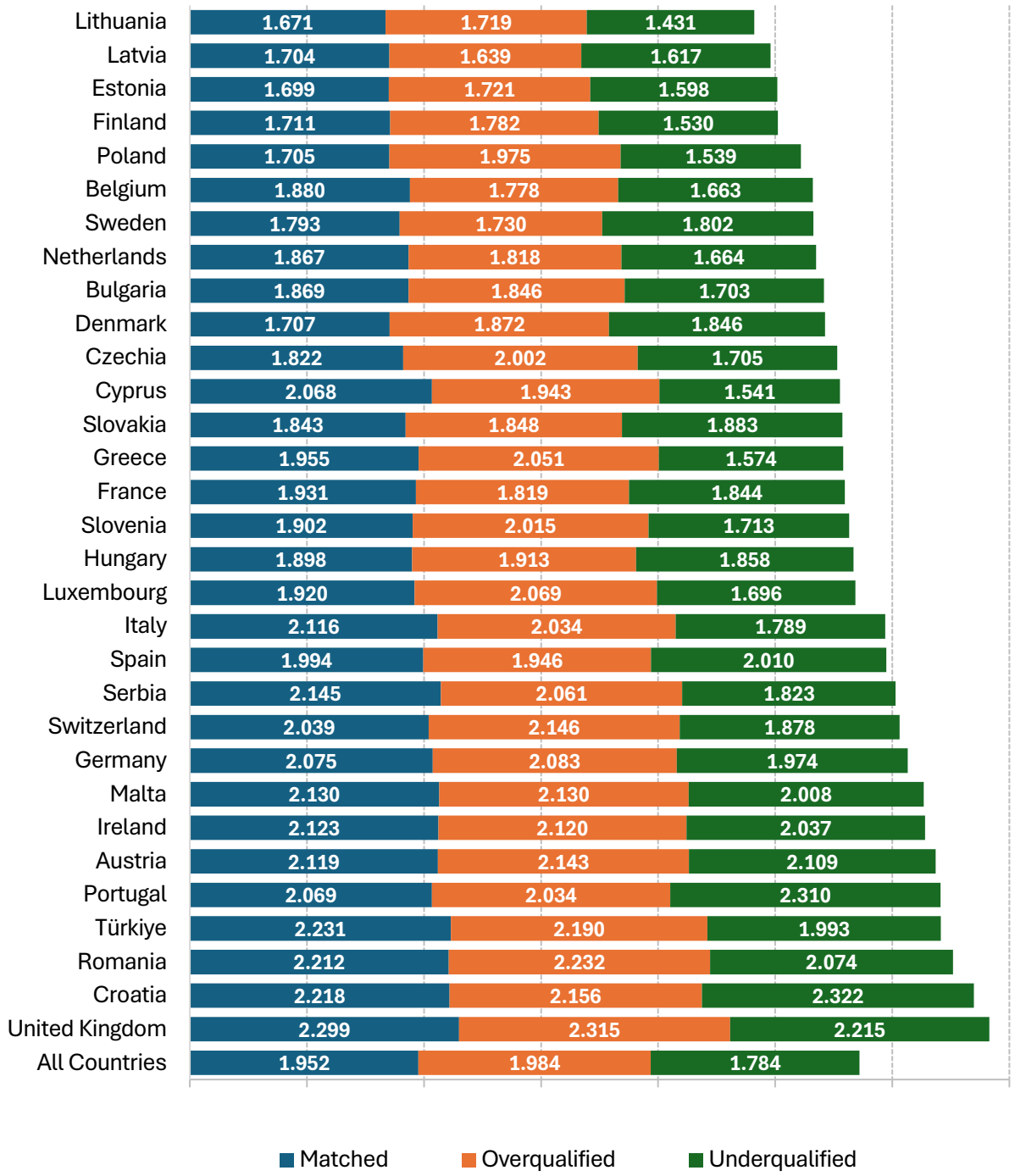


Figure 3-31 reports the weighted average scores of the Digital Financial Literacy index across wealth deciles, based on respondents' self-reported net household wealth (defined as the total value of all assets owned by the household, after deducting liabilities such as debts or loans) ranked from the 1st (lowest) to the 10th (highest) decile. In All Countries, the increase with wealth is relatively small compared to the previous foundational decision skill indices, i.e., from 1.86 to 2.00, a gap of +0.14.

Stronger positive gradients appear in Cyprus (+0.53), Hungary (+0.50) and Germany (+0.47). Several countries show non-monotonic or reversed patterns at higher wealth decile, including Poland (-0.37), Malta (-0.32) and the Netherlands (-0.27). The highest 10th-decile average score is in Germany (2.46), while the lowest 1st-decile level is in Hungary (1.49).

Figure 3-32 reports weighted average Digital Financial Literacy scores by skills-matching status, linking individual skill profiles to respondents' perceived fit between their qualifications and the demands of their main job. Overall, in All Countries, overqualified respondents score slightly above matched (1.98 vs 1.95), and both are clearly above underqualified (1.78). Comparing matched to the mismatched average (1.88), matched workers have a match premium of 0.07. This occurs because the relatively low underqualified score pulls the mismatched average below matched even when overqualified is marginally higher. In most countries, underqualified is the lowest category, but it becomes the highest group in several cases (e.g., Croatia, Portugal, Spain, Slovakia, and Sweden), which reduces or reverses the matched-mismatched difference. The largest dispersion across mismatch categories is visible in Cyprus (0.53) and Greece (0.48), while some countries show only small differences (e.g., Austria).

3.2.2 Media and Information Literacy

The Media and Information Literacy index captures decision-relevant competencies that shape how individuals evaluate, verify, and use information in the digital age. As news consumption increasingly takes place through online platforms and social media, individuals face higher exposure to misleading content, low-quality sources, and algorithmically curated information environments. In this setting, the ability to assess credibility and cross-check information is central not only for informed civic participation, but also for everyday economic and social decisions that depend on reliable information. Research in economics highlights that distorted or low-quality information can affect beliefs, well-being, and political outcomes, and that digital media can change both the volume and the slant of information people receive (Allcott & Gentzkow, 2017; Levy, 2021).

The index is constructed using items that cover three main components of media and information literacy: (i) credibility assessment strategies (how respondents judge whether an online news item is trustworthy), (ii) verification behaviour when encountering suspicious or controversial claims, and (iii) understanding of the media's core roles in society. Together, these items capture practical skills that are relevant across countries and socio-economic groups, while remaining simple enough for harmonised measurement in a cross-country survey.

Specifically, the Media and Information Literacy index (range 0-3) is constructed from the following three TRAILS-I survey questions:

Q35. How do you usually assess whether an online news article is trustworthy? *Please select the response that best reflects your typical behaviour.*

1. *I check who published it and whether I recognise or trust the source*
2. *I see if it appears on multiple websites or platforms I follow*
3. *I focus on whether it seems well-written and matches what I already know*
4. *I usually share or bookmark it first, and check later if needed*

5. *I don't really have a consistent way to check*
98. *I don't know*

Q36. When you come across a piece of information online that seems suspicious or controversial, what are you most likely to do?
1. *Search online to see if other sources confirm it*
2. *Ask someone I trust what they think about it*
3. *Ignore it unless it's from a source I usually follow*
4. *Share it to see what others say or react*
5. *Assume it's false unless it's from a mainstream news outlet*
98. *I don't know*

Q37. What do you think are the most important roles of media in society today?
Please select up to two.
1. *Informing people about current events and public affairs*
2. *Providing a space for debate and different opinions*
3. *Holding governments and powerful actors accountable*
4. *Entertaining or distracting people*
5. *Reinforcing cultural or national values*
98. *I don't know*

Conceptually, these questions provide strong coverage of the intended domain. Q35 captures whether respondents rely on source-based credibility checks or simple "surface cues" and prior beliefs. Q36 focuses on active verification behaviour, distinguishing respondents who are more likely to cross-check or seek confirmation from those who default to ignoring or sharing without validation. Q37 captures a foundational understanding of why media matters in society, particularly its role in informing citizens, enabling debate, and holding power to account, which is closely linked to how individuals interpret news content and its relevance. Although Q37 allows up to two selections, the 0–3 scaling remains appropriate because each of the three questions contributes at most one point to the index. As in the other skill indices, the explicit "I don't know" response option reduces random error by discouraging guessing.

This measurement approach is supported by a growing literature showing that the information environment affects beliefs and behaviour, and that skills for evaluating information can be strengthened. Recent studies show that a brief media literacy intervention improves people's ability to distinguish false from true content more broadly than fact-checking alone, consistent with the idea that literacy builds transferable evaluation skills (Berger et al., 2025; List et al., 2024). In addition, the work of Levy (2021) highlights the importance of how people navigate information flows, finding that changes in exposure to ideologically slanted news on social media affect news consumption patterns and can shift inter-party support.

Table 3-5 presents the correlation matrix for the Media and Information Literacy Index and its three constituent dimensions: credibility assessment, fact-checking behaviour, and media role understanding. Each component is strongly and positively correlated with the overall index ($r = 0.626–0.663$, $p < 0.01$), indicating that all three items contribute substantively to the composite measure. Credibility assessment ($r = 0.663$) and fact-checking behaviour ($r = 0.661$) display nearly identical associations with the index, while media role understanding ($r = 0.626$) also shows a robust

relationship. The similarity in magnitude across these correlations suggests a balanced structure, with no single item disproportionately influencing the index. This pattern provides clear evidence of convergent validity, supporting the interpretation of the index as a coherent measure of media and information literacy.

Table 3-5: Media and Information Literacy index correlation matrix

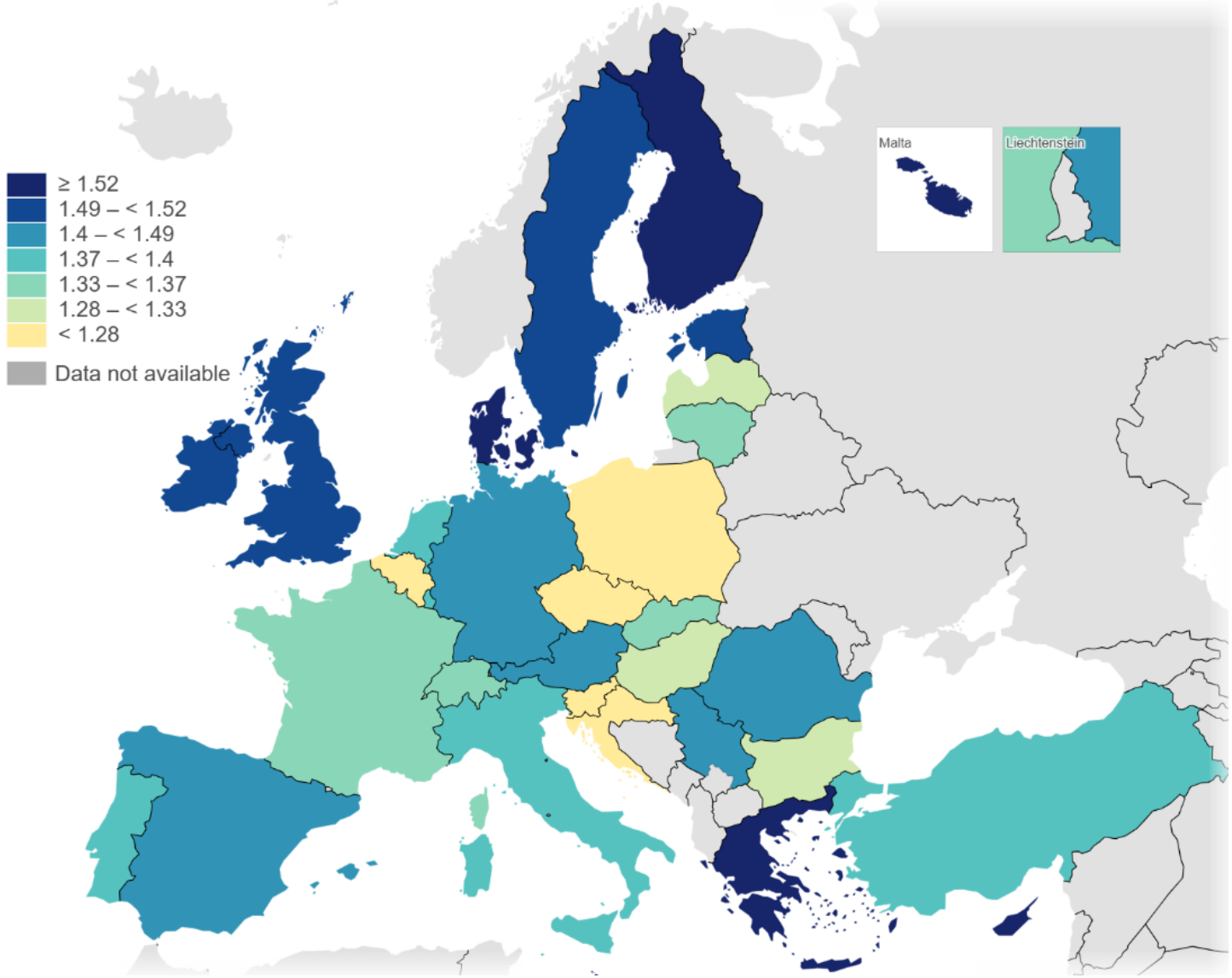
	Media and Information Literacy Index	Credibility assessment	Fact-checking behaviour	Media role understanding
Media and Information Literacy Index	1.000			
Q35: Credibility assessment	0.663**	1.000		
Q36: Fact-checking behaviour	0.661**	0.174**	1.000	
Q37: Media role understanding	0.626**	0.116**	0.112**	1.000

In contrast, the inter-item correlations are modest ($r = 0.112–0.174$, $p < 0.01$), indicating that while the dimensions are related, they capture distinct competencies. The strongest inter-item relationship is observed between credibility assessment and fact-checking behaviour ($r = 0.174$), which is theoretically consistent, as individuals who evaluate source credibility are also more likely to verify information. The weaker associations involving media role understanding ($r = 0.112–0.116$) suggest that understanding the normative functions of media in society represents a somewhat different aspect of literacy compared to practical verification behaviours. Overall, the correlation structure supports the statistical validity of the Media and Information Literacy Index as a multidimensional yet internally coherent construct, combining complementary knowledge and behavioural components without evidence of redundancy.

Figure 3-33 presents the weighted average of the Media and Information Literacy index (0–3) across countries. Results are grouped using a quintile (equal-count) classification, which divides the distribution into seven classes with an equal number of values, ensuring a balanced distribution across categories (legend cut-offs shown). The map indicates higher average scores in parts of Northern Europe (e.g., Finland and Sweden), the UK and Ireland, while lower averages are more visible in parts of Central and Eastern Europe and selected countries in the EU periphery. Grey shading denotes countries with no available data.

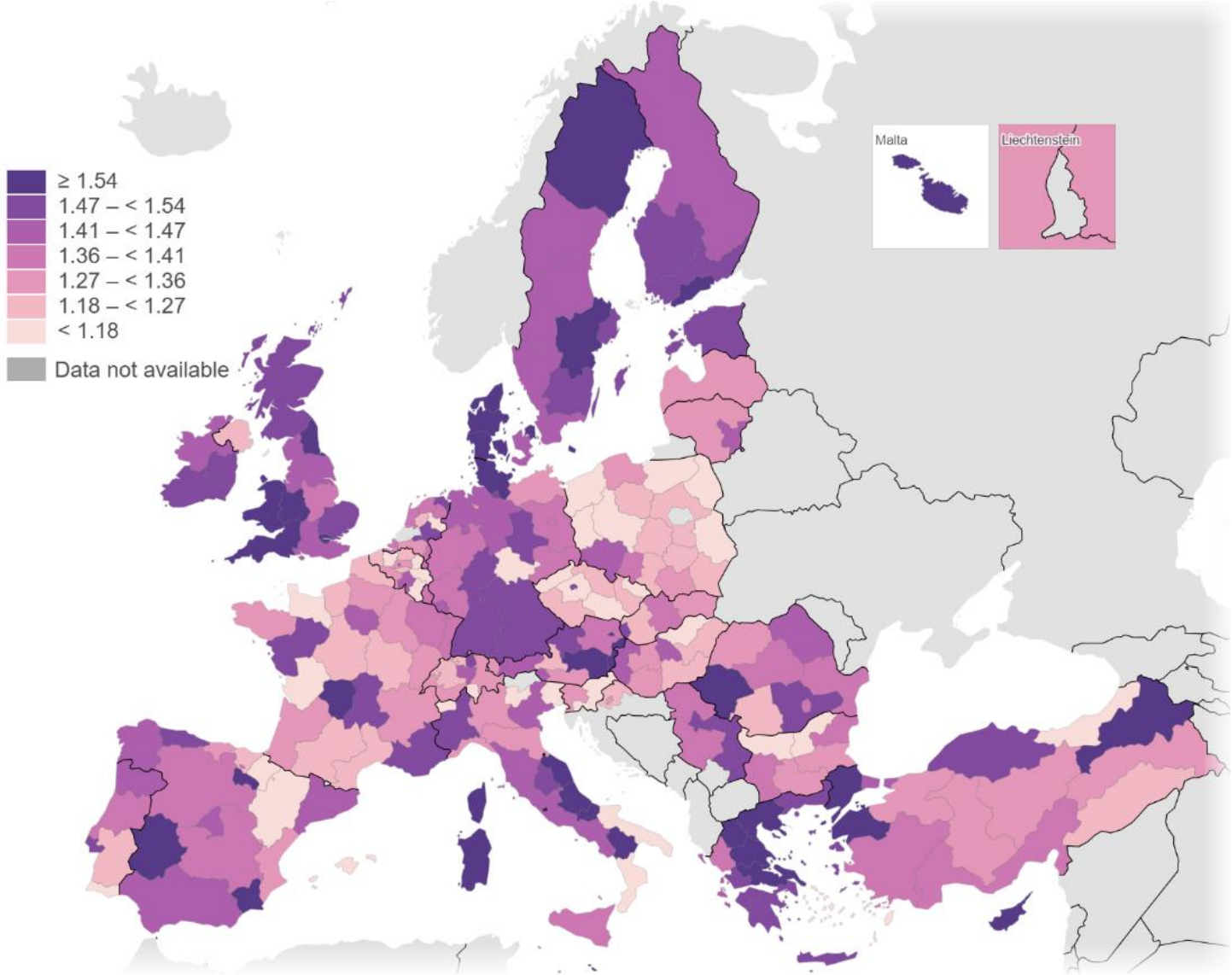
Figure 3-34 shows the same indicator at the regional level (NUTS-2 for most countries and NUTS-1 for the UK, Germany, and Turkey due to data availability), using the same equal-count classification approach. The regional view highlights substantial within-country variation, with several countries combining higher- and lower-scoring regions rather than displaying a uniform national pattern. As in the country map, grey areas indicate missing regional data.

Figure 3-33: Media and Information Literacy by country



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 3-34: Media and Information Literacy by region



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figures 3-35 to 3-40 provide a systematic descriptive profile of the Media and Information Literacy index across key socio-demographic and labour-market groups. For each subgroup breakdown, weighted averages are reported both by country and for the pooled sample ("All Countries"), enabling comparisons of within-country subgroup differences alongside cross-country variation in overall levels. This structure helps to identify whether disparities are broadly shared across Europe, for example, stronger skills among younger or more educated groups, or whether they vary with national media environments and institutional contexts.

Figure 3-35 shows the gender breakdown in Media and Information Literacy index, reporting weighted average scores for women and men by country and overall. Although there are different patterns across countries, in All Countries, men score slightly higher than women (1.431 versus 1.350), implying a modest gap of about +0.081. However, the direction and size of gender differences vary across countries, indicating that gender disparities are not uniform. The largest male advantages are observed in Luxembourg (+0.30), Romania (+0.19), and Denmark (+0.18), suggesting more pronounced gender differentiation in these settings. A small number of countries show reversals, with women scoring higher in Cyprus (around -0.10) and slightly in Bulgaria, France, and the Netherlands, pointing to contexts where women may be at least as strong in identifying reliable information and navigating media content. Gender differences are close to zero in some countries, e.g., , Austria, while in terms of overall levels, Denmark records the highest male average, and Cyprus records the highest female average.

Figure 3-36 presents the age breakdown in Media and Information Literacy index, reporting weighted average scores across six age groups. Overall, in All Countries, scores peak among those aged 25-34 (1.509), very close to the 18-24 group (1.500), and then decline steadily with age, reaching 1.309 among those aged 65-80. This pattern is consistent with the idea that younger cohorts, who have grown up in more digital media environments, may be more accustomed to navigating online information, assessing sources, and recognising misleading content, whereas older cohorts may face higher costs of adaptation to rapidly evolving media landscapes. The magnitude of age differences varies across countries. Large age gaps are visible in Estonia and Denmark, where younger cohorts score substantially higher, and Czechia also exhibits a notable decline toward older ages. At the same time, some countries maintain relatively high scores across the age distribution, e.g., Malta, Denmark, and Finland tend to rank among the highest in most age groups. By contrast, Croatia, Poland, and Belgium more frequently appear among the lowest.

Figure 3-37 reports weighted average Media and Information Literacy scores by education level, distinguishing three categories: low (early childhood to lower secondary), medium (upper secondary to short-cycle tertiary), and high (tertiary education, from short-cycle programmes to doctoral studies). The overall pattern, in All Countries, shows a strong positive gradient (Low 1.059, Medium 1.281, High 1.521), indicating that educational attainment is closely linked to the skills needed to interpret information critically and evaluate source credibility. Cross-country differences remain substantial even within education groups. Among the highly educated, the highest averages are recorded in Austria (1.723), Finland (1.702), and Denmark (1.697), while the lowest High-education averages are in Slovenia (1.320), Croatia (1.365), and Poland (1.370). The size of the education gap (High minus Low) also varies markedly across countries, with particularly large gaps in the Netherlands (0.74), Luxembourg (0.67), and Hungary (0.64), suggesting strong stratification by education in these contexts. By contrast, the gradient is much smaller in Spain (0.12) and Serbia (0.18), indicating weaker differentiation by education. Finally, Slovenia is the main non-monotonic case, where the high-education category scores below the Low-education category.

Figure 3-38 shows the weighted average scores of the Media and Information Literacy index across income deciles, based on respondents' self-reported annual net disposable income (including wages, self-employment income, property income and government benefits) ranked from the 1st (lowest) to the 10th (highest) decile. Overall, in All Countries, the gradient is positive: 1.35 (1st) to 1.55 (10th), a gap of +0.21. The largest increases occur in Bulgaria (+0.47), Hungary (+0.47) and Malta (+0.43), while Denmark shows a clear negative gradient (-0.23) and the Netherlands a smaller reversal (-0.05). The highest 10th-decile average score is again in Malta (1.96), whereas the lowest 1st-decile average score is in Bulgaria (1.04).

Figure 3-39 reports the weighted average scores of the Media and Information Literacy index across wealth deciles, based on respondents' self-reported net household wealth (defined as the total value of all assets owned by the household, after deducting liabilities such as debts or loans) ranked from the 1st (lowest) to the 10th (highest) decile. The overall pattern, in All Countries, is upward, from 1.30 (1st decile) to 1.54 (10th decile), a gap of +0.24. Wealth gradients are especially large in Malta (+0.82), Latvia (+0.77) and Switzerland (+0.65), while they are essentially flat in Denmark (+0.01). A few countries show slight reversals at the top (e.g., Spain and Poland, both close to zero but negative). The highest 10th-decile average score is in Malta (1.95), and the lowest 1st-decile average score is in Latvia (0.79).

Figure 3-40 reports weighted average Media and Information Literacy scores by skills-matching status, linking individual skill profiles to respondents' perceived fit between their qualifications and the demands of their main job. Overall, in All Countries, overqualified respondents score highest (1.46), followed by matched (1.41), with underqualified lowest (1.27). The matched score (1.41) exceeds the mismatched average (1.37), implying a match premium of 0.05. Although matched is not consistently the top category, the lower underqualified score keeps the average mismatched level below matched overall. Underqualified is typically lowest, but it is the highest group in some countries (e.g., Türkiye, Spain, Switzerland, and Croatia), reducing the matched-mismatched gap. Differences between overqualified and underqualified are largest in Austria (0.65) and Greece (0.59).

Figure 3-35: Gender breakdown in Media and Information Literacy by country

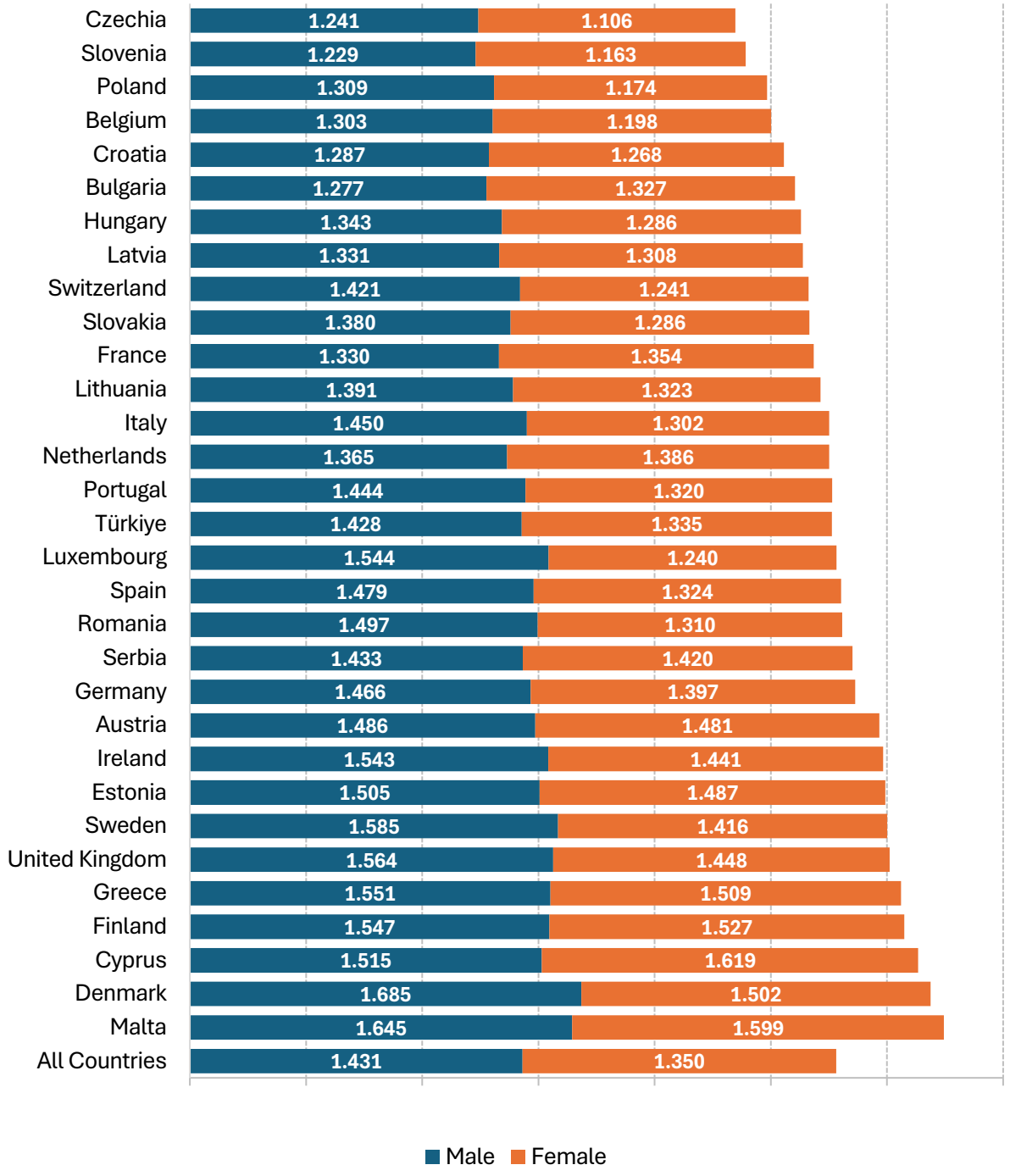


Figure 3-36: Age breakdown in Media and Information Literacy by country

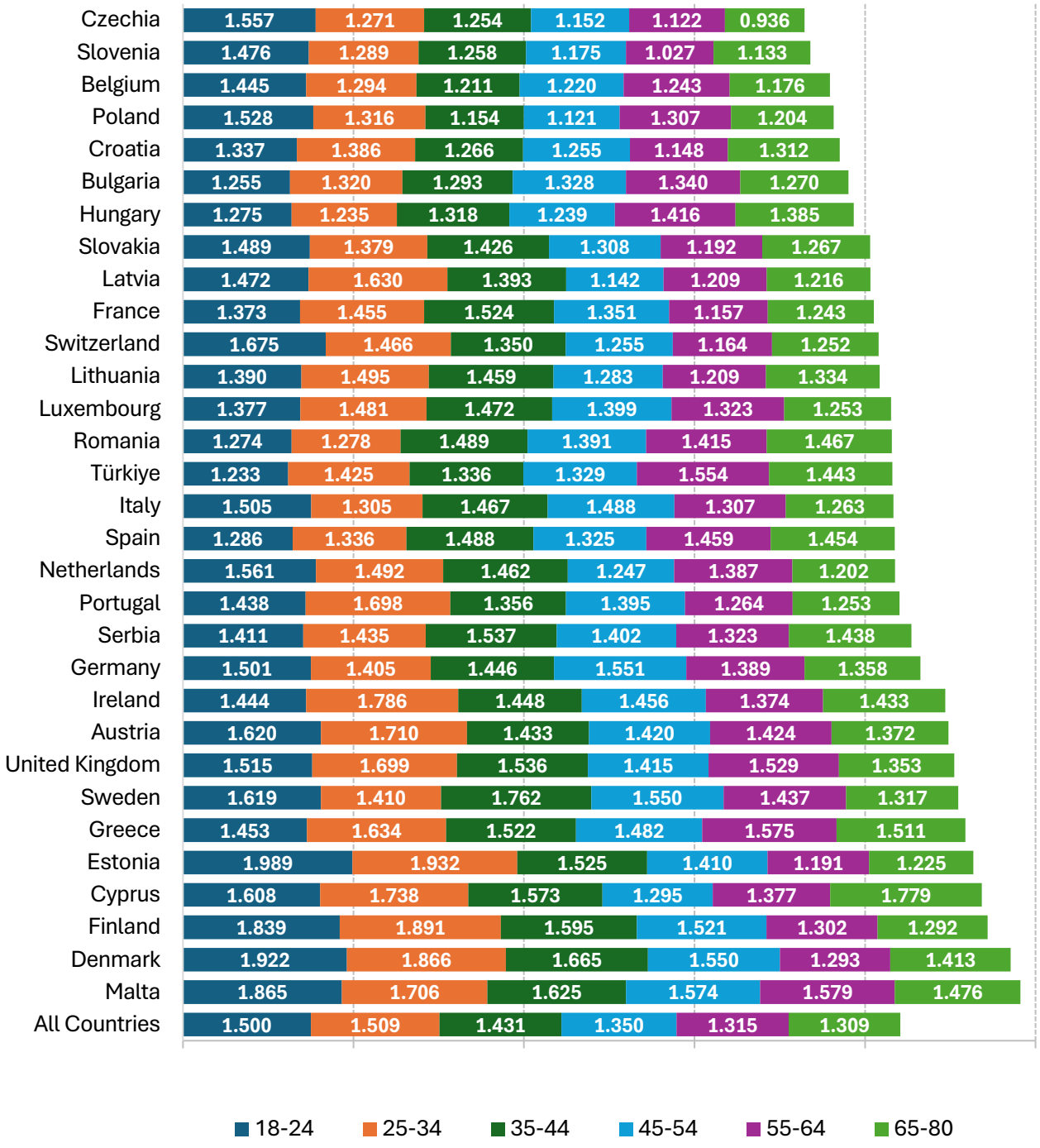


Figure 3-37: Educational breakdown in Media and Information Literacy by country

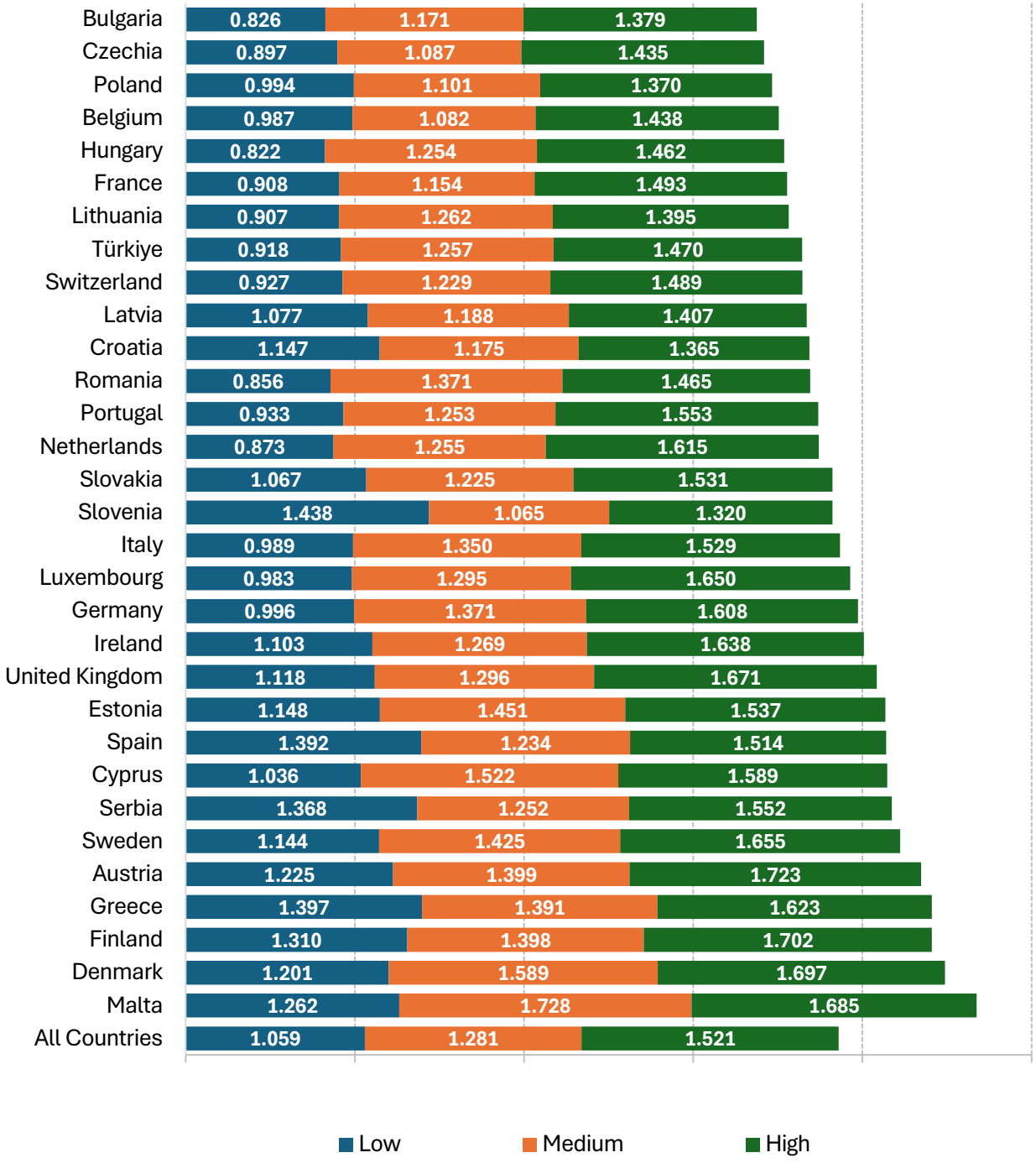


Figure 3-38: Income Composition in Media and Information Literacy by country

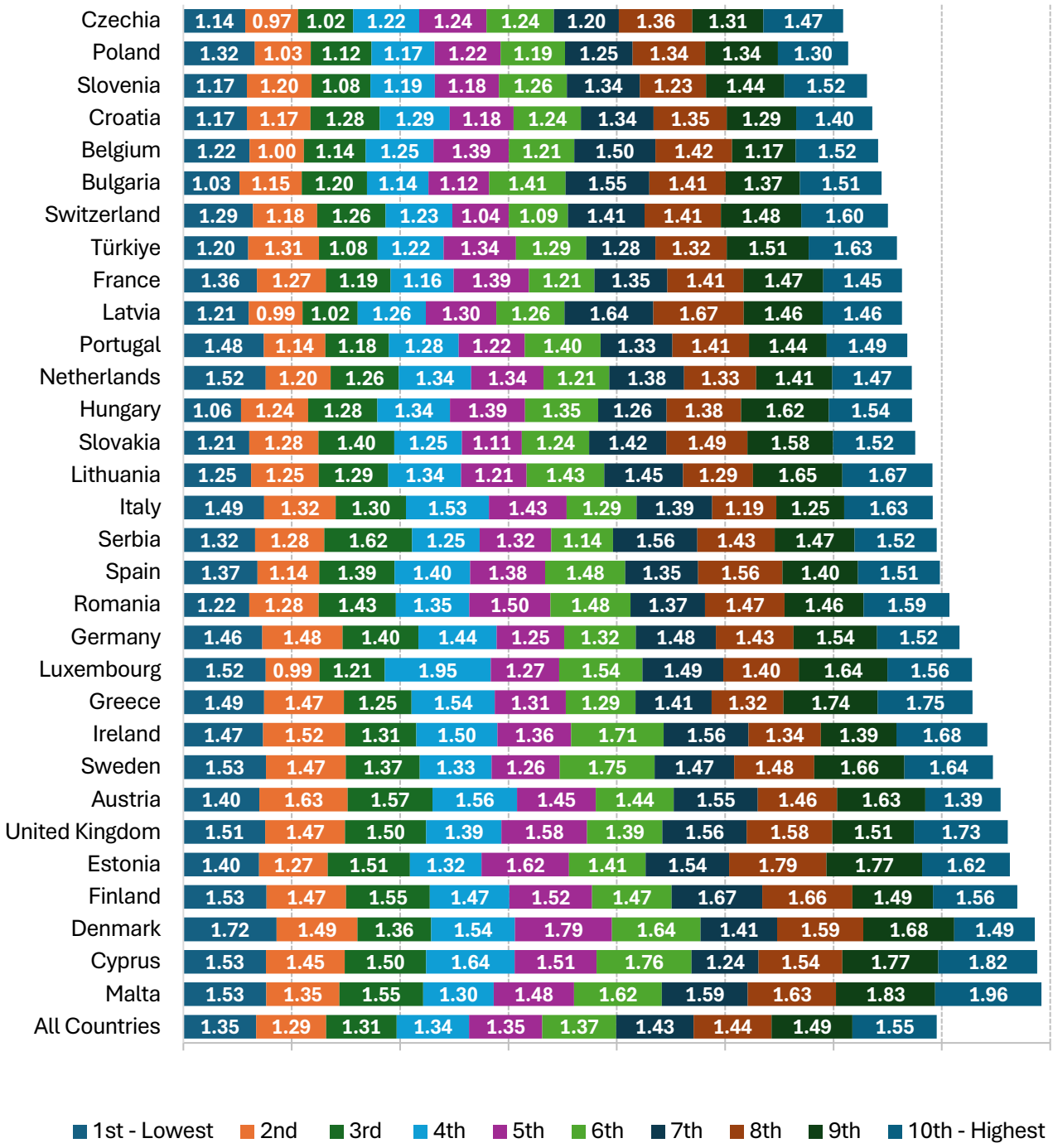


Figure 3-39: Wealth Composition in Media and Information Literacy by country

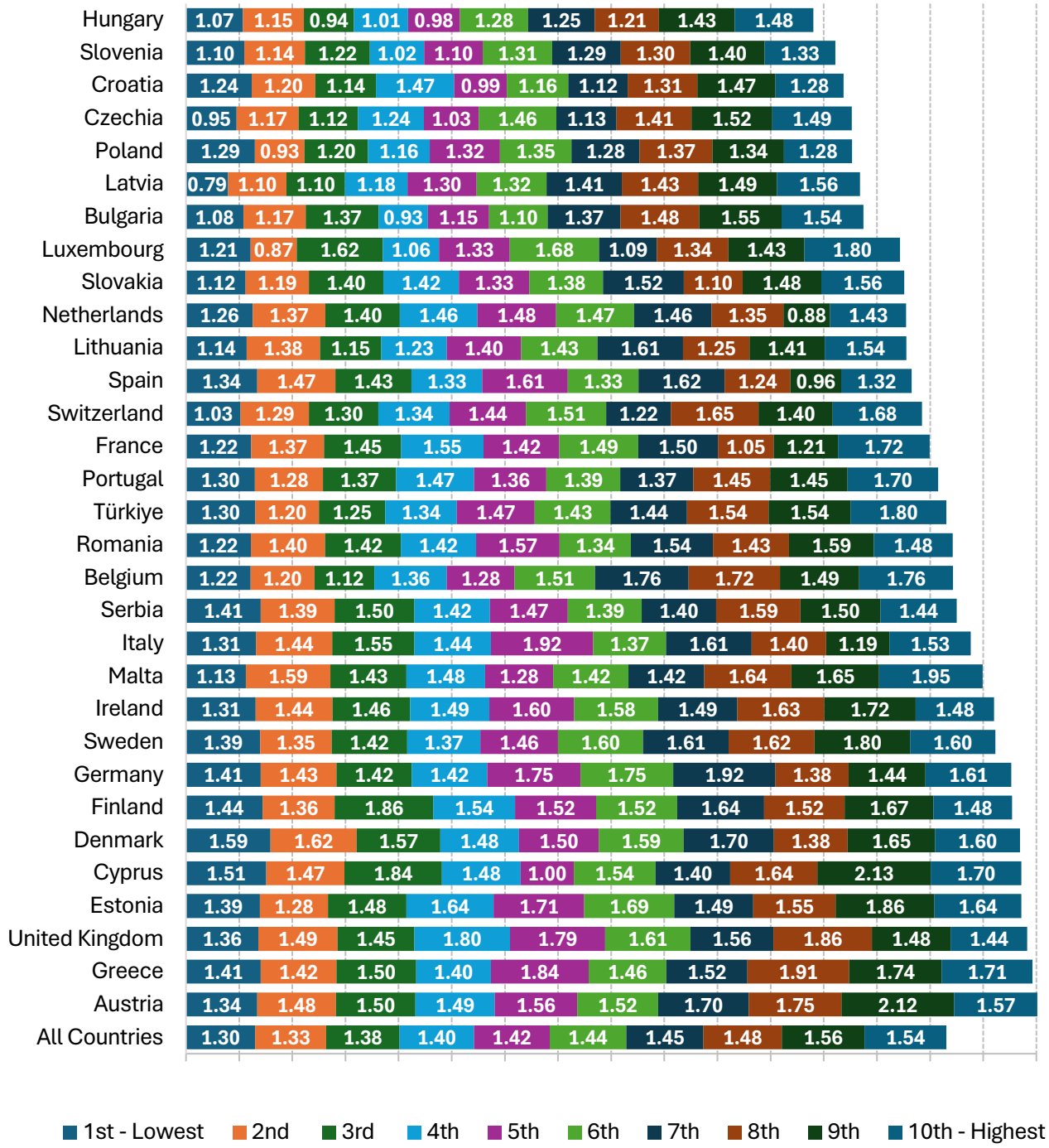
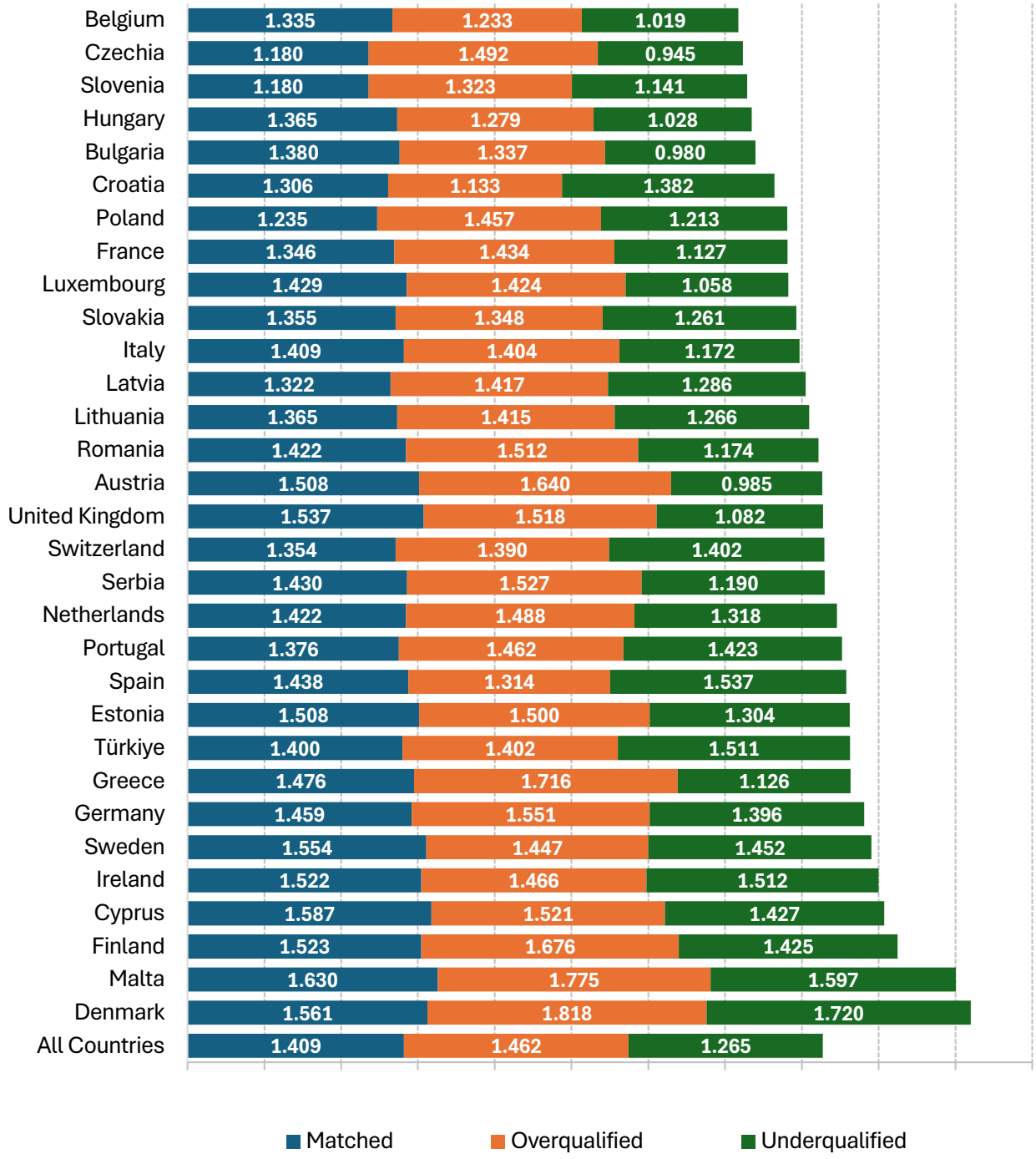


Figure 3-40: Skills Mismatch in Media and Information Literacy by country



3.2.3 Artificial Intelligence (AI) Literacy

The Artificial Intelligence (AI) Literacy index captures individuals' ability to recognise where AI is used, understand what current AI systems can (and cannot) do, identify key ethical risks, and anticipate AI-related demands in their work lives. This set of skills is increasingly important because AI is diffusing rapidly across tasks and occupations, reshaping how work is organised and how decisions are made. Recent evidence shows that deploying AI tools in workplaces can raise productivity, with particularly large gains for less experienced workers, implying that workers' ability to understand and use these tools may become an important source of inequality in the labour market (Brynjolfsson et al., 2025). In addition, research tracking task-level exposure to AI suggests that AI adoption can create substitution pressures in certain tasks and occupations, even when aggregate employment effects are muted by offsetting firm-level adjustments (Agrawal et al., 2019).

The AI Literacy index is constructed from three questions covering: (i) recognition of AI applications in everyday technologies, (ii) understanding of current AI capabilities and limitations, and (iii) awareness of widely discussed ethical concerns. This combination is designed to capture both factual knowledge (what AI is and where it appears) and decision-relevant judgement (how to think about risks and likely labour-market relevance). The index ranges from 0 to 7, which is appropriate because the instrument combines multiple knowledge components (including questions where several options may be correct) with a graded measure of perceived job relevance. The multi-select questions can contribute more than one point (or to be coded using "correct set" rules) giving a richer but still transparent scale, while keeping the measure interpretable and comparable.

Specifically, the Artificial Intelligence (AI) Literacy index (range 0-7) is constructed from the following three TRAILS-I survey questions:

Q44. Which of the following examples involve the use of AI? Please select all that apply.

1. *A robot vacuum that maps your home to clean more efficiently*
2. *A calculator performing a basic arithmetic operation*
3. *A recommendation system suggesting movies on a streaming platform*
4. *A spam filter that learns to detect unwanted emails*
5. *A digital thermometer showing temperature*

98. *I don't know*

Q45. Which of the following statements best describes the current capability of AI systems?

1. *AI can think, feel, and understand emotions like a human*
2. *AI can make decisions based on patterns in large data sets, but lacks consciousness or empathy*
3. *AI systems are fully autonomous and always objective*
4. *AI can solve any complex problem better than humans*

98. *I don't know*

Q46. Which of the following are commonly discussed ethical concerns about the use of AI systems? Please select all that apply.

1. *AI systems may reinforce existing social biases*

2. *AI always makes fair and neutral decisions*
3. *Personal data may be misused or collected without consent*
4. *AI can replace all types of human judgment*
5. *People may not understand how decisions are made by AI*

98 *I don't know*

Conceptually, these items provide strong coverage of what the index is intended to measure. Q44 tests whether respondents can distinguish AI-enabled systems (learning, prediction, recommendation) from simple deterministic tools. Q45 addresses a common misconception: many people think AI is either "human-like" or inherently "objective," but it is a pattern-recognition tool without human understanding or empathy. Finally, Q46 captures awareness of three widely cited governance risk (bias, privacy/data misuse, and opacity/limited explainability), which are central to current debates about how AI should be regulated and deployed. As before, the explicit "I don't know" response option helps reduce guessing and improves interpretability by distinguishing uncertainty from incorrect beliefs.

This measurement approach is consistent with the existing studies on AI and work. A growing body of literature shows that AI adoption can change productivity and task allocation within firms, implying that complementary skills, such as understanding AI systems and their limitations, may become increasingly valuable (e.g., Acemoglu & Restrepo, 2020; Jovanovic & Rousseau, 2025). More broadly, task-based economic frameworks emphasise that the labour-market consequences of AI depend on whether AI substitutes for tasks or complements workers by enabling new or redesigned tasks, reinforcing the importance of monitoring "AI readiness" as part of transferable skill measurement (Acemoglu et al., 2022). In addition, experimental evidence on generative AI tools shows large effects on performance in cognitively intensive tasks, highlighting why basic AI understanding is relevant well beyond ICT occupations (Noy & Zhang, 2023).

Figure 3-41 reports the weighted average of the AI Literacy index (0-7) across countries. Results are displayed using a quintile (equal-count) classification, which divides the distribution into seven classes with an equal number of values, ensuring a balanced distribution across categories (legend cut-offs shown). The map indicates higher average AI literacy in parts of Northern and Western Europe (e.g., Finland, Denmark, Ireland, and the UK), while lower averages are more visible in South-Eastern Europe and Turkey. Grey shading denotes countries with no available data.

Figure 3-42 shows the same indicator at the regional level (NUTS-2 for most countries; NUTS-1 for the UK, Germany, and Turkey), applying the same equal-count classification approach. The regional pattern underscores strong within-country heterogeneity, with several countries combining higher- and lower-scoring regions rather than exhibiting a uniform national profile. As above, grey areas indicate missing regional data.

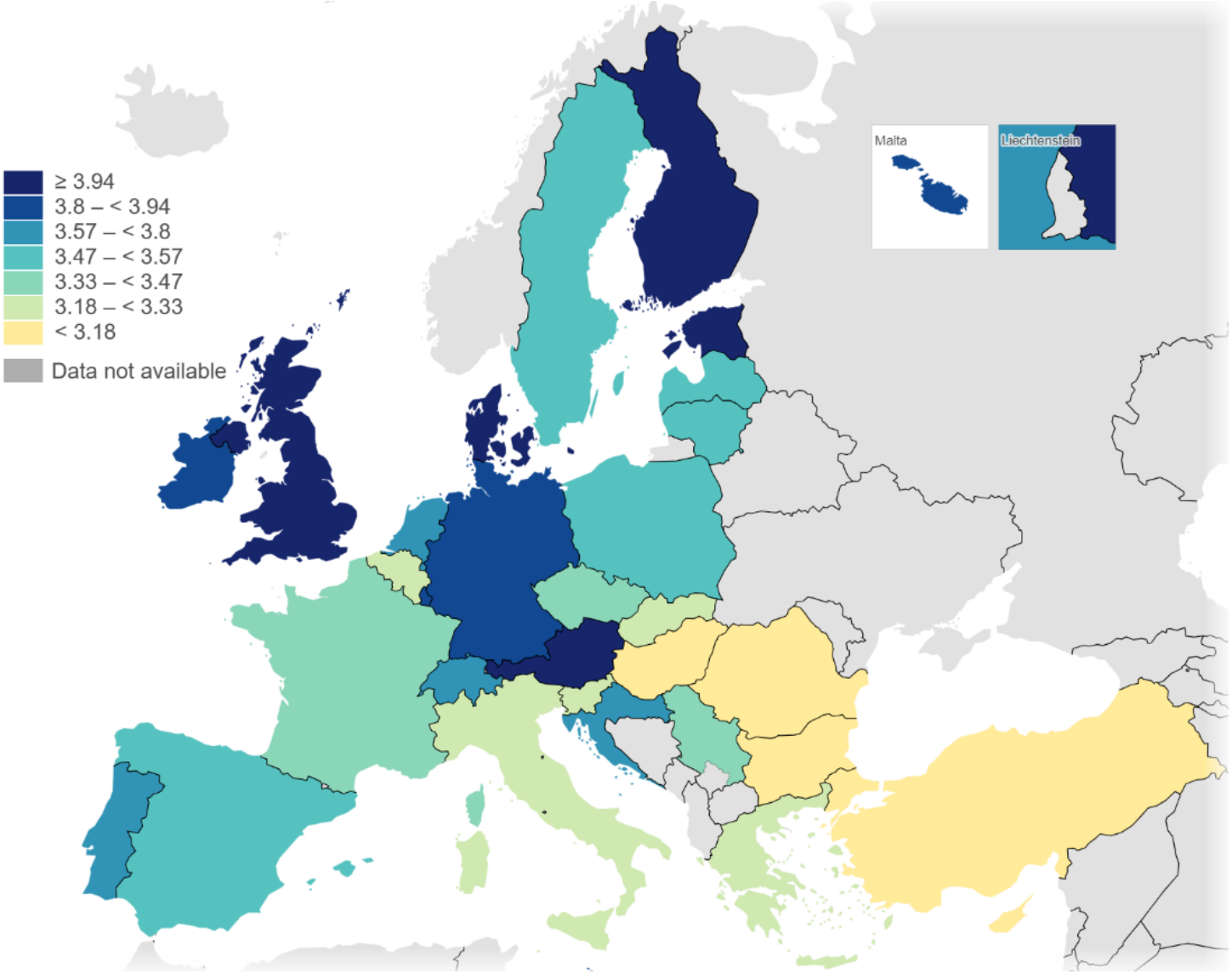
Table 3-6 presents the correlation matrix for the Artificial Intelligence (AI) Literacy Index and its three components: understanding AI in everyday life, knowledge of AI capabilities, and awareness of ethical concerns related to AI systems. Each item shows a strong and statistically significant correlation with the overall index ($r = 0.568–0.603$, $p < 0.01$). The highest association is observed for AI in everyday life ($r = 0.603$), followed by AI capabilities understanding ($r = 0.583$) and ethical awareness ($r = 0.568$). The relatively similar magnitude of these coefficients indicates that all three dimensions contribute meaningfully and fairly evenly to the composite index. This pattern provides evidence of convergent validity, suggesting that the index captures a coherent underlying construct of AI literacy rather than being driven by a single dominant dimension.

Table 3-6: Artificial Intelligence (AI) Literacy index correlation matrix

	Artificial Intelligence (AI) Literacy index	AI in everyday life	AI capabilities understanding	Ethical awareness
Artificial Intelligence (AI) Literacy index	1.000			
Q44: AI in everyday life	0.603**	1.000		
Q45: AI capabilities understanding	0.583**	0.287**	1.000	
Q46: Ethical awareness	0.568**	0.263**	0.323**	1.000

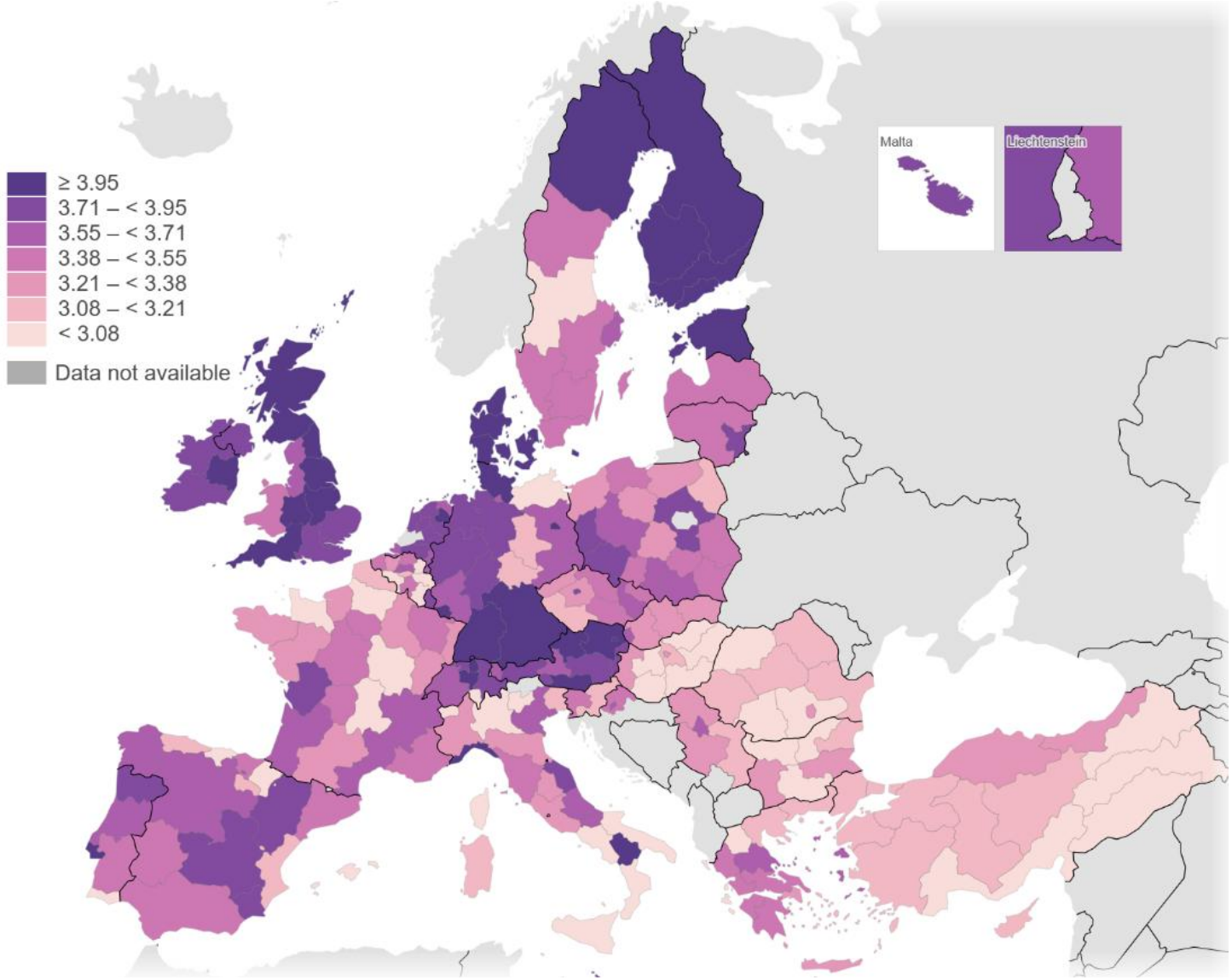
The inter-item correlations, however, are moderate in size ($r = 0.263–0.323$, $p < 0.01$), and notably stronger than those observed in several other literacy domains. The strongest association appears between AI capabilities understanding and ethical awareness ($r = 0.323$), which is theoretically plausible, as deeper knowledge of AI's technical functioning may enhance awareness of its societal and ethical implications. Similarly, AI in everyday life correlates moderately with both capabilities understanding ($r = 0.287$) and ethical awareness ($r = 0.263$), suggesting that familiarity with AI applications is linked to broader conceptual and normative understanding. Unlike domains where inter-item correlations were very low, this structure indicates a more tightly integrated construct. Overall, the correlation pattern supports the statistical validity of the AI Literacy Index as a coherent and internally connected, yet still multidimensional, measure of AI-related knowledge and awareness.

Figure 3-41: Artificial Intelligence (AI) Literacy by country



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 3-42: Artificial Intelligence (AI) Literacy by region



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figures 3-43 to 3-48 provide a systematic descriptive profile of the Artificial Intelligence (AI) literacy index across key socio-demographic and labour-market groups. For each subgroup breakdown, weighted averages are reported both by country and for the pooled sample ("All Countries"), allowing to compare within-country disparities alongside cross-country differences in overall levels. This structure helps to identify whether disparities by gender, age, education, income, wealth and employment characteristics are broad regularities across Europe or whether they differ in magnitude depending on national contexts, technology diffusion, and labour-market composition.

Figure 3-43 depicts the gender breakdown in Artificial Intelligence (AI) Literacy index, reporting weighted average scores for women and men by country and overall. The pattern in All Countries favours men with 3.696 versus 3.438 (gap +0.258), implying an average gap of about +0.258. This difference is sizeable relative to several other skill domains and suggests that AI-related knowledge and understanding may be more unevenly distributed by gender. The magnitude of the gender gap varies across countries. The largest differentials are observed in Luxembourg (+0.65), Switzerland (+0.55), and Czechia (+0.52), indicating contexts in which men's average AI literacy substantially exceeds women's. Most countries display higher male scores, with Bulgaria as the main exception, where the gender difference slightly favours women but is essentially zero (around -0.01). In terms of overall country levels, Denmark and Finland show the highest male averages, consistent with strong performance in AI-related skills in these countries, whereas the lowest values for both genders are concentrated in Türkiye and Hungary, pointing to comparatively lower AI literacy levels at the population level.

Figure 3-44 reports the age breakdown in Artificial Intelligence (AI) Literacy index, reporting weighted average scores across six age groups. Overall, in All countries, the index peaks among those aged 25-34 (3.793) and then declines steadily with age, reaching 3.404 among those aged 65-80. This pattern is consistent with cohort-based differences in exposure to digital technologies and AI applications, with younger adults likely having more frequent contact with AI-enabled tools through education, work, and everyday digital services. However, the steepness of the age profile varies substantially across countries. Estonia is a particularly strong example of large cohort differences, with very high scores among the youngest group and much lower scores among the oldest, suggesting rapid generational change in AI familiarity. Sizeable age gaps are also present in Luxembourg and Latvia. In terms of overall levels, Finland, Estonia, and Denmark typically rank among the highest-scoring countries across age groups, whereas Bulgaria, Cyprus, and Romania tend to record the lowest averages. These cross-country differences indicate that both cohort effects and national context matter for AI literacy, and that lower-scoring countries may face a double challenge of both lower overall levels and steeper declines among older cohorts.

Figure 3-45 reports weighted average Artificial Intelligence (AI) Literacy scores by education level, distinguishing three categories: low (early childhood to lower secondary), medium (upper secondary to short-cycle tertiary), and high (tertiary education, from short-cycle programmes to doctoral studies). Overall, in All Countries, this index exhibits the steepest education positive gradient (Low 2.658, Medium 3.316, High 3.881), indicating strong stratification by educational attainment. This is an expected pattern given that higher education is more likely to provide exposure to digital concepts, data-oriented reasoning, and formal training environments where AI-related topics are discussed, as well as access to occupations that require interacting with advanced technologies. Among the highly educated, the highest averages are in Denmark (4.664), Finland (4.664), and Austria (4.579), while the lowest High-education averages are observed in Türkiye (3.289), Cyprus (3.296), and Bulgaria (3.384). Education gaps (High minus Low) are especially large in Cyprus (2.56), Ireland (2.10), and the Netherlands (2.00), pointing to strong educational stratification in these

contexts, whereas the gaps are comparatively small in Croatia (0.60), Greece (0.68), and Slovenia (0.69), suggesting weaker differentiation by education. Estonia is the only case where the Medium-education group scores slightly below the low-education group, although the high-education group remains clearly the top-scoring category, indicating that the overall association between education and AI literacy remains positive even where small non-monotonicities appear.

Figure 3-46 shows the weighted average scores of the AI Literacy index across income deciles, based on respondents' self-reported annual net disposable income (including wages, self-employment income, property income and government benefits) ranked from the 1st (lowest) to the 10th (highest) decile. Overall, in All Countries, the average score of the index increases from 3.44 (1st) to 3.93 (10th), a gap of +0.49. The steepest positive gradients are in Hungary (+1.20), Estonia (+1.11) and Lithuania (+1.11), while several high-income countries display flat or reversed pattern (e.g., Denmark with -0.27, the Netherlands with -0.21, and Italy with -0.12). The highest 10th-decile average score is in Estonia (4.88), and the lowest 1st-decile average score is in Hungary (2.47).

Figure 3-47 reports the weighted average scores of the AI Literacy index across wealth deciles, based on respondents' self-reported net household wealth (defined as the total value of all assets owned by the household, after deducting liabilities such as debts or loans) ranked from the 1st (lowest) to the 10th (highest) decile. Overall, in All Countries, AI literacy rises from 3.27 in the lowest wealth decile to 4.00 in the highest (gap +0.73), with a broadly increasing pattern. The largest wealth gradients are in Belgium (+1.93), Estonia (+1.53) and Malta (+1.45). By contrast, the pattern is reversed in a small set of countries, most notably the Netherlands (-1.36) and Poland (-0.41), with Spain also slightly negative (-0.02), indicating substantial non-monotonicity in those cases. The highest 10th-decile value is in Estonia (4.83), while the lowest 1st-decile value is in Türkiye (2.63).

Figure 3-48 reports weighted average AI Literacy scores by skills-matching status, linking individual skill profiles to respondents' perceived fit between their qualifications and the demands of their main job. Overall, in All Countries, overqualified respondents score highest (3.79), matched are lower (3.61), and underqualified are lowest (3.33). Comparing matched to the mismatched average (3.56), the matched premium is 0.05. Thus, although overqualified respondents have higher scores on average, the average scores of underqualified respondents are considerably lower and therefore the scores of mismatched individuals are still slightly lower than matched ones. This ranking is common across countries, but there are exceptions where underqualified scores are the highest (e.g., Portugal and Ireland). Mismatch-related dispersion is especially large in Luxembourg (1.96) and also sizeable in Greece (1.12).

Figure 3-43: Gender breakdown in Artificial Intelligence (AI) Literacy by country

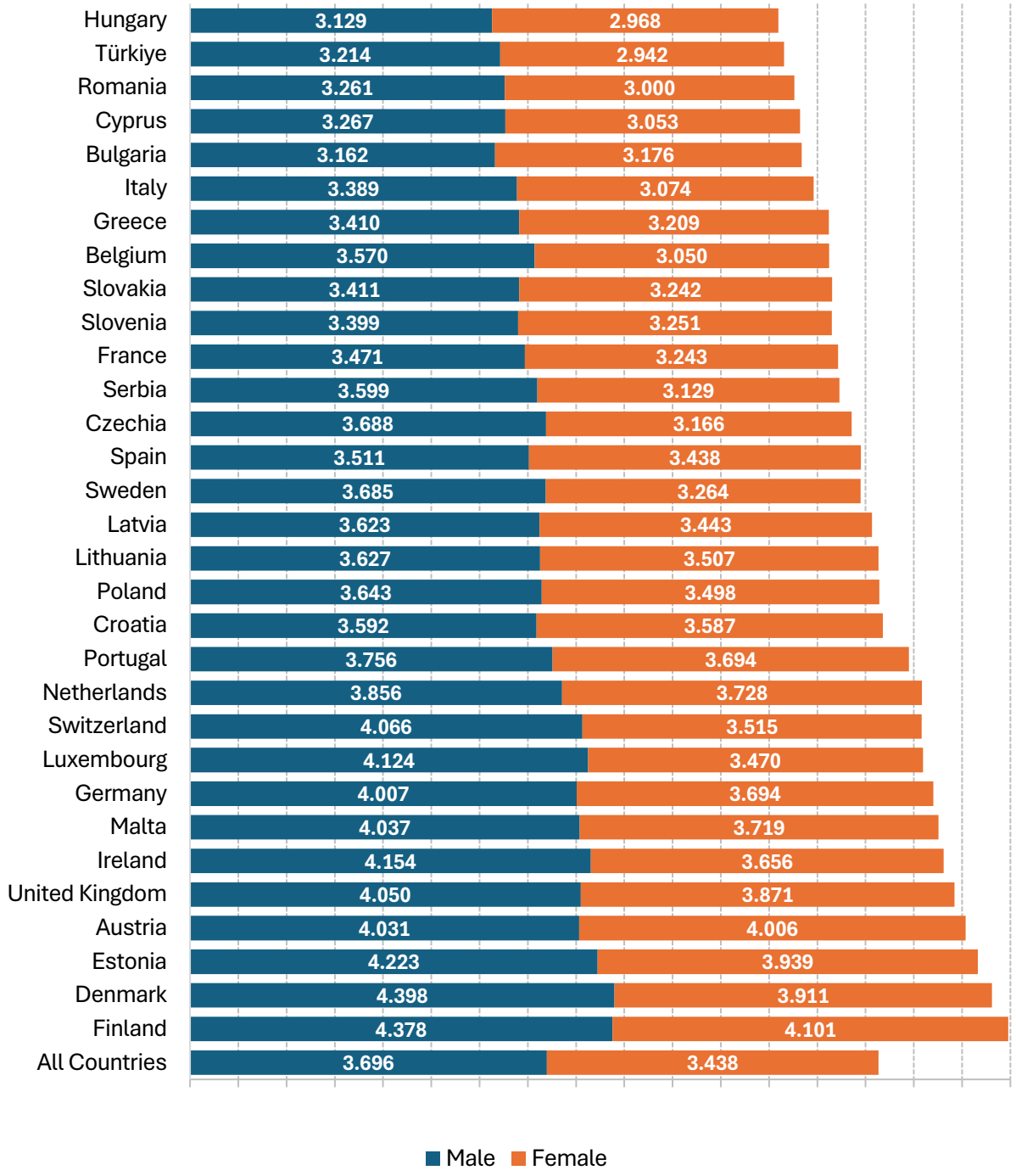


Figure 3-44: Age breakdown in Artificial Intelligence (AI) Literacy by country

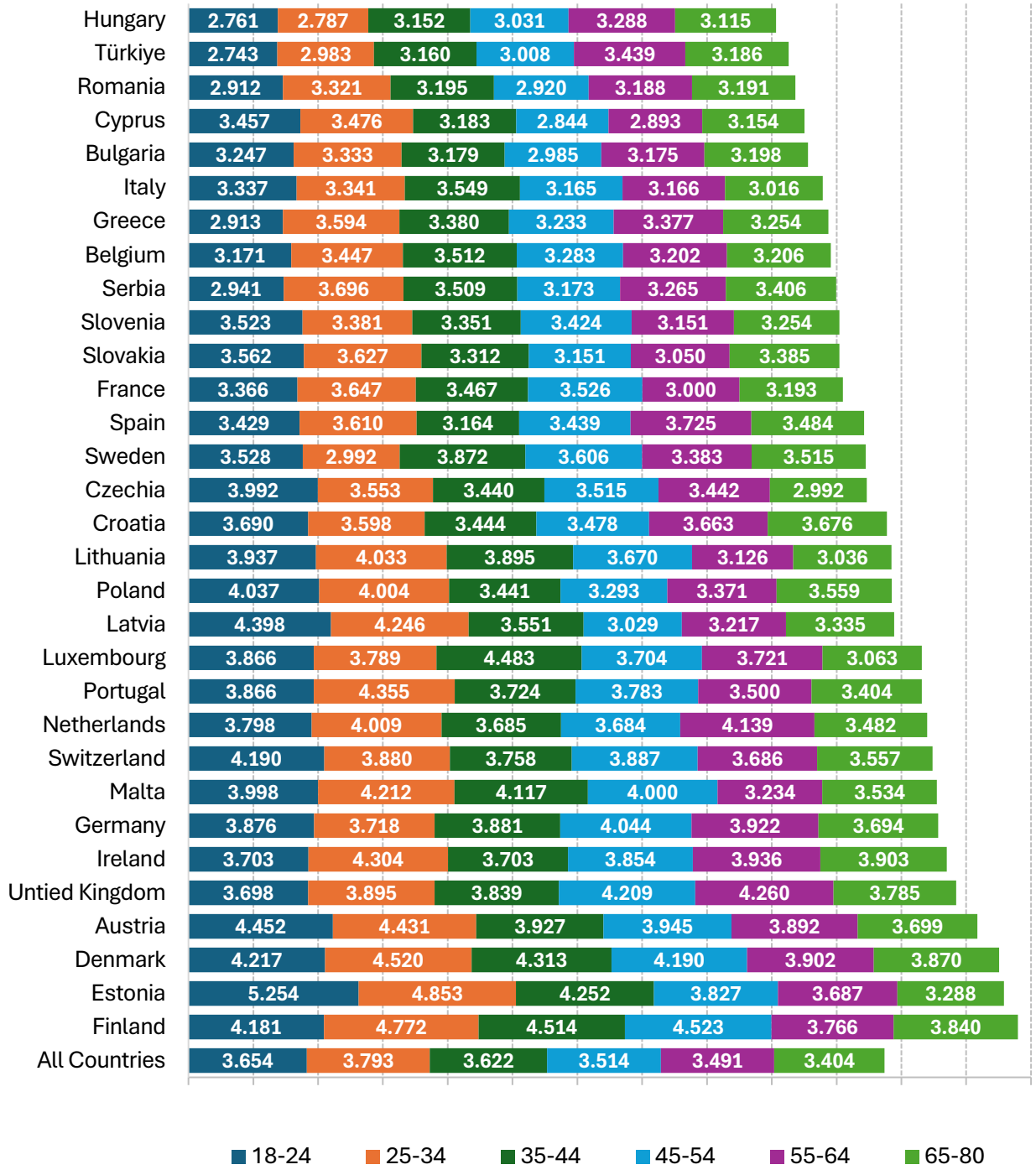


Figure 3-45: Educational breakdown in Artificial Intelligence (AI) Literacy by country

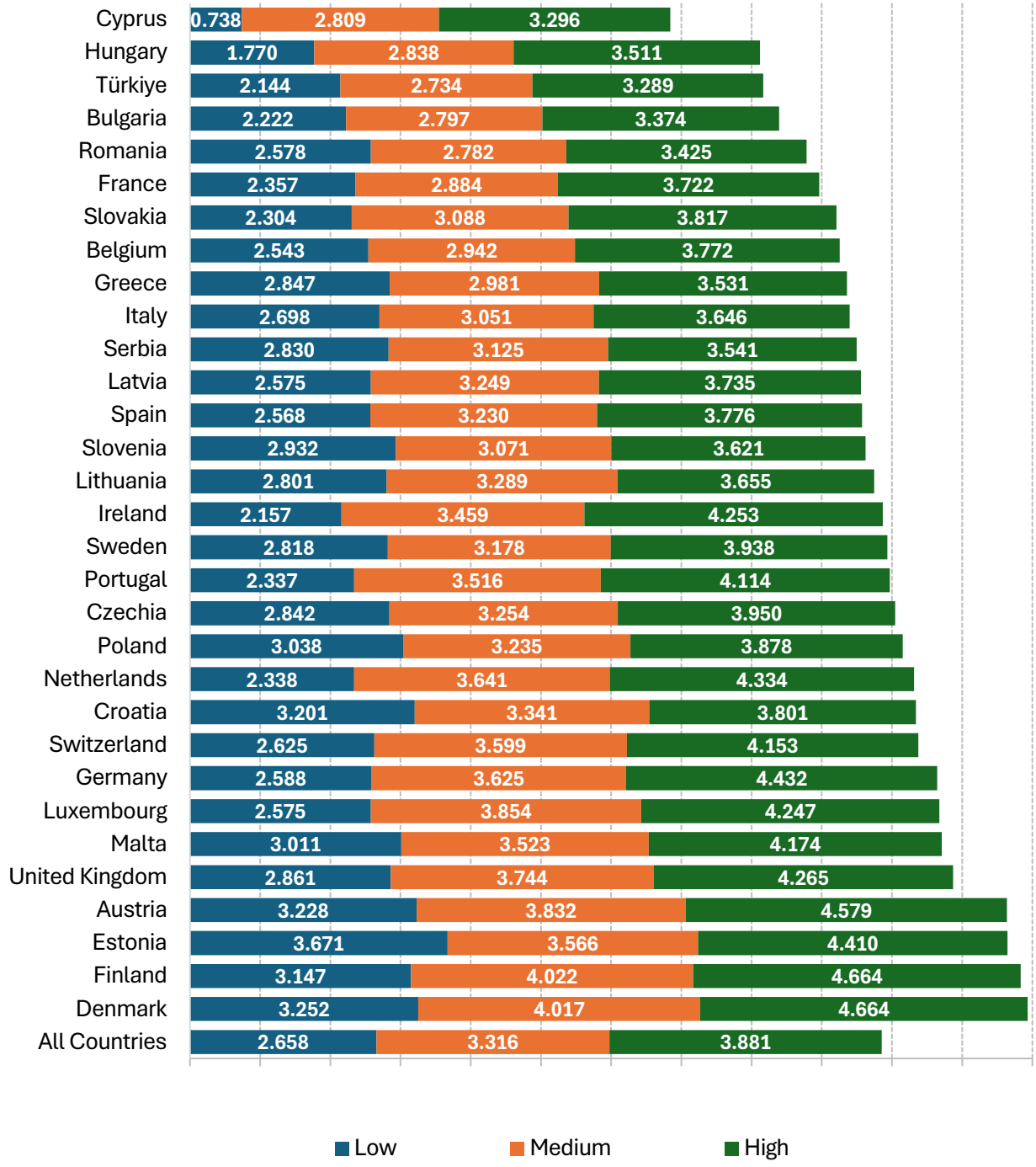


Figure 3-46: Income Composition in Artificial Intelligence (AI) Literacy by country

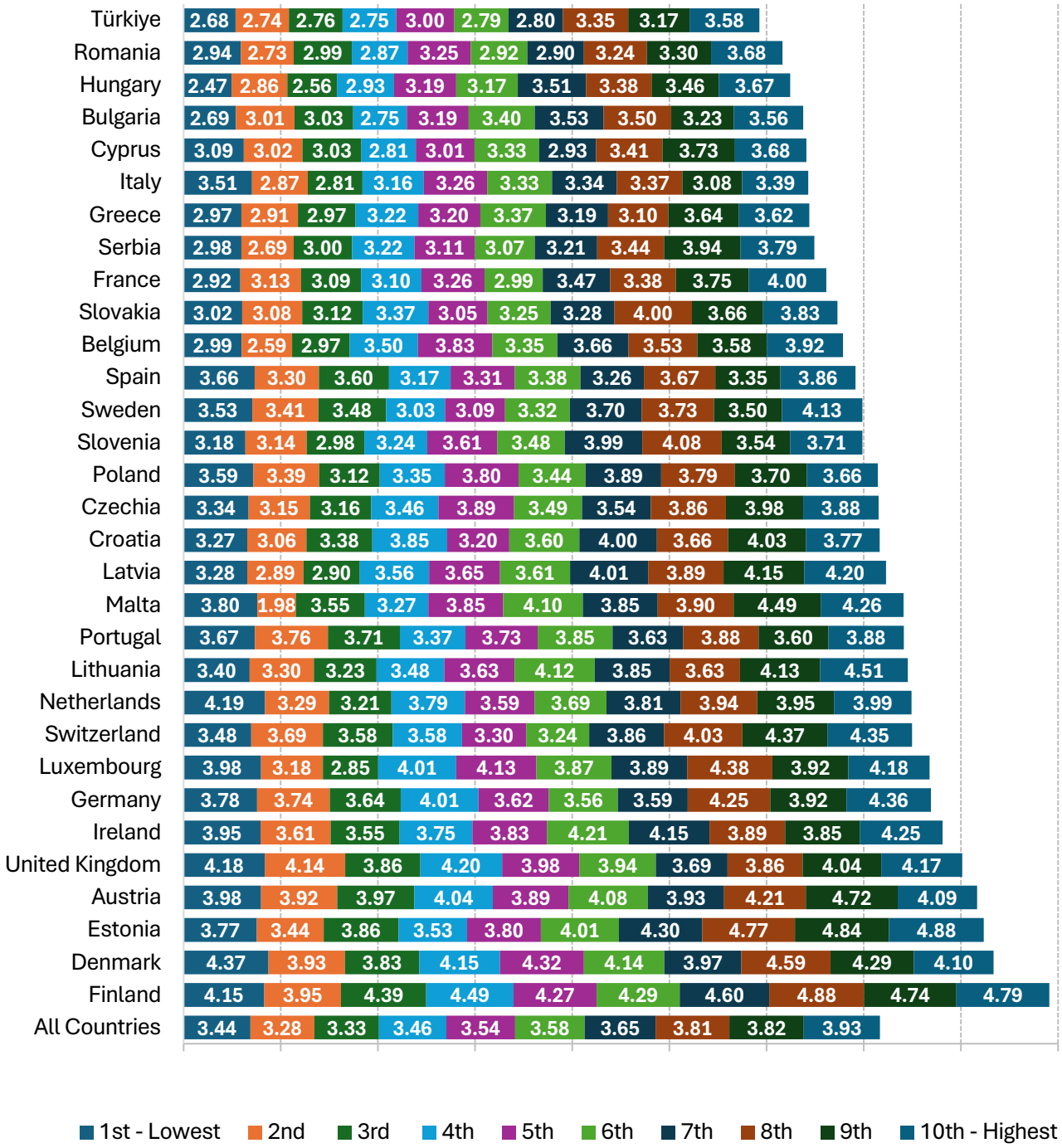


Figure 3-47: Wealth Composition in Artificial Intelligence (AI) Literacy by country

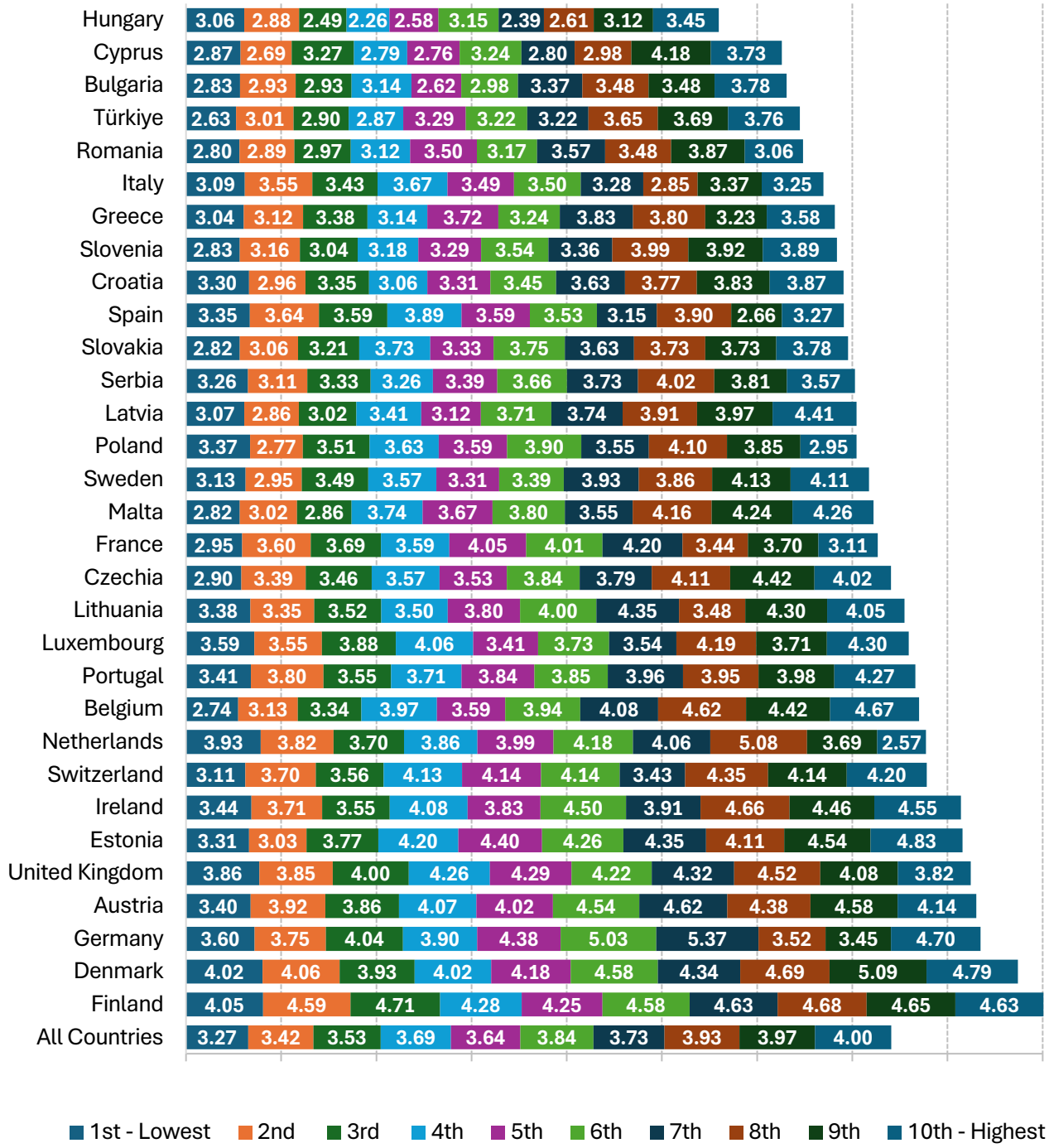
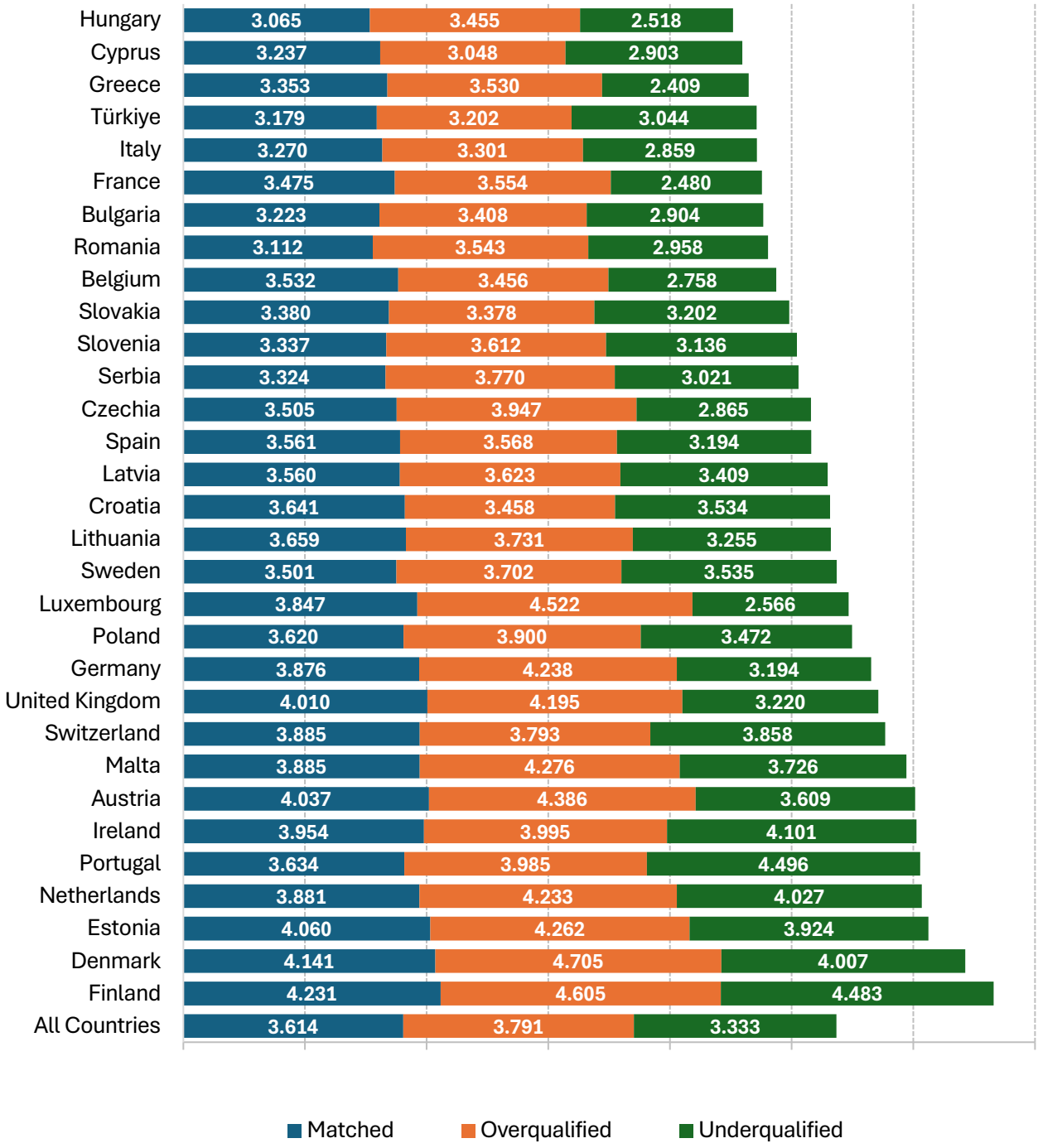


Figure 3-48: Skills Mismatch in Artificial Intelligence (AI) Literacy by country



3.2.4 Data and Programming Literacy

The Data and Programming Literacy index captures a set of digital-era capabilities that increasingly shape individuals' productivity, employability, and ability to function in data-rich environments. Across European labour markets, tasks that involve working with data (even in basic formats), interpreting outputs, and interacting with computational systems are spreading beyond ICT occupations into administration, finance, logistics, marketing, public services, and many other job families (Vuorikari et al., 2022). At the same time, the rapid diffusion of AI tools is shifting how tasks are executed and how quickly skill requirements evolve, making it valuable not only to possess technical skills, but also to feel capable of applying them in practice. Evidence from vacancy data shows sustained "upskilling" in employer requirements within occupations, particularly for technology-related competences, consistent with the view that digital and analytical capabilities are increasingly rewarded (Hershbein & Kahn, 2018).

The Data and Programming Literacy index is based on respondents' self-assessment of their confidence in performing five practical tasks that are increasingly common in data-rich workplaces: working with spreadsheets (charts and formulas), understanding basic programming logic, interpreting code, and adapting to AI tools. Measuring confidence complements the knowledge-based items because it captures whether individuals feel capable of applying these skills in practice. This has implications for real-world outcomes: individuals who are more confident are typically more likely to use digital tools, take on data-related tasks, and engage in learning opportunities when new technologies are introduced.

Specifically, the Data and Programming Literacy index is constructed from a single question that measures confidence across five distinct elements. Respondents rate each element on a 0–10 scale (0 = not confident at all; 10 = fully confident):

Q48. How confident are you in your ability to do the following? Please rate your confidence on a scale from 0 (not confident at all) to 10 (fully confident).

1. *Create a chart or graph from a spreadsheet*
2. *Understand basic programming logic (e.g., loops, conditions)*
3. *Write a simple formula (e.g., in Excel or Google Sheets)*
4. *Understand what a piece of code does, even if you didn't write it*
5. *Adapt to working with AI systems in your job (now or in the future)*

<u>*Columns*</u>
0 = Not confident at all
1
2
3
4
5
6
7
8
9
10 = Fully confident

98. Don't know

To ensure comparability with the other skill indices and to focus on the breadth of capabilities, the Data and Programming Literacy index ranges from 0 to 5 by converting each of the five elements into an indicator of whether the respondent reports at least moderate confidence (using a common cutoff on the 0-10 scale) and then summing across elements. This construction yields an interpretable count of how many core digital/data competences an individual feels able to perform (0 = none; 5 = all five). The explicit "Don't know" category also helps limit noise from forced answers.

Conceptually, the five elements provide good coverage of the intended Data and Programming Literacy index. The spreadsheet components (charting and formulas) capture baseline data handling and numeracy-in-context that is widely required across non-technical occupations. Basic programming logic captures foundational computational thinking, while code comprehension reflects an increasingly common workplace reality in which workers must understand, audit, or adapt automated. Finally, the AI-adaptation item anchors the index in the current transition: as AI tools permeate everyday workflows, the ability to adapt one's tasks and interpret AI results becomes a practical skill in itself.

This measurement strategy is also aligned with the economics literature on technological change and skills. Research shows that digital technologies can be skill-complementary, raising the productivity of workers performing non-routine analytical tasks and contributing to changing wage structures and demand for capabilities tied to technology use (e.g., Akerman et al, 2015). More recent studies using detailed job-posting data show that the skill content of jobs changes rapidly, implying that workers benefit from adaptable, broadly applicable digital competencies rather than narrow, static task knowledge (Deming & Noray, 2020). Finally, Babina et al. (2024), using a measure of firm-level AI investments from employee resumes indicates that AI can reshape organisational processes and production, increasing the value of employees who can effectively operate alongside these systems and understand their limitations.

Table 3-7 presents the correlation matrix for the Data and Programming Literacy Index and its five constituent competencies: spreadsheet charting, programming logic, formula writing, code comprehension, and adaptation to AI in the workplace. Each item shows a very strong and statistically significant correlation with the overall index ($r = 0.755–0.833$, $p < 0.01$). Programming logic exhibits the highest association ($r = 0.833$), followed closely by spreadsheet charting ($r = 0.821$) and formula writing ($r = 0.814$), while code comprehension ($r = 0.793$) and AI work adaptation ($r = 0.755$) also display robust relationships. The uniformly high magnitude of these correlations indicates strong internal consistency and suggests that all five dimensions contribute substantially to a common underlying construct. Compared to other literacy domains, this index appears particularly cohesive, providing strong evidence of convergent validity.

The inter-item correlations are also moderate to high ($r \approx 0.477–0.727$), indicating a more tightly integrated structure than observed in other literacy blocks. The strongest relationship is between programming logic and code comprehension ($r = 0.727$), which is theoretically consistent, as understanding programming structures directly supports the ability to interpret code. Similarly, spreadsheet charting and formula writing are highly correlated ($r = 0.720$), reflecting shared computational and data-handling skills. While these stronger associations suggest conceptual

overlap across technical competencies, they do not indicate redundancy; rather, they reflect complementary dimensions within a broader digital-technical skill set. Overall, the correlation structure provides strong support for the statistical validity of the Data and Programming Literacy Index as a coherent and internally consistent measure of applied digital and computational capability.

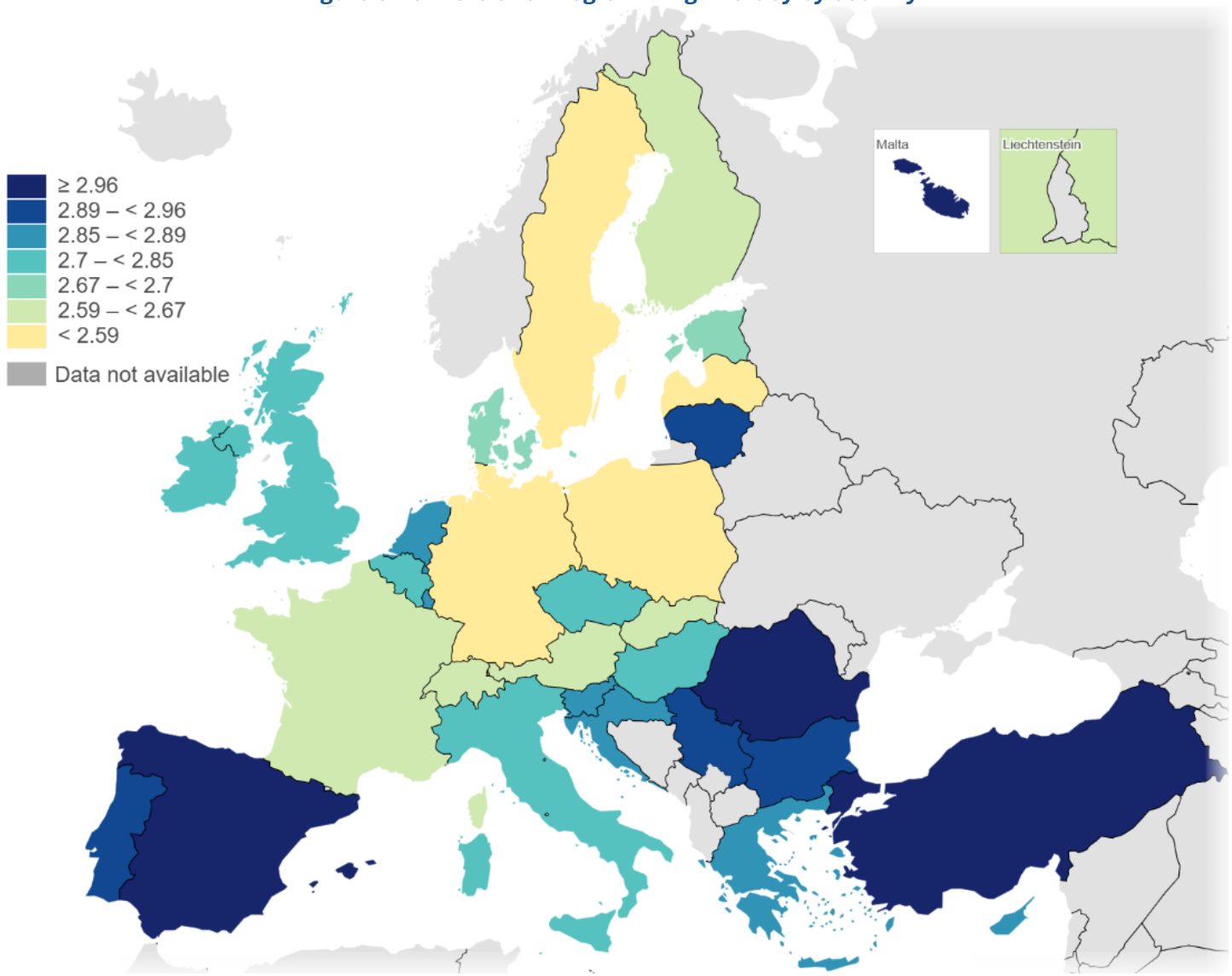
Table 3-7: Data and Programming Literacy index correlation matrix

	Data and Programming Literacy index	Spreadsheet charting	Programming logic	Formula writing	Code comprehension	AI work adaptation
Data and Programming Literacy index	1.000					
1. Spreadsheet charting	0.8212**	1.000				
2. Programming logic	0.8331**	0.5507**	1.000			
3. Formula writing	0.8139**	0.7203**	0.5416**	1.000		
4. Code comprehension	0.7925**	70.4887**	0.7272**	0.4767**	1.000	
5/ AI work adaptation	0.7546**	0.537	0.5115**	0.5277**	0.4817**	1.000

Figure 3-49 reports the weighted average of the Data and Programming Literacy index (0–5) across countries. Results are displayed using a quintile (equal-count) classification, which divides the distribution into seven classes with an equal number of values, ensuring a balanced distribution across categories (legend cut-offs shown). Interestingly, the map suggests higher averages in Romania, and Portugal, and lower averages in Central and Northern European countries (e.g., Germany, Sweden, Poland, Latvia). Grey shading denotes countries with no available data.

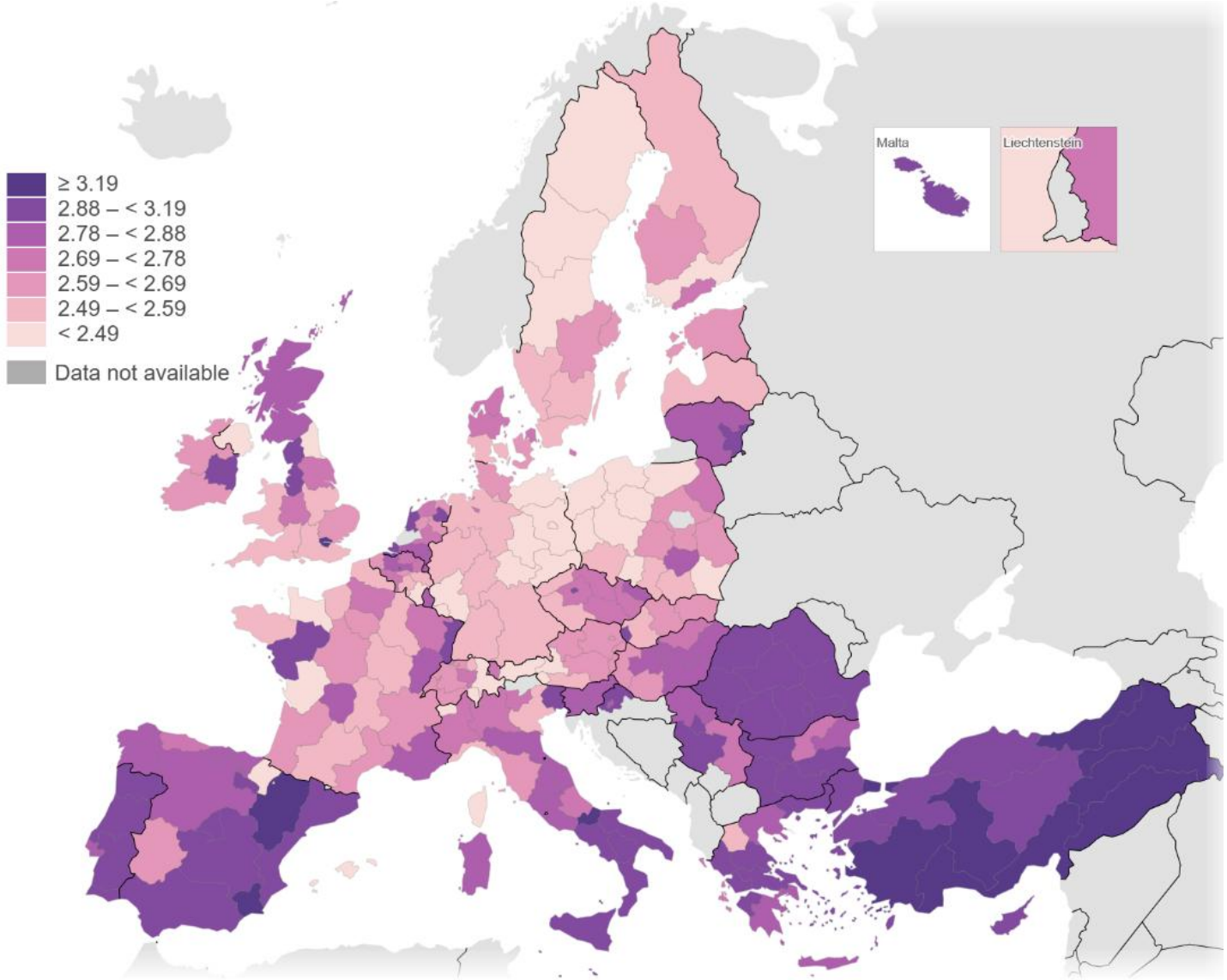
Figure 3-50 shows the same indicator at the regional level (NUTS-2 for most countries; NUTS-1 for the UK, Germany, and Turkey due to data availability), using the same equal-count classification approach. The regional map highlights strong within-country heterogeneity, with several countries combining higher- and lower-scoring regions rather than exhibiting a uniform national pattern. Grey areas indicate missing regional data.

Figure 3-49: Data and Programming Literacy by country



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 3-50: Data and Programming Literacy by region



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figures 3-51 to 3-52 provide a systematic descriptive profile of the Data and Programming Literacy index across key socio-demographic and labour-market groups. For each subgroup breakdown, weighted averages are reported both by country and for the pooled sample ("All Countries"), enabling comparisons of within-country disparities alongside cross-country differences in overall levels. This descriptive structure helps to identify whether disparities by gender, age, education, income, wealth and employment characteristics reflect broad regularities or whether they vary with national patterns of digital adoption, training opportunities, and occupational structures.

Figure 3-51 reports the gender breakdown in Data and Programming Literacy index, reporting weighted average scores for women and men. Across countries, men score higher, and the overall gap, in All Countries, is sizeable with 2.934 versus 2.628 (gap +0.306). The magnitude of the gap varies substantially across national contexts. The largest differentials are observed in Finland (+0.56), Austria (+0.52), and the United Kingdom (+0.48), indicating settings where data and programming skills are particularly unevenly distributed by gender. In contrast, gaps are smallest in Türkiye (+0.03), Lithuania (+0.08), and Poland (+0.08), suggesting near parity in average scores. In terms of overall levels, Türkiye stands out as the top-performing country for both genders, which implies that high average scores there are not confined to one group. Conversely, women's lowest average scores are observed in Germany, Finland, and Austria, indicating that low female performance contributes to the large gender gaps in some countries.

Figure 3-52 depicts the age breakdown in Data and Programming Literacy index, reporting weighted average scores across six age groups. This index shows one of the strongest age gradients: average scores decline almost continuously from 3.076 among those aged 18-24 to 2.409 among those aged 65-80. This age profile is consistent with cohort-based differences in exposure to computing and programming, as younger groups are more likely to have encountered digital tools, coding environments, and data-related tasks through education and early-career job requirements. The steepness of the decline varies across countries. The largest drops are visible in Estonia, the United Kingdom, and Malta, where older cohorts score substantially below younger cohorts, suggesting particularly strong generational divides in these settings. Türkiye again stands out with consistently high scores across all age groups, indicating a relatively narrow age gap in levels. By contrast, Switzerland, Finland, and Sweden record among the lowest scores on average, suggesting weaker overall performance in this index even if the age pattern differs across countries. Overall, the figure indicates that data and programming skills are strongly concentrated among younger cohorts, with important implications for digital inclusion and training needs among older workers.

Figure 3-53 reports weighted average Data and Programming Literacy scores by education level, distinguishing three categories: low (early childhood to lower secondary), medium (upper secondary to short-cycle tertiary), and high (tertiary education, from short-cycle programmes to doctoral studies). The overall pattern, in All Countries, increases with education (Low 2.287, Medium 2.592, High 2.993), indicating that formal education is positively associated with data and programming capabilities. This pattern is expected given that higher education increases the likelihood of exposure to quantitative methods, formal training in digital tools, and occupations that require interacting with data and software. However, the strength of the education association varies across countries. Some countries show weaker or non-monotonic gradients, suggesting that these skills can also be acquired through non-formal channels, vocational pathways, or workplace learning. Among High-educated respondents, the highest averages are observed in Türkiye (3.321), Romania (3.188), and Malta (3.160), while the lowest High-education scores appear in Poland (2.717), Latvia (2.756), and Germany (2.778). The education gap (High minus Low) is particularly large in Greece (1.31), the United Kingdom (1.00), and Finland (0.98), pointing to strong educational stratification in

these contexts. By contrast, the gap is close to zero in Poland, indicating that educational attainment differentiates these skills relatively little there. These cross-country differences suggest that the extent to which data and programming skills are linked to formal education depends on national education systems, training provision, and the distribution of data-related tasks across occupations.

Figure 3-54 shows the weighted average scores of the Data and Programming Literacy index across income deciles, based on respondents' self-reported annual net disposable income (including wages, self-employment income, property income and government benefits) ranked from the 1st (lowest) to the 10th (highest) decile. In All Countries, this index shows one of the strongest overall upward gradients, rising from 2.59 (1st) to 3.23 (10th), a gap of +0.64. The largest increases occur in Latvia (+1.15), Estonia (+1.06) and Slovenia (+0.95), whereas the smallest gradients are in Malta (+0.17), Denmark (+0.28) and Portugal (+0.37). The highest 10th-decile average score is in Estonia (3.63), and the lowest 1st-decile average score is in Poland (2.20).

Figure 3-55 reports the weighted average scores of the Data and Programming Literacy index across wealth deciles, based on respondents' self-reported net household wealth (defined as the total value of all assets owned by the household, after deducting liabilities such as debts or loans) ranked from the 1st (lowest) to the 10th (highest) decile. Overall, in All Countries, the gradient is strong: 2.58 (1st-decile) to 3.09 (10th-decile), a gap of +0.52. The steepest increases are present in Latvia (+1.03), Greece (+0.96) and the United Kingdom (+0.90), while the gradient is small in Lithuania (+0.11) and Croatia (+0.18). Malta stands out with a reversed pattern (-0.20). The highest 10th-decile average score is in Greece (3.64), and the lowest 1st-decile average score is in Switzerland (2.21).

Figure 3-56 reports weighted average Data and Programming Literacy scores by skills-matching status, linking individual skill profiles to respondents' perceived fit between their qualifications and the demands of their main job. Overall, in All Countries, overqualified respondents score highest (2.91), followed by matched (2.79), with underqualified lowest (2.60). The matched score (2.79) is only slightly above the mismatched average (2.76), implying a small match premium of 0.04. Overqualified average score is consistently the highest and underqualified average score the lowest, so the mismatched average remains close to matched across most countries. The largest differences across mismatch categories appear in Luxembourg (0.93) and Cyprus (0.83), while some countries show comparatively modest dispersion (e.g., Poland).

Figure 3-51: Gender breakdown in Data and Programming Literacy by country

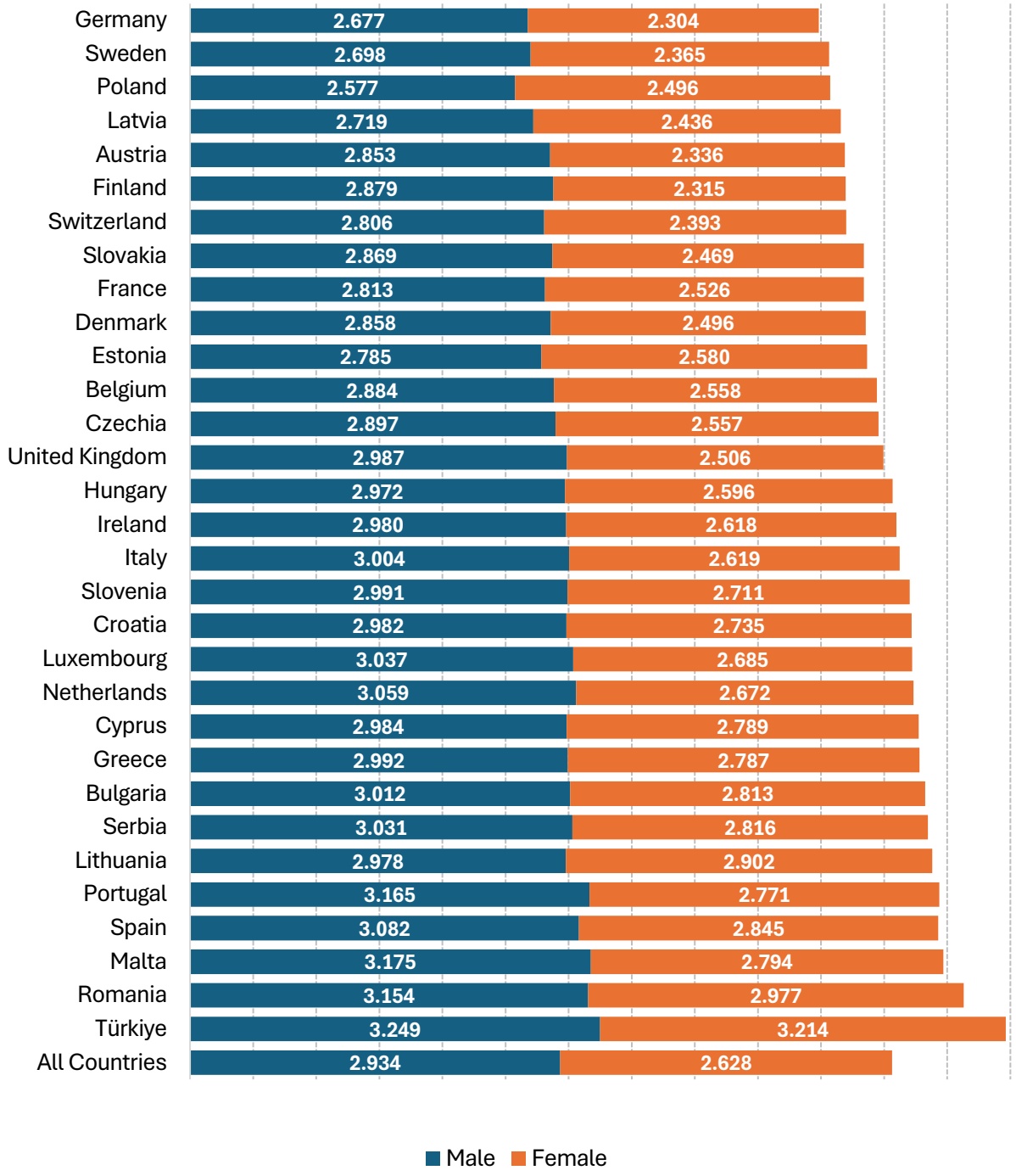


Figure 3-52: Age breakdown in Data and Programming Literacy by country

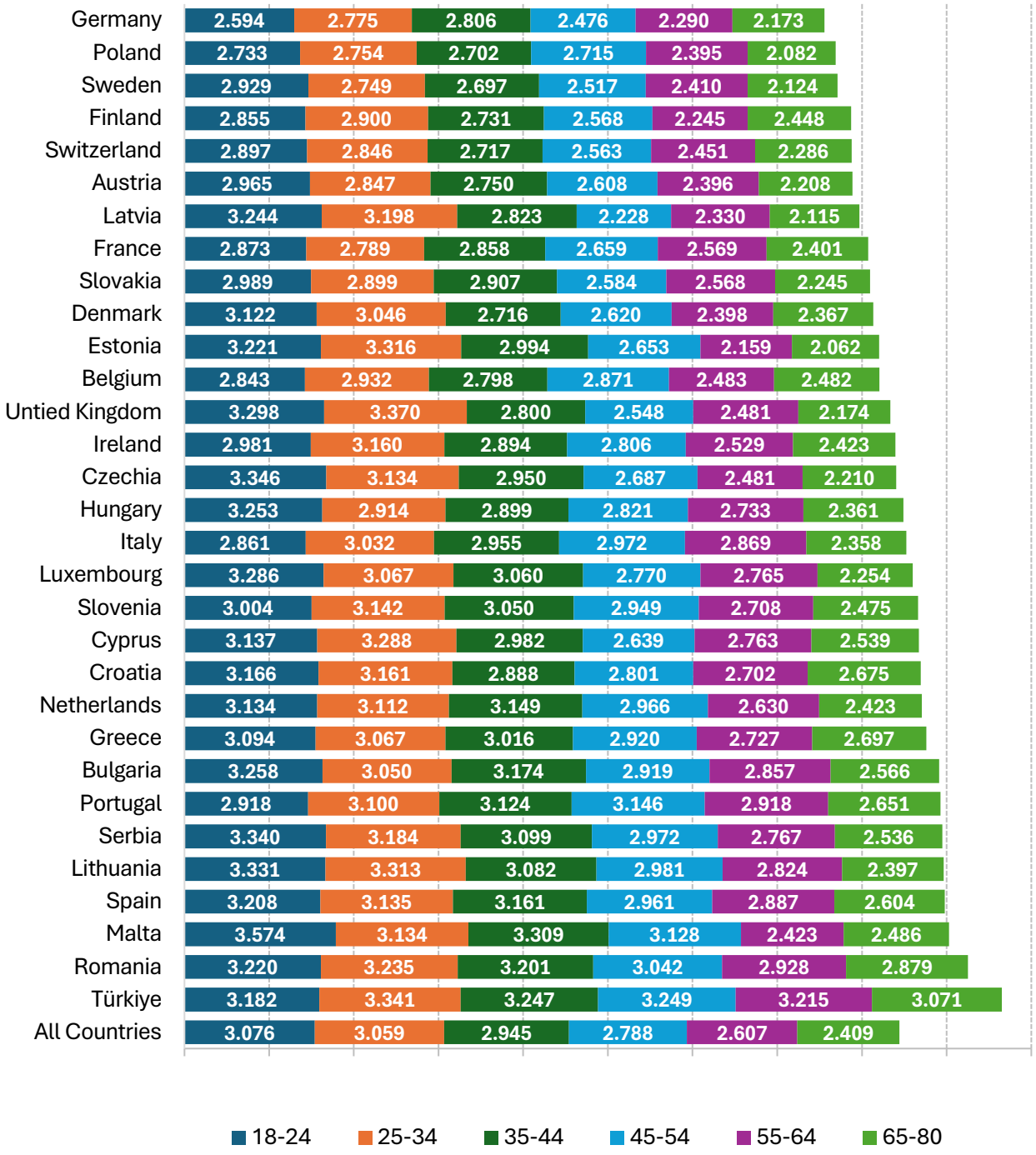


Figure 3-53: Educational breakdown in Data and Programming Literacy by country

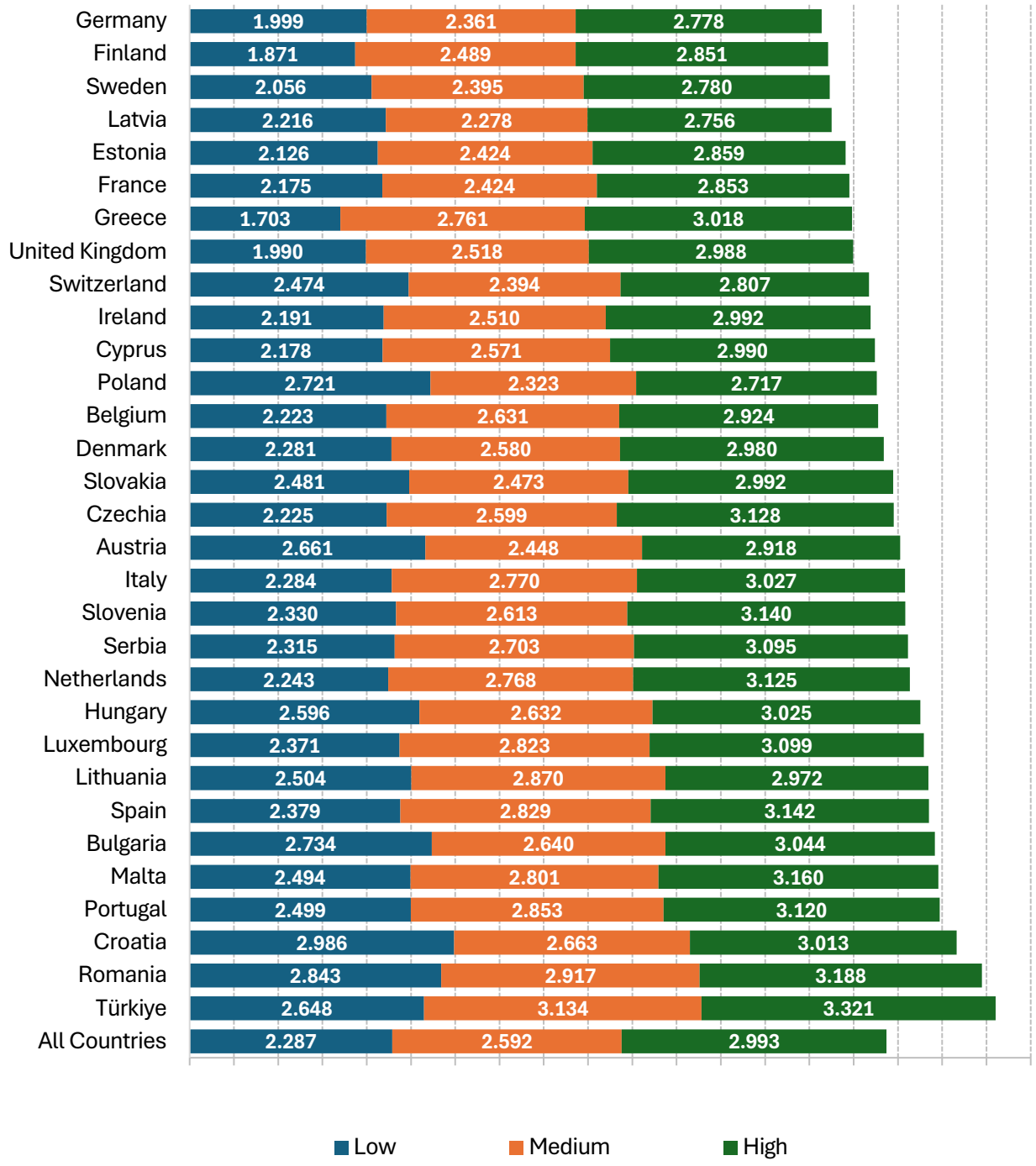


Figure 3-54: Income Composition in Data and Programming Literacy by country

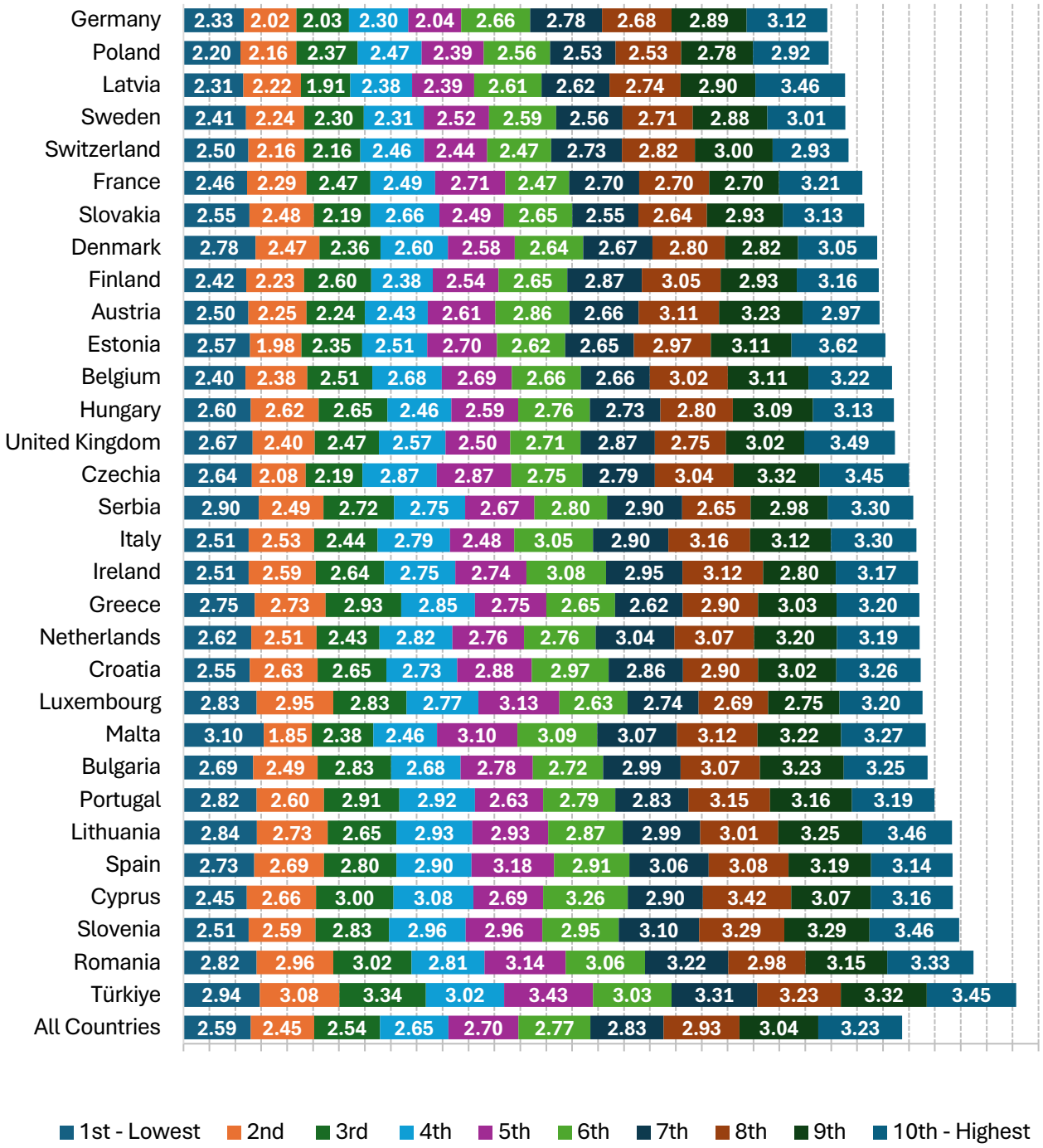


Figure 3-55: Wealth Composition in Data and Programming Literacy by country

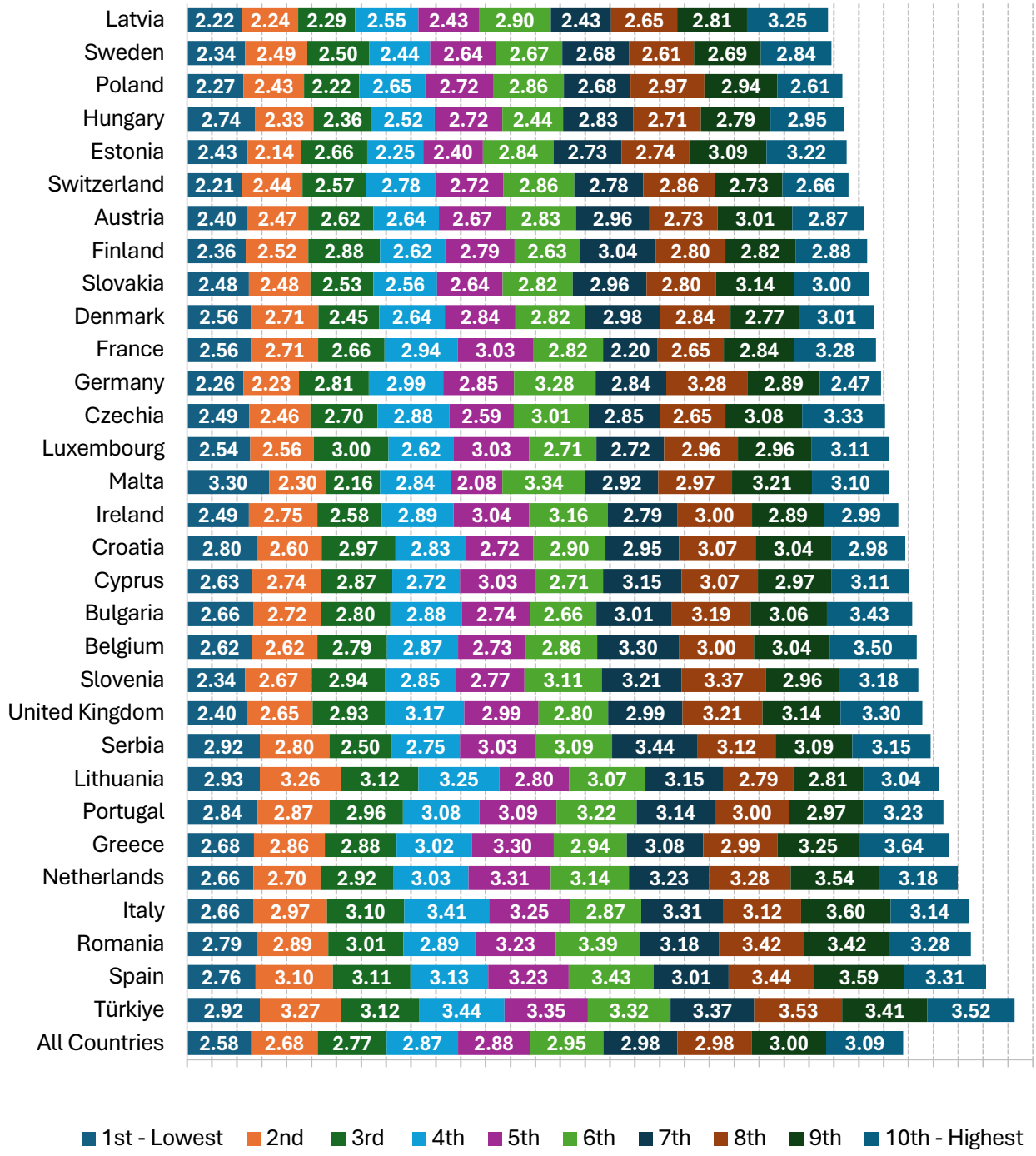
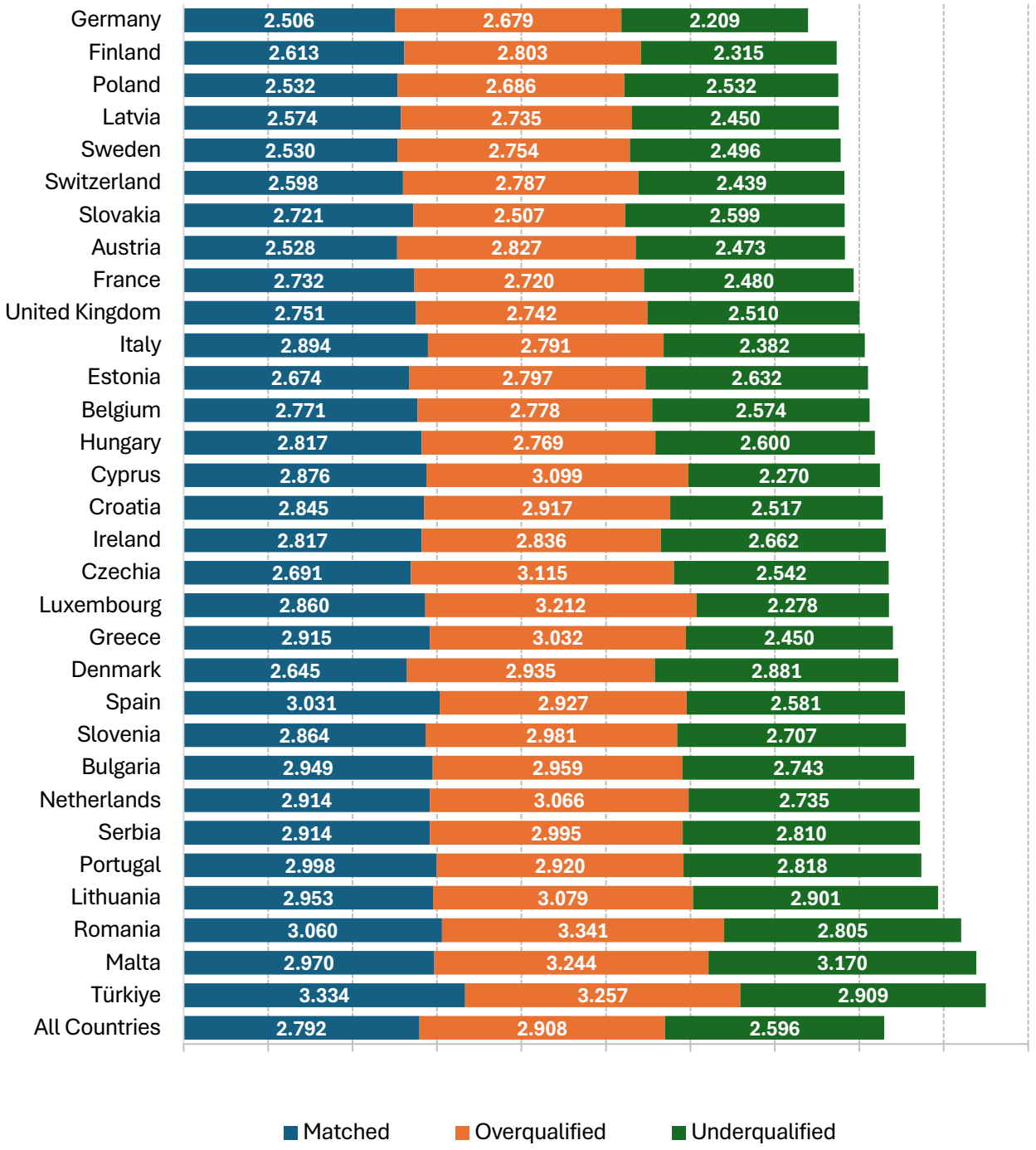


Figure 3-56: Skills Mismatch in Data and Programming Literacy by country



3.3 Civic and Green Skills

3.3.1 Political Literacy

The Political Literacy index captures a set of basic competencies related to individuals' ability to know about and participate in democratic decision-making. Citizens are repeatedly exposed to complex policy choices (e.g., taxation and redistribution, social protection, regulation of digital platforms, climate policy, etc). Political literacy matters because it shapes whether individuals can interpret political information, understand where and how decisions are made, and participate in ways that strengthen accountability. Political-economy research shows that citizen engagement and the information environment can affect political behaviour and, ultimately, the quality of governance and public outcomes (e.g., Levy, 2021; Kartal & Tyran, 2022).

The index is constructed from three questions that cover (i) political participation, (ii) knowledge of the domestic political system, and (iii) knowledge of a core EU democratic institution. Each component is coded as an indicator (0/1) and summed, yielding an index that ranges from 0 to 3. This range is appropriate because it yields a transparent measure of the number of the three-core political-literacy elements a respondent demonstrates, while keeping the measure comparable across countries. In addition, the EU-institution item that represents one of the three components, for non-EU countries it has a lower weight.

Specifically, the Political Literacy index (range 0-3) is constructed from the following three TRAILS-I survey questions:

Q25. In the past 36 months, have you participated in any of the following political activities? Please select all that apply.
1. *Voted in a national election*
2. *Voted in a European election (scripter: include this option only in the EU27 countries)*
3. *Signed a petition*
4. *Attended a political meeting*
5. *Contacted a politician or public official*
97. *None of the above*
98. *I don't know*
99. *I prefer not to answer*

Q26. How many political parties are currently represented in your national parliament?
___ *Give a number with up to 2-digits*
98. I don't know
99. I prefer not to answer

Q27. Which of the following EU institutions is directly elected by citizens of EU member states?
1. *The European Parliament*
2. *The European Commission*
3. *The Council of the European Union*
98. *I don't know*

99. *I prefer not to answer*

Conceptually, the three items provide complementary coverage. Q25 captures revealed political engagement over a meaningful window (36 months), going beyond a single election moment and including both electoral and non-electoral participation. To avoid over-weighting individuals who select multiple activities, the index can treat Q25 as a single participation indicator (e.g., 1 if at least one activity is reported; 0 if "none of the above"), which strengthens comparability across countries and groups. Q26 measures a concrete piece of political system knowledge, namely awareness of party representation in the national parliament, which serves as an indicator of whether respondents can track basic features of their political system. Q27 captures institutional knowledge at the EU level by testing whether respondents know which EU body is directly elected, an essential element for democratic accountability in a multi-level governance context. Finally, the explicit "I don't know" response option helps reduce random error by limiting guessing.

This measurement approach is also consistent with evidence from existing studies showing why participation and basic institutional understanding are economically relevant. For example, Levy (2021) demonstrates that social-media news exposure can causally affect political attitudes and polarisation, while Kartal and Tyran (2022) show that misinformation and overconfidence can undermine democratic choice. Related evidence on media's political effects (Durante et al., 2019) and on digital political advertising (Beknazar-Yuzbashev & Stalinski, 2022) reinforces that modern political participation and belief formation increasingly operate through mediated and digital channels. Finally, cross-country evidence documents that affective polarisation has evolved substantially across democracies, underscoring the importance of skills that support informed engagement rather than disengagement or misinformed participation (Boxell, et al., 2024).

Table 3-8: Political Literacy index correlation matrix

	Political Literacy index	Political participation	Domestic political system knowledge	EU institution knowledge
Political Literacy index	1.000			
Q25: Political participation	0.690**	1.000		
Q26: Domestic political system knowledge	0.667**	0.157**	1.000	
Q27: EU institution knowledge	0.642**	0.217**	0.251**	1.000

Table 3-8 presents the correlation matrix for the Political Literacy Index and its three constituent dimensions: political participation, knowledge of the domestic political system, and knowledge of EU institutions. Each component exhibits a strong and statistically significant correlation with the overall index ($r = 0.642–0.690$, $p < 0.01$). Political participation shows the highest association with the index ($r = 0.690$), followed by domestic political system knowledge ($r = 0.667$) and EU institution

knowledge (r = 0.642). The relatively similar magnitude of these coefficients suggests that all three dimensions contribute meaningfully and fairly evenly to the composite measure. This pattern provides evidence of convergent validity, indicating that the index captures a coherent underlying construct of political literacy that integrates both behavioural and cognitive elements.

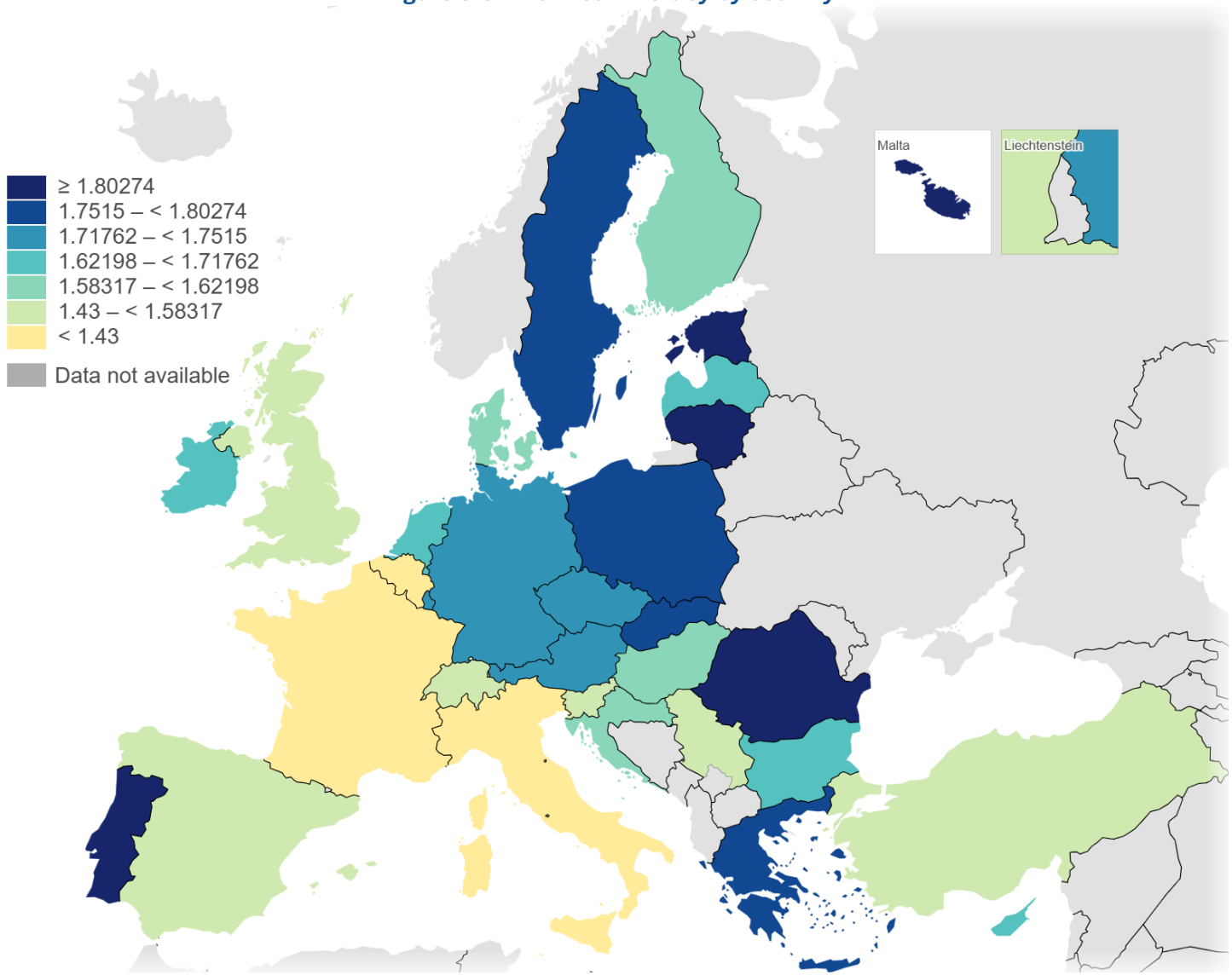
The inter-item correlations, however, are modest (r = 0.157–0.251, $p < 0.01$), suggesting that the components measure related but distinct aspects of political literacy. Political participation is only weakly associated with domestic system knowledge (r = 0.157) and moderately associated with EU institution knowledge (r = 0.217), indicating that active engagement in political activities does not necessarily imply high levels of institutional knowledge. The strongest inter-item relationship appears between domestic political system knowledge and EU institution knowledge (r = 0.251), which is theoretically consistent, as both reflect factual understanding of governance structures. Overall, the correlation structure supports the statistical validity of the Political Literacy Index as a multidimensional yet coherent construct, combining behavioural engagement and institutional knowledge without evidence of redundancy.

Figure 3-57 maps the weighted country average of the Political Literacy index (0-3) based on the TRAILS-I survey. Results are grouped using a quintile classification, which divides the distribution into seven classes of an equal number of values, ensuring a balanced comparison across categories (cut-offs shown in the legend). The map indicates cross-country variation, with higher averages in Northern and Central/Eastern Europe (e.g., Sweden, Estonia, Lithuania, Romania) as well as some Southern countries (e.g., Portugal and Greece), while lower averages are observed in parts of Western and Southern Europe (including France, Spain, and Italy). Countries with data not available are shown in grey.

Figure 3-58 shows the weighted regional average of the Political Literacy index (0-3) at the NUTS-2 level for most countries and at NUTS-1 for the UK, Germany, and Turkey due to data availability. As in the country-level map, results are grouped using a quantile (equal-count) classification. The map reveals within-country variation, with clusters of higher- and lower-scoring regions that are not always visible in the country averages. Overall, the figure highlights that political literacy is not only a cross-country phenomenon but also varies meaningfully within countries, with neighbouring regions sometimes falling into different parts of the distribution. Grey areas indicate regions with no available data.

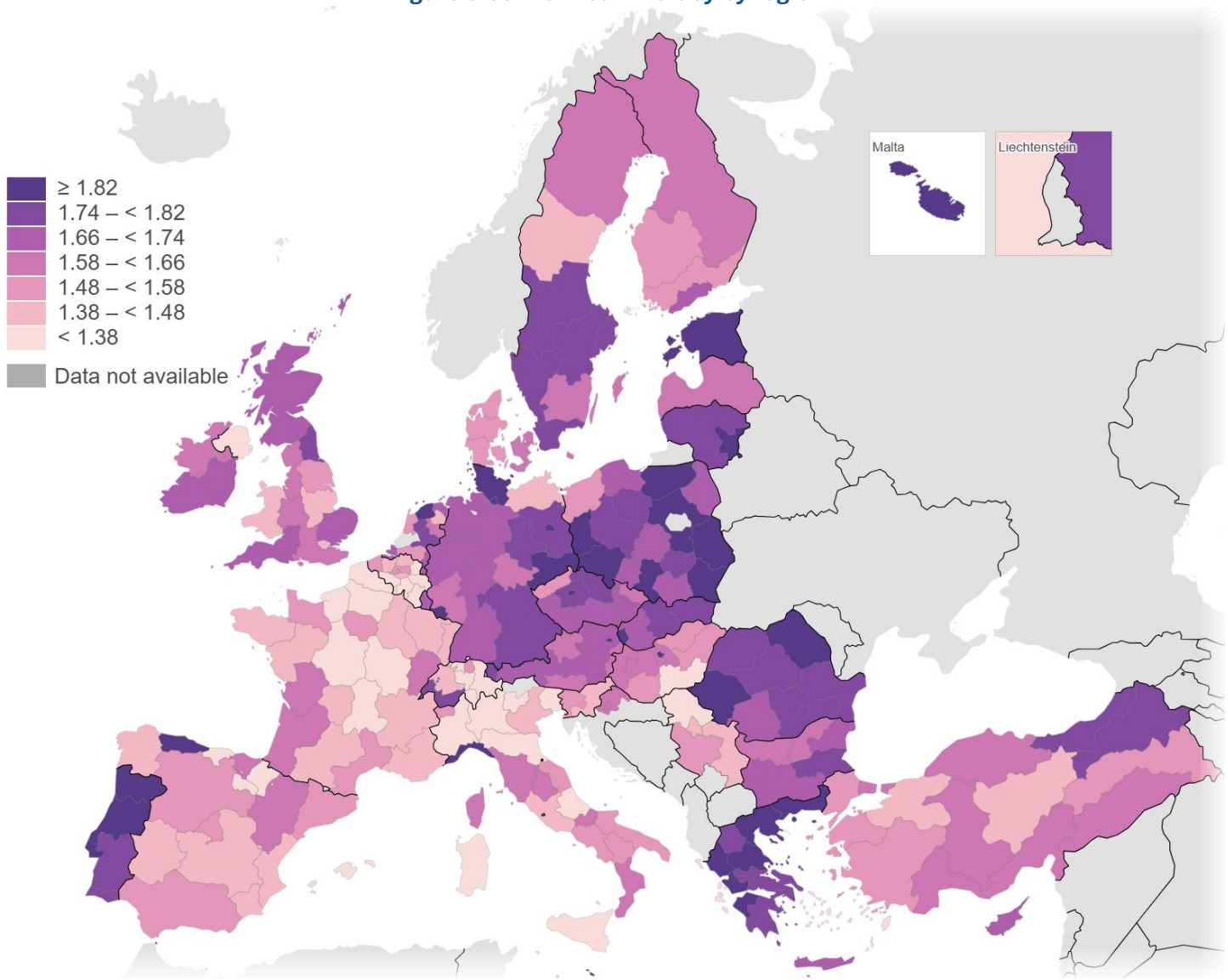
Figures 3-59 to 3-64 provide a systematic descriptive profile of the Political Literacy index across key socio-demographic and labour-market groups. For each breakdown, weighted averages are reported both by country and for the pooled sample ("All Countries"), enabling comparisons of within-country disparities alongside cross-country differences in overall levels. This structure makes it possible to assess whether gaps by gender, age, education, income, wealth and employment characteristics are common features across countries or whether they vary with institutional and cultural context.

Figure 3-57: Political Literacy by country



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 3-58: Political Literacy by region



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 3-59 presents the gender breakdown in Political Literacy index, reporting weighted average scores for women and men by country and overall. Overall, in All Countries averages are 1.852 (men) versus 1.472 (women), implying a gap of about +0.38 index points. Importantly, men score higher than women in every country, indicating that the gender disparity is not driven by a small subset of contexts but is a broad regularity in the data. The size of the gap varies across countries, however. The largest differences are observed in Cyprus (+0.70), Germany (+0.60), and Hungary (+0.55), suggesting particularly pronounced disparities in these settings. The smallest gaps, though still substantial, appear in Croatia (+0.20), the Netherlands (+0.22), and Malta (+0.23), pointing to countries where gender differences in political literacy are less marked. In terms of levels, Estonia and Malta record the highest averages for both genders, indicating relatively strong political literacy overall, whereas women's lowest average scores are concentrated in Belgium, Italy, and France. Taken together, the figure suggests that political literacy is systematically lower among women across Europe, with considerable cross-country variation in the magnitude of the disparity.

Figure 3-60 presents the age breakdown in Political Literacy index, reporting weighted average scores across six age groups. Overall, in All Countries, scores increase strongly with age, rising from 1.432 among those aged 18-24 to 1.907 among those aged 65-80. This age profile is consistent with the accumulation of civic knowledge over the life course through repeated exposure to elections, institutional interactions, and ongoing engagement with political information. The steepness of the age-related increase differs across countries. The largest cohort differences are observed in Cyprus, Malta, and Hungary, indicating that political literacy rises particularly sharply with age in these contexts, potentially reflecting stronger generational divides in civic knowledge or engagement. At the same time, Malta and Estonia tend to score highly across all age groups, suggesting relatively broad-based political literacy rather than performance concentrated in only older cohorts. By contrast, Switzerland, Serbia, and Italy more frequently appear among the lower-scoring countries, indicating comparatively weaker levels of political literacy across the age distribution. Overall, the results point to a strong age pattern in political literacy, combined with substantial differences in levels and cohort gaps across countries.

Figure 3-61 reports weighted average Political Literacy scores by education level, distinguishing three categories: low (early childhood to lower secondary), medium (upper secondary to short-cycle tertiary), and high (tertiary education, from short-cycle programmes to doctoral studies). Overall, in All Countries, political literacy index increases with education (Low 1.246, Medium 1.539, High 1.809), highlighting a strong link between educational attainment and civic knowledge and understanding of political institutions. This pattern is expected given that education enhances general cognitive skills, increases exposure to civic and social science content, and is correlated with political interest and information acquisition. Cross-country dispersion remains substantial even among the highly educated. High-educated respondents score highest in Estonia (2.270), Malta (2.180), and Slovakia (2.063), whereas the lowest high-education averages are observed in Serbia (1.495), Belgium (1.501), and France (1.555). The size of the education gap (High minus Low) varies markedly across contexts: it is strongest in Cyprus (1.28), Hungary (1.15), and Slovakia (1.04), indicating pronounced stratification by education, while it is relatively small in Croatia (0.17) and Malta (0.22), suggesting weaker differentiation by education in these settings. Ireland exhibits a minor non-monotonicity, with the Medium-education group scoring slightly below the Low-education group, although the High-education group remains the top category. Overall, the figure indicates that educational attainment is a key correlate of political literacy, but that the strength of this association varies across national contexts.

Figure 3-59: Gender breakdown in Political Literacy by country

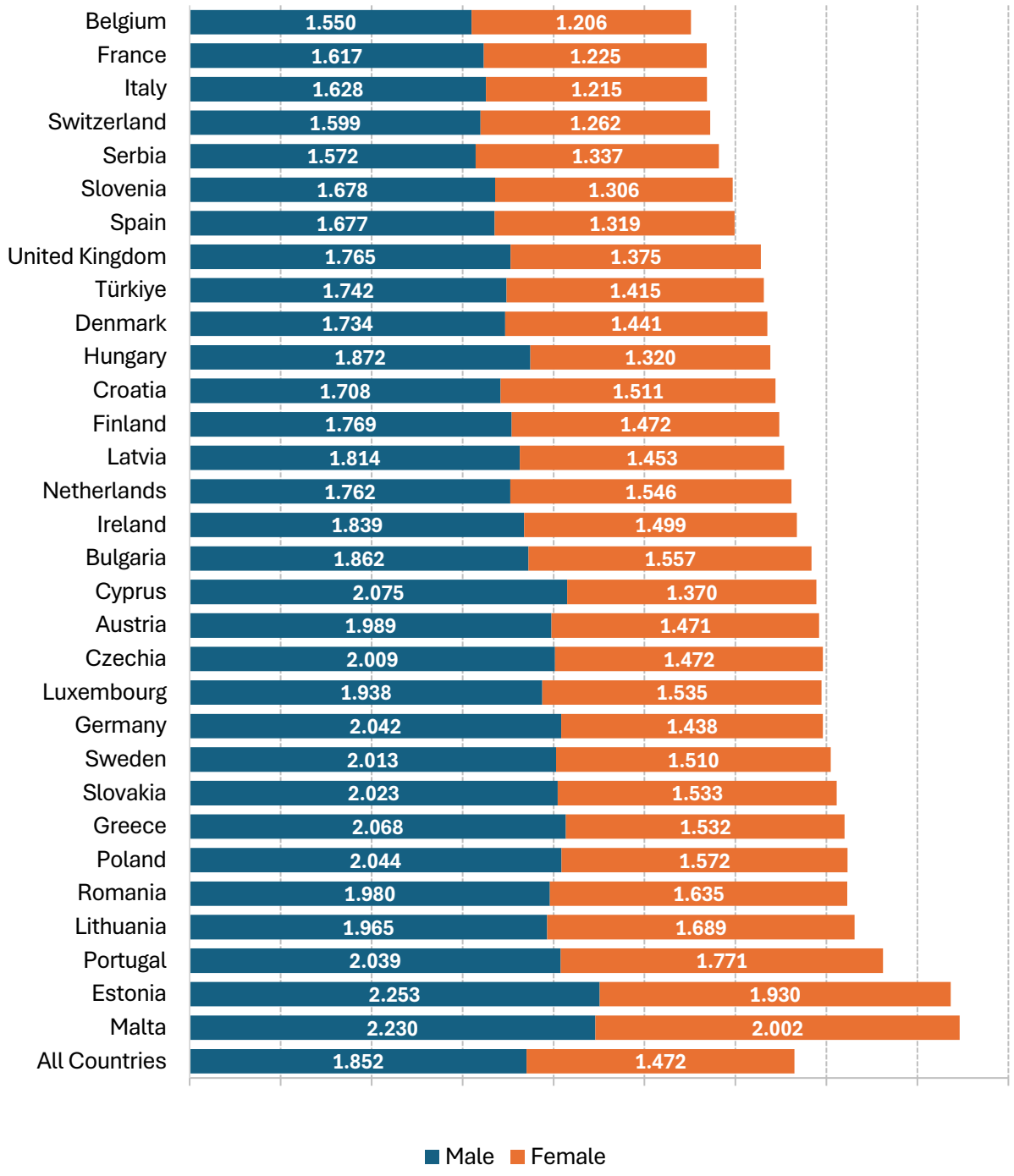


Figure 3-60: Age breakdown in Political Literacy by country

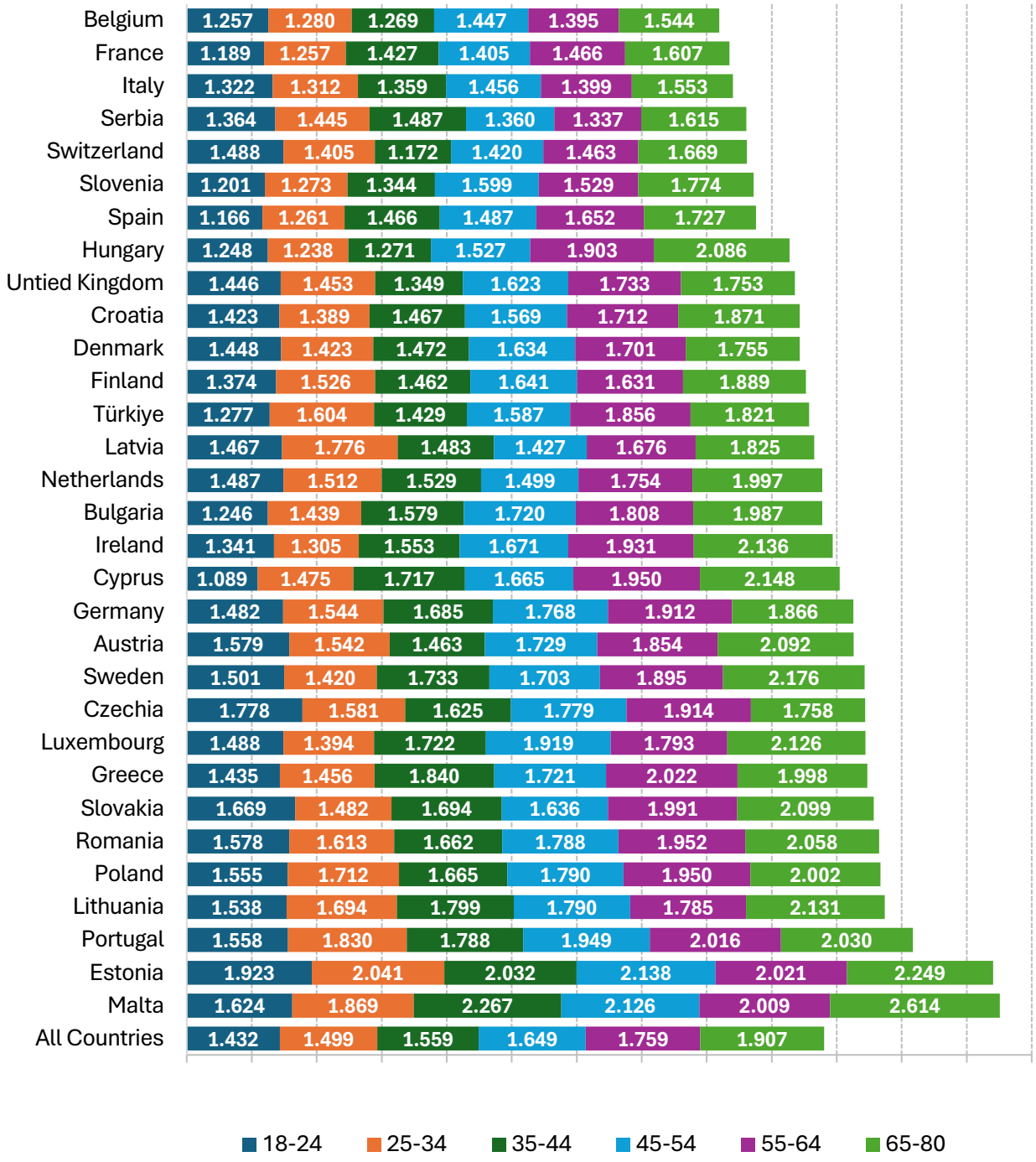


Figure 3-61: Educational breakdown in Political Literacy by country

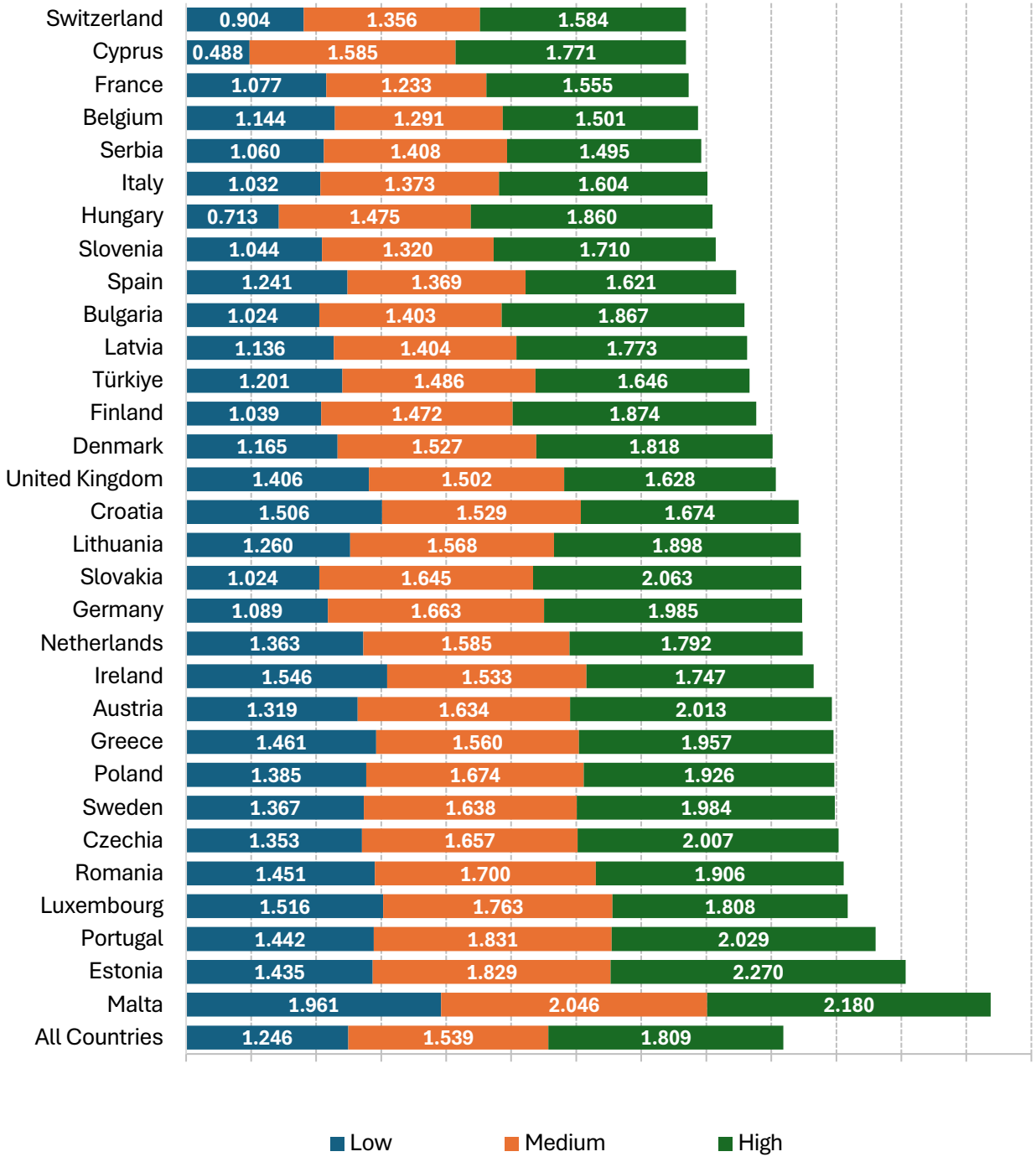


Figure 3-62: Income Composition in Political Literacy by country

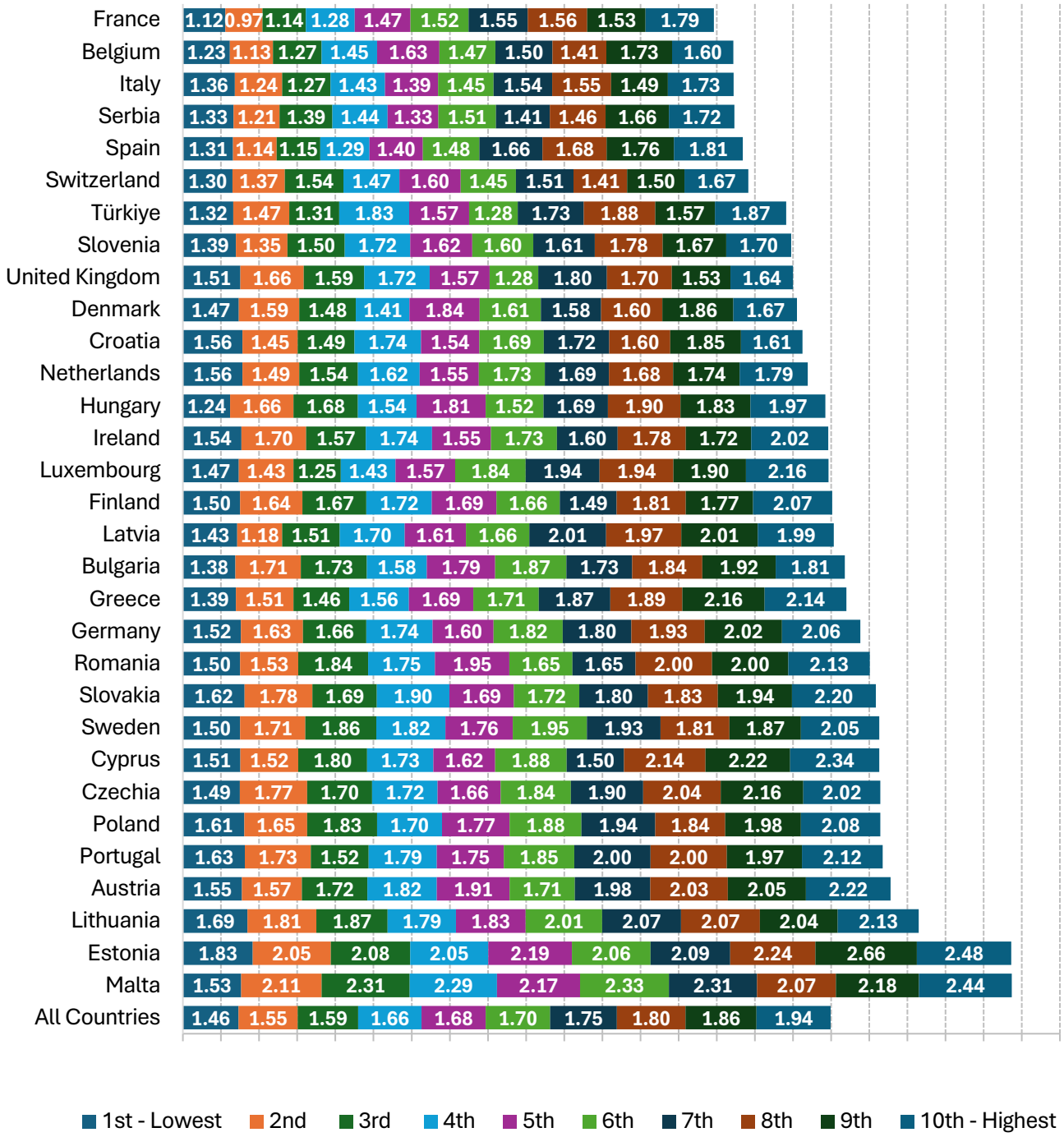


Figure 3-63: Wealth Composition in Political Literacy by country

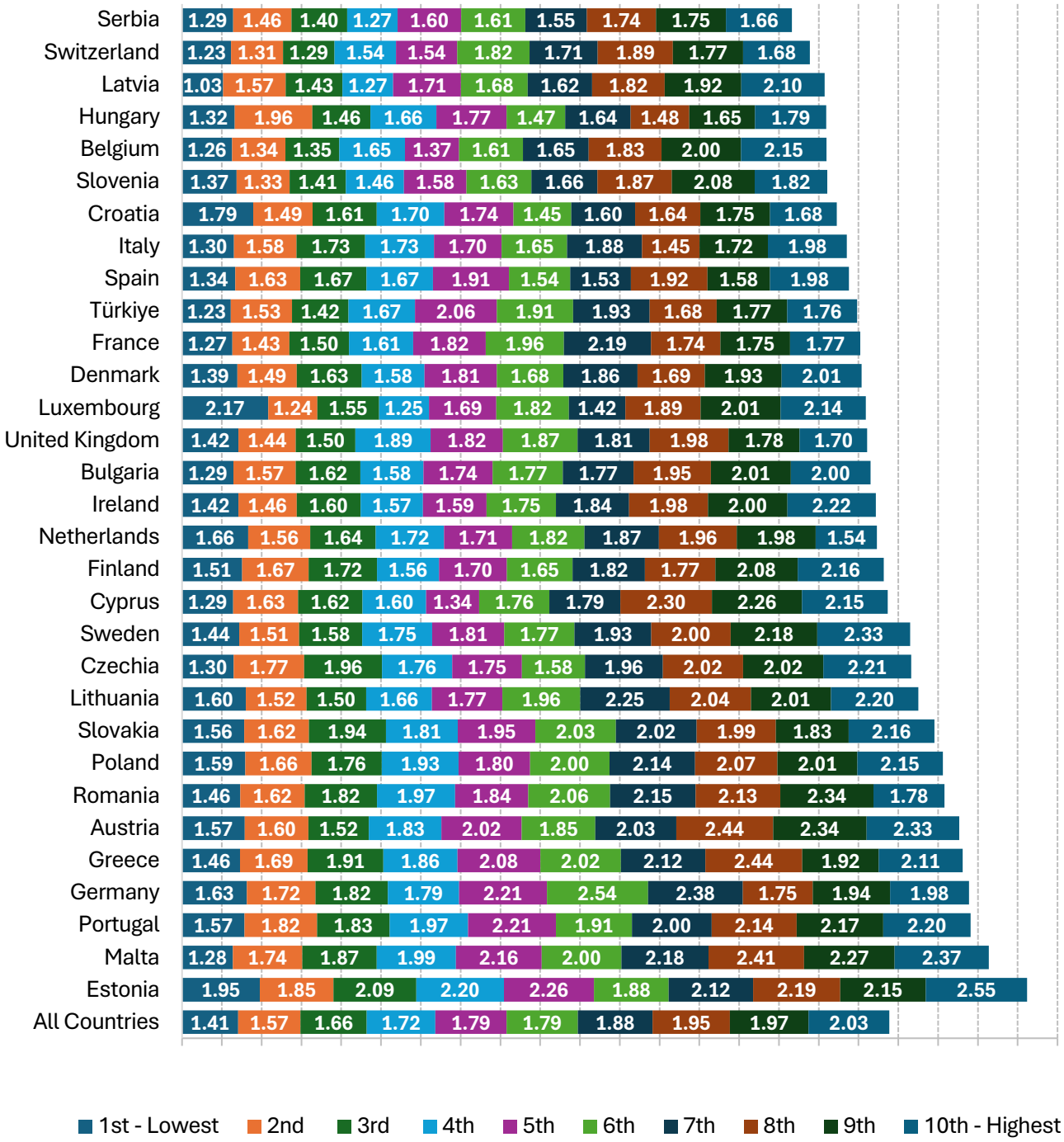


Figure 3-64: Skills Mismatch in Political Literacy by country

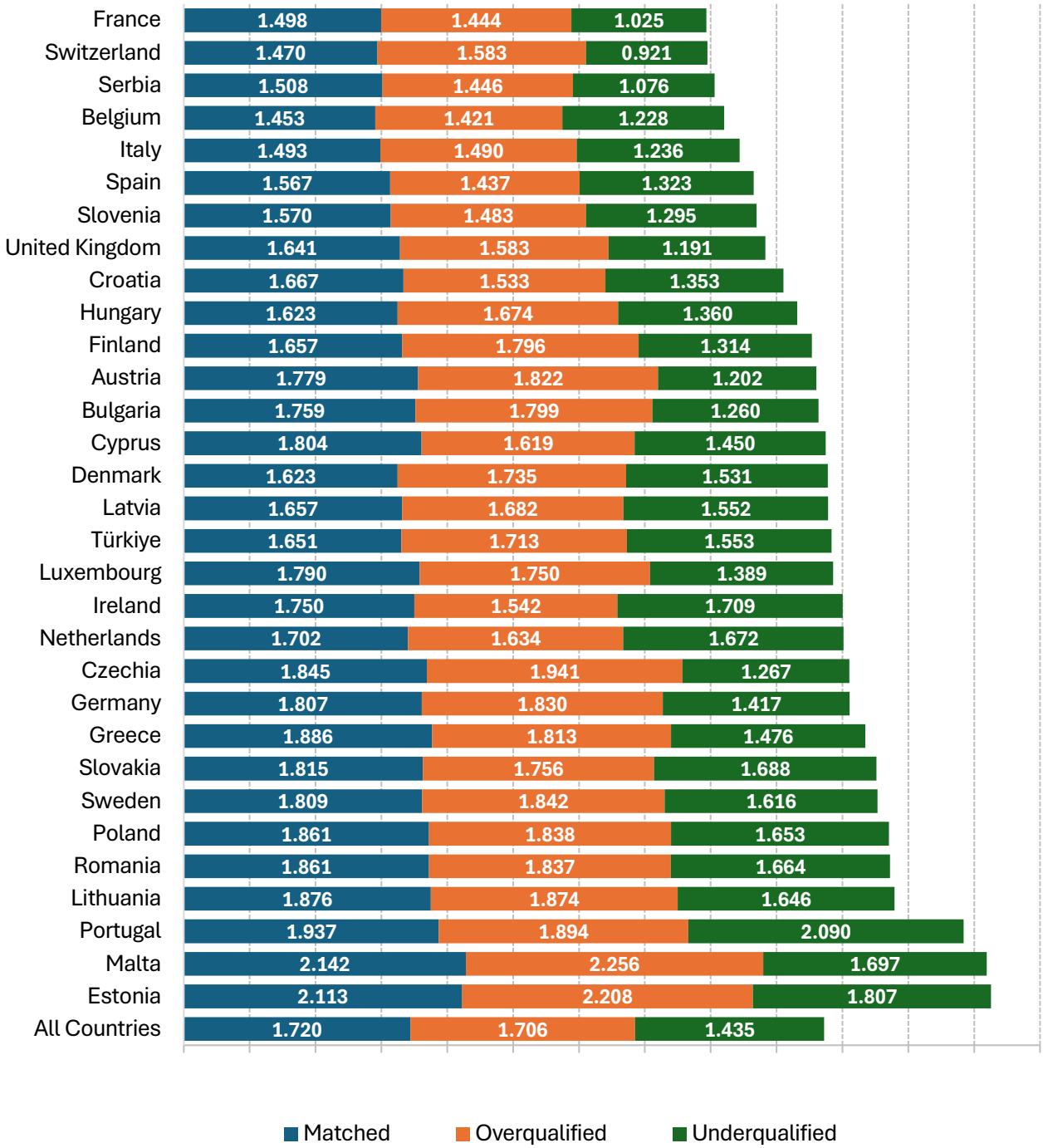


Figure 3-62 shows the weighted average scores of the Political Literacy index across income deciles, based on respondents' self-reported annual net disposable income (including wages, self-employment income, property income and government benefits) ranked from the 1st (lowest) to the 10th (highest) decile. In All Countries, political literacy increases from 1.46 (1st) to 1.94 (10th), a gap of +0.48, and the gradient is positive in all countries. The steepest patterns are in Malta (+0.91),

Cyprus (+0.83) and Greece (+0.75), while Croatia (+0.05), the United Kingdom (+0.13) and Denmark (+0.21) show comparatively small income differences. The highest 10th-decile average score is in Estonia (2.48), and the lowest 1st-decile average score is in France (1.11).

Figure 3-63 reports the weighted average scores of the Political Literacy index across wealth deciles, based on respondents' self-reported net household wealth (defined as the total value of all assets owned by the household, after deducting liabilities such as debts or loans) ranked from the 1st (lowest) to the 10th (highest) decile. In All Countries, political literacy increases smoothly with wealth deciles from 1.41 to 2.03 (gap +0.62), and the overall pattern is strictly monotonic. The largest wealth gradients appear in Malta (+1.09), Latvia (+1.07) and Czechia (+0.91). A small number of countries show slightly negative wealth differences (e.g., the Netherlands -0.13 and Croatia -0.10), suggesting non-monotonicity at the top in those cases. The highest 10th-decile average score is in Estonia (2.55), while the lowest 1st-decile average score is in Latvia (1.03).

Figure 3-64 reports weighted average Political Literacy scores by skills-matching status, linking individual skill profiles to respondents' perceived fit between their qualifications and the demands of their main job. Overall, in All Countries, matched respondents score marginally above overqualified (1.72 vs 1.71), and both are well above underqualified (1.43). The matched average score (1.72) exceeds the mismatched average (1.57), implying a match premium of 0.15, one of the larger premia across indices. This reflects a sizeable penalty associated with underqualification in this domain. Underqualified average score is the lowest in almost all countries. Only Portugal is a notable exception where underqualified is highest, reducing the matched-mismatched contrast. The largest mismatch-related dispersion occurs in Czechia (0.67) and Switzerland (0.66), whereas some countries show very small differences (e.g., the Netherlands).

3.3.2 Environmental Literacy

The Environmental index captures individuals' understanding of key environmental issues and climate-related topics, which is increasingly essential for everyday choices with environmental consequences (e.g. energy use, transportation, consumption). Households face a growing set of decisions with environmental content (energy consumption and conservation, technology adoption such as renewables or efficiency upgrades, and responses to mitigation policies). In this context, limited understanding of core climate mechanisms and policy targets can translate into misperceptions about the effectiveness of different actions and instruments, weakening the quality of private decisions and the feasibility of collective action. Consistent with this view, economics research shows that information constraints and literacy-related gaps shape energy-related behaviours and investments, and that beliefs and understanding about climate issues are tightly linked to support for climate policies and their distributional acceptability (e.g., Allcott & Rogers, 2014; Brent & Ward, 2018; Douenne & Fabre, 2022).

This index is constructed from three items capturing complementary "minimum competencies" for climate-relevant decision-making: (i) understanding the primary cause of climate change; (ii) recognising a key renewable energy technology; and (iii) knowing a central policy benchmark that frames EU climate action. This combination aligns with the trend in environmental economics literature, where behavioural responses depend not only on preferences and constraints, but also

on correct mental models and the ability to interpret policy-relevant information. Each question contributes one point if answered correctly; the index therefore ranges from 0 to 3, with higher values indicating better understanding these fundamentals.

Specifically, the Environmental Literacy index (range 0-3) is constructed from the following three TRAILS-I survey questions:

Q29. Which of the following is the primary cause of global climate change?
1. *Ozone layer depletion*
2. *Greenhouse gas emissions from human activities*
3. *Natural variations in Earth's temperature*
98. *I don't know*

Q30. Which of the following is considered a renewable energy source?
1. *Coal*
2. *Natural gas*
3. *Solar energy*
98. *I don't know*

Q31. What is the EU's target for reducing greenhouse gas emissions (gases that trap heat in the atmosphere and cause climate change) by 2030 compared to 1990 levels?
1. *20%*
2. *40%*
3. *55%*
99. *I don't know*

Conceptually, the three items jointly validate the intended skill domain. Q29 measures understanding of the anthropogenic greenhouse-gas mechanism, arguably the single most important "first principle" for interpreting climate claims and policy rationales. Q30 captures basic knowledge of mitigation technologies by distinguishing renewable from fossil energy sources, which is directly relevant for evaluating household energy choices and public investments. Q31 adds policy literacy by testing awareness of a widely used reference point for European climate governance, anchoring respondents' awareness of the institutional framing of climate policy and the scale of intended mitigation. The 0-3 range preserves a clear count interpretation, of how many of the three-core environmental-literacy elements a respondent demonstrates, while remaining easy to interpret in descriptive analysis and comparable across countries. Finally, the explicit "I don't know" option reduce random error measurement, making low scores more indicative of limited knowledge rather than random choice.

The measurement approach is consistent with existing studies, showing that cognition and knowledge constraints matter for environmentally relevant choices. For example, work on energy economics, shows that information and beliefs are behaviourally relevant for energy and environmental outcomes, whether through sustained responses to energy-related information (Allcott & Rogers, 2014) or through the complexity of evaluating energy-efficiency investments and their realised impacts (Fowlie et al., 2018). In addition, attitudes and willingness to act on climate issues have also evolved over time and across contexts, reinforcing the importance of measurable

knowledge and engagement as part of the human-capital foundations of climate action (Carlsson et al., 2021).

Table 3-9: Environmental Literacy index correlation matrix

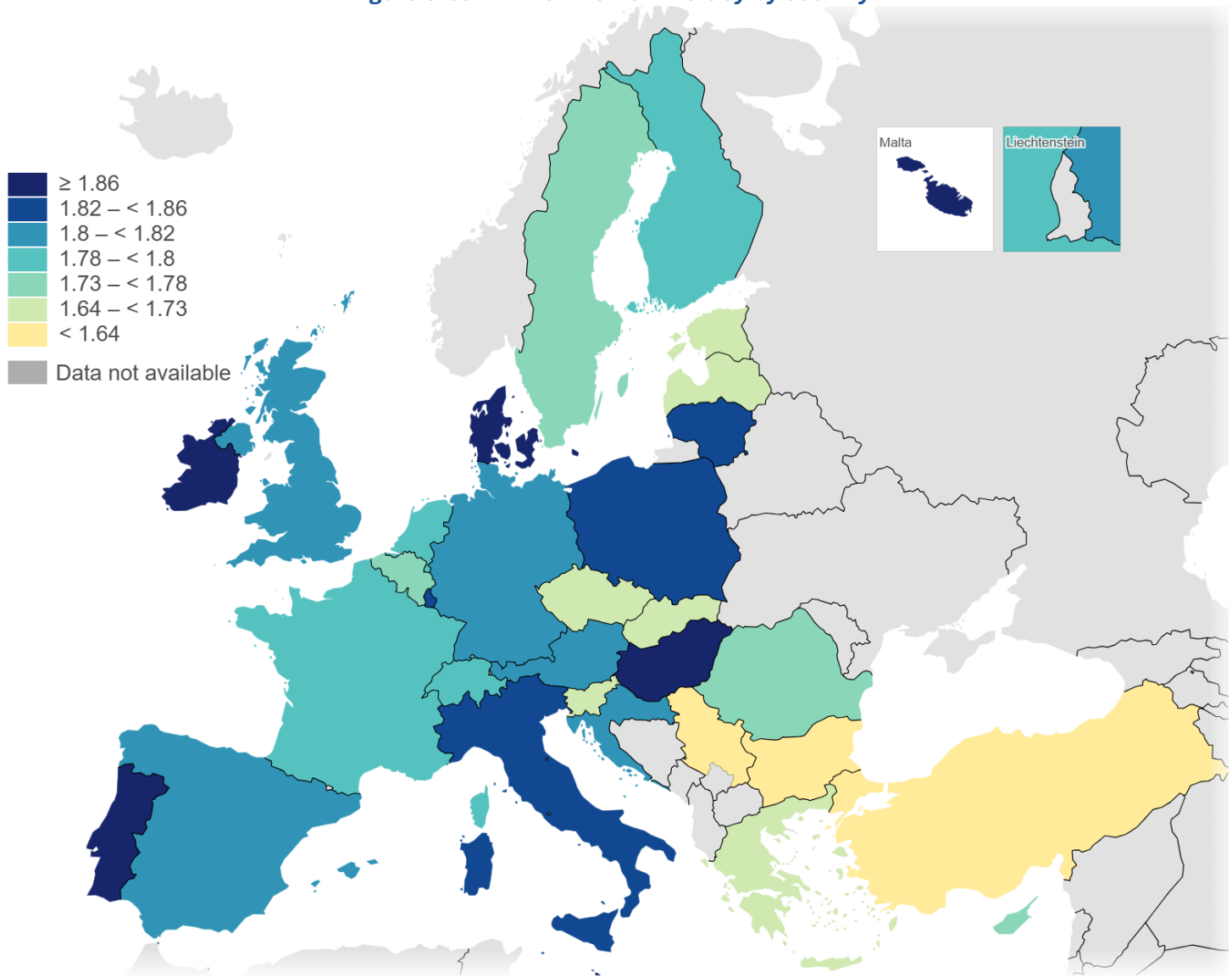
	Environmental Literacy index	Climate change cause	Renewable technology	EU climate benchmark
Environmental Literacy index	1.000			
Q29: Climate change cause	0.735**	1.000		
Q30: Renewable technology	0.516**	0.151**	1.000	
Q31: EU climate benchmark	0.594**	0.052**	0.049**	1.000

In Table 3-9, the correlation matrix for the Environmental Literacy Index indicates a generally coherent but somewhat uneven internal structure across its three components: understanding of the primary cause of climate change (Q29), knowledge of renewable energy technologies (Q30), and awareness of the EU's climate benchmark target (Q31). Each item is positively and significantly correlated with the overall index ($r = 0.516–0.735$, $p < 0.01$), supporting convergent validity. The strongest association is observed for knowledge of the main cause of climate change ($r = 0.735$), suggesting that this item is the most central component of the index. The EU climate benchmark ($r = 0.594$) and renewable technology knowledge ($r = 0.516$) also contribute meaningfully, though to a lesser extent. The variation in magnitudes indicates that while all three items load onto the same broader construct, factual knowledge about the scientific cause of climate change appears to be the strongest anchor of the index.

The inter-item correlations, however, are notably low ($r = 0.049–0.151$), particularly between the EU climate benchmark and both other items ($r = 0.052$ and $r = 0.049$). This suggests that knowledge of EU-specific policy targets is largely independent from understanding climate science or renewable technologies. Similarly, the modest correlation between climate change cause and renewable technology ($r = 0.151$) indicates that scientific understanding does not necessarily translate into knowledge of technological solutions. While the low inter-item correlations reduce the likelihood of redundancy, they also imply that environmental literacy in this survey captures conceptually distinct domains-scientific knowledge, technological awareness, and policy familiarity-rather than a tightly unified skill set. Overall, the structure supports the statistical validity of the index as a multidimensional construct, though it may exhibit lower internal consistency compared to other literacy domains with stronger inter-item associations.

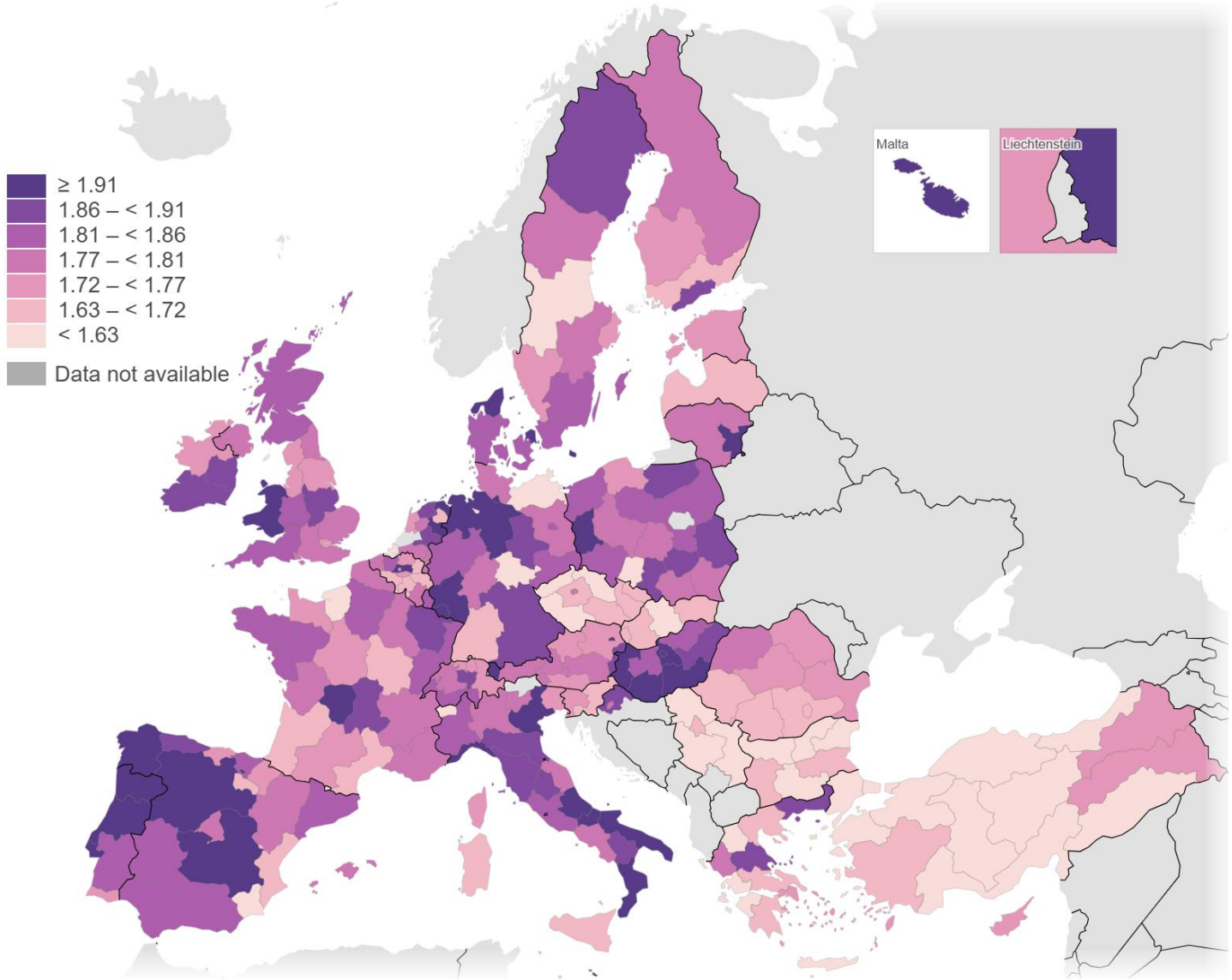
Figure 3-65 maps the weighted average of the Environmental Literacy index (0-3) across countries, using a quintile (equal-count) classification, which splits the distribution into classes with an equal number of values (legend cut-offs shown). The map suggests comparatively higher averages in several Western/Northern and Central European countries (e.g., Ireland, Denmark, Poland and Hungary), while lower averages are more prevalent in parts of South-Eastern Europe and the non-EU neighbour in the sample (e.g., Romania, Bulgaria, and Turkey). Grey areas indicate countries where data are not available.

Figure 3-65: Environmental Literacy by country



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 3-66: Environmental Literacy by region



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 3-66 shows the same indicator at the regional level, reported at NUTS-2 for most countries and at NUTS-1 for the UK, Germany, and Turkey due to data availability. The classification method is consistent with the country map (quintiles with equal numbers of values per class). that is masked by national averages. Higher-scoring clusters appear in parts of the South-Western Europe and Italy, alongside several regions in Central/Northern Europe, whereas lower-scoring regions are concentrated in much of South-Eastern Europe and across Turkey; several large countries show a mix of higher- and lower-performing regions rather than a uniform national profile. As above, grey areas denote missing data.

Figures 3-67 to 3-72 provide a systematic descriptive profile of the Environmental Literacy index across key socio-demographic and labour-market groups. For each breakdown, weighted averages are reported both by country and for the pooled sample ("All Countries"), enabling comparisons of within-country disparities alongside cross-country variation in overall levels. This structure helps to identify whether differences by gender, age, education, income, wealth and employment characteristics appear as broad regularities, or whether they depend on national context, including differences in environmental policy salience, climate-related communication, and green-transition exposure in households and workplaces.

Figure 3-67 shows the gender breakdown in Environmental Literacy index, reporting weighted average scores for women and men. Overall, in All Countries, men score higher than women, with a moderate average gap: 1.850 for men versus 1.694 for women (gap +0.156). While the direction of the difference is consistent, the magnitude varies across countries. The largest gender differentials are observed in Luxembourg (+0.33), Slovakia (+0.30), and Cyprus (+0.26), suggesting that gender disparities in environmental literacy are more pronounced in these settings. The smallest gaps appear in Croatia (+0.04), Slovenia (+0.06), and Estonia (+0.07), indicating near parity in average environmental literacy between women and men. In terms of levels, Hungary stands out as among the highest-scoring countries for men, suggesting relatively strong environmental literacy at least for this group. Women's lowest averages are concentrated in Türkiye and Slovakia, indicating that low overall performance in these contexts is compounded by comparatively lower scores among women.

Figure 3-68 depicts the age breakdown in Environmental Literacy index, reporting weighted average scores across six age groups. Unlike most indices, the overall age profile, in All Countries, is almost flat, ranging roughly between 1.752 and 1.793, with only a mild rise into ages 55-64 (1.794) and little change thereafter. This relatively stable age pattern suggests that environmental literacy, as captured by this index, may be less driven by life-cycle accumulation or cohort-based technology exposure than domains such as digital skills or AI literacy. Instead, environmental knowledge may be shaped by shared public information and broad societal exposure that affects age groups more evenly. Nevertheless, some countries display clearer cohort patterns. Estonia, for example, shows lower scores among older groups, indicating a negative age association in that context, while other countries exhibit peaks in late working ages, such as Türkiye around ages 55-64. In terms of cross-country levels, Hungary, Malta, and Portugal tend to score relatively high across age groups, whereas Czechia, Slovakia, and Bulgaria are more often among the lowest-scoring countries. These patterns indicate that country context matters more than age in shaping environmental literacy levels, even though specific countries can still exhibit notable cohort differences.

Figure 3-69 reports weighted average Environmental Literacy scores by education level, distinguishing three categories: low (early childhood to lower secondary), medium (upper secondary to short-cycle tertiary), and high (tertiary education, from short-cycle programmes to doctoral

studies). The overall education gradient, in All Countries, is present but modest (Low 1.570, Medium 1.711, High 1.844). This suggests that formal education contributes to environmental literacy, but the degree of stratification is not as steep as in domains more directly tied to formal training or advanced cognitive skills. Cross-country variation is considerable even among the highly educated. High-educated respondents score highest in Hungary (2.055), Portugal (1.988), and Malta (1.982), while the lowest High-education averages are observed in Bulgaria (1.644), Serbia (1.679), and Türkiye (1.685). The education gap (High minus Low) is particularly large in Slovakia (0.51), Germany (0.50), and Cyprus (0.50), indicating strong differentiation by education in these contexts. By contrast, the gap is very small in Croatia (0.02), Greece (0.06), and Slovenia (0.06), suggesting that educational differences in environmental literacy are limited there. Overall, the figure indicates that environmental literacy is positively associated with education, but that the strength of this association varies widely across countries, potentially reflecting differences in how environmental topics are integrated into education and public discourse.

Figure 3-70 shows the weighted average scores of the Environmental Literacy index across income deciles, based on respondents' self-reported annual net disposable income (including wages, self-employment income, property income and government benefits) ranked from the 1st (lowest) to the 10th (highest) decile. The overall pattern, in All Countries, is again positive but modest, from 1.70 (1st) to 1.91 (10th), implying +0.21. The largest positive gradients are in Greece (+0.50), Slovakia (+0.41) and Serbia (+0.41), while the Netherlands stands out with a negative income gradient (-0.13) and Denmark, which has a flat/slightly negative gradient (-0.01). The highest 10th-decile average score is in Hungary (2.10), and the lowest 1st-decile average score in Serbia (1.38).

Figure 3-71 reports the weighted average scores of the Environmental Literacy index across wealth deciles, based on respondents' self-reported net household wealth (defined as the total value of all assets owned by the household, after deducting liabilities such as debts or loans) ranked from the 1st (lowest) to the 10th (highest) decile. The overall pattern, in All Countries, is positive but moderate compared to the previous indices: 1.68 (1st) to 1.95 (10th), gap +0.26. The strongest gradients are in Greece (+0.63), Türkiye (+0.51) and Germany (+0.47), while the pattern is almost flat in Luxembourg (0.00). The Netherlands and Switzerland show negative wealth differences (-0.18 and -0.12, respectively). The highest 10th-decile average score is in Germany (2.24), and the lowest 1st-decile average score is in Slovakia (1.43).

Figure 3-72 reports weighted average Environmental Literacy scores by skills-matching status, linking individual skill profiles to respondents' perceived fit between their qualifications and the demands of their main job. Overall, in All Countries, the top two groups are nearly identical, matched (1.80) and overqualified (1.79), while underqualified is lower (1.65). Comparing matched to the mismatched average (1.72), the matched premium is 0.08. The matched-mismatched gap is therefore driven mainly by the lower underqualified scores rather than differences between matched and overqualified. Underqualified is the lowest group in most countries, but it becomes the highest in Malta and Cyprus, reducing the matched-mismatched separation. Dispersion across mismatch groups is largest in Serbia (0.50) and Malta (0.44), while some countries show near-parity across groups (e.g., Türkiye).

Figure 3-67: Gender breakdown in Environmental Literacy by country

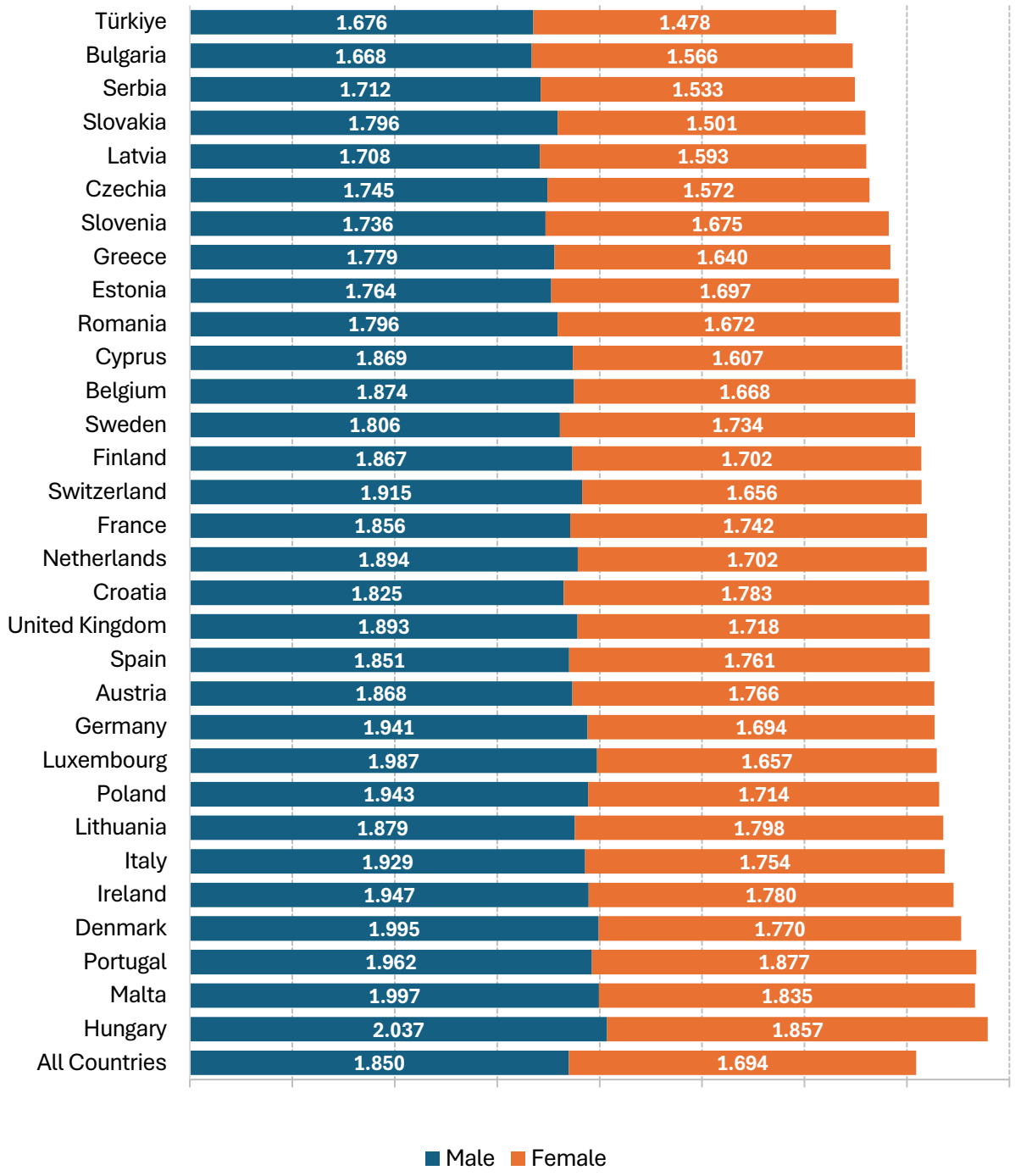


Figure 3-68: Age breakdown in Environmental Literacy by country

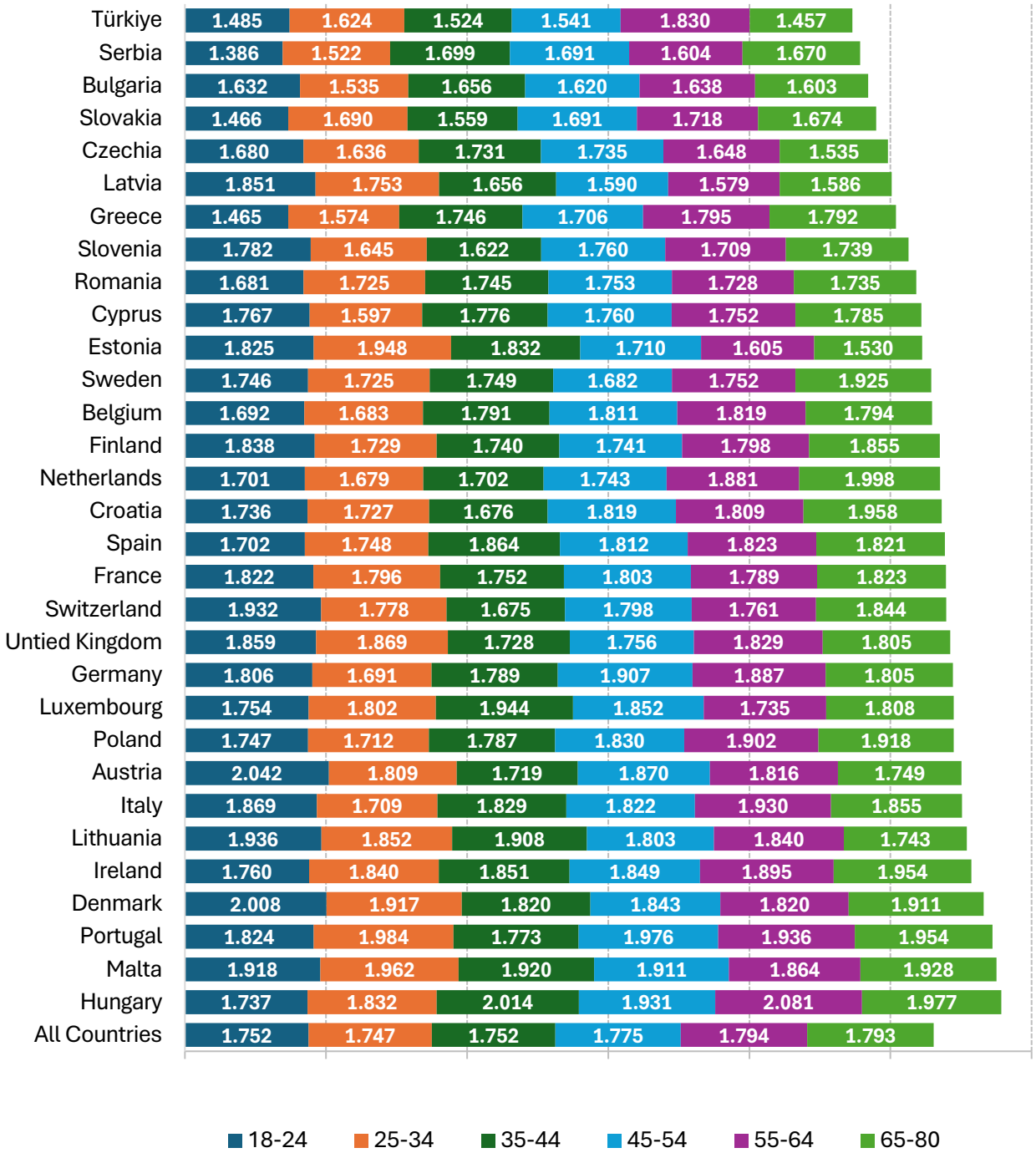


Figure 3-69: Educational breakdown in Environmental Literacy by country

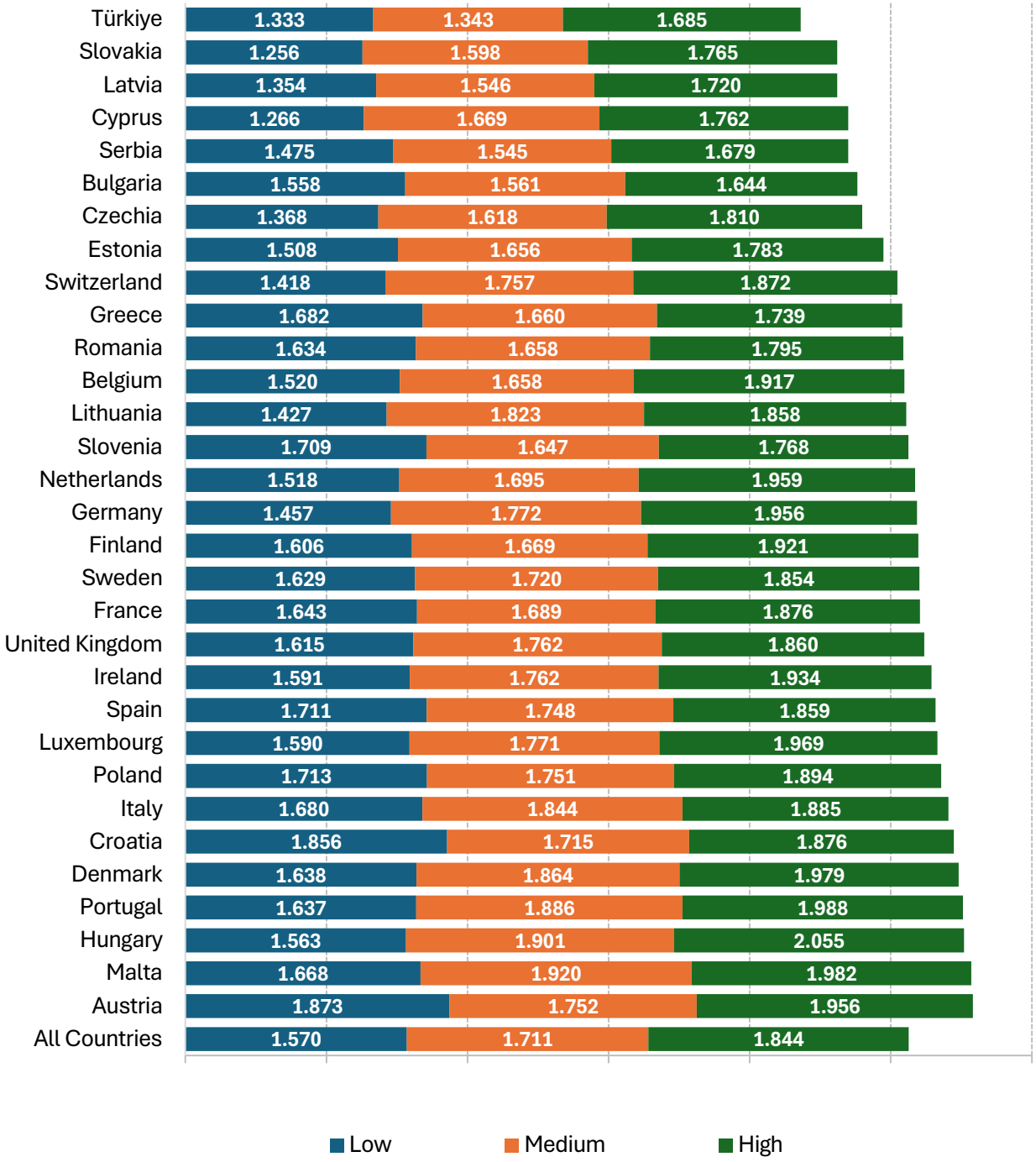


Figure 3-70: Income Composition in Environmental Literacy by country

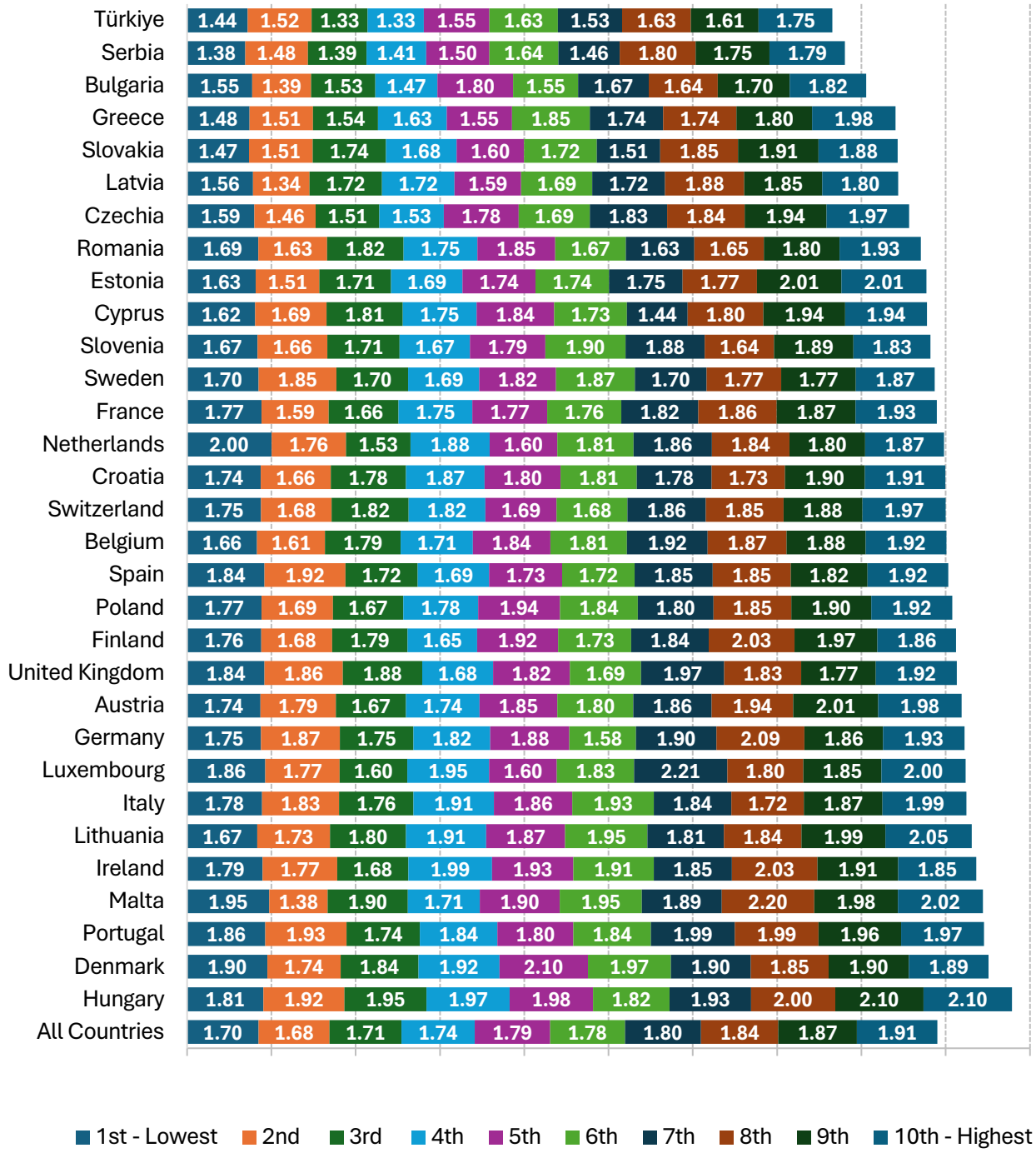


Figure 3-71: Wealth Composition in Environmental Literacy by country

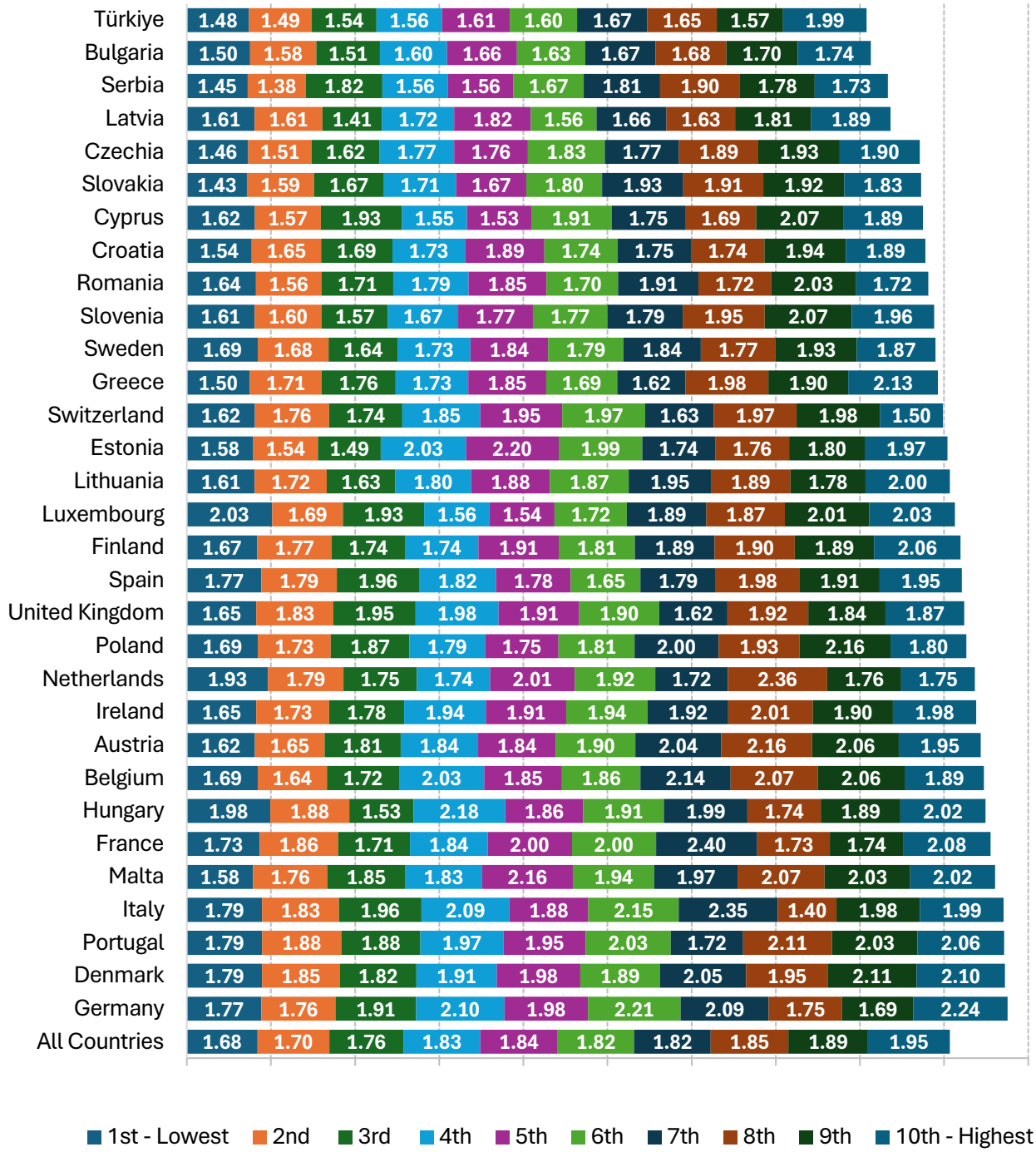
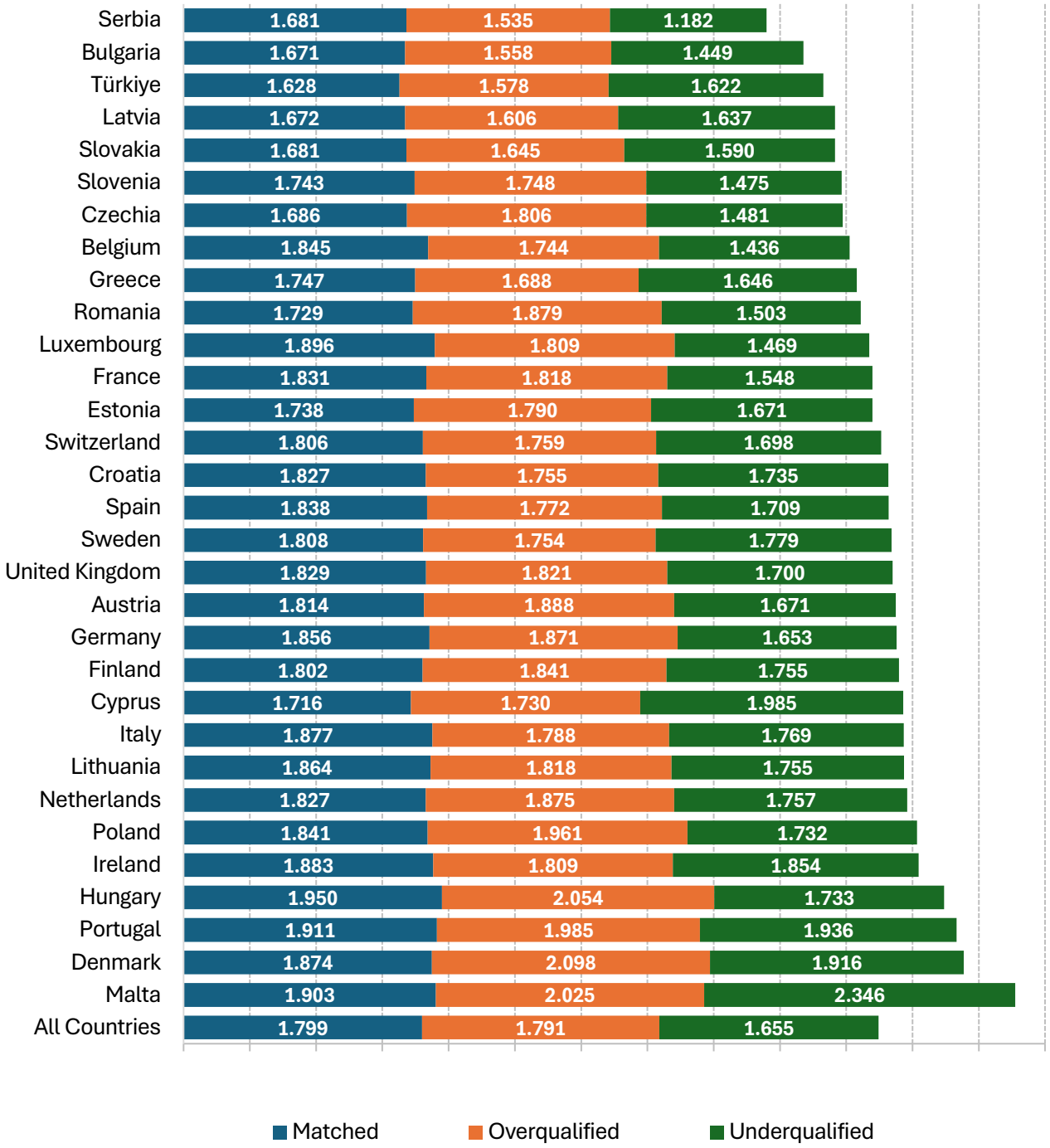


Figure 3-72: Skills Mismatch in Environmental Literacy by country



3.3.3 Sustainable Financial Literacy

The Sustainable Financial Literacy index captures individuals' ability to understand corporate social responsibility (CSR) and, more broadly, the environmental, social, and governance (ESG) dimensions that increasingly shape corporate behaviour, financial markets, and household financial choices. As sustainable investing and ESG-labelled products have expanded, individuals are more often exposed, directly or indirectly through pension plans, mutual funds, and banking products, to claims about firms' environmental impact, labour practices, and governance quality. A basic understanding of what sustainable responsibility looks like (as opposed to purely symbolic action) therefore becomes a decision-relevant skill for evaluating information, avoiding greenwashing, and aligning financial choices with preferences. This is consistent with research showing that sustainability considerations affect investor demand and capital allocation (Hartzmark and Sussman, 2019), and with theoretical and empirical work linking sustainability characteristics and climate risk to asset prices and expected returns (Bolton and Kacperczyk, 2021).

This index is constructed from three items that map closely to the core ESG pillars (environmental performance, social responsibility, and governance/oversight) and therefore provide a compact but conceptually coherent measure of CSR-related understanding. Importantly, this domain is information-intensive and noisy: ESG assessments and ratings often diverge across providers, making it harder for non-experts to evaluate corporate claims. This strengthens the case for measuring a baseline level of literacy about what responsible business practices involve (Berg et al., 2022).

Specifically, the Sustainable Financial Literacy index (range 0-3) is constructed from the following three TRAILS-I survey questions:

Q14. Which of the following company actions best demonstrates a commitment to reducing environmental harm over time?
1. *Reducing emissions from production processes*
2. *Running advertising campaigns about green values*
3. *Offsetting emissions without making changes to the way the company operates (i.e., instead of reducing the pollution they cause, the company pays for projects elsewhere – like planting trees – that remove or save the same amount of pollution from the air.)*
98. *I don't know*

Q15. Which of the following best describes a socially responsible business practice?
1. *Offering loyalty discounts to customers*
2. *Ensuring safe working conditions and fair pay*
3. *Prioritising profits even if workers face poor conditions*
98 *I don't know*

Q16. Why is it important for a company to have independent members on its board of directors?
1. *To allow faster business decisions*
2. *To improve oversight and reduce conflicts of interest*
3. *To ensure directors always agree with the Chief Executive Officer*
99. *98. I don't know*

Conceptually, these items provide strong coverage of the intended construct. Q14 distinguishes between real operational decarbonisation and actions that may be primarily reputational, which is central for interpreting firms' climate claims in contexts where carbon exposure and climate risk matter for valuation and investor behaviour (Bolton and Kacperczyk, 2021). Q15 captures whether respondents recognise that CSR includes core labour and workplace standards (safety and fair pay), aligning with evidence that social practices relating to employees are economically relevant and can be reflected in firm outcomes and market valuation (Edmans, 2011). Q16 targets a foundational governance mechanism, independent oversight, linked to limiting conflicts of interest and strengthening monitoring, a central theme in the corporate governance literature and recent evidence on board design and independence mandates.

In addition, the index's 0-3 range of the is appropriate because it preserves a transparent count interpretation, how many of these three core CSR/ESG elements a respondent demonstrates, while remaining simple and comparable for cross-country use in a harmonised survey setting. Finally, the explicit "I don't know" option helps reduce guessing and improves interpretability, especially in a domain where individuals may be exposed to ESG/CSR language without having a clear understanding of its content.

Table 3-10 : Sustainable Financial Literacy index correlation matrix

	Sustainable Financial Literacy index	Environmental commitment	Social responsibility	Board independence
Sustainable Fin. Literacy index	1.000			
Q14: Environmental commitment	0.741**	1.000		
Q15: Social responsibility	0.707**	0.251**	1.000	
Q16: Board independence	0.726**	0.232**	0.400**	1.000

Table 3-11 presents the correlation matrix for the Sustainable Financial Literacy Index and its three components: environmental commitment (Q14), social responsibility (Q15), and board independence (Q16). Each item shows a strong and statistically significant correlation with the overall index ($r = 0.707–0.741$, $p < 0.01$), indicating that all three dimensions contribute substantively and relatively evenly to the composite measure. Environmental commitment exhibits the highest association with the index ($r = 0.741$), followed by board independence ($r = 0.726$) and social responsibility ($r = 0.707$). The consistently high correlations suggest strong convergent validity, supporting the interpretation of the index as a coherent measure of sustainable financial literacy that integrates environmental, social, and governance (ESG) dimensions.

The inter-item correlations are moderate ($r = 0.232–0.400$, $p < 0.01$), indicating meaningful conceptual overlap without redundancy. The strongest association is observed between social

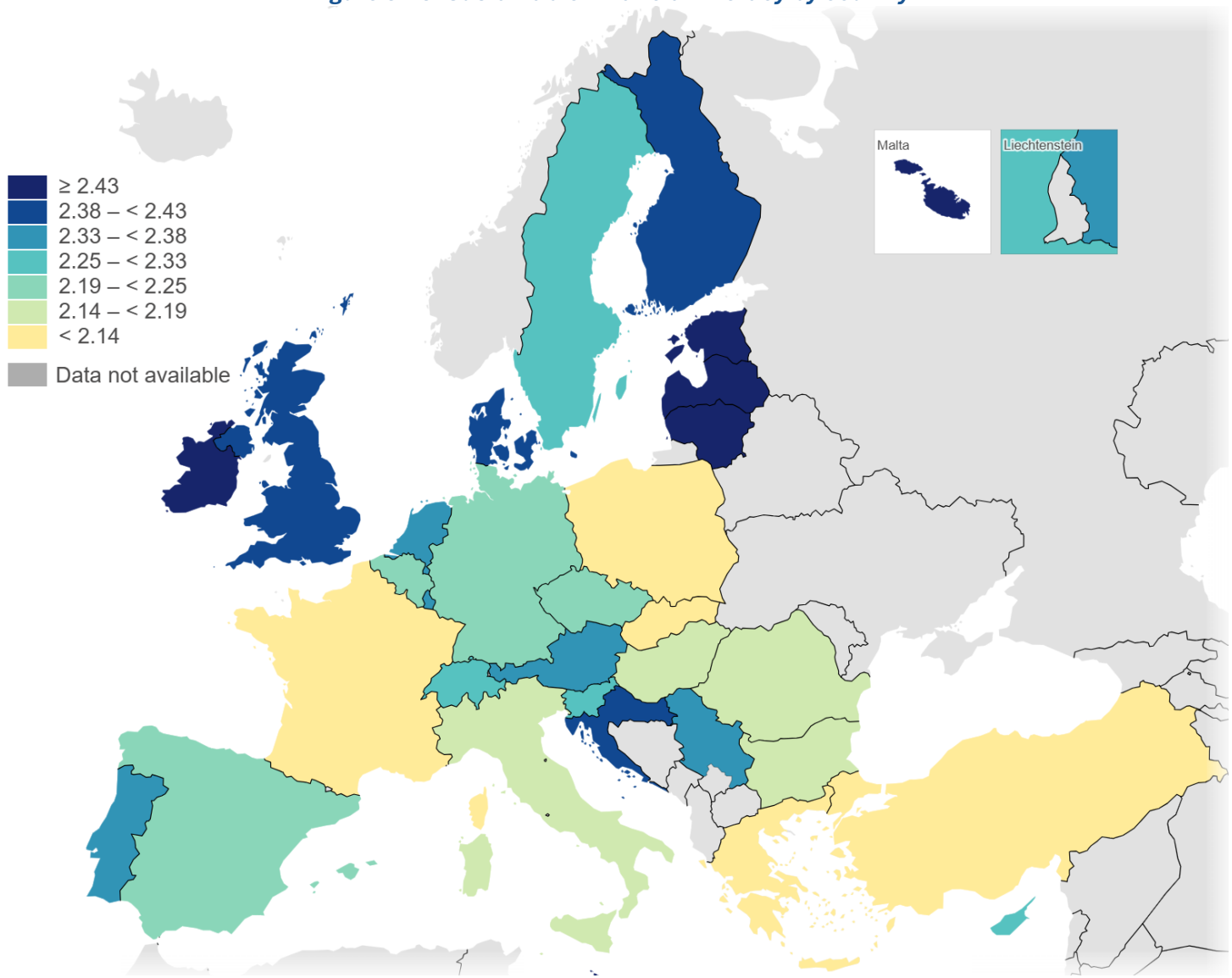
responsibility and board independence (r = 0.400), which is theoretically consistent, as both reflect governance and ethical oversight considerations within corporate structures. The relationships between environmental commitment and the other two items (r = 0.232–0.251) are weaker but still positive, suggesting that environmental literacy represents a related yet somewhat distinct component within the broader ESG framework. Compared to other literacy domains where inter-item correlations were very low, this structure indicates a more integrated conceptual framework. Overall, the correlation pattern provides strong evidence for the statistical validity of the Sustainable Financial Literacy Index as a multidimensional yet internally coherent construct aligned with established ESG principles.

The regional map applies the same equal-count classification approach, dividing the distribution of the Sustainable Financial Literacy index (0–3) into seven classes with an equal number of observations. Results are shown at the NUTS-2 level for most countries and at NUTS-1 for the United Kingdom, Germany, and Turkey, reflecting differences in territorial statistical structures. This regional representation allows for a more granular assessment of within-country variation, highlighting subnational disparities that may be obscured in country-level averages. Figure 3-19 complements this perspective by presenting the weighted country-level averages of the Sustainable Financial Literacy index. Using the same equal-count (seven-class) classification, darker shades indicate higher levels of understanding of CSR/ESG principles. Higher scores are concentrated in several Northern and Western European countries - including Ireland, the United Kingdom, Finland, Latvia, Estonia, and Lithuania - whereas a number of Southern and parts of Eastern and South-Eastern European countries fall into lower classes. This pattern points to substantial cross-country variation in sustainable financial literacy across Europe. Grey shading denotes countries for which data are not available.

Figure 3-73 shows the same indicator at the regional level (NUTS-2 for most countries and NUTS-1 for the UK, Germany, and Turkey). The classification approach is consistent with the country map (equal-count classes). It reveals substantial within-country heterogeneity: countries with mid-range national averages often contain both high- and low-scoring regions, suggesting that sustainable financial literacy is spatially clustered and not well captured by national means alone. As above, grey areas indicate missing regional data.

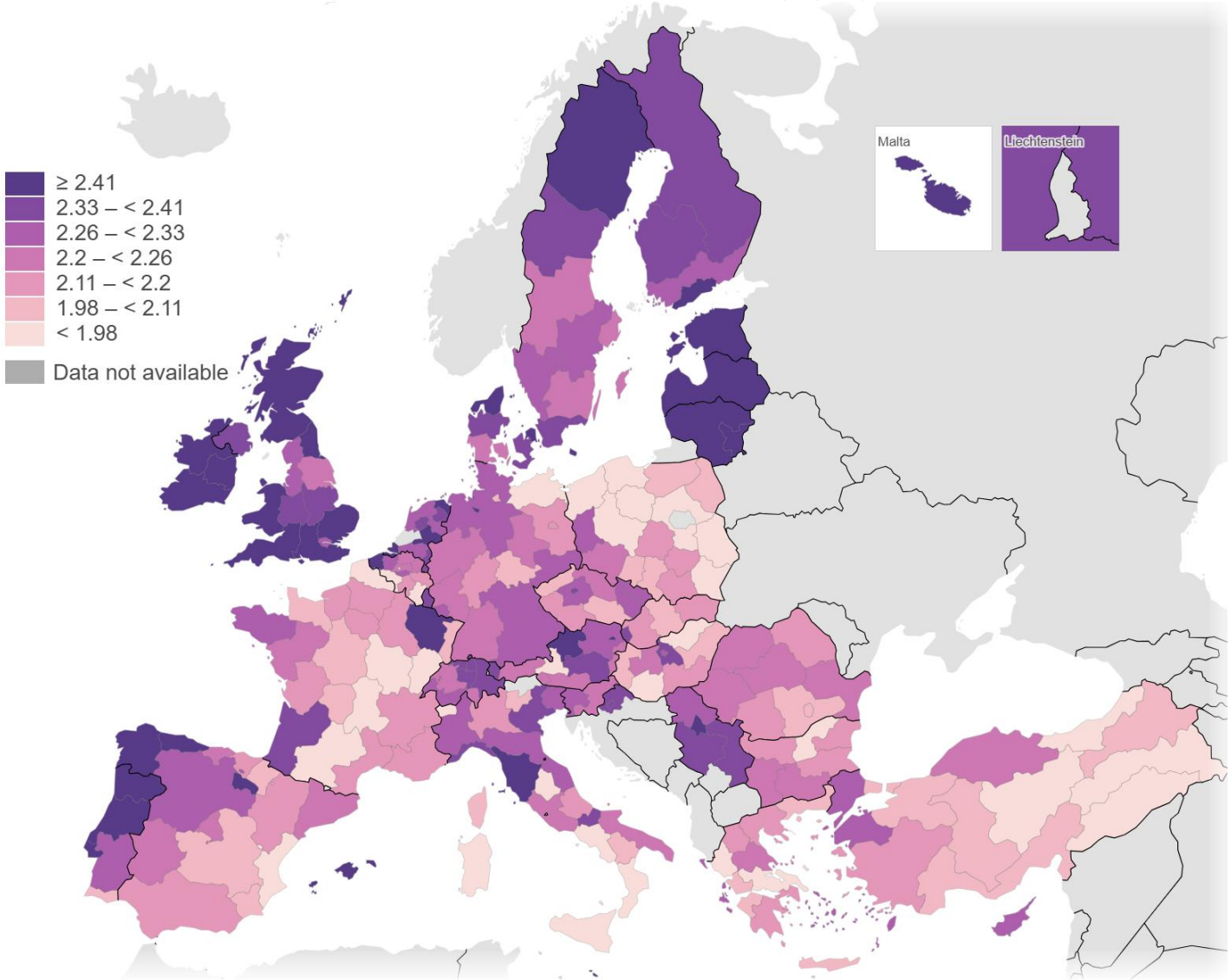
Figure 3-74 reports the weighted average scores of the Sustainable Financial Literacy index across wealth deciles, based on respondents' self-reported net household wealth (defined as the total value of all assets owned by the household, after deducting liabilities such as debts or loans) ranked from the 1st (lowest) to the 10th (highest) decile. Overall, in All Countries, the index rises from 2.10 to 2.54 across the wealth distribution (gap +0.44). Wealth gradients are largest in Slovakia (+0.68), Slovenia (+0.65) and Switzerland (+0.64). Several countries show a mild reversal at the top, e.g., Spain (-0.09) and France (-0.07, while the Netherlands is close to flat (-0.02). The highest 10th-decile average score is in Ireland (2.80), and the lowest 1st-decile average score is in Slovakia (1.80).

Figure 3-73: Sustainable Financial Literacy by country



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 3-74: Sustainable Financial Literacy by region



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figures 3-75 to 3-80 provide a systematic descriptive profile of the Sustainable Financial Literacy index across key socio-demographic and labour-market groups. For each subgroup breakdown, weighted averages are reported both by country and for the pooled sample ("All Countries"), enabling comparisons of within-country disparities alongside cross-country differences in overall levels. This structure helps to identify whether subgroup differences are broadly similar across Europe or whether they vary in ways that reflect differences in institutional context and exposure to sustainability-related information.

Figure 3-75 depicts the gender breakdown in Sustainable Financial Literacy index, reporting weighted average scores for women and men. Overall, in All Countries, the gender gap is very small: 2.308 for men versus 2.261 for women, a difference of about +0.047. However, some countries display a female advantage, highlighting that the direction of gender differences is not uniform in this index. The largest male advantages are observed in Switzerland (+0.24), Italy (+0.18), and Luxembourg (+0.18), indicating contexts where men's scores exceed women's more clearly. Conversely, women score higher in Croatia (-0.09), Spain (-0.08), and Estonia (-0.07), with smaller female advantages also visible in countries such as the Netherlands and Sweden. Several countries report near-zero gender gaps (e.g., Latvia, Greece, Serbia), suggesting close parity. In terms of levels, Estonia and Malta record among the highest scores for both genders, indicating broadly strong sustainable financial literacy in these contexts, whereas Türkiye is among the lowest for both women and men.

Figure 3-76 shows the age breakdown in Sustainable Financial Literacy, reporting weighted average scores across six age groups. The overall pattern, in All Countries, shows a steady increase with age from 2.053 among those aged 18-24 to 2.442 among those aged 65-80. This monotonic pattern is consistent with the accumulation of knowledge and experience relevant to sustainability and finance over the life course, including exposure to environmental issues, household financial decisions, and potentially increased attention to long-term risks and planning at older ages. The magnitude of age differences varies across countries. Age gaps are particularly large in Hungary, Luxembourg, and Sweden, where younger cohorts score noticeably below older cohorts, suggesting stronger cohort differences in exposure to sustainability-related financial concepts. In terms of country levels, Estonia, Malta, and Lithuania tend to score relatively high across age groups, indicating strong performance that is not confined to older respondents. By contrast, Türkiye, France, and Hungary more frequently record lower values, pointing to comparatively weaker sustainable financial literacy across the age distribution.

Figure 3-77 reports weighted average Sustainable Financial Literacy scores by education level, distinguishing three categories: low (early childhood to lower secondary), medium (upper secondary to short-cycle tertiary), and high (tertiary education, from short-cycle programmes to doctoral studies). Overall, in All Countries, average index's scores increase with education (Low 1.933, Medium 2.181, High 2.412), indicating that educational attainment is strongly associated with sustainable financial literacy. This pattern is expected given that education is linked to stronger general skills (numeracy, comprehension) as well as greater exposure to information about sustainability and finance through formal curricula and information environments. Cross-country differences remain large even among highly educated respondents. The highest High-education averages are observed in Estonia (2.726), Finland (2.595), and Malta (2.575), while the lowest are in Türkiye (2.127), Poland (2.148), and Greece (2.230). Education gradients (High minus Low) are especially pronounced in Cyprus (1.27), Hungary (1.17), and Lithuania (0.82), indicating strong stratification by education. By contrast, the gradient is small in Serbia (0.11) and Bulgaria (0.12), suggesting weaker differentiation by education in these contexts. Malta is the main case showing a

mild non-monotonicity, with the Medium-education group slightly exceeding the High-education group, which may reflect compositional differences within education categories or the role of non-formal learning channels.

Figure 3-78 shows the weighted average scores of the Sustainable Financial Literacy index across income deciles, based on respondents' self-reported annual net disposable income (including wages, self-employment income, property income and government benefits) ranked from the 1st (lowest) to the 10th (highest) decile. In All Countries, the index rises from 2.16 (1st) to 2.41 (10th), a gap of +0.25. The most pronounced gradients are found in Hungary (+0.62), Serbia (+0.58) and Luxembourg (+0.56), whereas a few countries show mild reversals at the top compared to the bottom, most notably the United Kingdom (-0.07) and Denmark (-0.07) and the Netherlands (-0.06). The highest 10th-decile average score is in Estonia (2.77), while the lowest 1st- decile average score is in Hungary (1.88).

Figure 3-79 presents the weighted average scores of the Sustainable Financial Literacy index across wealth deciles, based on respondents' self-reported net household wealth (defined as the total value of all assets owned by the household, after deducting liabilities such as debts or loans) ranked from the 1st (lowest) to the 10th (highest) decile. Overall, in All Countries, the index rises from 2.10 to 2.54 across the wealth distribution (gap +0.44). Wealth gradients are largest in Slovakia (+0.68), Slovenia (+0.65) and Switzerland (+0.64). Several countries show a mild reversal at the top, e.g., Spain (-0.09) and France (-0.07, while the Netherlands is close to flat (-0.02). The highest 10th-decile average score is in Ireland (2.80), and the lowest 1st-decile average score is in Slovakia (1.80).

Figure 3-80 reports weighted average Sustainable Financial Literacy scores by skills-matching status, linking individual skill profiles to respondents' perceived fit between their qualifications and the demands of their main job. Overall, in All Countries, matched (2.34) and overqualified (2.33) average scores are almost identical, and both exceed underqualified average (2.09). Comparing matched to the mismatched average (2.21), the matched score implies a match premium of 0.13. As with environmental literacy, the premium is mainly driven by the lower underqualified scores rather than gaps between matched and overqualified. Underqualified is lowest in almost all countries, but it is the highest group in Portugal and Croatia. The widest mismatch-related differences appear in Austria (0.71) and Czechia (0.56), whereas differences are comparatively small in countries such as the Netherlands.

Figure 3-75: Gender breakdown in Sustainable Financial Literacy by country

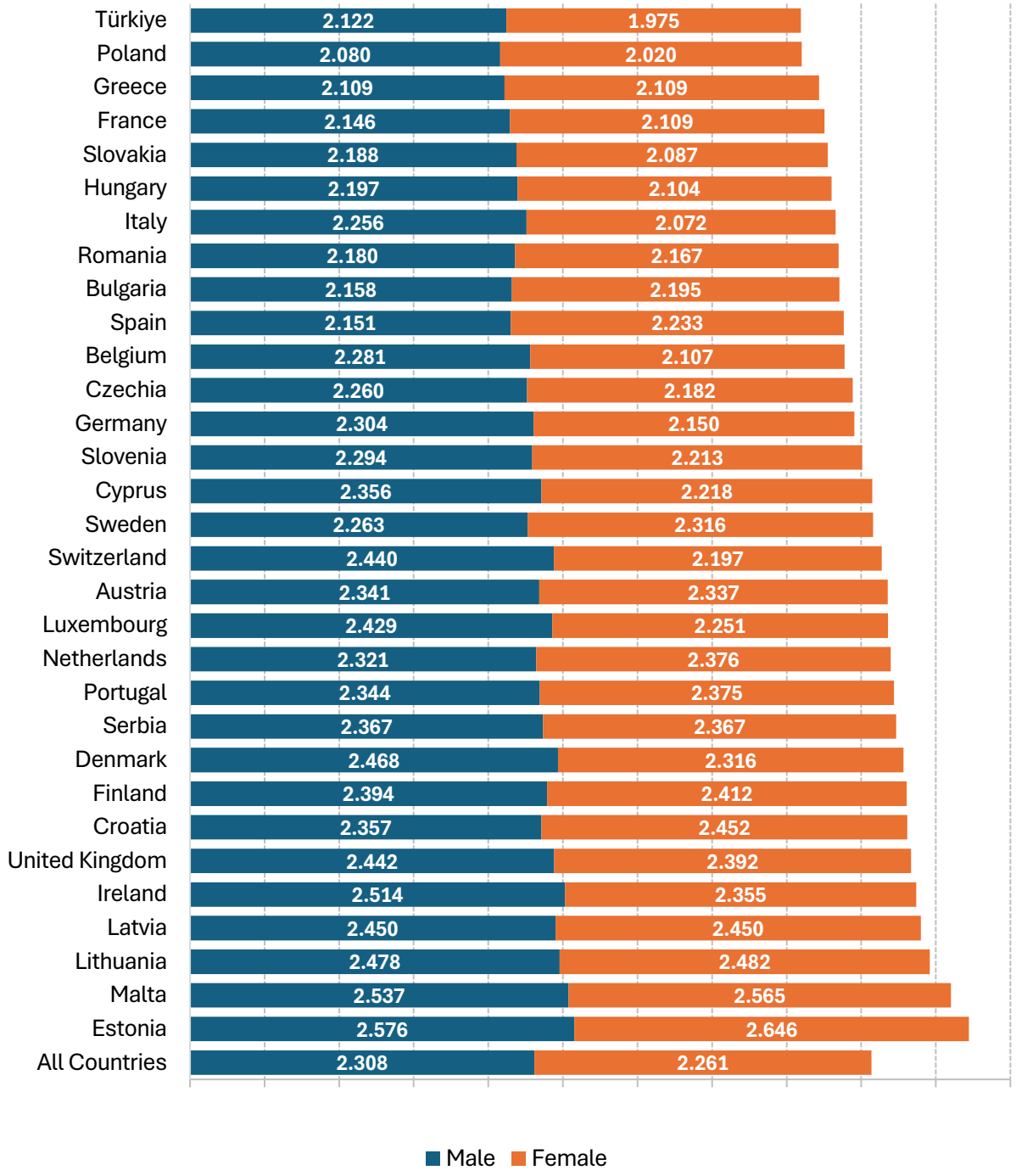


Figure 3-76: Age breakdown in Sustainable Financial Literacy by country

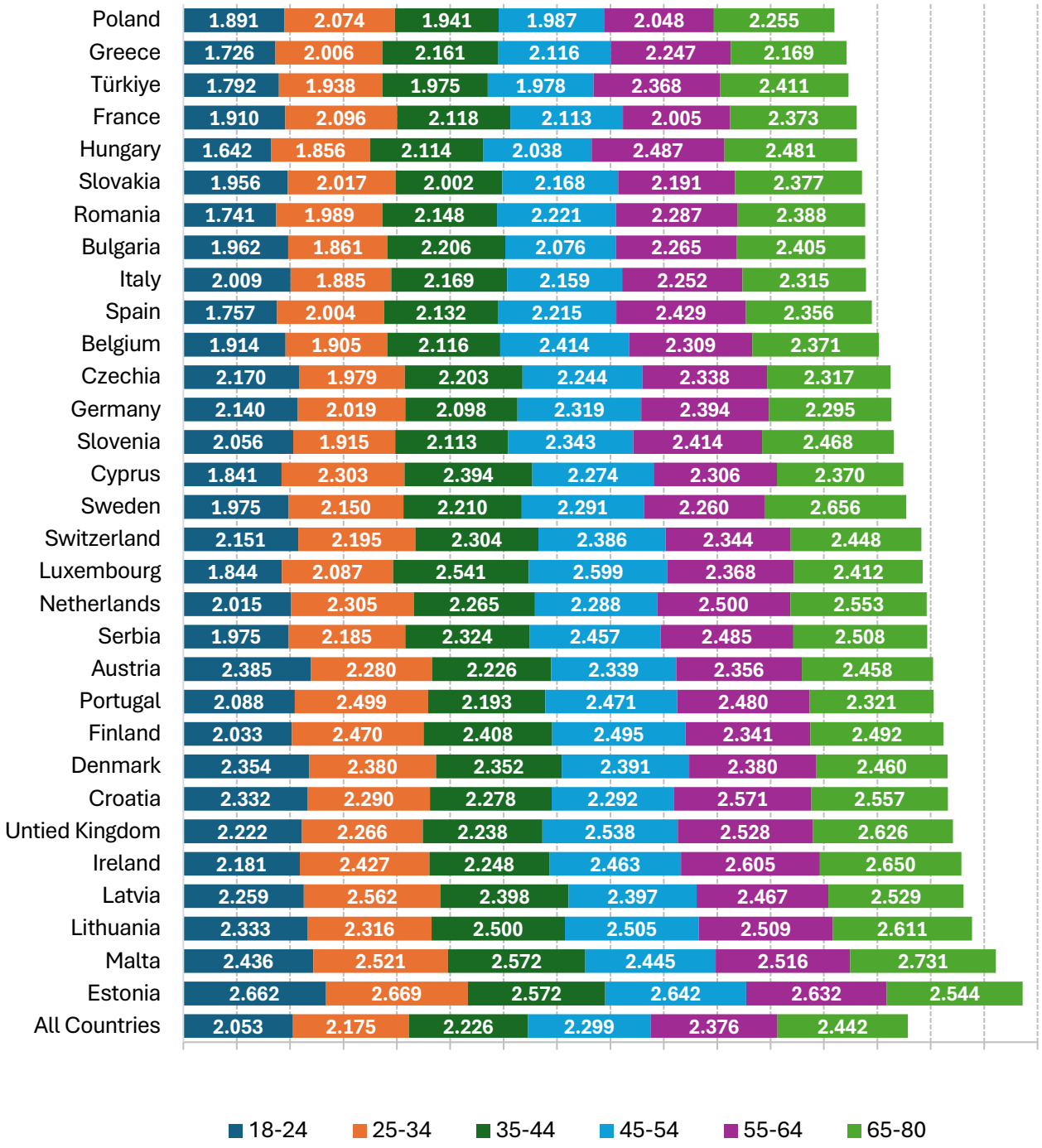


Figure 3-77: Educational breakdown in Sustainable Financial Literacy by country

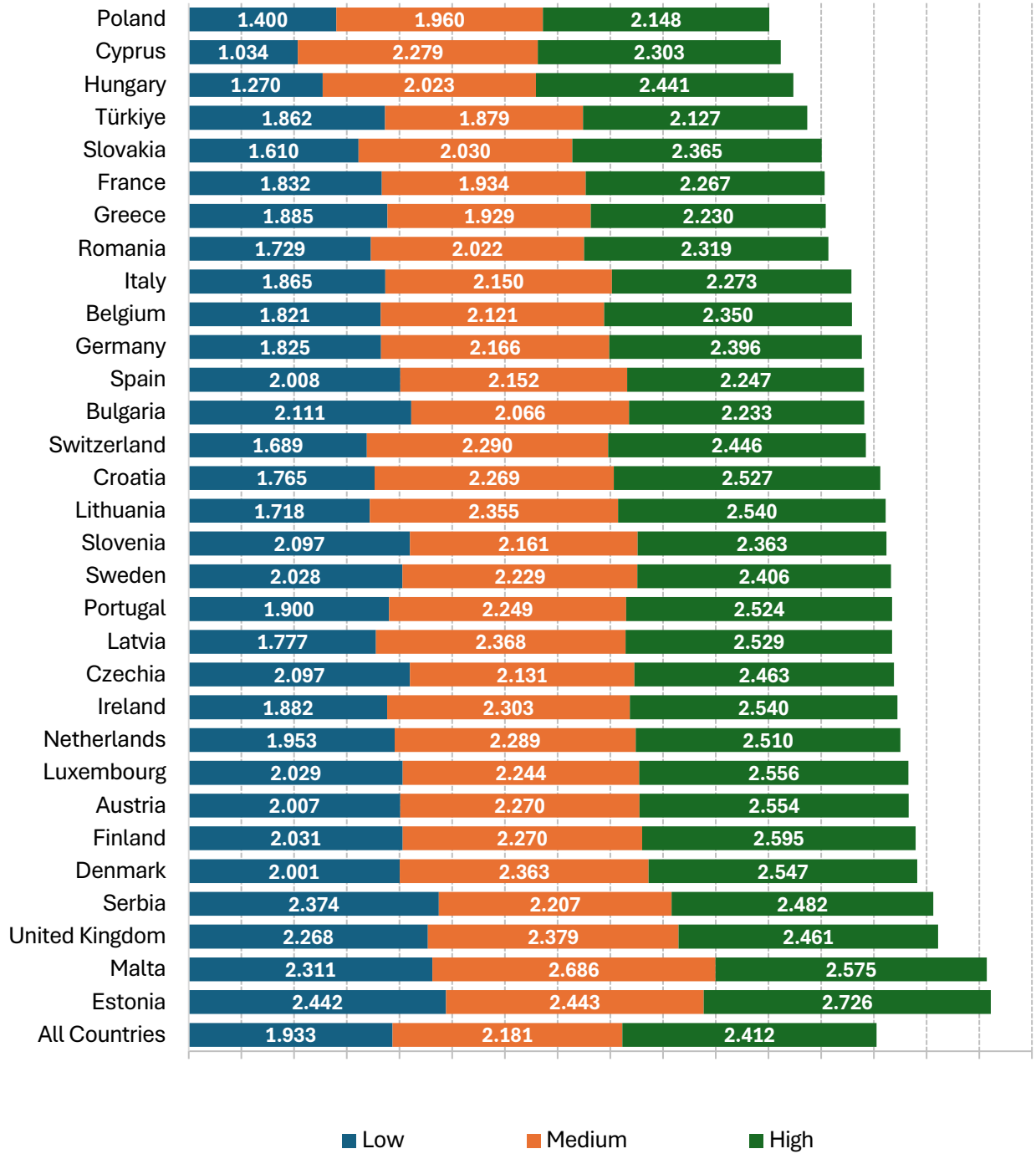


Figure 3-78 Income Composition in Sustainable Financial Literacy by country

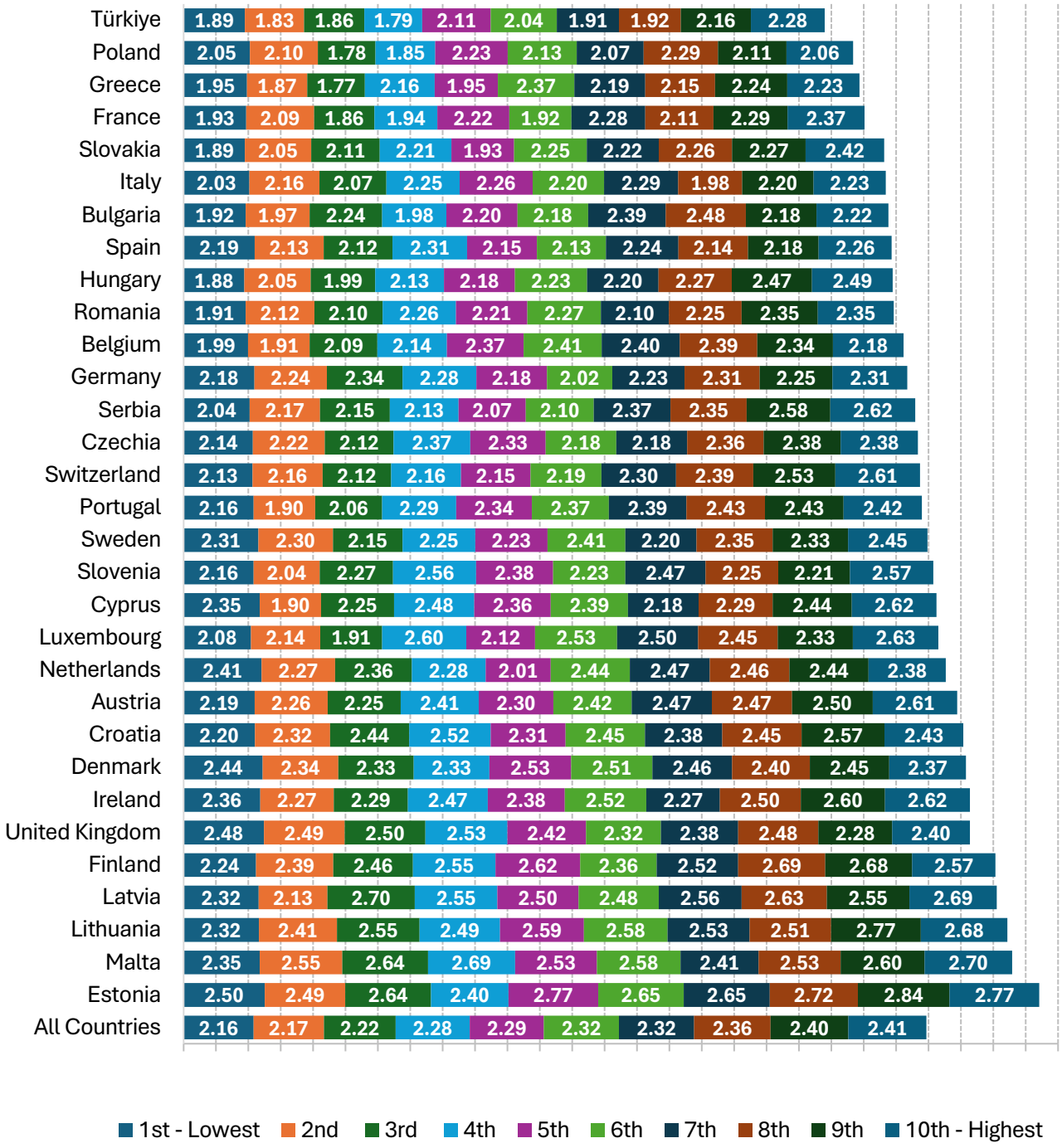


Figure 3-79 Wealth Composition in Sustainable Financial Literacy by country

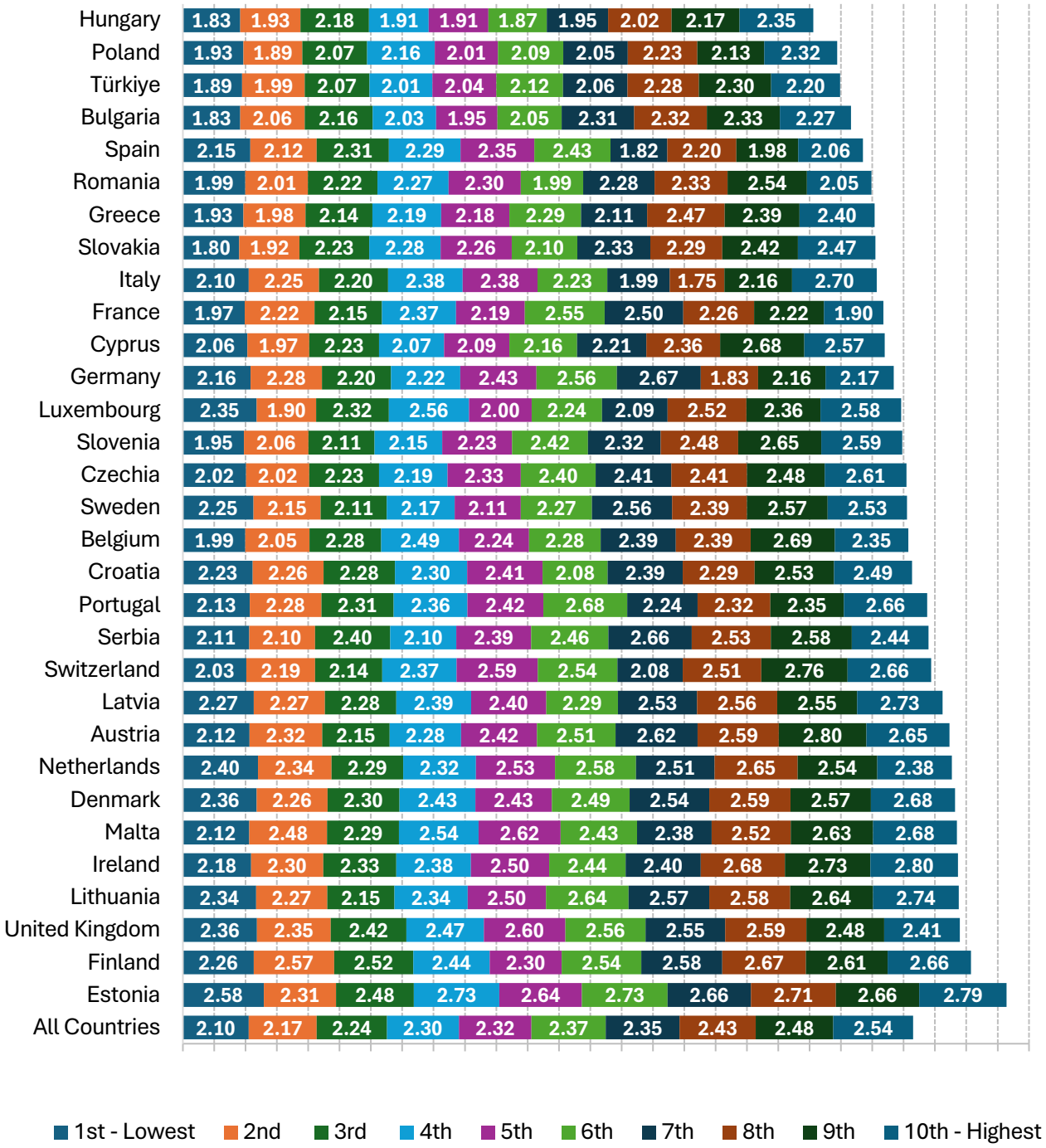
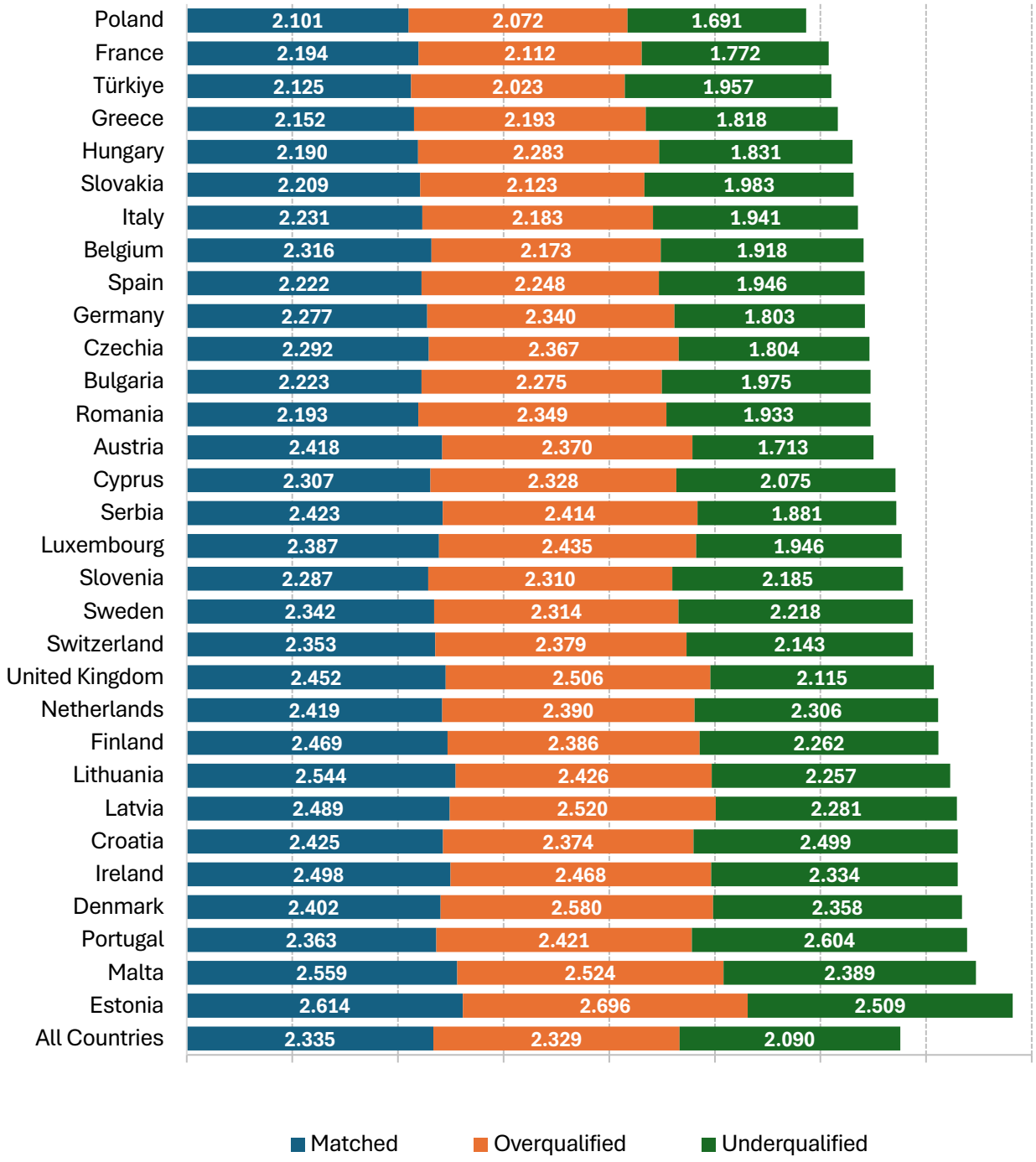


Figure 3-80 Skills Mismatch in Sustainable Financial Literacy by country



3.4 Human and Social Transferable Skills

3.4.1 Human Literacy

The Human Literacy index captures a set of basic competencies related to individuals' ability to engage constructively with others through inclusive social identification, empathy, and effective collaboration in diverse settings. Human literacy is increasingly relevant as a portable skill for both labour-market performance and social cohesion. A growing share of work is organised around teamwork, client interaction, and coordination across diverse groups; as a result, interpersonal competencies and social skills are increasingly rewarded in the labour market (Deming, 2017). At the same time, cultural and political fragmentation heightens the value of citizens' capacity to maintain cooperative relationships across lines of difference, making human literacy a plausible addition to a new skills taxonomy alongside more conventional cognitive and digital competencies.

To capture this concept, the Human Literacy Index aggregates three survey items that corresponds to three core elements: (i) inclusive identification with "unity in diversity," (ii) empathic responding to colleagues' stress, and (iii) constructive collaboration in culturally diverse teams. Each item is coded as one point when the respondent selects the response, yielding an additive index ranging from 0 to 3.

Specifically, the Human Literacy index (range 0-3) is constructed from the following three TRAILS-I survey questions:

Q38. To what extent do you personally identify with the EU motto "United in Diversity"?
This motto refers to the idea that Europeans are stronger together, despite differences in culture, language, or history.

1. *I strongly identify with this motto and feel it reflects my personal values*
2. *I somewhat identify with it, but I'm unsure how it applies in practice*
3. *I don't feel it represents me, even if I understand the idea*
4. *I've never really thought about it*
98. *I don't know*
99. *I prefer not to answer*

Q39. When a colleague expresses frustration or stress at work, which of the following best reflects how you usually respond?

1. *I ask them if they want to talk and try to listen without judging*
2. *I check in briefly, but usually give them space to handle it on their own*
3. *I try to distract them or change the topic to something more neutral*
4. *I generally avoid getting involved in emotional situations at work*
98. *I don't know*
99. *I prefer not to answer*

Q40. Imagine you are working in a diverse team with people from different cultural backgrounds. How do you usually approach this?

1. *I actively encourage open conversation about different working styles and perspectives*

2. *I try to be respectful but avoid focusing on cultural differences*
3. *I mostly concentrate on my own work and avoid managing team dynamics*
4. *I find it challenging and sometimes feel misunderstood or disconnected*
98. *I don't know*
99. *I prefer not to answer*

Conceptually, Q38 captures an individual's orientation toward an inclusive identity ("stronger together despite differences"), which is directly relevant for cooperation in diverse communities and workplaces. Q39 targets empathic, non-judgmental listening which is a practical interpersonal competence that supports trust-building and conflict reduction in day-to-day interactions. Q40 measures the ability to translate respect for diversity into active coordination practices (encouraging dialogue about differing cultures and perspectives), which is closely aligned with the economics of team production: when social divisions are salient and unmanaged, coordination and productivity can deteriorate, whereas integrative practices can mitigate frictions (Hjort, 2014).

This measure is consistent with a large economics literature in economics showing that interpersonal and social competencies are economically consequential. For example, work in labour economics documents rising returns to social skills, reflecting shifts in task content and organisational forms (Deming, 2017). Related evidence in organisational and development economics shows that group divisions can causally reduce productivity within firms, highlighting why skills that facilitate cooperation across differences are valuable (Falk et al., 2018). Finally, research in behavioural and experimental economics provides validated measurement frameworks for pro-social preferences (e.g., trust, reciprocity, altruism), reinforcing the idea that dispositions underpinning supportive behaviour and cooperative engagement can be meaningfully captured with carefully designed survey instruments (Alesina et al., 2002; Hjort, 2014).

Table 3-11: Human Literacy index correlation matrix

	Human Literacy index	Inclusive identity	Workplace empathy	Cross-cultural collaboration
Human Literacy index	1.000			
Q38: Inclusive identity	0.570**	1.000		
Q39: Workplace empathy	0.724**	0.104**	1.000	
Q40: Cross-cultural collaboration	0.742**	0.182**	0.299**	1.000

Table 3-11 presents the correlation matrix for the Human Literacy Index and its three components: inclusive identity, workplace empathy, and cross-cultural collaboration. Each dimension is positively and statistically significantly correlated with the overall index ($r = 0.570–0.742$, $p < 0.01$), indicating that all three items contribute meaningfully to the composite construct. The strongest associations are observed for cross-cultural collaboration ($r = 0.742$) and workplace empathy ($r = 0.724$), suggesting that these relational and behavioural competencies form the core of the index.

Inclusive identity shows a more moderate but still substantial correlation (r = 0.570), indicating that identification with broader social inclusiveness is related to, but somewhat less central than, practical interpersonal skills. Overall, these patterns provide evidence of convergent validity and suggest that the index coherently captures a broader human literacy construct grounded in social awareness and interaction.

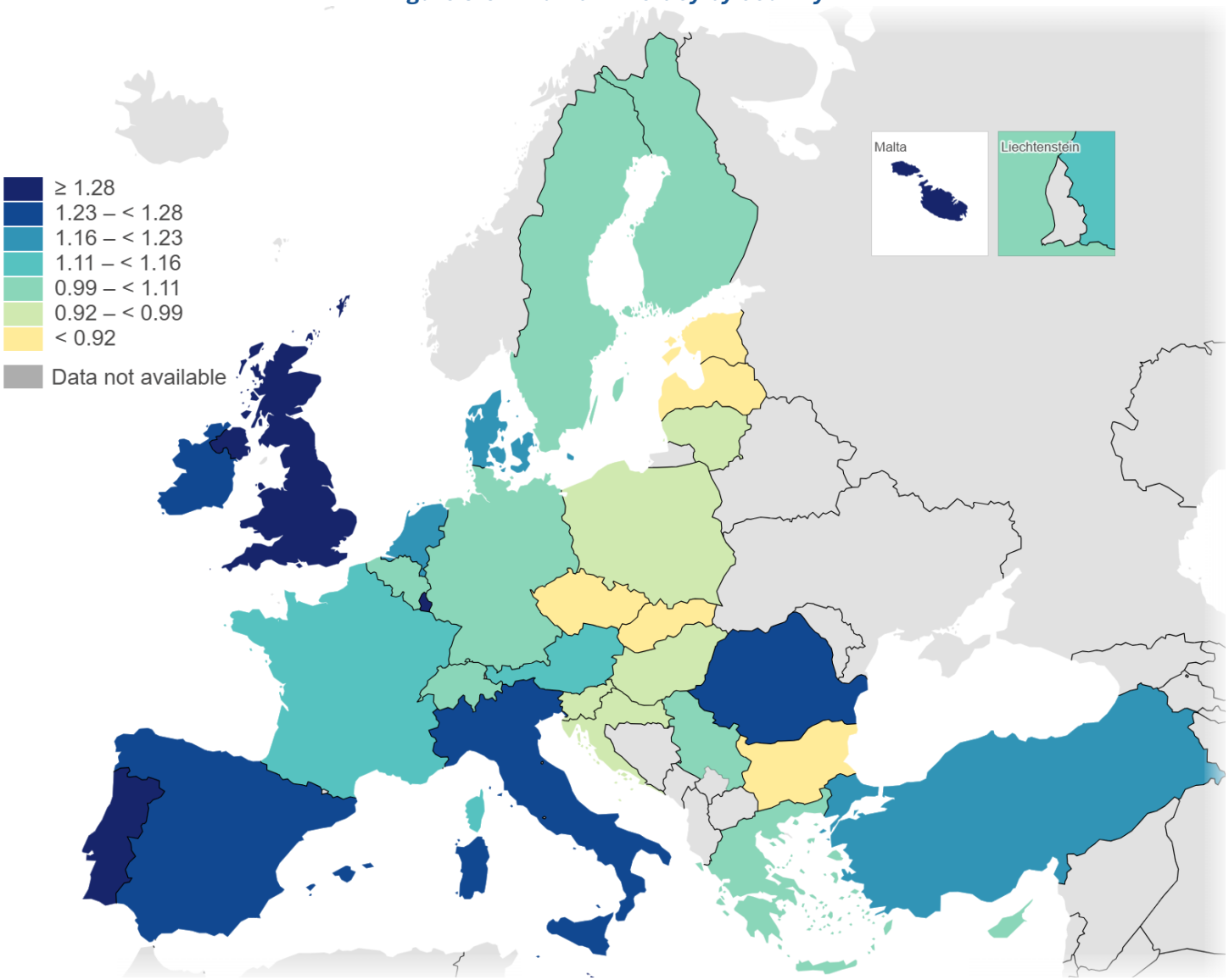
The inter-item correlations, however, are uneven in magnitude. The relationship between workplace empathy and cross-cultural collaboration is moderate (r = 0.299), which is theoretically consistent, as empathetic understanding facilitates effective collaboration across diverse groups. In contrast, inclusive identity exhibits relatively weak associations with workplace empathy (r = 0.104) and only modest association with cross-cultural collaboration (r = 0.182). This suggests that holding an inclusive identity orientation does not necessarily translate directly into empathetic behaviour or collaborative competence. Rather than indicating redundancy, this pattern reflects the multidimensional nature of human literacy, combining attitudinal identification with behavioural and relational skills. Overall, the correlation structure supports the statistical validity of the Human Literacy Index as a coherent yet internally differentiated construct.

Figure 3-81 maps the weighted average of the Human Literacy index (0-3) based on the by country. Results are grouped using a quintile classification, which divides the distribution into seven classes of an equal number of values, ensuring a balanced comparison across categories (cut-offs shown in the legend). Higher (darker) averages are depicted in Southern and Eastern Europe (Portugal, Spain, Italy, Romania), while several Northern and some Central/Western countries fall into the lower (lighter shades) averages, suggesting meaningful cross-country heterogeneity. Countries with data not available are shown in grey.

Figure 3-82 shows the weighted regional average of the Human Literacy index (0-3) at the NUTS-2 level for most countries and at NUTS-1 for the UK, Germany, and Turkey due to data availability. As in the country-level map, results are grouped using a quantile (equal-count) classification. The map reveals within-country variation, with clusters of higher- and lower-scoring regions that are not always visible in the country averages. The map reveals substantial within-country variation, with neighbouring regions often falling into different classes, indicating that regional social and institutional environments likely matter for the distribution of this skill. Grey areas indicate regions with no available data.

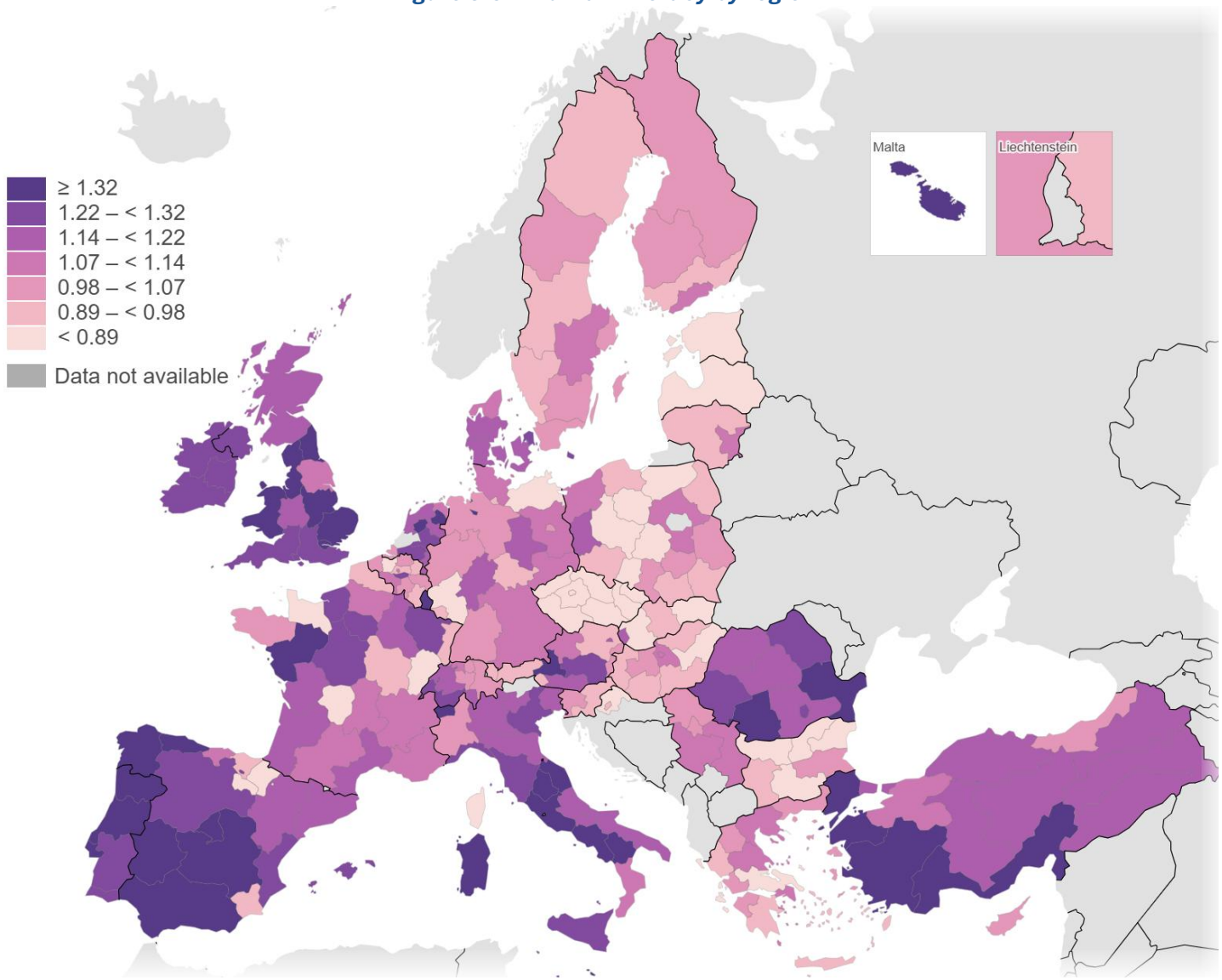
Figures 3-83 to 3-88 provide a systematic descriptive profile of the Human Literacy index across key socio-demographic and labour-market groups. For each subgroup breakdown, weighted averages are reported both by country and for the pooled sample ("All Countries"), enabling comparisons of within-country disparities alongside cross-country differences in overall levels. This structure helps to assess whether patterns by population subgroups are broadly similar across Europe or whether they vary in ways that reflect differences in workplace organisation, social norms, and opportunities for developing interpersonal competencies.

Figure 3-81: Human Literacy by country



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 3-82: Human Literacy by region



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 3-83 shows the gender breakdown in Human Literacy index, reporting weighted average scores for women and men. Overall, in All Countries, women score higher than men (1.109 versus 1.034), implying a modest female advantage of about -0.075 index points. The direction of the gap is consistent across countries. A small male advantage appears only in a few cases, such as Portugal (+0.07), Türkiye (+0.05), and the Netherlands (+0.04), and even there the differences are limited in size. By contrast, the largest female advantages are observed in Finland (-0.23), Denmark (-0.22), and Luxembourg (-0.21), suggesting more pronounced gender differentiation in these contexts. Several countries report near parity (e.g., Serbia, Hungary, Slovakia), indicating that gender differences are not universal in magnitude and can be small in some national settings. In terms of levels, Portugal and Malta stand out as among the highest-scoring countries for both women and men, whereas Czechia and Latvia tend to record among the lowest averages. Overall, the figure suggests a modest but relatively widespread female advantage in human literacy, combined with meaningful cross-country variation in average levels.

Figure 3-84 reports the age breakdown in Human Literacy index, reporting weighted average scores across six age groups. Overall, in All Countries, the age profile is broadly stable and exhibits a mild U-shape: average scores are 1.094 among those aged 18-24, decline to around 1.032 in midlife (45-54), and then rise again to 1.110 among those aged 65-80. This pattern suggests that human literacy, as captured by the index, does not follow a simple monotonic life-cycle accumulation process and may reflect compensatory mechanisms, such as early-life social engagement, midlife time constraints, and later-life experience in interpersonal settings. Cross-country age profiles are more heterogeneous than for many other indices. Latvia, for example, shows a marked decline with age, while some countries display a local peak in early or mid-adulthood (e.g., the United Kingdom around 25–34), indicating that the relationship between age and human literacy depends on country context. In terms of overall levels across age groups, Luxembourg, Portugal, and Malta typically appear among the highest-scoring countries, whereas Croatia, Bulgaria, and Estonia more often record the lowest averages.

Figure 3-85 reports weighted average Human Literacy scores by education level, distinguishing three categories: low (early childhood to lower secondary), medium (upper secondary to short-cycle tertiary), and high (tertiary education, from short-cycle programmes to doctoral studies). Compared with other indices, the overall education gradient, in All Countries, is relatively small (Low 0.932, Medium 0.978, High 1.166), indicating that human literacy is less strongly stratified by formal education than indices more closely tied to cognitive or technical knowledge. Cross-country patterns are also more mixed, suggesting that interpersonal capabilities may be developed through a wide range of channels beyond formal schooling, including workplace experience, family and community interactions, and social learning. Among the highly educated, the highest averages are observed in Luxembourg (1.712), the United Kingdom (1.469), and Portugal (1.442), while the lowest High-education averages are found in Latvia (0.665), Czechia (0.736), and Estonia (0.887). Education gaps (High minus Low) vary considerably across countries, with largest to be observed in Luxembourg (0.73), Italy (0.51), and Hungary (0.48), indicating stronger stratification by education in these contexts. By contrast, several countries show near-equal scores across education categories (e.g., Slovakia, Serbia, Slovenia), including cases where the medium-education group scores slightly below the low-education group. Overall, the figure suggests that while education is positively

associated with human literacy in the aggregate, the relationship is weaker and more context-dependent than for many other indices.

Figure 3-86 shows the weighted average scores of the Human Literacy index across income deciles, based on respondents' self-reported annual net disposable income (including wages, self-employment income, property income and government benefits) ranked from the 1st (lowest) to the 10th (highest) decile. Overall, in All Countries, average scores increase from 0.99 (1st) to 1.29 (10th), corresponding to +0.30, although gradients vary across countries. The strongest patterns appear in Italy (+0.58), Lithuania (+0.52) and Cyprus (+0.41), while Latvia (+0.02) and Czechia (+0.04) are close to flat, and Denmark shows a small negative gradient (-0.04). The highest 10th-decile decile average score is in Luxembourg (1.68), and the lowest 1st-decile decile average score in Latvia (0.60).

Figure 3-87 reports the weighted average scores of the Human Literacy index across wealth deciles, based on respondents' self-reported net household wealth (defined as the total value of all assets owned by the household, after deducting liabilities such as debts or loans) ranked from the 1st (lowest) to the 10th (highest) decile. Overall, in All Countries, differences by wealth decile are relatively small, i.e., from 1.06(1st) to 1.16(10th), gap +0.10, and the pattern varies across countries. The steepest gradients are in Türkiye (+0.54), Germany (+0.54) and France (+0.48), whereas the pattern is close to flat in Sweden (+0.03) and Greece (+0.04). The Netherlands shows a reversed pattern (-0.21). The highest 10th-decile average score is in Türkiye (1.58), and the lowest 1st-decile average score is in Latvia (0.56).

Figure 3-88 reports weighted average Human Literacy scores by skills-matching status, linking individual skill profiles to respondents' perceived fit between their qualifications and the demands of their main job. Overall, in All Countries, matched respondents score highest (1.12), then overqualified (1.06), and underqualified have the lowest score (0.85). Comparing matched to the mismatched average (0.96), the implied match premium is 0.17. Cross-country patterns are more heterogeneous. Several countries show overqualified as the lowest group score, while the underqualified group is highest in some cases (e.g., the Netherlands and Serbia). The largest dispersion across mismatch categories is observed in Luxembourg (0.54) and Hungary (0.43).

Figure 3-83: Gender breakdown in Human Literacy by country

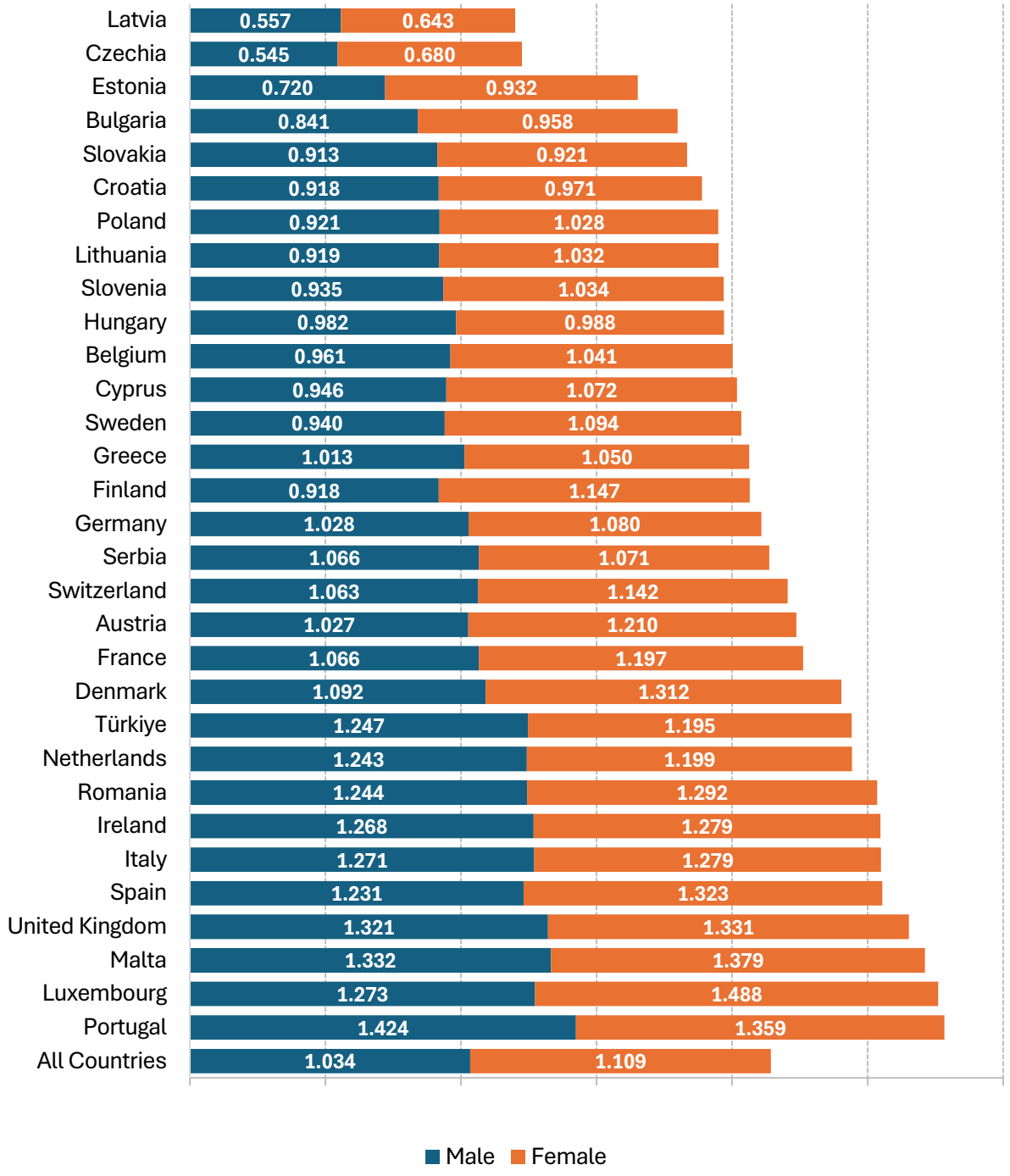


Figure 3-84: Age breakdown in Human Literacy by country

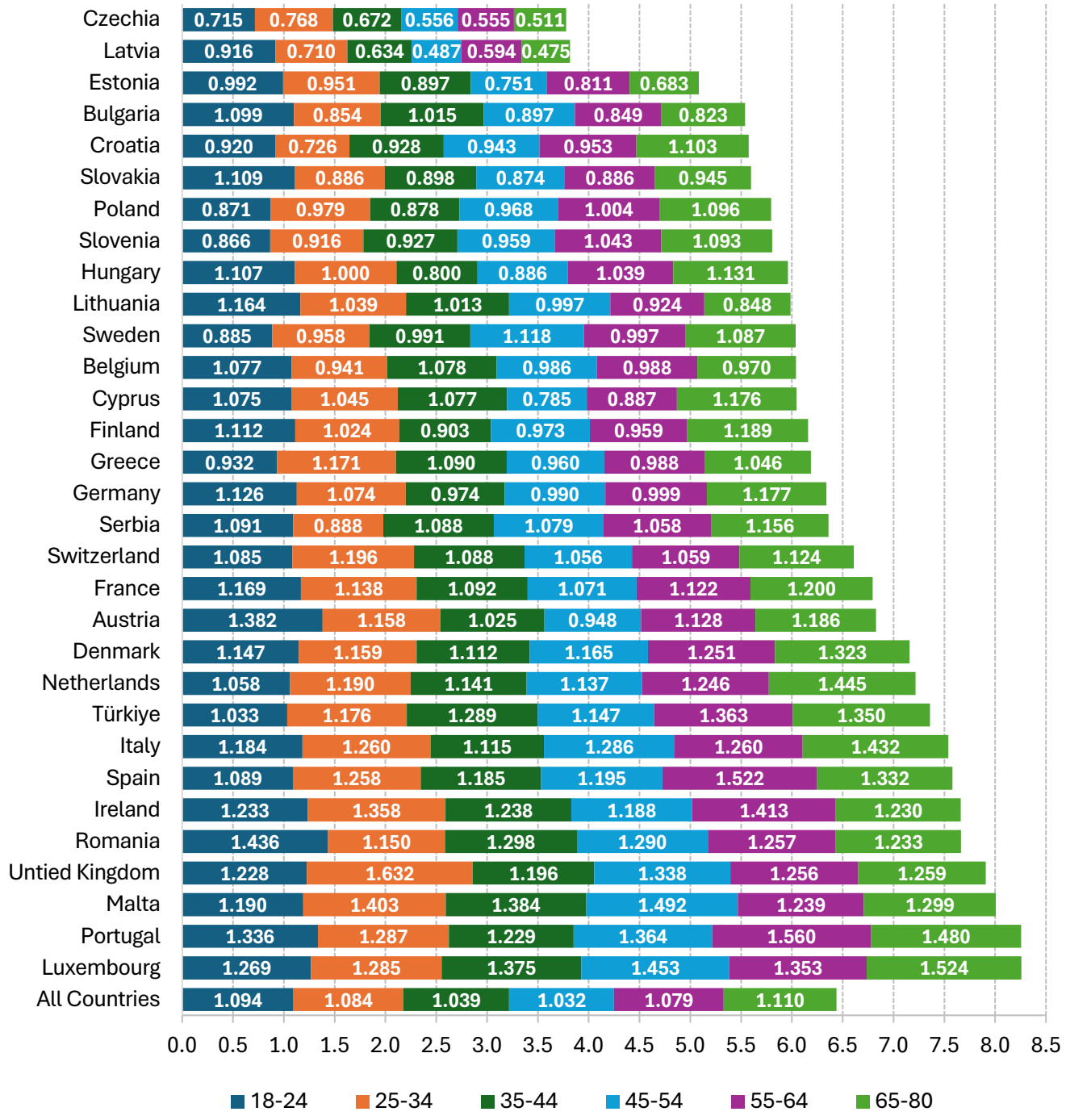


Figure 3-85: Educational breakdown in Human Literacy by country

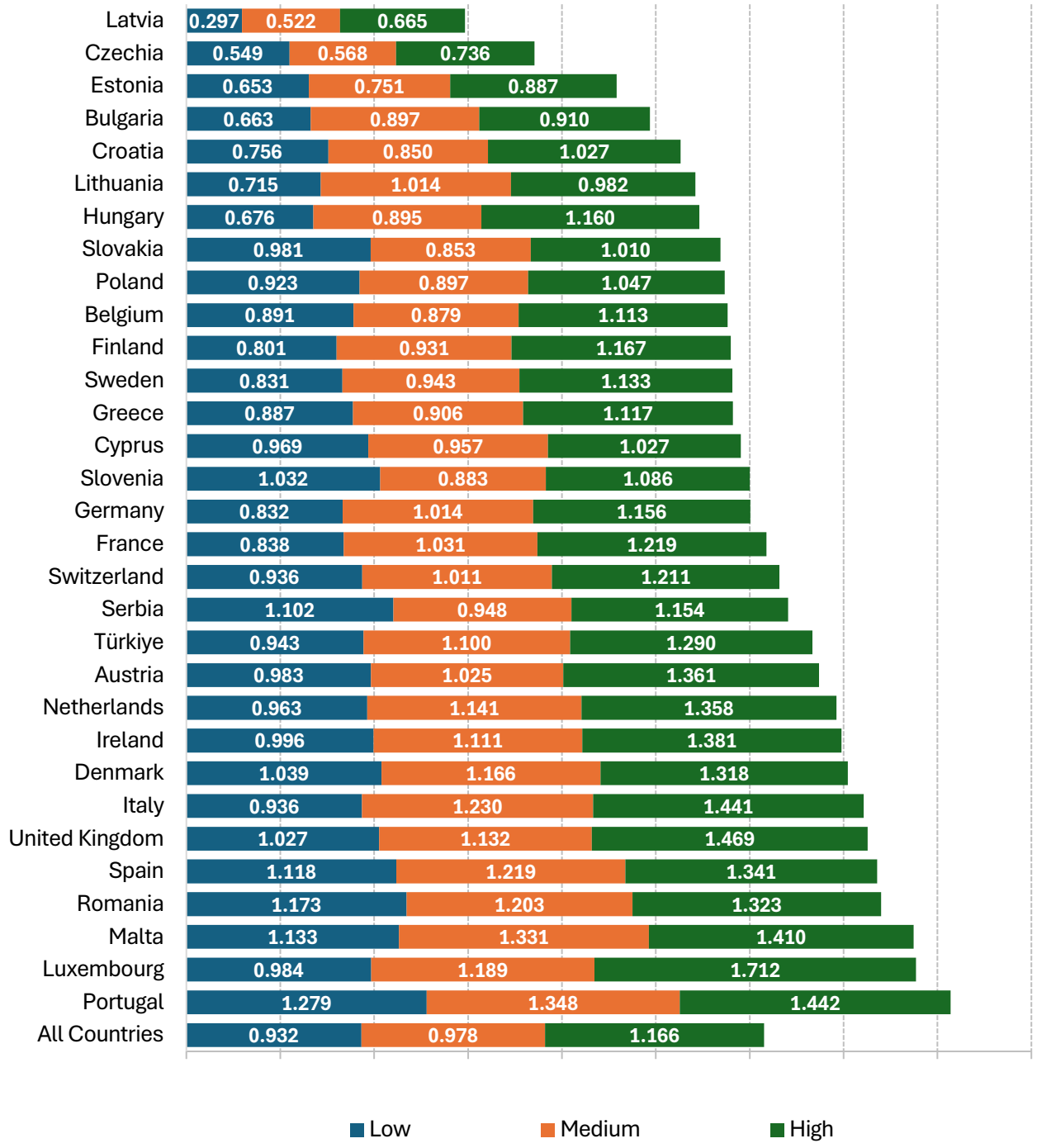


Figure 3-86: Income Composition in Human Literacy by country

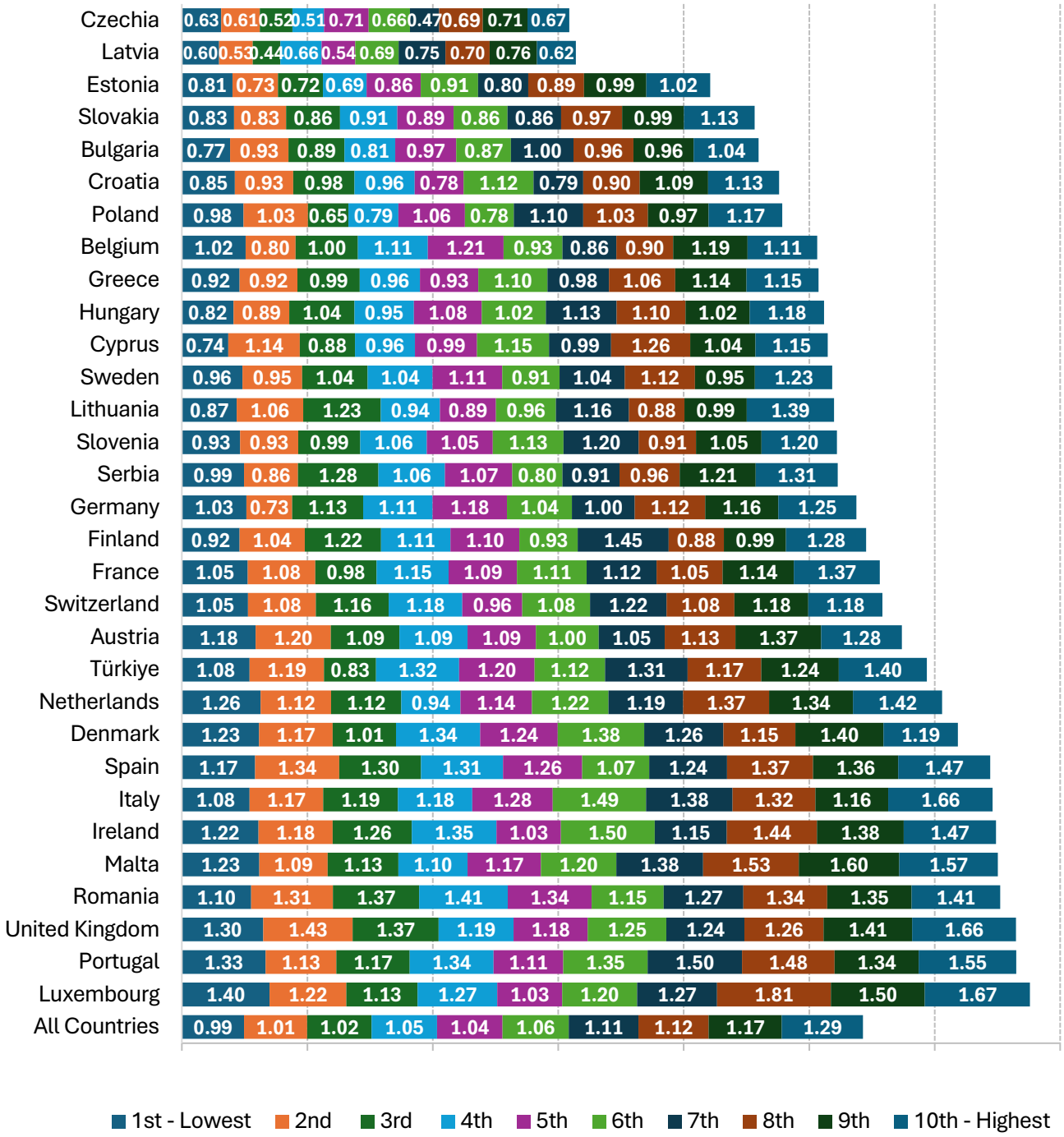


Figure 3-87: Wealth Composition in Human Literacy by country

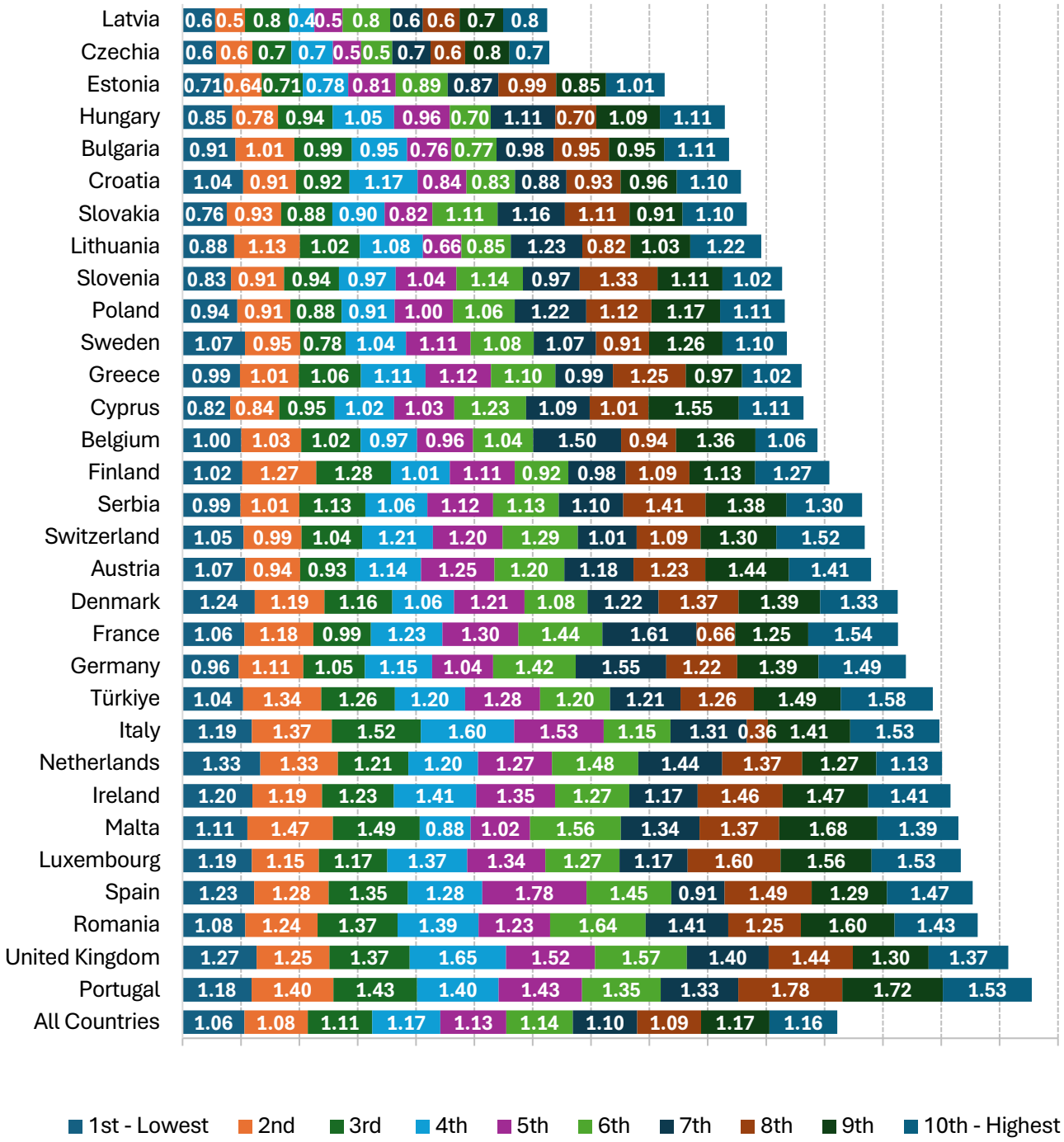
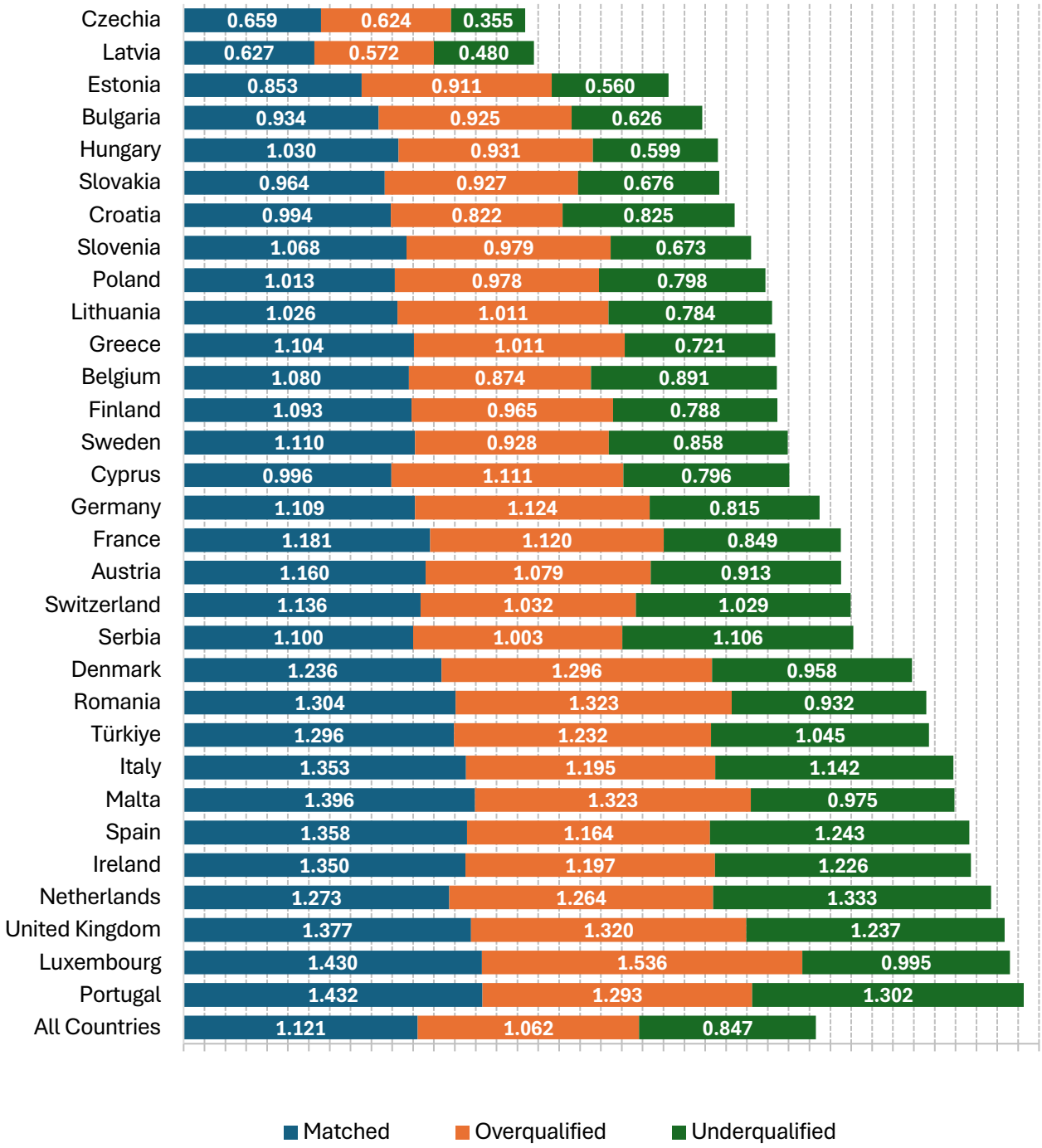


Figure 3-88: Skills Mismatch in Human Literacy by country



3.4.2 Cultural Agility

The Cultural Agility index captures individuals' capacity to communicate, collaborate, and make judgments effectively in culturally diverse environments, which is becoming increasingly relevant as workplaces and public life are shaped by diversity and multiculturalism. In such settings, economic performance depends not only on formal skills but also on the ability to build trust, interpret unfamiliar norms, and avoid coordination failures that can arise from cultural distance. Literature in economics shows that social divisions within workplaces can translate into measurable productivity losses, consistent with the view that frictions in communication and cooperation carry real economic costs (e.g., Hjort, 2014). At the same time, cultural diversity can be economically valuable, for instance linked to prosperity and innovative capacity, yet these gains are more likely to materialise when individuals and organisations can effectively integrate heterogeneous perspectives rather than fragment into parallel groups (Alesina et al., 2016; Campo et al., 2022). This rationale aligns with broader labour-economics evidence that interpersonal and collaborative skills become increasingly rewarded as tasks shift toward teamwork and non-routine problem solving.

Specifically, the Cultural Agility index (range 0-3) is constructed from the following three TRAILS-I survey questions:

Q41. When you interact with someone from a different cultural background, how do you usually try to approach the conversation? *Please select the option that best reflects your own experience.*

1. *I try to listen actively and ask questions to understand their views*
2. *I focus on common ground and avoid cultural topics unless they bring it up*
3. *I usually treat everyone the same, regardless of cultural background*
4. *I sometimes feel unsure or uncomfortable navigating these conversations*

98. *I don't know*
99. *I prefer not to answer*

Q42. You're invited to a professional event in EU country where the customs differ from what you're used to. How do you typically respond?

1. *I research local customs beforehand and try to adapt*
2. *I follow social cues during the event and adjust as needed*
3. *I stick to my own way of doing things unless explicitly told otherwise*
4. *I avoid unfamiliar settings when I feel uncertain about local norms*

98. *I don't know*
99. *I prefer not to answer*

Q43. People often rely on cultural stereotypes, especially when they're unsure how to behave. Which of the following best describes your view?

1. *Stereotypes can be misleading – I prefer to learn about individuals directly*
2. *I sometimes use general cultural patterns as a starting point, but keep an open mind*
3. *I think stereotypes are useful because they help predict what to expect*
4. *I tend to avoid unfamiliar cultures because I worry about making mistakes*

98. *I don't know*
99. *I prefer not to answer*

Conceptually, each question corresponds to a distinct pillar of cultural agility. Q41 captures a deliberative, other-oriented interaction style (active listening and inquiry), which is a practical mechanism for reducing misunderstandings and building trust when common reference points are weaker. This maps naturally into the concepts of teamwork and social skills, where communication and cooperative production are key complements to technical competence (Hjort, 2014). Q42 measures adaptive behaviour under unfamiliar norms, precisely the capability that helps individuals operate effectively when implicit rules differ across contexts, limiting the coordination costs associated with cultural distance. Q43 targets how individuals use (or reject) stereotypes as decision heuristics: a preference for learning about people as individuals reflects a stance that can mitigate biased inference and frictions in exchange, consistent with evidence that cultural bias can distort economic interactions and trust (Deming, 2017). Taken together, these three components provide a theoretically grounded coverage of the skill as defined here: effective cross-cultural interaction, norm-sensitive adaptation, and stereotype-aware judgment.

As before, the 0-3 range preserves a transparent count interpretation: the score equals the number of core cultural-agility elements (out of three) that a respondent demonstrates. This aggregation is comparable across countries and socio-demographic groups and avoids over-precision that would be difficult to justify from three items. Finally, the explicit "I don't know" (and "prefer not to answer") options help limit forced responses and reduce guessing, improving the interpretability of low scores as reflecting genuine uncertainty or non-engagement with the underlying skill components.

Table 3-12 presents the correlation matrix for the Cultural Agility Index and its three components: cross-cultural communication, adaptation to customs, and stereotype awareness. Each item is positively and statistically significantly correlated with the overall index ($r = 0.509–0.674$, $p < 0.01$), indicating that all three dimensions contribute to the composite construct. The strongest associations are observed for adaptation to customs ($r = 0.674$) and cross-cultural communication ($r = 0.647$), suggesting that behavioural flexibility and communicative competence form the core of cultural agility as measured here. Stereotype awareness shows a more moderate correlation with the index ($r = 0.509$), indicating that while attitudinal openness is an important component, it is somewhat less central than behavioural adaptability. Overall, the pattern supports the convergent validity of the index as a coherent measure of intercultural competence.

Table 3-12: Cultural Agility index correlation matrix

	Cultural Agility index	Cross-cultural communication	Adaptation to customs	Stereotype awareness
Cultural Agility index	1.000			
Cross-cultural communication	0.647**	1.000		
Adaptation to customs	0.674**	0.224**	1.000	
Stereotype awareness	0.509**	-0.017**	-0.032**	1.000

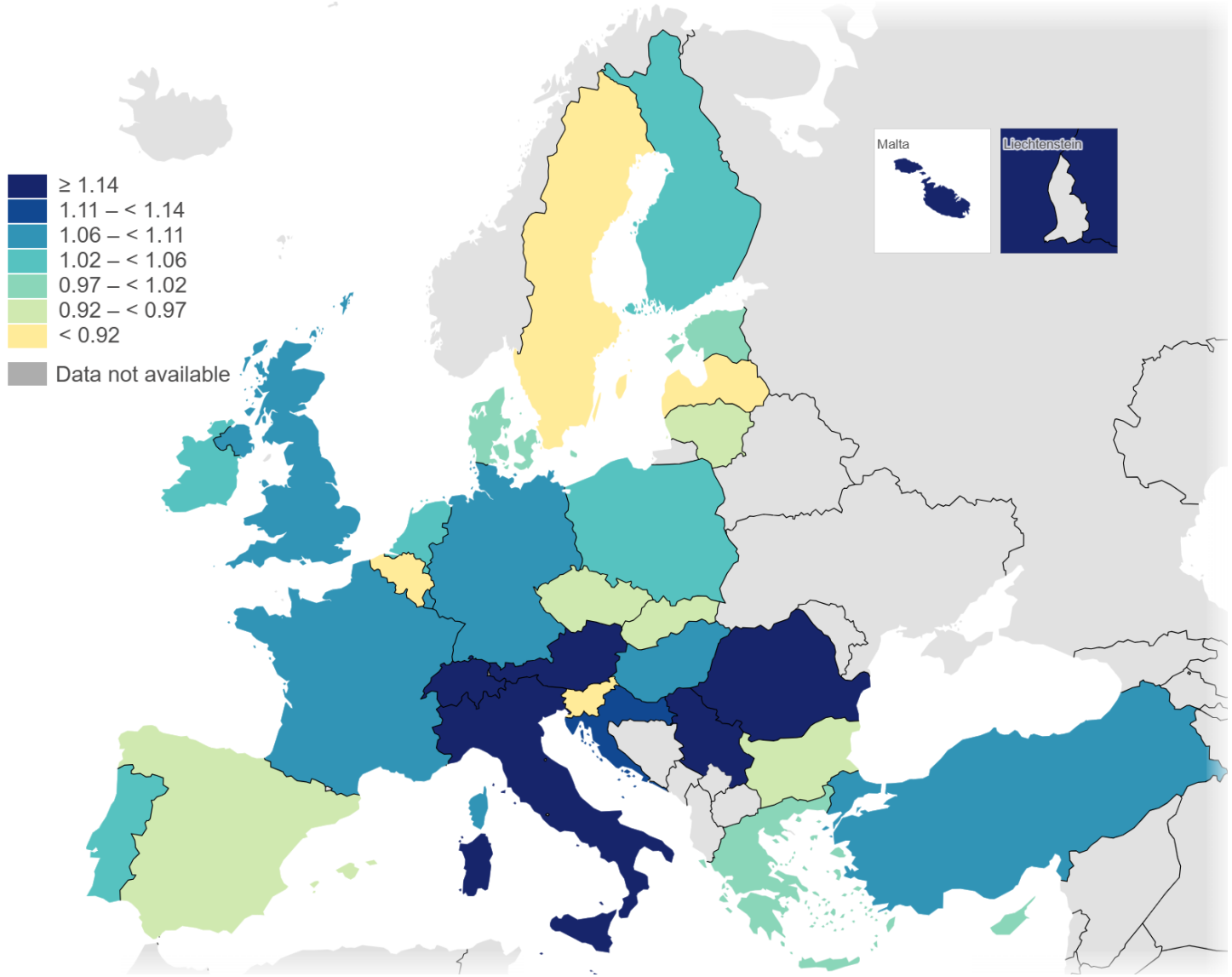
The inter-item correlations, however, reveal a differentiated internal structure. Cross-cultural communication and adaptation to customs are modestly correlated (r = 0.224), which is theoretically consistent, as effective communication often facilitates behavioural adaptation in unfamiliar cultural settings. In contrast, stereotype awareness shows virtually no correlation with cross-cultural communication (r = -0.017) or adaptation to customs (r = -0.032). These near-zero associations suggest that awareness of stereotypes operates relatively independently from practical intercultural skills. Rather than indicating measurement error, this pattern points to the multidimensional nature of cultural agility, combining cognitive-attitudinal awareness with behavioural competencies. Overall, the correlation structure supports the statistical validity of the Cultural Agility Index as a coherent yet internally differentiated construct, though the weak associations involving stereotype awareness may warrant further psychometric examination.

Figure 3-89 maps the weighted country average of the Cultural Agility index (0-3) and applies a quintile (equal-count) classification, which splits the distribution into seven classes with an equal number of values. suggests clear cross-country differences: several Central/South-Eastern European countries fall in the upper classes (darker shades), whereas a set of Western and Northern countries are concentrated in intermediate classes, and a smaller group of countries appear in the lowest classes (lightest shades). Overall, the map indicates that average cultural-agility levels vary meaningfully across countries rather than clustering tightly around a single European-wide level. Countries with data not available are shown in grey.

Figure 3-90 shows the weighted regional average of the Human Literacy index (0-3) at the NUTS-2 level for most countries and at NUTS-1 for the UK, Germany, and Turkey due to data availability. As in the country-level map, results are grouped using a quantile (equal-count) classification. Many countries display a mix of higher- and lower-scoring regions, with neighbouring regions sometimes falling into different classes, consistent with within-country differences in exposure to diverse workplaces, mobility, and socio-demographic composition. Grey areas indicate regions with no available data.

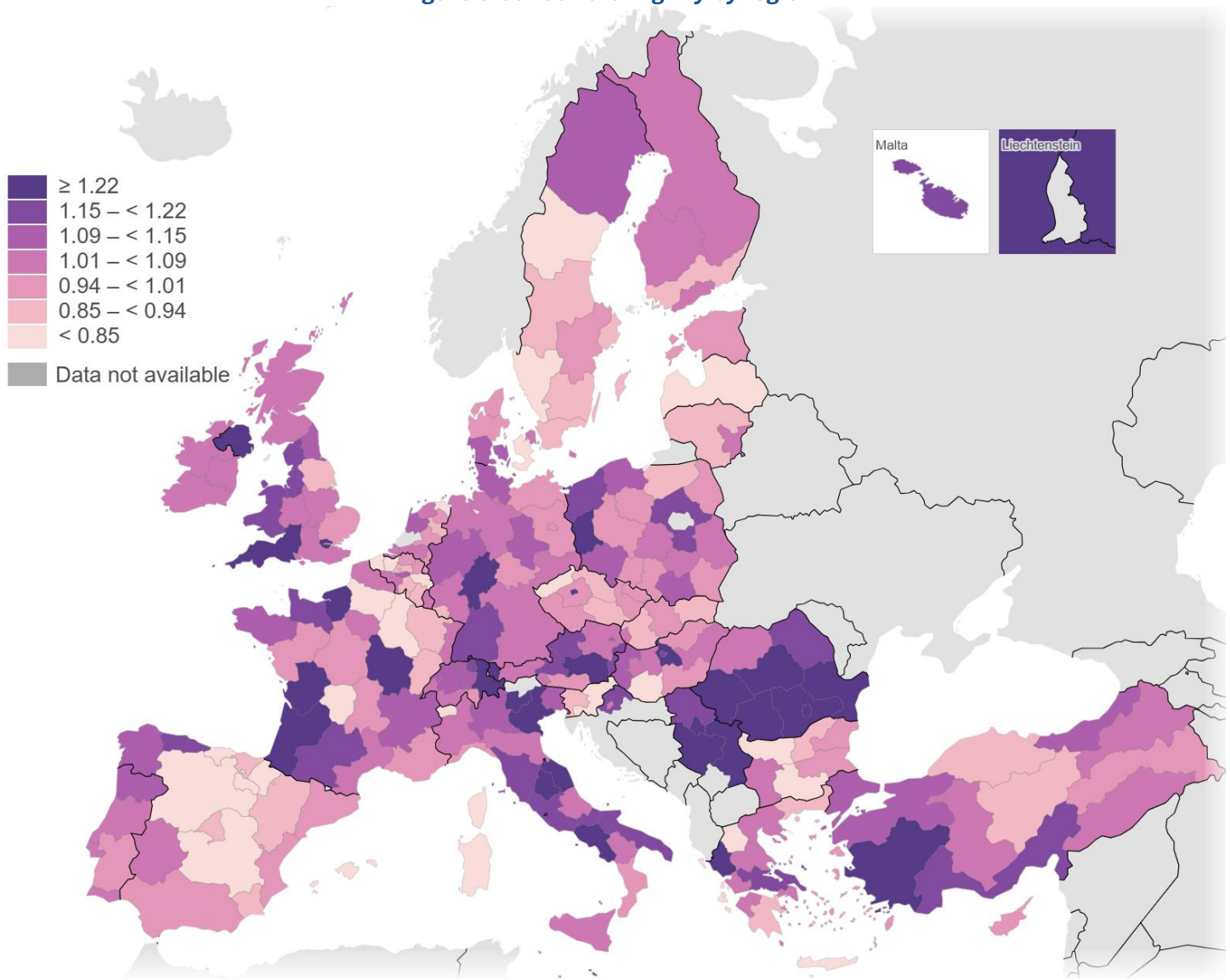
Figures 3-91 to 3-96 provide a systematic descriptive profile of the Cultural Agility index across key socio-demographic and labour-market groups. For each subgroup breakdown, weighted averages are reported both by country and for the pooled sample ("All Countries"), enabling comparisons of within-country differences alongside cross-country variation in overall levels. This structure helps to assess whether differences by subgroups appear as broadly shared regularities or whether they vary in ways that reflect national contexts and social environments.

Figure 3-89: Cultural Agility by country



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 3-90: Cultural Agility by region



Note: Authors' calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)

Figure 3-91 depicts the gender breakdown in Cultural Agility index, reporting weighted average scores for women and men. Overall, in All Countries, women score slightly higher than men (1.053 versus 1.018), implying a small female advantage of about -0.035. Although modest in the aggregate, the gender difference shows meaningful cross-country variation in both magnitude and direction. The largest female advantages are observed in Lithuania (-0.19), Finland (-0.17), and Estonia (-0.15), with Denmark also showing a sizeable female advantage, suggesting that gender differences in cultural agility can be more pronounced in certain settings. Men score higher in a smaller subset of countries, most notably Italy (+0.10) and Germany (+0.07), while several countries report near parity (e.g., Latvia, Greece, Luxembourg). In terms of overall levels, Romania and Sweden rank among the highest-scoring countries for both genders, whereas Latvia tends to be at the lower end for both women and men.

Figure 3-92 presents the age breakdown in Cultural Agility index, reporting weighted average scores across six age groups. Overall, in All Countries, cultural agility increases gradually with age, rising from 0.962 among those aged 18-24 to 1.076 among those aged 65-80. This profile suggests a modest life-cycle accumulation of culturally adaptive skills, potentially through repeated exposure to diverse social environments, workplace interactions, and broader life experience. However, the extent of age-related change varies considerably across countries. The steepest age increases appear in Romania, Hungary, and Cyprus, indicating stronger cohort differences or a greater role for life-cycle learning in these contexts, while other countries show relatively modest variation across age groups. In terms of overall country levels, Romania, Serbia, and Malta tend to record among the highest scores across the age distribution, whereas Spain, Belgium, and Sweden more frequently appear among the lowest.

Figure 3-93 reports weighted average Cultural Agility scores by education level, distinguishing three categories: low (early childhood to lower secondary), medium (upper secondary to short-cycle tertiary), and high (tertiary education, from short-cycle programmes to doctoral studies). The overall, in All Countries, average scores display a clear education pattern (Low 0.802, Medium 0.960, High 1.126), indicating that educational attainment is positively associated with cultural agility. This relationship is plausible given that education may broaden exposure to diverse perspectives, strengthen communication and social reasoning skills, and increase opportunities to interact across cultural contexts. Cross-country differences remain substantial even among the highly educated. High-educated respondents score highest in Serbia (1.371), Romania (1.354), and Austria (1.268), while the lowest High-education averages are observed in Latvia (0.903), Lithuania (0.966), and Spain (1.000). The education gap (high minus low) is largest in the Netherlands (0.53), Finland (0.52), and Hungary (0.50), indicating strong stratification by education in these contexts, whereas it is very small in Slovenia (0.01), suggesting minimal differentiation by education level.

Figure 3-94 shows the weighted average scores of the Cultural Agility index across income deciles, based on respondents' self-reported annual net disposable income (including wages, self-employment income, property income and government benefits) ranked from the 1st (lowest) to the 10th (highest) decile. Overall, in All Countries, the index rises from 0.94 (1st) to 1.16 (10th), a gap of +0.23. The strongest gradients are present in Cyprus (+0.42), Türkiye (+0.39) and Serbia (+0.38), while Romania (+0.02) and Slovakia (+0.02) are nearly flat and Denmark shows a small negative gradient (-0.07). The highest 10th-decile average score is in Serbia (1.40), and the lowest 1st-decile average score is in Latvia (0.74).

Figure 3-91: Gender breakdown in Cultural Agility by country

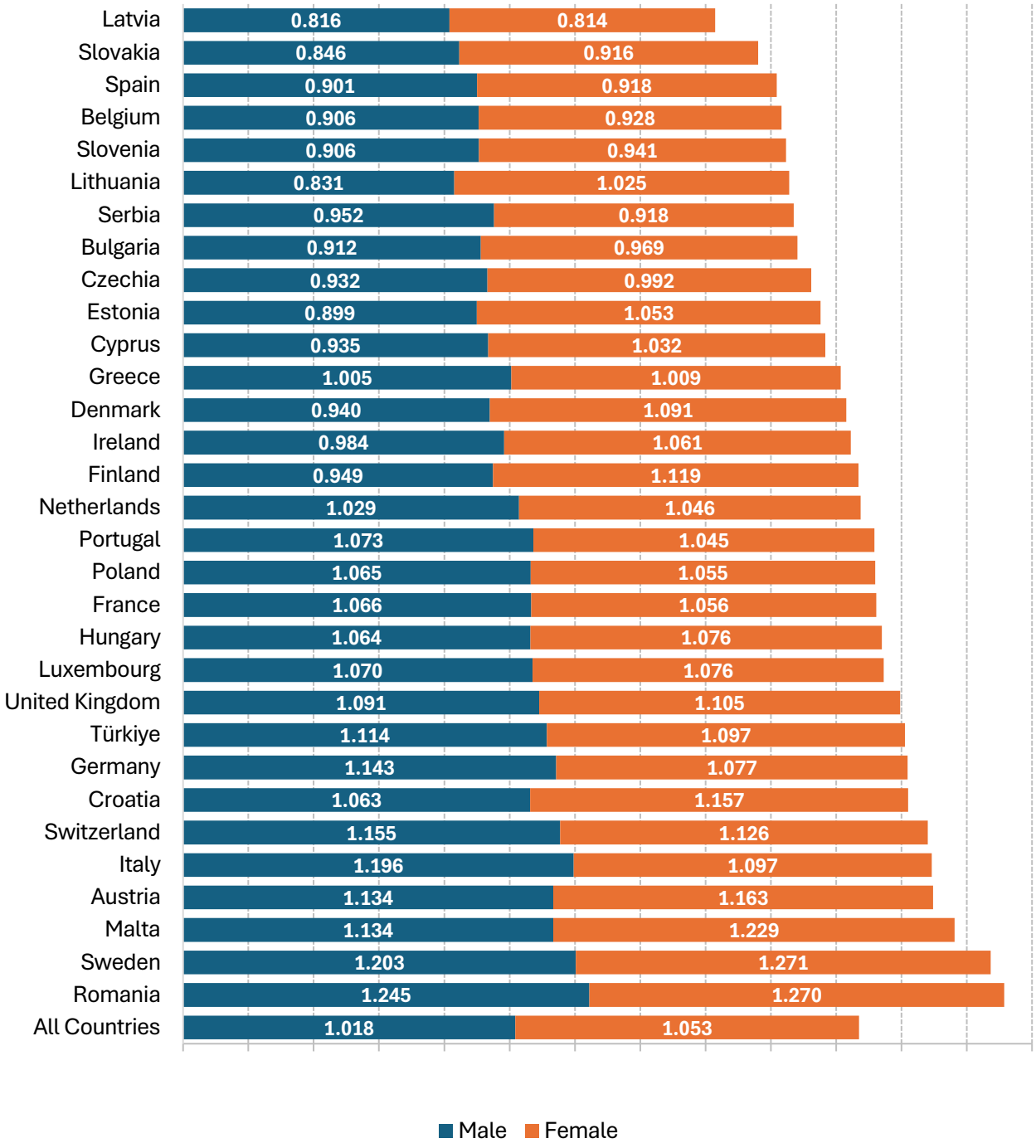


Figure 3-92: Age breakdown in Cultural Agility by country

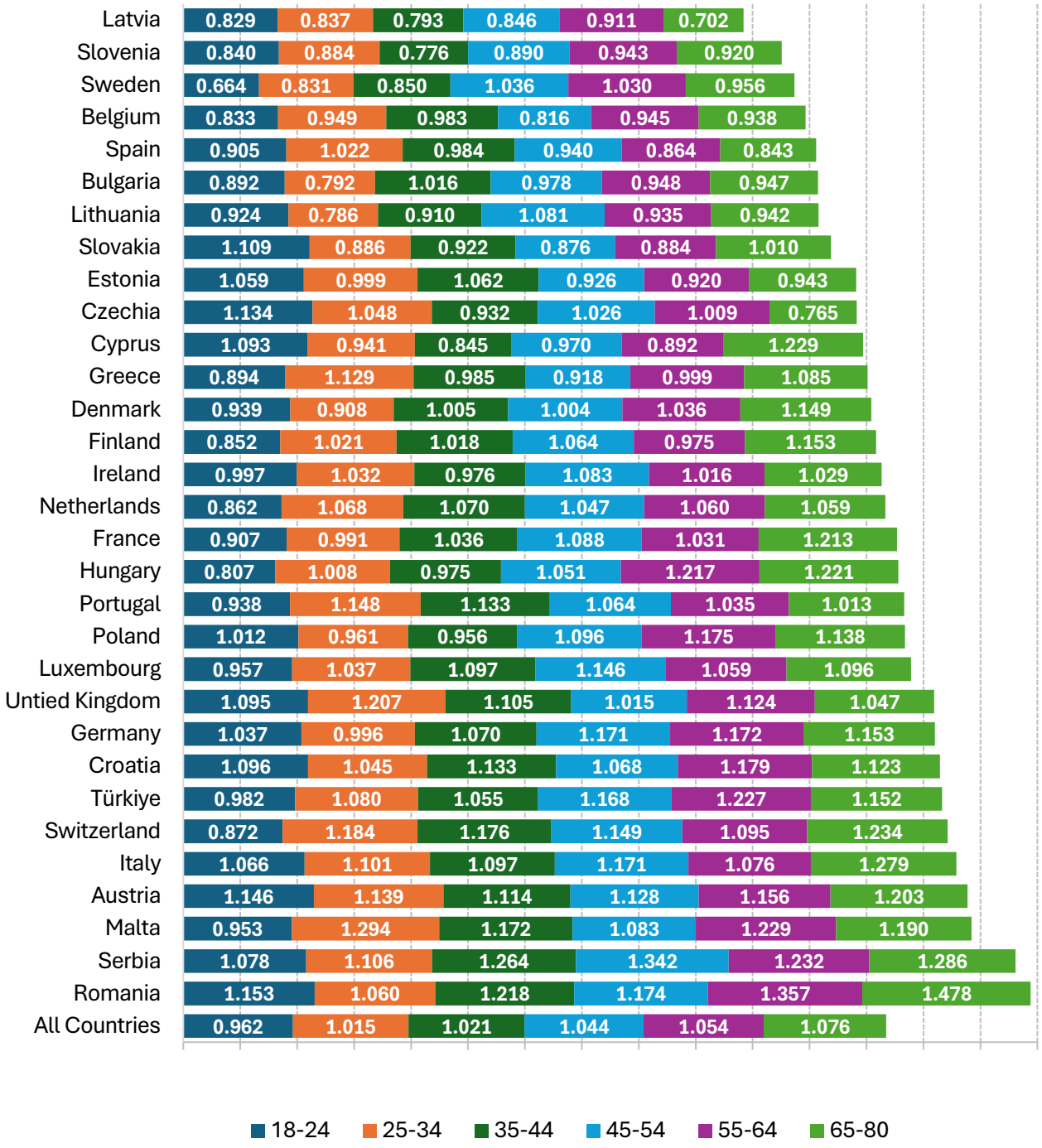


Figure 3-93: Educational breakdown in Cultural Agility by country

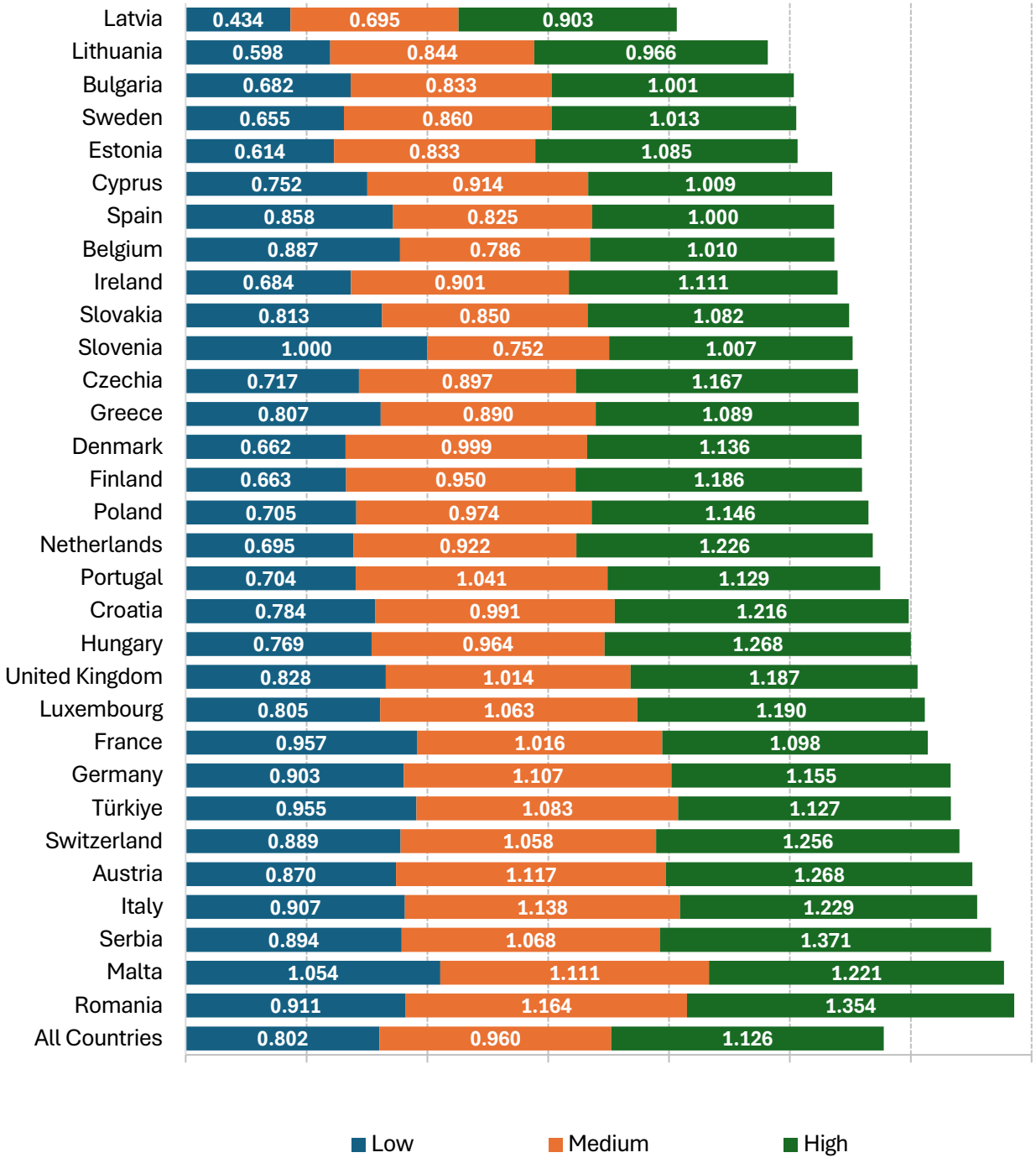


Figure 3-94: Income Composition in Cultural Agility by country

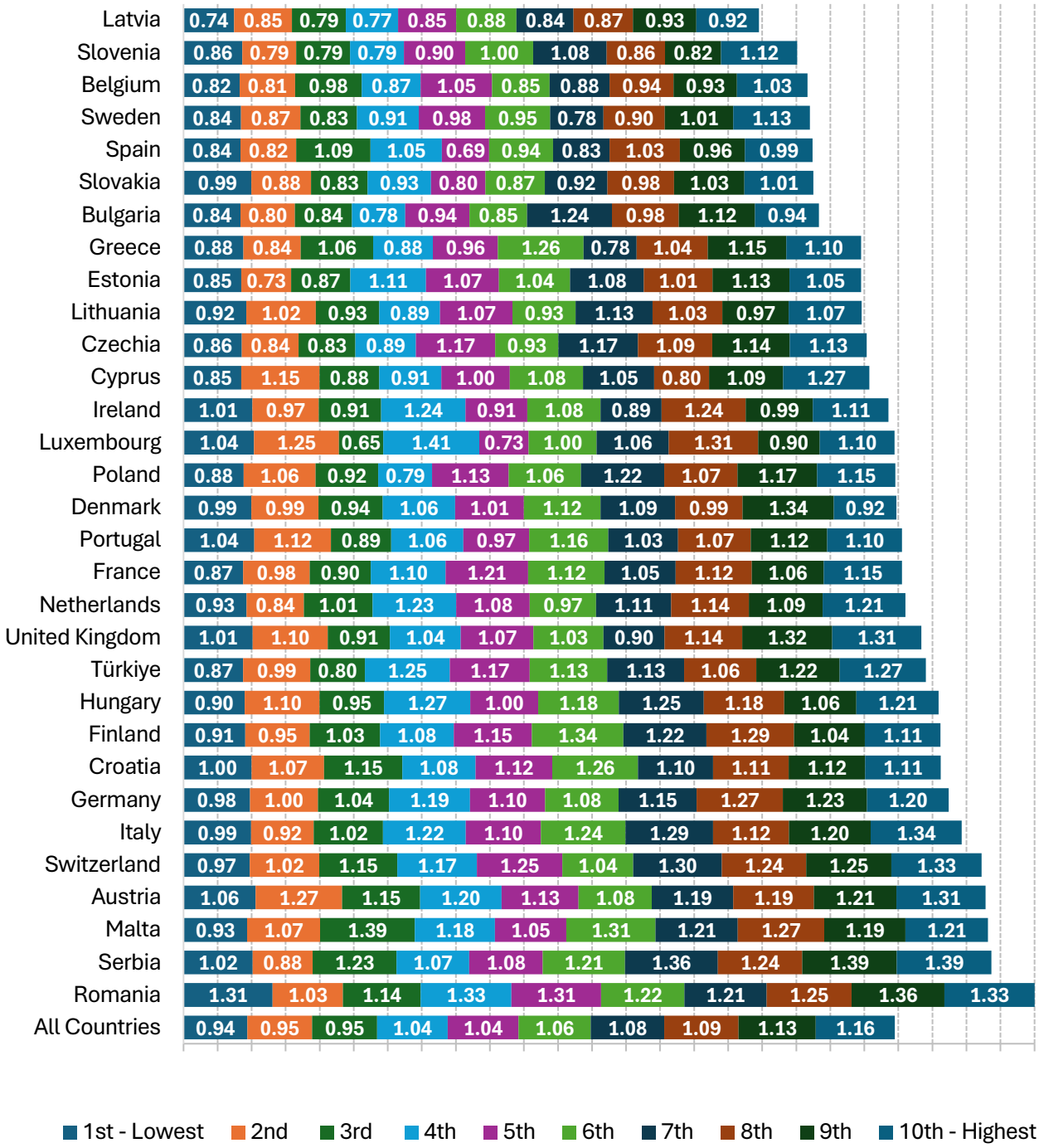


Figure 3-95: Wealth Composition in Cultural Agility by country

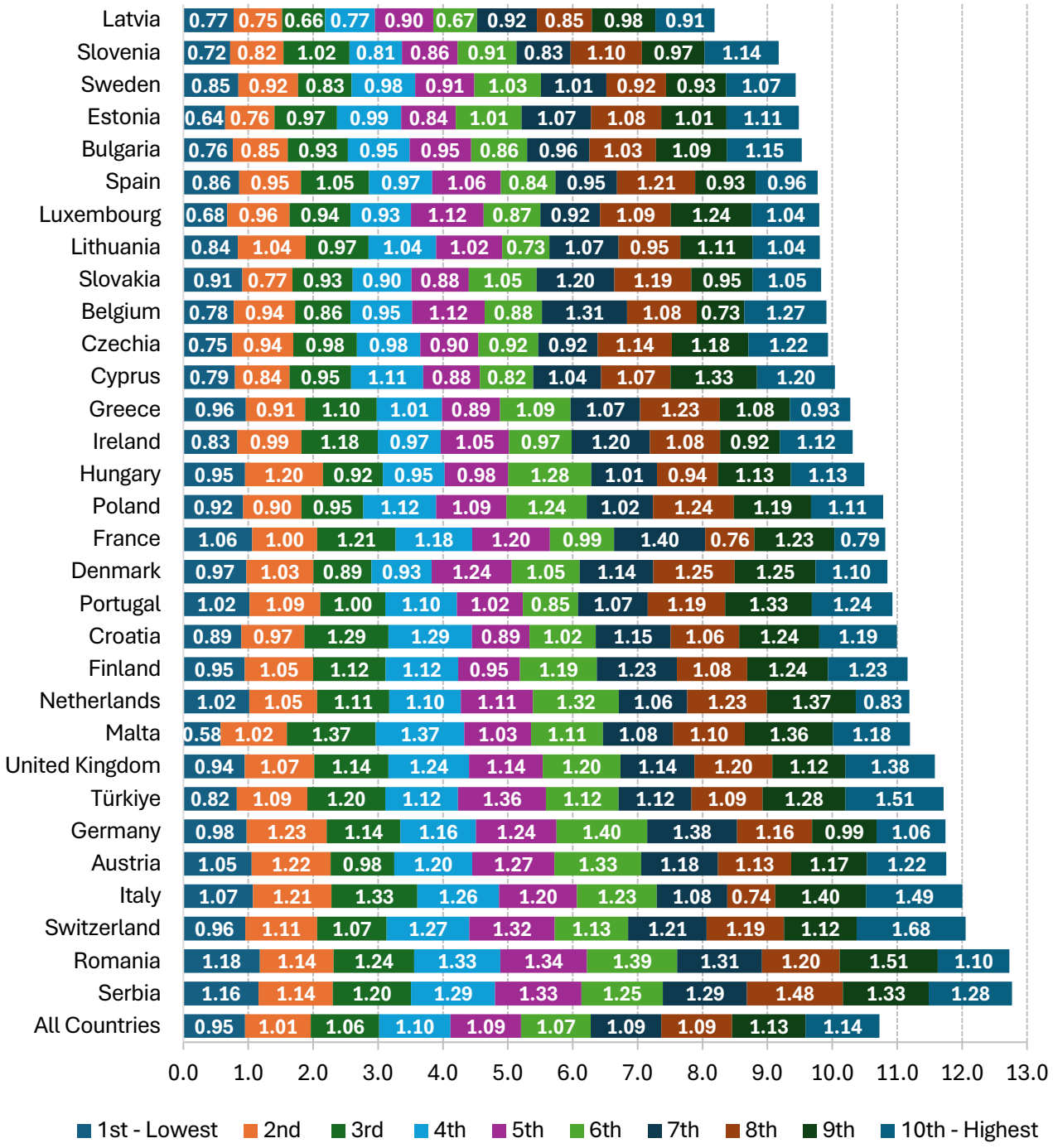


Figure 3-96: Skills Mismatch in Cultural Agility by country

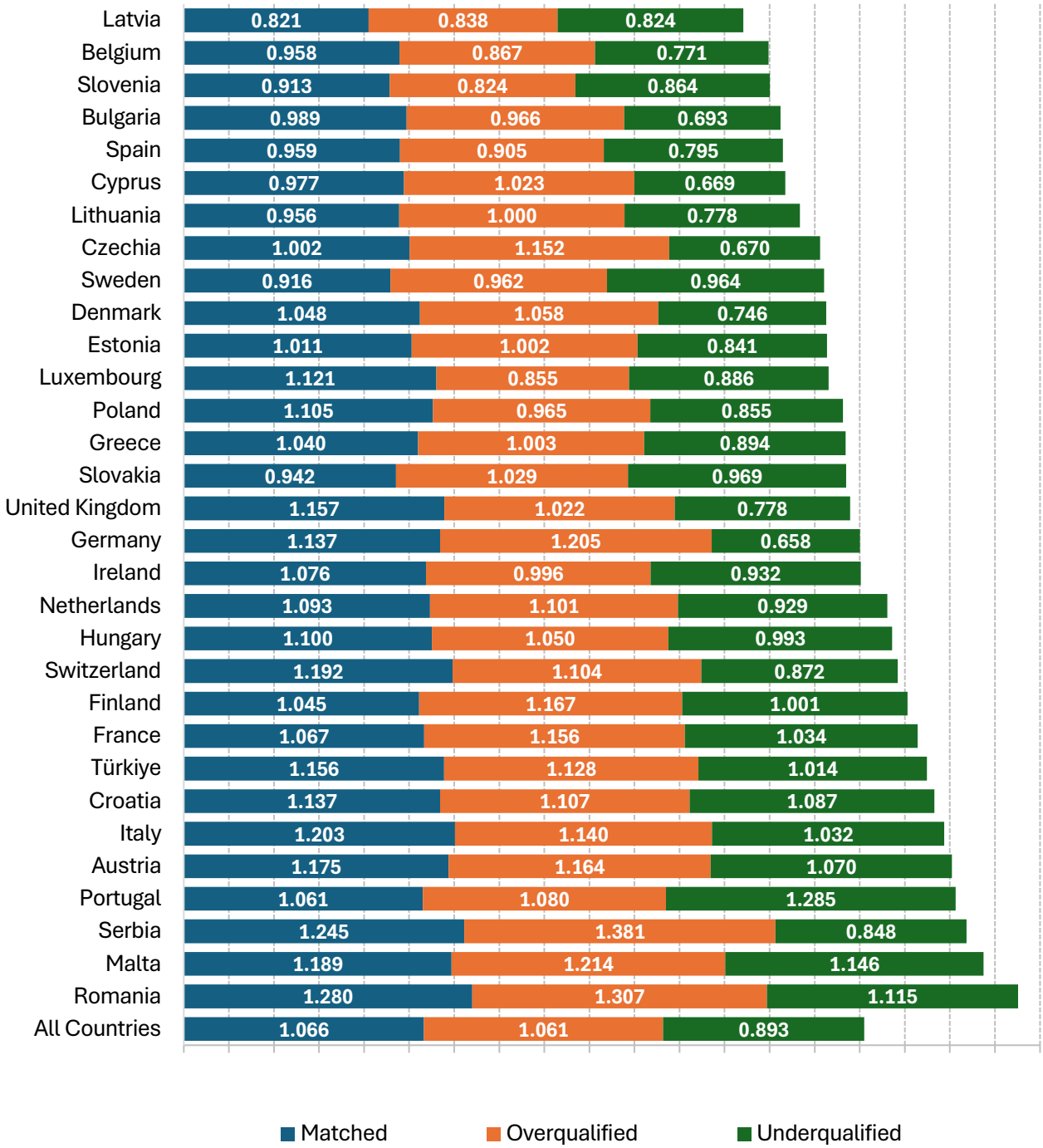


Figure 3-95 reports the weighted average scores of the Cultural Agility index across wealth deciles, based on respondents' self-reported net household wealth (defined as the total value of all assets owned by the household, after deducting liabilities such as debts or loans) ranked from the 1st (lowest) to the 10th (highest) decile. Overall, in All Countries, average scores increase from 0.95 (1st)

to 1.14 (10th), a gap of +0.19, although with some non-monotonicity. The strongest wealth gradients appear in Switzerland (+0.73), Türkiye (+0.69) and Malta (+0.61). In contrast, France (-0.27), the Netherlands (-0.19) and Romania (-0.08) display reversed wealth differences. The highest 10th-decile average score is in Switzerland (1.68), while the lowest 1st-decile average score is in Malta (0.58).

Figure 3-96 reports weighted average Cultural Agility scores by skills-matching status, linking individual skill profiles to respondents' perceived fit between their qualifications and the demands of their main job. Overall, in All Countries, matched (1.07) and overqualified (1.06) are very close, while underqualified is lower (0.89). Comparing matched to the mismatched average (0.98), matched respondents exhibit a match premium of 0.10. The premium is driven by the lower underqualified score, since matched and overqualified are nearly identical. Underqualified group has the lowest average scores in most countries, but it becomes the highest group in Portugal and Sweden, reducing or reversing the matched-mismatched gap there. The largest separations across mismatch categories occur in Germany (0.55) and Serbia (0.53), whereas some countries show almost no dispersion (e.g., Latvia).

3.5 Correlations between literacy domains

The pairwise-correlation matrix of Table 3-13 provides an overview of how the twelve literacy domains relate to one another at the construct level. Overall, the pattern is characterized by uniformly positive and statistically significant correlations ($p < 0.01$), but generally moderate in magnitude. Most coefficients fall within the range of $r \approx 0.10–0.30$, indicating that while the literacy domains are related, they are clearly not redundant. This structure suggests the presence of a broader underlying competence dimension-potentially reflecting general cognitive skills, educational attainment, or overall civic awareness-while simultaneously supporting the conceptual distinctiveness of each literacy construct.

A first notable pattern is the relatively strong clustering around Artificial Intelligence Literacy and Sustainable Financial Literacy. Artificial Intelligence Literacy correlates moderately with several domains, including Media and Information Literacy ($r = 0.381$), Sustainable Financial Literacy ($r = 0.381$), Financial Literacy ($r = 0.341$), Environmental Literacy ($r = 0.269$), and Political Literacy ($r = 0.265$). This suggests that AI literacy is embedded within a broader knowledge ecosystem that combines technological, informational, and civic competencies. Similarly, Sustainable Financial Literacy shows comparatively strong associations with Financial Literacy ($r = 0.356$), Artificial Intelligence Literacy ($r = 0.381$), Health and Medical Literacy ($r = 0.299$), and Environmental Literacy ($r = 0.292$). This pattern is theoretically consistent, as ESG-related understanding requires integration of financial, environmental, governance, and technological knowledge. These domains appear to form a semi-integrated cluster of economically and societally oriented literacies.

A second cluster emerges among the more traditional civic and knowledge-based domains. Financial Literacy correlates moderately with Political Literacy (r = 0.282), Environmental Literacy (r = 0.247), and Retirement Literacy (r = 0.251), indicating overlap between economic knowledge and institutional or policy-related understanding. Political Literacy, in turn, correlates with Environmental Literacy (r = 0.217) and Sustainable Financial Literacy (r = 0.251), reflecting the interdependence of governance knowledge and policy awareness. Media and Information Literacy is moderately associated with AI Literacy (r = 0.381), Digital Financial Literacy (r = 0.243), and Political Literacy (r = 0.233), which aligns with the idea that navigating information environments is central to both digital and civic competence.

In contrast, Data and Programming Literacy appears comparatively more isolated. Its correlations with other domains are generally weak (most below r = 0.17), and especially low with Health and Medical Literacy (r = 0.025), Sustainable Financial Literacy (r = 0.023), Environmental Literacy (r = 0.078), and Political Literacy (r = 0.096). This suggests that technical computational skills represent a more specialized capability that does not strongly overlap with broader civic or societal knowledge domains. While Data and Programming Literacy correlates modestly with Artificial Intelligence Literacy (r = 0.165) and Digital Financial Literacy (r = 0.162), these relationships remain moderate, reinforcing the interpretation that technical proficiency is distinct from applied digital or societal awareness.

Finally, Human Literacy and Cultural Agility form a relatively cohesive interpersonal cluster. Human Literacy correlates most strongly with Cultural Agility (r = 0.320), indicating a meaningful conceptual overlap between inclusive identity, empathy, and intercultural competence. Their correlations with other literacy domains are positive but generally modest (mostly r ≈ 0.10–0.21), suggesting that interpersonal and relational skills are related to-but largely distinct from-knowledge-based literacies. This differentiation is theoretically coherent: civic, financial, and technological knowledge do not automatically translate into interpersonal adaptability or cultural awareness.

Taken together, the matrix supports both convergent and discriminant validity at the construct level. The positive correlations indicate that all literacy domains are embedded within a broader competence framework, while the moderate magnitudes and differentiated clustering patterns demonstrate that each index captures a substantively distinct dimension. There is no evidence of multicollinearity or redundancy across domains, which strengthens the justification for treating the twelve literacy constructs as analytically separable components within a multidimensional literacy framework.

Table 3-13: Literacy pairwise correlation matrix

	Financial Literacy	Retirement Literacy	Health and Medical Literacy	Digital Financial Literacy	Media and Information Literacy	Artificial Intelligence Literacy	Data and Programming Literacy	Political Literacy	Environmental Literacy	Sustainable Financial Literacy	Human Literacy	Cultural Agility
Financial	1.000											
Retirement	0.251**	1.000										
Health and Medical	0.232**	0.186**	1.000									
Digital Financial	0.203**	0.140**	0.175**	1.000								
Media and Information	0.220**	0.161**	0.193**	0.243**	1.000							
Artificial Intelligence	0.341**	0.248**	0.288**	0.268**	0.381**	1.000						
Data and Programming	0.158**	0.106**	0.025**	0.162**	0.143**	0.165**	1.000					
Political	0.282**	0.192**	0.201**	0.144**	0.233**	0.265**	0.096**	1.000				
Environmental	0.247**	0.163**	0.255**	0.172**	0.200**	0.269**	0.078**	0.217**	1.000			
Sustainable Financial	0.356**	0.233**	0.299**	0.226**	0.268**	0.381**	0.023**	0.251**	0.292**	1.000		
Human Literacy	0.104**	0.075**	0.147**	0.187**	0.211**	0.196**	0.117**	0.144**	0.184**	0.186**	1.000	
Cultural Agility	0.132**	0.108**	0.133**	0.159**	0.183**	0.194**	0.104**	0.134**	0.134**	0.164**	0.320**	1.000

4. Individual literacy profiles across the EU and beyond

This section presents the empirical results based on the TRAILS-I survey, examining how the newly constructed skill indices are associated with individual characteristics and resilience-related outcomes. The aim is to move beyond descriptive patterns and provide a systematic, comparable assessment of which socio-demographic and economic factors are most strongly related to each skill index. The analysis remains within the scope of Task 5.2, namely it focuses on measurement, mapping, and associations, and does not attempt to identify causal effects or evaluate specific policy interventions.

Empirically, we estimate a common set of regression specifications in which the dependent variable is one of the twelve indices introduced in Section 3. For each index, we report results from six model variants that progressively introduce different sets of explanatory variables. These sets cover (i) demographic characteristics, (ii) income-related variables, (iii) labour-market characteristics, and (iv) indicators capturing aspects of economic resilience. Presenting the results in this structure makes it easier to compare patterns across the different skill indices, see which relationships remain stable when we add more controls, and assess whether disadvantages such as low income or labour-market insecurity are systematically associated with lower levels of the decision-relevant literacy and human/social transferable skill indices that are central to the green and digital transitions.

The section is organised around twelve regression tables, one for each skill index, each reporting the six specifications. Throughout, coefficients are interpreted as conditional associations rather than causal estimates, and the discussion focuses on the direction, relative magnitude, and robustness of key relationships across models and skill domains.

4.1 Empirical Strategy

This subsection describes the empirical approach used to assess how the newly constructed literacy/skill indices are related to individual characteristics and resilience-related outcomes in the TRAILS-I survey. The aim of the empirical analysis is to present conditional associations, i.e., how skill levels vary across individuals with different demographic profiles, economic resources, and job characteristics once common contextual factors are taken into account. While the analysis is descriptive, adopting a common reduced-form regression specification provides a consistent approach for comparing conditional correlations across skill indices and for assessing the robustness of observed patterns to gradual addition of covariates.

For each of the twelve indices described in Section 3, we estimate ordinary least squares (OLS) regressions in which the dependent variable is the relevant index score. Most indices range from 0 to 3, while a small number have wider ranges (e.g., AI Literacy and Data and Programming Literacy). Given that these measures are bounded and discrete, OLS is interpreted as capturing differences in average skill levels across groups and along the distribution of economic resources. The main advantage of this approach is comparability. Coefficients are measured in index points, allowing

comparisons across specifications within each skill domain. The same framework also facilitates comparisons across indices, even when their scales differ, as long as results are interpreted as conditional mean differences.

The baseline specification includes country fixed effects and takes the form:

$$Literacy_{ic} = \alpha + X_i\beta + \gamma_c + \varepsilon_{ic}$$

where $Literacy_{ic}$ denotes the value of a given literacy/skill index for individual i in country c, X_i is a vector of individual-level covariates, γ_c captures country fixed effects, and ε_{ic} is an error term. The dependent variable is the relevant index score. Country fixed effects absorb all time-invariant country characteristics that might influence both the level of skills and the distribution of covariates, such as institutional settings, education systems, labour-market structures, or broad differences in exposure to the green and digital transitions. As a result, coefficients in this specification are identified from within-country differences, comparing individuals who live in the same country but differ in demographics, resources, and job characteristics.

To check whether results are sensitive to a finer contextual control, we also estimate models with regional fixed effects. In this alternative specification, country fixed effects are replaced by region fixed effects defined at NUTS-2 for most countries and at NUTS-1 for the United Kingdom, Germany, and Turkey, reflecting data availability. The specification is:

$$Literacy_{ir} = \alpha + X_i\beta + \delta_r + \varepsilon_{ir}$$

where δ_r denotes fixed effects for region r. Regions are defined at NUTS-2 for most countries and at NUTS-1 for the United Kingdom, Germany, and Turkey, reflecting data availability. This approach controls for sub-national differences in economic structure, local labour markets, and institutional environments, and ensures that estimates are driven by variation among individuals within the same region rather than across regions within a country.

Across all models, the set of explanatory variables includes:

- Demographic characteristics: gender, age, marital status, and educational attainment level (ISCED codes) and employment status. These variables capture core life-course and human-capital gradients that are expected to be closely related to decision-relevant literacies and transferable skills.
- Economic factors: income deciles and wealth deciles. These variables proxy for both current economic position and longer-run accumulated resources, which may shape exposure to complex decision environments (e.g., finance, pensions, digital services) and access to learning opportunities.
- Job-related characteristics: the number of tasks performed in the respondent's main job. These variable captures task complexity or task breadth and provides a parsimonious way to link skill levels to job content, consistent with the goal of situating skills in the contexts in which they are used and developed.

For each skill index, results are reported across six specifications that progressively add these sets of variables. This structure makes it possible to assess whether certain associations, such as gaps by education, income, or job task intensity, are robust to alternative controls and whether some relationships are mainly explained by correlated characteristics. Throughout, the coefficients are

interpreted as conditional mean differences in index scores associated with the included covariates, holding constant the other regressors and the fixed effects.

In all regressions, we compute heteroskedasticity-robust standard errors clustered at the relevant contextual level. For country fixed-effects models, standard errors are clustered at the country level. For regional fixed-effects models, standard errors are clustered at the regional level (NUTS-2, or NUTS-1 where applicable). Clustering accounts for the possibility that unobserved shocks, measurement features, or contextual factors may induce correlation in the regression residuals among individuals within the same country or region, which would otherwise lead to overly precise inference. Finally, results are reported as conditional associations between the covariates and each skill index. Thus, the discussion focuses on the sign and relative size of coefficients, and on whether relationships persist as additional controls are added.

4.2 Empirical Results

This subsection presents the regression results for the twelve skill/literacy indices introduced in Section 3, reported in twelve separate tables where the dependent variable is the relevant index in each case. In all tables, columns (1)-(4) report OLS estimates with country fixed effects: column (1) includes demographic controls, while columns (2)-(4) progressively add income deciles, wealth deciles, and job-task controls, respectively. Column (5) replicates the specification in column (4) but replaces country fixed effects with regional fixed effects (NUTS-2 for most countries and NUTS-1 for the UK, Germany, and Turkey), and column (6) applies the same regional fixed-effects specification to the working-age subsample. Robust standard errors are clustered at the country level in columns (1)-(4) and at the regional level in columns (5)-(6).

Table 4-1 reports OLS estimates for the Financial Literacy index (0-3) across six specifications. Across all models, gender is statistically significant at the 1% level: men score significantly higher than women, with coefficients ranging from 0.312 to 0.365, all statistically significant at the 1% level. This translates into an advantage of about 15-17% relative to the model's linear prediction (as summarised in the "% Gender Effect" row), and the estimate remains essentially unchanged when using regional instead of country fixed effects and when restricting the sample to working-age respondents (column 6). In contrast, the coefficient for non-binary respondents is statistically insignificant in all specifications, reflecting limited sample size in that category.

Age effects are weak in almost all models. In the country fixed-effects specifications (columns 1-4), neither the linear nor the quadratic age term is statistically significant. With regional fixed effects (column 5), the quadratic term becomes marginally significant and positive, and in the working-age specification (column 6) the linear term is negative and statistically significant at the 5% level, while the quadratic term is positive and strongly significant at the 1% level. Taken together, these results indicate a nonlinear relationship between age and financial literacy. Rather, any remaining age pattern appears sensitive to the fixed-effects structure and sample restriction.

Marital status shows a small but statistically significant positive association with financial literacy in columns (1)-(3), but the coefficient becomes statistically insignificant when job tasks control is included (column 4). With regional fixed effects (column 5) the married coefficient is again positive and significant at the 5% level, while it becomes insignificant in the working-age sample (column 6). Widow/divorced status is generally not statistically different from single, except in column (6), where

it is negative and marginally significant. Respondents with "unknown" marital status are consistently estimated to have lower literacy than singles, which is likely capturing non-response patterns.

Education shows a clear and highly robust pattern relative to the reference group (primary education), with consistently higher outcomes at higher levels of educational attainment. Starting at upper secondary education (ISCED 3), coefficients are statistically significant across all specifications at the 1% level, and the magnitude rises with attainment. In the fully controlled country fixed-effects model (column 4), the estimated differences relative to primary education are about 0.274 (upper secondary), 0.294 (post-secondary non-tertiary), 0.372 (short-cycle tertiary), 0.515 (bachelor), 0.630 (master), and 0.552 (doctoral), all statistically significant at the 1% level. Coefficients for lower secondary education (ISCED 2) are small and not statistically significant. This monotonic pattern indicates that financial literacy is strongly associated with formal educational attainment even after conditioning on income, wealth, and job-task breadth.

Employment status is also strongly related to financial literacy. In the baseline model (column 1), relative to the reference inactive group, the estimated coefficients are positive for the self-employed (about 0.287) and employed (about 0.265), smaller but still positive for the unemployed (about 0.158) and retired (about 0.242), and largest for students (about 0.460); all are statistically significant at the 1% level. After adding income and wealth controls (columns 2-4), the coefficients decline in magnitude but remain statistically significant for the employed, self-employed, unemployed, and retired across columns (2)-(5). Taken together, the estimates show that stronger labour market attachment is associated with higher financial literacy, even after controlling for demographics and education, although part of the underlying relationship is due to income and wealth, as reflected in the attenuation of the coefficients once these controls are added. In column (6), the coefficients for "retired" and "student/pupil" are close to zero, which is expected because these groups are largely excluded by the sample restriction and therefore provide little variation for identifying differences within the working-age population.

The income-decile coefficients (reported in columns 2, 4, 5, and 6), estimated relative to the "prefer not to say" group, which is non-trivial in size, rise monotonically from the middle to the top of the income distribution and are almost uniformly statistically significant. In the full country fixed-effects model (column 4), coefficients are statistically significant at 1% level and range from about 0.144 in decile 4 up to 0.350 in decile 10, implying substantially higher financial literacy among higher-income respondents even after controlling for demographics, education, and employment. Lower income deciles show weaker and less consistent differences: decile 1 is positive and marginally significant in columns (2) and (4) and becomes significant in column (5), while decile 2 is not statistically different from the reference and decile 3 loses significance once job-task controls are included.

The wealth deciles (reported in column 3, again relative to "prefer not to say" group) show a similarly strong gradient, indicating that higher wealth deciles are associated with significantly higher financial literacy. Coefficients from decile 3 to decile 10 are positive and statistically significant at 1% level. In contrast, the bottom wealth decile is modestly negative (-0.042) and statistically significant at the 10% level, while wealth decile 2 is not significantly different from the reference.

Number of distinct tasks in the main job is positively related to financial literacy and statistically significant at the 1% level. In columns (4)-(6), each additional distinct job-task type is linked to a 0.038-0.043 increase in the index. This association is stable across country and regional fixed effects, suggesting that financial literacy is higher in jobs characterised by broader task portfolios,

Table 4-1: Financial literacy - OLS regression estimates

	Country fixed effects			Regional fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Gender: Male	0.365***	0.321***	0.325***	0.312***	0.313***	0.318***
	[0.017]	[0.017]	[0.016]	[0.017]	[0.012]	[0.014]
"-": Nonbinary	-0.012	0.014	0.001	0.026	0.014	0.003
	[0.134]	[0.136]	[0.135]	[0.132]	[0.138]	[0.157]
"-": Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age of respondent	0.001	-0.001	0.002	-0.001	-0.001	-0.008**
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Age of respondent (squared)	0.031	0.045	0.016	0.054	0.050*	0.134***
	[0.035]	[0.033]	[0.034]	[0.034]	[0.030]	[0.040]
Marital status: Married	0.066***	0.038*	0.038*	0.033	0.037**	0.020
	[0.019]	[0.019]	[0.019]	[0.019]	[0.017]	[0.018]
"-": Widow/Divorced	0.004	-0.006	0.007	-0.010	-0.008	-0.053*
	[0.030]	[0.029]	[0.029]	[0.029]	[0.027]	[0.030]
"-": Unknown	-0.034	-0.057*	-0.053	-0.061*	-0.055**	-0.070***
	[0.033]	[0.033]	[0.033]	[0.033]	[0.022]	[0.025]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
ISCED 2: Lower secondary education	0.045	0.043	0.043	0.035	0.036	0.079
	[0.068]	[0.065]	[0.067]	[0.065]	[0.063]	[0.072]
"-" 3: Upper secondary education	0.316***	0.294***	0.295***	0.274***	0.276***	0.324***
	[0.056]	[0.054]	[0.056]	[0.054]	[0.059]	[0.067]
"-" 4: Post-secondary non-tertiary educ.	0.342***	0.321***	0.309***	0.294***	0.301***	0.380***
	[0.068]	[0.067]	[0.066]	[0.066]	[0.070]	[0.080]
"-" 5: Short-cycle tertiary education	0.442***	0.402***	0.402***	0.372***	0.374***	0.425***
	[0.061]	[0.059]	[0.060]	[0.058]	[0.057]	[0.067]
"-" 6: Bachelor's or equivalent level	0.605***	0.546***	0.550***	0.515***	0.518***	0.603***
	[0.057]	[0.054]	[0.057]	[0.054]	[0.058]	[0.067]
"-" 7: Master's or equivalent level	0.738***	0.664***	0.668***	0.630***	0.634***	0.730***
	[0.062]	[0.060]	[0.062]	[0.060]	[0.060]	[0.068]
"-" 8: Doctoral or equivalent level	0.689***	0.589***	0.594***	0.552***	0.553***	0.658***
	[0.054]	[0.052]	[0.054]	[0.052]	[0.068]	[0.080]
"-" 1: Primary education	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Employment status: Self-employed	0.287***	0.223***	0.230***	0.200***	0.196***	0.195***
	[0.045]	[0.044]	[0.042]	[0.043]	[0.046]	[0.047]
"-": Employed	0.265***	0.163***	0.200***	0.152***	0.149***	0.142***
	[0.037]	[0.039]	[0.034]	[0.039]	[0.039]	[0.039]
"-": Unemployed	0.158***	0.159***	0.152***	0.156***	0.155***	0.154***
	[0.049]	[0.049]	[0.049]	[0.049]	[0.047]	[0.047]
"-": Homemaker/looking after home	0.088	0.053	0.050	0.061	0.070	0.070
	[0.053]	[0.051]	[0.050]	[0.051]	[0.053]	[0.054]
"-": Other employed (prefer not to say)	-0.062	0.004	-0.031	0.004	0.016	0.024
	[0.064]	[0.064]	[0.065]	[0.063]	[0.050]	[0.051]
"-": Retired	0.242***	0.188***	0.200***	0.176***	0.174***	0.001
	[0.042]	[0.042]	[0.040]	[0.042]	[0.041]	[0.001]
"-": Student/pupil (full time)	0.460***	0.450***	0.432***	0.468***	0.467***	0.001
	[0.043]	[0.044]	[0.042]	[0.043]	[0.049]	[0.001]
"-": Inactive	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Income: Decile 10	–	0.365***	–	0.350***	0.349***	0.334***
		[0.029]		[0.028]	[0.024]	[0.025]
"-": Decile 9	–	0.316***	–	0.307***	0.308***	0.299***

		[0.029]		[0.028]	[0.025]	[0.027]
"-": Decile 8	–	0.278***	–	0.267***	0.267***	0.259***
		[0.022]		[0.021]	[0.022]	[0.025]
"-": Decile 7	–	0.270***	–	0.262***	0.261***	0.264***
		[0.029]		[0.029]	[0.023]	[0.026]
"-": Decile 6	–	0.201***	–	0.195***	0.198***	0.204***
		[0.029]		[0.028]	[0.025]	[0.029]
"-": Decile 5	–	0.204***	–	0.196***	0.200***	0.195***
		[0.028]		[0.027]	[0.024]	[0.028]
"-": Decile 4	–	0.150***	–	0.144***	0.152***	0.148***
		[0.028]		[0.028]	[0.025]	[0.029]
"-": Decile 3	–	0.065*	–	0.059	0.067**	0.049
		[0.036]		[0.035]	[0.028]	[0.035]
"-": Decile 2	–	0.024	–	0.021	0.030	0.025
		[0.032]		[0.032]	[0.026]	[0.032]
"-": Decile 1	–	0.051*	–	0.051*	0.056**	0.039
		[0.027]		[0.027]	[0.023]	[0.025]
"-": Prefer not to say	–	*{Ref.}*	–	*{Ref.}*	*{Ref.}*	*{Ref.}*
Wealth: Decile 10	–	–	0.367***	–	–	–
			[0.026]			
"-": Decile 9	–	–	0.312***	–	–	–
			[0.027]			
"-": Decile 8	–	–	0.309***	–	–	–
			[0.026]			
"-": Decile 7	–	–	0.242***	–	–	–
			[0.028]			
"-": Decile 6	–	–	0.258***	–	–	–
			[0.029]			
"-": Decile 5	–	–	0.172***	–	–	–
			[0.024]			
"-": Decile 4	–	–	0.138***	–	–	–
			[0.029]			
"-": Decile 3	–	–	0.106***	–	–	–
			[0.027]			
"-": Decile 2	–	–	0.025	–	–	–
			[0.030]			
"-": Decile 1	–	–	-0.042*	–	–	–
			[0.022]			
"-": Prefer not to say	–	–	*{Ref.}*	–	–	–
Number of distinct job task types	–	–	–	0.043***	0.043***	0.038***
				[0.004]	[0.003]	[0.004]
Country Fixed Effects	+	+	+	+	-	-
Regional Fixed Effects	–	–	–	–	+	+
% Gender Effect	17.36%	15.23%	15.45%	14.83%	14.86%	15.26%
Linear prediction	2.1052	2.1052	2.1052	2.1052	2.1052	2.0835
No. of Observations	29,872	29,872	29,872	29,872	29,872	21,564

Notes: The dependent variable is the financial literacy index (0-3), with higher values indicating higher literacy levels. Columns (1)-(4) report OLS estimates with country fixed effects: column (1) includes demographic controls, while columns (2)-(4) additionally introduce income, wealth, and job-task controls, respectively. Column (5) replicates column (4) with regional fixed effects and column (6) applies the regional fixed effects specification to the working-age sample. Robust standard errors are clustered at the country level in (1)-(4) and at the regional level in (5)-(6). ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

consistent with the idea that more complex task environments may be associated with higher general decision capabilities (or with selection of higher-skill individuals into such jobs).

Overall, the estimates indicate that financial literacy is strongly and robustly associated with being male, with higher educational attainment, with higher income and wealth positions, and with broader task content in the main job. By contrast, age and marital status effects are comparatively small and less stable across specification.

Table 4-2 reports OLS estimates for the Retirement Literacy index (range 0–3), across six specifications. Across all specifications, men exhibit higher retirement literacy than women (reference group). The estimated male coefficient ranges from 0.091 to 0.135 index points and is statistically significant at the 1% level in every column. Interpreting magnitudes using the table's "% Gender Effect" row (computed relative to the reported linear prediction), the male advantage corresponds to roughly 9-14% higher predicted retirement literacy (from 9.31% in the working-age regional fixed effects specification to 14.21% in the baseline country fixed effects specification). By contrast, the coefficient for the nonbinary category is small and statistically insignificant throughout, with relatively large standard errors.

Age displays a robust nonlinear (inverted U-shape) relationship with retirement literacy. The linear age term is positive, while the squared term is negative, and both are statistically significant at the 1% level in all specifications, consistent with an inverted-U relationship. This indicates that retirement literacy rises with age at younger ages but the marginal increase diminishes and eventually turns down at older ages.

Regarding marital status, being married, relative to single respondents (reference group), is associated with a modest increase in retirement literacy in the baseline model (0.042), statistically significant at the 5% level in column (1). However, this association becomes statistically insignificant when additional covariates are included (columns 2-6). Widow/divorced status is statistically insignificant in all columns. A notable exception is the "marital status: unknown" category, which is consistently negative (approximately -0.067 to -0.082) and becomes statistically significant at the 5% level in columns (2)-(4) and at the 1% level in columns (5)-(6), indicating systematically lower retirement literacy among respondents not reporting marital status.

Education attainment level exhibits a strong and monotonic education gradient relative to primary education (reference group). Lower secondary education (ISCED 2) is statistically insignificant in every column. From upper secondary onward, coefficients are uniformly positive and large, and statistically significant at the 1% level across all specifications: roughly 0.146-0.185 (upper secondary), 0.209-0.248 (post-secondary non-tertiary), 0.197-0.260 (short-cycle tertiary), 0.309-0.389 (bachelor's), 0.392-0.487 (master's), and 0.325-0.448 (doctoral). These estimates indicate sizeable differences in retirement literacy by educational attainment that remain highly robust to the inclusion of fixed effects and further controls.

Regarding employment status, the self-employed, relative to inactive respondents (reference group), show consistently higher retirement literacy (0.115-0.197), statistically significant at the 1% level in all columns. Being employed is also positive, but the magnitude is smaller and less stable across specifications: it is statistically significant at the 1% level in columns (1) and (3), at the 10% level in columns (2), (5), and (6), and statistically insignificant in column (4). Unemployment is associated with higher retirement literacy than inactivity (around 0.085-0.095) and is statistically significant at the 5% level in every specification. Homemakers/looking after home and the "other employed (prefer not to say)" category are statistically insignificant throughout. Retired respondents

are estimated to have higher retirement literacy in the country fixed effects models (columns 1-4), with coefficients ranging from 0.060 to 0.110 and significant at 10% - 1% depending on the column. However, the association becomes statistically insignificant under regional fixed effects (column 5) and is essentially zero in the working-age specification (column 6), consistent with retirement status being less relevant once the sample is restricted. Students/pupils exhibit a positive and precisely estimated coefficient (around 0.163-0.187, statistically significant at the 1% level) in columns (1)-(5) but are effectively not informative in the working-age model (column 6), again reflecting the sample restriction.

Income seems to be positively related to retirement literacy, reporting positive and statistically significant coefficients mainly for deciles above the 3rd decile. Specifically, in columns (2), (4), (5), and (6), higher income deciles are associated with significantly higher retirement literacy, with coefficients generally rising toward the top of the distribution: for example, the top decile is about 0.298-0.310 and is statistically significant at the 1% level in all income specifications. Middle-to-upper deciles (roughly 4-9) are also consistently positive and statistically significant, mostly at the 1% level (with decile 4 typically significant at the 5% level). By contrast, the bottom deciles (1-2) are statistically insignificant throughout, and decile 3 is positive and significant in some specifications but becomes statistically insignificant in the working-age regional fixed effects model (column 6).

Wealth (included in column 3) exhibits a similarly strong pattern: deciles 4-10 are positive and statistically significant at the 1% level (with the top wealth decile about 0.329). Deciles 2-3 are small positive effects and statistically significant at the 10% level, while the bottom wealth decile is negative (about -0.039) and statistically significant at the 10% level, indicating a negative relationship between the low end of income distribution and retirement literacy.

Finally, job-task breadth is a robust correlate of retirement literacy: the number of distinct job task types appears an estimated coefficient of approximately 0.029-0.030 which is statistically significant at the 1% level in columns (4)-(6). This implies that greater task variety/complexity is associated with higher retirement literacy even after accounting for fixed effects and other covariates.

Overall, the estimates indicate the retirement literacy is strongly and robustly associated with being male, with labour market attachment, with an inverted-U age profile, with higher educational attainment, higher income and wealth, as well as with broader task content in the main job.

Table 4-2: Retirement Literacy - OLS regression estimates

	Country fixed effects			Regional fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Gender: Male	0.135***	0.097***	0.101***	0.092***	0.093***	0.091***
	[0.014]	[0.014]	[0.012]	[0.014]	[0.010]	[0.012]
"-": Nonbinary	-0.026	-0.004	-0.012	0.004	0.007	0.000
	[0.099]	[0.103]	[0.101]	[0.101]	[0.094]	[0.103]
"-": Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age of respondent	0.023***	0.021***	0.024***	0.021***	0.021***	0.018***
	[0.004]	[0.003]	[0.004]	[0.003]	[0.003]	[0.004]
Age of respondent (squared)	-0.222***	-0.210***	-0.235***	-0.204***	-0.206***	-0.174***
	[0.039]	[0.037]	[0.037]	[0.037]	[0.030]	[0.042]
Marital status: Married	0.042**	0.015	0.018	0.012	0.015	0.009
	[0.017]	[0.018]	[0.017]	[0.018]	[0.015]	[0.017]
"-": Widow/Divorced	0.014	0.006	0.016	0.003	0.004	-0.003
	[0.024]	[0.023]	[0.024]	[0.024]	[0.020]	[0.025]
"-": Unknown	-0.047	-0.067**	-0.062**	-0.069**	-0.069***	-0.082***
	[0.030]	[0.031]	[0.030]	[0.032]	[0.021]	[0.024]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
ISCED 2: Lower secondary education	0.005	0.007	0.004	0.002	-0.009	0.010
	[0.053]	[0.050]	[0.052]	[0.049]	[0.051]	[0.064]
"-" 3: Upper secondary education	0.185***	0.171***	0.167***	0.157***	0.146***	0.184***
	[0.046]	[0.043]	[0.045]	[0.043]	[0.043]	[0.053]
"-" 4: Post-secondary non-tertiary educ.	0.248***	0.233***	0.222***	0.215***	0.209***	0.242***
	[0.047]	[0.045]	[0.047]	[0.044]	[0.050]	[0.059]
"-" 5: Short-cycle tertiary education	0.260***	0.231***	0.228***	0.211***	0.197***	0.230***
	[0.050]	[0.048]	[0.049]	[0.047]	[0.045]	[0.056]
"-" 6: Bachelor's or equivalent level	0.389***	0.341***	0.343***	0.319***	0.309***	0.353***
	[0.054]	[0.050]	[0.052]	[0.049]	[0.043]	[0.054]
"-" 7: Master's or equivalent level	0.487***	0.424***	0.427***	0.401***	0.392***	0.442***
	[0.051]	[0.047]	[0.049]	[0.046]	[0.045]	[0.055]
"-" 8: Doctoral or equivalent level	0.448***	0.360***	0.367***	0.335***	0.325***	0.387***
	[0.057]	[0.051]	[0.054]	[0.049]	[0.056]	[0.070]
"-" 1: Primary education	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Employment status: Self-employed	0.197***	0.141***	0.149***	0.125***	0.119***	0.115***
	[0.040]	[0.038]	[0.038]	[0.039]	[0.038]	[0.038]
"-": Employed	0.152***	0.068*	0.100***	0.060	0.055*	0.061*
	[0.037]	[0.036]	[0.035]	[0.036]	[0.033]	[0.033]
"-": Unemployed	0.090**	0.092**	0.085**	0.090**	0.090**	0.095**
	[0.040]	[0.039]	[0.038]	[0.039]	[0.040]	[0.039]
"-": Homemaker/looking after home	0.022	-0.007	-0.009	-0.002	-0.006	0.000
	[0.043]	[0.042]	[0.041]	[0.043]	[0.038]	[0.037]
"-": Other employed (prefer not to say)	-0.013	0.041	0.008	0.041	0.047	0.038
	[0.040]	[0.041]	[0.040]	[0.040]	[0.044]	[0.045]
"-": Retired	0.110***	0.068*	0.077**	0.060*	0.056	0.001
	[0.038]	[0.036]	[0.036]	[0.035]	[0.035]	[0.001]
"-": Student/pupil (full time)	0.187***	0.175***	0.163***	0.187***	0.184***	0.001
	[0.046]	[0.045]	[0.045]	[0.046]	[0.040]	[0.001]
"-": Inactive	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Income: Decile 10	–	0.310***	–	0.300***	0.300***	0.298***
		[0.033]		[0.032]	[0.025]	[0.027]
"-": Decile 9	–	0.229***	–	0.223***	0.222***	0.225***

		[0.028]		[0.027]	[0.024]	[0.027]
"-": Decile 8	–	0.164***	–	0.156***	0.161***	0.168***
		[0.023]		[0.023]	[0.021]	[0.024]
"-": Decile 7	–	0.166***	–	0.161***	0.161***	0.149***
		[0.031]		[0.031]	[0.027]	[0.030]
"-": Decile 6	–	0.118***	–	0.113***	0.116***	0.102***
		[0.029]		[0.028]	[0.025]	[0.027]
"-": Decile 5	–	0.134***	–	0.129***	0.135***	0.093***
		[0.024]		[0.024]	[0.025]	[0.030]
"-": Decile 4	–	0.063***	–	0.059**	0.060**	0.058**
		[0.022]		[0.022]	[0.024]	[0.029]
"-": Decile 3	–	0.053***	–	0.049**	0.054**	0.040
		[0.019]		[0.019]	[0.023]	[0.030]
"-": Decile 2	–	-0.015	–	-0.017	-0.011	-0.013
		[0.016]		[0.016]	[0.021]	[0.026]
"-": Decile 1	–	-0.007	–	-0.007	0.000	0.014
		[0.019]		[0.019]	[0.018]	[0.022]
"-": Prefer not to say	–	*{Ref.}*	–	*{Ref.}*	*{Ref.}*	*{Ref.}*
Wealth: Decile 10	–	–	0.329***	–	–	–
			[0.039]			
"-": Decile 9	–	–	0.298***	–	–	–
			[0.034]			
"-": Decile 8	–	–	0.238***	–	–	–
			[0.030]			
"-": Decile 7	–	–	0.201***	–	–	–
			[0.037]			
"-": Decile 6	–	–	0.153***	–	–	–
			[0.029]			
"-": Decile 5	–	–	0.156***	–	–	–
			[0.030]			
"-": Decile 4	–	–	0.104***	–	–	–
			[0.028]			
"-": Decile 3	–	–	0.039*	–	–	–
			[0.019]			
"-": Decile 2	–	–	0.038*	–	–	–
			[0.021]			
"-": Decile 1	–	–	-0.039*	–	–	–
			[0.022]			
"-": Prefer not to say	–	–	*{Ref.}*	–	–	–
Number of distinct job task types	–	–	–	0.029***	0.030***	0.030***
				[0.004]	[0.004]	[0.005]
Country Fixed Effects	+	+	+	+	-	-
Regional Fixed Effects	–	–	–	–	+	+
% Gender Effect	14.21%	10.23%	10.64%	9.63%	9.73%	9.31%
Linear prediction	0.9519	0.9519	0.9519	0.9519	0.9519	0.9785
No. of Observations	29,872	29,872	29,872	29,872	29,872	21,564

Notes: The dependent variable is the retirement literacy index (0-3), with higher values indicating higher literacy levels. Columns (1)-(4) report OLS estimates with country fixed effects: column (1) includes demographic controls, while columns (2)-(4) additionally introduce income, wealth, and job-task controls, respectively. Column (5) replicates column (4) with regional fixed effects and column (6) applies the regional fixed effects specification to the working-age sample. Robust standard errors are clustered at the country level in (1)-(4) and at the regional level in (5)-(6). ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4-3 reports OLS estimates for the Health and Medical Literacy index (0-3) across six specifications. Across all models, men score lower on the health and medical literacy index than women (reference group). The male coefficient ranges from -0.126 to -0.168 index points and is statistically significant at the 1% level in every column. Using the table's "% Gender Effect" row (computed relative to the reported linear prediction), this corresponds to approximately 5.7% to 7.7% lower predicted health literacy for men, with the largest magnitude in the working-age regional fixed effects specification (-7.70%). The nonbinary coefficient is small relative to its standard error and is statistically insignificant in all columns.

Age exhibits a robust nonlinear pattern. Specifically, the linear age term is positive and statistically significant at the 1% level throughout, while the squared age term is negative and statistically significant (at the 5% level in most columns and at the 10% level in column (4)). This indicates an inverted-U relationship, namely health and medical literacy tends to rise with age, but at a diminishing rate and eventually declines at older ages.

Regarding marital status, being married, relative to single respondents (reference group), is associated with higher health literacy in every specification, with coefficients of 0.064-0.090 that are statistically significant at the 1% level throughout. Widow/divorced status is statistically insignificant in all columns. Not reporting marital status ("unknown") is associated with lower health and medical literacy: the effect is statistically significant at the 10% level in columns (2) and (4), and at the 5% level in columns (5)-(6), while it is statistically insignificant in columns (1) and (3).

Education shows a strong and monotonic upward gradient relative to primary education (reference). Lower secondary education (ISCED 2) is statistically insignificant in all columns (and effectively zero in column (6)). From upper secondary onwards, all coefficients are positive and statistically significant at the 1% level in every specification, increasing with educational attainment level: approximately 0.190-0.216 (upper secondary), 0.231-0.260 (post-secondary non-tertiary), 0.290-0.333 (short-cycle tertiary), 0.329-0.385 (bachelor's), 0.418-0.484 (master's), and 0.377-0.459 (doctoral). These are substantively large differences and highly robust to fixed effects and additional controls.

In the baseline model (column 1), relative to inactive respondents (reference group), self-employment is associated with higher health and medical literacy, with a coefficient of 0.093 and statistically significant at the 5% level. However, it becomes statistically insignificant once income/wealth and job-task controls are included and under regional fixed effects. Being employed exerts a positive coefficient in all columns, but it is only statistically significant at the 1% level in column (1) and at the 5% level in column (3), and statistically insignificant elsewhere. Unemployment, homemaker status, and "other employed (prefer not to say)" are statistically insignificant throughout. Retired respondents have higher health literacy in the full-sample specifications with coefficients ranging from 0.088 to 0.132 and significant at 10%-1% across columns (1)-(5), but the estimate is essentially zero and statistically insignificant in the working-age specification in column (6). Students/pupils display a large positive association in the full sample (0.293-0.318, statistically significant at the 1% level in columns (1)-(5)), while the coefficient is near zero and statistically insignificant in the working-age model.

The income-decile coefficients (reported in columns 2, 4, 5, and 6), estimated relative to the "prefer not to say" group, which is non-trivial in size, show a clear gradient. Specifically, upper-middle and top income deciles (4-10) are consistently positive and statistically significant at the 1% level in columns (2), (4), (5), and (6), with the top decile around 0.191-0.202. In contrast, the bottom deciles 1-3 are small and statistically insignificant across these specifications.

The wealth deciles (reported in column 3, again relative to "prefer not to say" group) exhibit a similarly strong pattern. Specifically, upper-middle and top wealth deciles 4-10 are positive and statistically significant at the 1% level (top wealth decile 0.225), wealth decile 3 is positive and statistically significant at the 5% level (0.060), wealth decile 2 is statistically insignificant, and the bottom wealth decile is negative (-0.041) and statistically significant at the 5% level.

Job-task breadth is also positively related to health and medical literacy. Specifically, the number of distinct job task types has a coefficient of 0.028-0.029 and is statistically significant at the 1% level in columns (4)-(6), indicating that broader task exposure is systematically associated with higher health and medical literacy even after controlling for fixed effects and socioeconomic characteristics.

Overall, the estimates for health and literacy index suggest: a male disadvantage, an inverted-U age profile, a strong education upward gradient, a positive association with being married, the income/wealth upward gradients concentrated in the upper distribution, and a positive role of job-task breadth. These results are not driven solely by cross-country composition, while remaining best interpreted as associations in an observational framework.

Table 4-3: Health and Medical literacy - OLS regression estimates

	Country fixed effects			Regional fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Gender: Male	-0.126***	-0.152***	-0.149***	-0.158***	-0.156***	-0.168***
	[0.013]	[0.013]	[0.013]	[0.013]	[0.011]	[0.013]
"-": Nonbinary	-0.080	-0.060	-0.070	-0.052	-0.041	0.071
	[0.128]	[0.129]	[0.129]	[0.130]	[0.124]	[0.133]
"-": Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age of respondent	0.012***	0.011***	0.013***	0.010***	0.011***	0.013***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.002]	[0.004]
Age of respondent (squared)	-0.077**	-0.069**	-0.087**	-0.063*	-0.065**	-0.086**
	[0.031]	[0.032]	[0.032]	[0.032]	[0.027]	[0.042]
Marital status: Married	0.090***	0.073***	0.073***	0.070***	0.071***	0.064***
	[0.016]	[0.017]	[0.016]	[0.017]	[0.017]	[0.018]
"-": Widow/Divorced	0.021	0.014	0.023	0.012	0.011	-0.011
	[0.026]	[0.027]	[0.026]	[0.026]	[0.024]	[0.027]
"-": Unknown	-0.047	-0.060*	-0.057	-0.062*	-0.057**	-0.050**
	[0.034]	[0.034]	[0.034]	[0.034]	[0.022]	[0.023]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
ISCED 2: Lower secondary education	0.042	0.042	0.042	0.037	0.036	0.000
	[0.049]	[0.049]	[0.049]	[0.049]	[0.052]	[0.062]
"-" 3: Upper secondary education	0.216***	0.204***	0.204***	0.190***	0.191***	0.195***
	[0.043]	[0.043]	[0.043]	[0.043]	[0.048]	[0.057]
"-" 4: Post-secondary non-tertiary educ.	0.260***	0.249***	0.242***	0.231***	0.232***	0.250***
	[0.058]	[0.059]	[0.058]	[0.058]	[0.059]	[0.070]
"-" 5: Short-cycle tertiary education	0.333***	0.310***	0.310***	0.290***	0.292***	0.312***
	[0.040]	[0.039]	[0.040]	[0.039]	[0.048]	[0.058]
"-" 6: Bachelor's or equivalent level	0.385***	0.351***	0.353***	0.329***	0.331***	0.362***
	[0.041]	[0.040]	[0.041]	[0.039]	[0.046]	[0.054]
"-" 7: Master's or equivalent level	0.484***	0.441***	0.443***	0.418***	0.417***	0.452***
	[0.044]	[0.043]	[0.044]	[0.042]	[0.048]	[0.058]
"-" 8: Doctoral or equivalent level	0.459***	0.402***	0.404***	0.377***	0.379***	0.415***
	[0.050]	[0.048]	[0.048]	[0.047]	[0.053]	[0.067]
"-" 1: Primary education	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Employment status: Self-employed	0.093**	0.052	0.060	0.036	0.041	0.019
	[0.046]	[0.045]	[0.045]	[0.045]	[0.044]	[0.045]
"-": Employed	0.117***	0.052	0.080**	0.045	0.049	0.026
	[0.038]	[0.039]	[0.037]	[0.039]	[0.038]	[0.039]
"-": Unemployed	0.045	0.047	0.042	0.045	0.051	0.041
	[0.046]	[0.045]	[0.045]	[0.044]	[0.044]	[0.044]
"-": Homemaker/looking after home	0.063	0.041	0.041	0.047	0.061	0.045
	[0.041]	[0.041]	[0.040]	[0.041]	[0.046]	[0.046]
"-": Other employed (prefer not to say)	-0.048	-0.005	-0.033	-0.005	0.005	0.022
	[0.043]	[0.042]	[0.042]	[0.041]	[0.040]	[0.042]
"-": Retired	0.132***	0.096**	0.108**	0.088*	0.089**	0.001
	[0.044]	[0.044]	[0.044]	[0.044]	[0.042]	[0.001]
"-": Student/pupil (full time)	0.310***	0.305***	0.293***	0.317***	0.318***	0.001
	[0.048]	[0.048]	[0.046]	[0.048]	[0.047]	[0.001]
"-": Inactive	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Income: Decile 10	–	0.202***	–	0.192***	0.191***	0.193***
		[0.017]		[0.017]	[0.018]	[0.020]
"-": Decile 9	–	0.186***	–	0.180***	0.180***	0.178***

		[0.023]		[0.023]	[0.021]	[0.024]
"-": Decile 8	–	0.164***	–	0.156***	0.158***	0.169***
		[0.020]		[0.020]	[0.019]	[0.021]
"-": Decile 7	–	0.159***	–	0.154***	0.157***	0.155***
		[0.018]		[0.018]	[0.019]	[0.025]
"-": Decile 6	–	0.104***	–	0.100***	0.100***	0.090***
		[0.021]		[0.021]	[0.022]	[0.026]
"-": Decile 5	–	0.091***	–	0.086***	0.090***	0.081***
		[0.020]		[0.020]	[0.022]	[0.024]
"-": Decile 4	–	0.079***	–	0.076***	0.078***	0.083***
		[0.022]		[0.022]	[0.024]	[0.028]
"-": Decile 3	–	0.033	–	0.029	0.037	0.042
		[0.024]		[0.024]	[0.023]	[0.028]
"-": Decile 2	–	0.033	–	0.030	0.034	0.043
		[0.022]		[0.022]	[0.021]	[0.027]
"-": Decile 1	–	-0.001	–	-0.001	0.006	-0.020
		[0.018]		[0.018]	[0.019]	[0.023]
"-": Prefer not to say	–	*{Ref.}*	–	*{Ref.}*	*{Ref.}*	*{Ref.}*
Wealth: Decile 10	–	–	0.225***	–	–	–
			[0.022]			
"-": Decile 9	–	–	0.174***	–	–	–
			[0.020]			
"-": Decile 8	–	–	0.162***	–	–	–
			[0.031]			
"-": Decile 7	–	–	0.136***	–	–	–
			[0.026]			
"-": Decile 6	–	–	0.115***	–	–	–
			[0.025]			
"-": Decile 5	–	–	0.068***	–	–	–
			[0.018]			
"-": Decile 4	–	–	0.078***	–	–	–
			[0.020]			
"-": Decile 3	–	–	0.060**	–	–	–
			[0.022]			
"-": Decile 2	–	–	0.007	–	–	–
			[0.019]			
"-": Decile 1	–	–	-0.041**	–	–	–
			[0.019]			
"-": Prefer not to say	–	–	*{Ref.}*	–	–	–
Number of distinct job task types	–	–	–	0.029***	0.029***	0.028***
				[0.004]	[0.004]	[0.004]
Country Fixed Effects	+	+	+	+	-	-
Regional Fixed Effects	–	–	–	–	+	+
% Gender Effect	-5.72%	-6.90%	-6.76%	-7.16%	-7.09%	-7.70%
Linear prediction	2.2043	2.2043	2.2043	2.2043	2.2043	2.1813
No. of Observations	29,872	29,872	29,872	29,872	29,872	21,564

Notes: The dependent variable is the health literacy index (0-3), with higher values indicating higher literacy levels. Columns (1)-(4) report OLS estimates with country fixed effects, starting with demographic controls (1) and then adding income, wealth, and job-task controls in (2)-(4). Column (5) replicates (4) with regional fixed effects and column (6) applies the regional fixed effects specification to the working-age sample. Robust standard errors are clustered at the country level in (1)-(4) and at the regional level in (5)-(6). ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4-4 reports OLS estimates for the Digital Financial Literacy index (0-3) across six specifications. Relative to women (reference group), men display a small positive association with digital financial literacy in the country fixed effects specifications: the coefficient is 0.056 in column (1) and statistically significant at the 1% level and remains positive but smaller when adding income and wealth in columns (2) and (3). However, once job-task breadth is included in column (4) and when moving to regional fixed effects in columns (5) and (6), the male coefficient becomes statistically insignificant. Consistent with this attenuation, the table's % Gender Effect declines from 2.89% in column (1) to 0.77% in column (6), indicating that any male advantage is modest and not robust to richer controls and alternative fixed effects. By contrast, the coefficient for the nonbinary category is negative throughout (approximately -0.16 to -0.26) and statistically significant at the 10% level in column (1), at the 5% level in the working-age specification in column (6), but statistically insignificant in the remaining columns.

Age exhibits a nonlinear (U-shaped) pattern. Specifically, the linear age term is negative and statistically significant at the 5% level in columns (1) and (3), and at the 1% level in columns (2), (4), (5), and (6). While the age squared term is positive and statistically significant at the 5% level in columns (1), (2), and (4), at the 10% level in column (3), and at the 1% level in columns (5)-(6). Taken together, the signs imply that digital financial literacy decreases with age at lower ages, but the relationship turns upward at higher ages.

Regarding marital status seems not to be correlated with digital financial literacy. The coefficients for being married, widow/divorced, and marital status unknown are small and statistically insignificant in all specifications. This suggests limited independent association once fixed effects and other covariates are accounted for.

The results reveal a strong and highly robust education gradient relative to primary education (reference group). Lower secondary education (ISCED 2) is positive and statistically significant at the 5% level in columns (1)-(5) (around 0.116-0.131) but becomes statistically insignificant in the working-age specification in column (6). From upper secondary onwards, the coefficients are uniformly positive, large, and statistically significant at the 1% level in every column: approximately 0.252-0.294 for upper secondary, 0.268-0.337 for post-secondary non-tertiary, 0.295-0.359 for short-cycle tertiary, 0.342-0.417 for bachelor's, 0.377-0.462 for master's, and 0.278-0.382 for doctoral education. These magnitudes indicate substantial differences in digital financial literacy by educational attainment that are stable across fixed-effect structures and sample restrictions.

Relative to inactive respondents (reference), there is limited evidence that employment status per se increases digital financial literacy once other covariates are included. Self-employment and unemployment are statistically insignificant in all columns. Being employed becomes negative and statistically significant at the 10% level in the richer specifications with job-task breadth in columns (4) and (5) respectively but is statistically insignificant elsewhere (including the working-age model). Homemaker/looking after home is consistently negative once income and other controls are included. Specifically, it is statistically significant at the 5% level in columns (2)-(5) (around -0.084 to -0.094) and remains negative (-0.079) and statistically significant at the 10% level in the working-age specification in column (6). Retired status is statistically insignificant in columns (1)-(5), and effectively zero and statistically insignificant in column (6), consistent with retirement being largely irrelevant once the sample is restricted to working age. Students/pupils show a robust positive association in the full sample, about 0.149-0.181 and statistically significant at the 1% level in columns (1)-(5) but are essentially not informative in the working-age specification in column (6), which is mechanically consistent with the restriction.

The income-decile coefficients (reported in columns 2, 4, 5, and 6), estimated relative to the "prefer not to say" group, which is non-trivial in size, show a clear gradient. Specifically, all income deciles from 1 to 10 are positive and statistically significant at the 1% level, with larger coefficients at higher deciles (e.g., around 0.069-0.091 for decile 1 and 0.240-0.260 for decile 10).

The wealth deciles (reported in column 3, again relative to "prefer not to say" group) exhibit a similarly strong pattern. Specifically, wealth deciles from2 to 10 are positive and statistically significant at the 1% level, ranging from 0.079 in decile 2 to about 0.205-0.222 in the top deciles. In contrast wealth decile 1 is small (0.017) and statistically insignificant.

Job-task breadth is also a robust predictor. Specifically, the number of distinct job task types is positive and statistically significant at the 1% level in columns (4)-(6), with coefficients of 0.046 in columns (4)-(5) and 0.040 in column (6), indicating that broader task exposure is systematically associated with higher digital financial literacy.

Overall, the most stable correlates across specifications are the strong education gradient, the income and wealth gradients (when included), and the positive association with job-task breadth. In contrast, the male advantage is small and loses statistical significance once the full set of controls (and/or regional fixed effects) is introduced, suggesting that gender differences in digital financial literacy are comparatively sensitive to covariate adjustment and specification choice.

Table 4-4: Digital Financial literacy - OLS regression estimates

	Country fixed effects			Regional fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Gender: Male	0.056***	0.027**	0.031***	0.018	0.016	0.015
	[0.011]	[0.012]	[0.011]	[0.012]	[0.012]	[0.014]
"-": Nonbinary	-0.197*	-0.176	-0.187	-0.163	-0.171	-0.255**
	[0.113]	[0.113]	[0.113]	[0.112]	[0.118]	[0.121]
"-": Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age of respondent	-0.011**	-0.013***	-0.011**	-0.013***	-0.013***	-0.015***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.003]	[0.004]
Age of respondent (squared)	0.086**	0.095**	0.079*	0.104**	0.103***	0.131***
	[0.041]	[0.040]	[0.040]	[0.040]	[0.031]	[0.045]
Marital status: Married	0.017	0.001	0.001	-0.005	-0.003	-0.016
	[0.016]	[0.014]	[0.015]	[0.014]	[0.016]	[0.019]
"-": Widow/Divorced	-0.001	-0.008	0.001	-0.012	-0.012	-0.019
	[0.028]	[0.028]	[0.028]	[0.027]	[0.031]	[0.038]
"-": Unknown	0.030	0.014	0.016	0.010	0.010	0.007
	[0.020]	[0.019]	[0.019]	[0.019]	[0.019]	[0.021]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
ISCED 2: Lower secondary education	0.131**	0.127**	0.124**	0.118**	0.116**	0.089
	[0.056]	[0.056]	[0.057]	[0.055]	[0.058]	[0.067]
"-" 3: Upper secondary education	0.294***	0.276***	0.275***	0.255***	0.252***	0.270***
	[0.052]	[0.053]	[0.054]	[0.052]	[0.054]	[0.063]
"-" 4: Post-secondary non-tertiary educ.	0.337***	0.321***	0.313***	0.293***	0.291***	0.268***
	[0.068]	[0.069]	[0.069]	[0.068]	[0.063]	[0.075]
"-" 5: Short-cycle tertiary education	0.359***	0.331***	0.331***	0.299***	0.295***	0.325***
	[0.046]	[0.048]	[0.049]	[0.048]	[0.055]	[0.065]
"-" 6: Bachelor's or equivalent level	0.417***	0.378***	0.381***	0.345***	0.342***	0.367***
	[0.055]	[0.055]	[0.056]	[0.055]	[0.055]	[0.065]
"-" 7: Master's or equivalent level	0.462***	0.415***	0.420***	0.379***	0.377***	0.401***
	[0.053]	[0.054]	[0.055]	[0.054]	[0.055]	[0.065]
"-" 8: Doctoral or equivalent level	0.382***	0.319***	0.325***	0.281***	0.278***	0.352***
	[0.056]	[0.057]	[0.058]	[0.056]	[0.064]	[0.071]
"-" 1: Primary education	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Employment status: Self-employed	0.009	-0.033	-0.024	-0.057	-0.063	-0.059
	[0.044]	[0.043]	[0.043]	[0.042]	[0.043]	[0.044]
"-": Employed	0.015	-0.052	-0.025	-0.064*	-0.069*	-0.062
	[0.038]	[0.037]	[0.037]	[0.036]	[0.040]	[0.040]
"-": Unemployed	0.053	0.054	0.047	0.051	0.049	0.044
	[0.043]	[0.043]	[0.043]	[0.041]	[0.045]	[0.045]
"-": Homemaker/looking after home	-0.072	-0.093**	-0.094**	-0.084**	-0.092**	-0.079*
	[0.042]	[0.041]	[0.041]	[0.038]	[0.044]	[0.046]
"-": Other employed (prefer not to say)	0.028	0.072	0.051	0.073	0.070	0.077
	[0.046]	[0.045]	[0.048]	[0.046]	[0.053]	[0.054]
"-": Retired	-0.006	-0.046	-0.035	-0.059	-0.063	0.001
	[0.040]	[0.038]	[0.039]	[0.037]	[0.042]	[0.001]
"-": Student/pupil (full time)	0.163***	0.162***	0.149***	0.181***	0.174***	0.001
	[0.046]	[0.047]	[0.046]	[0.046]	[0.049]	[0.001]
"-": Inactive	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Income: Decile 10	–	0.260***	–	0.244***	0.245***	0.240***
		[0.026]		[0.026]	[0.022]	[0.025]
"-": Decile 9	–	0.249***	–	0.239***	0.241***	0.238***

		[0.027]		[0.028]	[0.026]	[0.030]
"-": Decile 8	–	0.211***	–	0.199***	0.204***	0.188***
		[0.023]		[0.023]	[0.027]	[0.030]
"-": Decile 7	–	0.222***	–	0.214***	0.216***	0.210***
		[0.029]		[0.029]	[0.024]	[0.029]
"-": Decile 6	–	0.188***	–	0.181***	0.184***	0.168***
		[0.018]		[0.018]	[0.022]	[0.026]
"-": Decile 5	–	0.170***	–	0.162***	0.165***	0.165***
		[0.031]		[0.030]	[0.026]	[0.031]
"-": Decile 4	–	0.141***	–	0.135***	0.135***	0.134***
		[0.026]		[0.026]	[0.026]	[0.029]
"-": Decile 3	–	0.098***	–	0.091***	0.095***	0.115***
		[0.025]		[0.025]	[0.025]	[0.032]
"-": Decile 2	–	0.092***	–	0.089***	0.089***	0.123***
		[0.023]		[0.023]	[0.023]	[0.032]
"-": Decile 1	–	0.069***	–	0.069***	0.071***	0.091***
		[0.023]		[0.023]	[0.019]	[0.023]
"-": Prefer not to say	–	*{Ref.}*	–	*{Ref.}*	*{Ref.}*	*{Ref.}*
Wealth: Decile 10	–	–	0.205***	–	–	–
			[0.019]			
"-": Decile 9	–	–	0.222***	–	–	–
			[0.022]			
"-": Decile 8	–	–	0.174***	–	–	–
			[0.023]			
"-": Decile 7	–	–	0.179***	–	–	–
			[0.027]			
"-": Decile 6	–	–	0.185***	–	–	–
			[0.020]			
"-": Decile 5	–	–	0.164***	–	–	–
			[0.023]			
"-": Decile 4	–	–	0.153***	–	–	–
			[0.015]			
"-": Decile 3	–	–	0.106***	–	–	–
			[0.019]			
"-": Decile 2	–	–	0.079***	–	–	–
			[0.021]			
"-": Decile 1	–	–	0.017	–	–	–
			[0.018]			
"-": Prefer not to say	–	–	*{Ref.}*	–	–	–
Number of distinct job task types	–	–	–	0.046***	0.046***	0.040***
				[0.004]	[0.004]	[0.005]
Country Fixed Effects	+	+	+	+	-	-
Regional Fixed Effects	–	–	–	–	+	+
% Gender Effect	2.89%	1.38%	1.61%	0.92%	0.84%	0.77%
Linear prediction	1.9250	1.9250	1.9250	1.9250	1.9250	1.9334
No. of Observations	29,872	29,872	29,872	29,872	29,872	21,564

Notes: The dependent variable is the digital financial literacy index (0-3), with higher values indicating higher literacy levels. Columns (1)-(4) report OLS estimates with country fixed effects, starting with demographic controls (1) and then adding income, wealth, and job-task controls in (2)-(4). Column (5) replicates (4) with regional fixed effects and column (6) applies the regional fixed effects specification to the working-age sample. Robust standard errors are clustered at the country level in (1)-(4) and at the regional level in (5)-(6). ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4-5 reports OLS estimates for the Media and Information Literacy index (0-3) across six specifications. Relative to women (reference group), men exhibit higher media and information literacy in every specification. The male coefficient ranges from 0.057 to 0.092 index points and is statistically significant at the 1% level throughout, implying a small but still robust male advantage on the 0-3 scale. Consistent with this, the table's "% Gender Effect" indicates that the male coefficient corresponds to roughly 4.1%-6.7% higher predicted media and information literacy relative to the reported linear prediction (about 1.39). For respondents identifying as nonbinary, the coefficient is positive and sizeable in columns (1)-(5) (around 0.258-0.305) and statistically significant at the 5% level, but it becomes statistically insignificant in the working-age specification in column (6), reflecting reduced precision (and/or limited variation) under the sample restriction.

Age does not seem to be a systematic correlate of media and information literacy. Both the linear and squared age terms are statistically insignificant across all specifications, providing no evidence of a robust age effect on media and information literacy.

Regarding marital status, relative to being single (reference group), being married is linked to a reduction of 0.036-0.064 points, with the estimate strengthening from statistical significance at the 10% level in column (1) to statistical significance at the 1% level in columns (4)-(6). Widow/divorced respondents also exert negative coefficients (about -0.059 to -0.083), with statistical significance rising from the 10% level in columns (1)-(3) to the 1% level in columns (5)-(6). Not reporting marital status ("unknown") is associated with a larger deficit (-0.088 to -0.109) and is statistically significant at the 1% level in every specification.

The estimates reveal a strong and monotonic relationship between media and information literacy and education attainment, relative to primary education (reference). Lower secondary education (ISCED 2) is close to zero and statistically insignificant throughout. From upper secondary upwards, coefficients are uniformly positive, large, and statistically significant at the 1% level in every column: approximately 0.177-0.225 (upper secondary), 0.198-0.269 (post-secondary non-tertiary), 0.276-0.346 (short-cycle tertiary), 0.394-0.480 (bachelor's), 0.478-0.575 (master's), and 0.414-0.534 (doctoral).

Regarding employment status, self-employment and unemployment (relative to inactive) are statistically insignificant in all specifications. Being employed becomes negative and statistically significant once more controls are introduced: the employed coefficient is -0.119 and significant at the 1% level in column (2), -0.095 and significant at the 5% level in column (3), and around -0.130 to -0.133 and significant at the 1% level in columns (4)-(6). Homemakers/looking after home consistently score lower than inactive respondents, with coefficients around -0.097 to -0.125 that are statistically significant at the 5% or 1% level across all specifications. The "other employed (prefer not to say)" category is positive (about 0.109-0.151) and becomes increasingly precisely estimated, reaching statistical significance at the 1% level in column (6). Retired status is statistically insignificant in the full-sample specifications in columns (1)-(5) and in the working-age model in column (6), the estimate is essentially zero and statistically insignificant, consistent with the sample restriction. Students/pupils show a strong positive association in the full sample (about 0.190-0.220) and statistically significant at the 1% level in columns (1)-(5), but the coefficient is effectively zero and statistically insignificant in the working-age specification, again consistent with the restriction.

The income-decile coefficients (reported in columns 2, 4, 5, and 6), estimated relative to the "prefer not to say" group, which is again non-trivial in size, show a clear positive gradient. Higher income deciles-particularly deciles 4-10, are consistently positive and statistically significant at the 5% or

1% level, with the top decile around 0.181-0.208 and significant at 1% level. Lower income deciles (1-2) are small and statistically insignificant, while decile 3 is only weakly related as it is significant at the 10% level in columns (2) and (5) and statistically insignificant in columns (4) and (6).

The wealth deciles (reported in column 3, again relative to "prefer not to say" group) also show a broadly increasing pattern. Specifically, wealth deciles 5-10 are positive and statistically significant (mostly at the 1% level, with top deciles around 0.180-0.186), wealth decile 3 is positive (0.044) and statistically significant at the 5% level, while the bottom wealth decile is negative (-0.038) and statistically significant at the 10% level. Wealth deciles 2 and 4 are statistically insignificant.

Job-task breadth is again a robust predictor. The number of distinct job task types is positive and statistically significant at the 1% level in columns (4)-(6), with coefficients of 0.053 in columns (4)-(5) and 0.046 in column (6), indicating that broader task exposure is systematically associated with higher media and information literacy.

Overall, the most stable patterns are the positive male differential, the large education upward gradient, the income and wealth upward gradients concentrated in the middle and upper parts of the distribution, and the positive association with job-task breadth. At the same time, the absence of statistically significant age effects and the negative coefficients for being married/widowed-divorced and for being employed (relative to inactivity) highlight that, conditional on observed covariates and fixed effects, media and information literacy correlates more strongly with education and socioeconomic resources than with lifecycle age profiles.

Table 4-5: Media and Information literacy - OLS regression estimates

	Country fixed effects			Regional fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Gender: Male	0.092***	0.067***	0.074***	0.057***	0.058***	0.065***
	[0.014]	[0.015]	[0.014]	[0.014]	[0.012]	[0.013]
"-": Nonbinary	0.258**	0.273**	0.267**	0.288**	0.305**	0.180
	[0.117]	[0.118]	[0.118]	[0.118]	[0.118]	[0.132]
"-": Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age of respondent	-0.004	-0.005	-0.003	-0.006	-0.005	-0.003
	[0.004]	[0.004]	[0.004]	[0.004]	[0.003]	[0.005]
Age of respondent (squared)	-0.003	0.005	-0.012	0.016	0.010	-0.012
	[0.040]	[0.040]	[0.040]	[0.040]	[0.031]	[0.048]
Marital status: Married	-0.036*	-0.053**	-0.050**	-0.059***	-0.054***	-0.064***
	[0.019]	[0.020]	[0.019]	[0.020]	[0.016]	[0.019]
"-": Widow/Divorced	-0.060*	-0.067*	-0.059*	-0.071**	-0.070***	-0.083***
	[0.033]	[0.034]	[0.033]	[0.033]	[0.025]	[0.031]
"-": Unknown	-0.088***	-0.101***	-0.097***	-0.105***	-0.101***	-0.109***
	[0.031]	[0.032]	[0.031]	[0.031]	[0.021]	[0.025]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
ISCED 2: Lower secondary education	-0.005	-0.005	-0.004	-0.016	-0.032	-0.012
	[0.062]	[0.063]	[0.064]	[0.062]	[0.057]	[0.066]
"-" 3: Upper secondary education	0.222***	0.212***	0.214***	0.186***	0.177***	0.225***
	[0.066]	[0.066]	[0.067]	[0.066]	[0.059]	[0.065]
"-" 4: Post-secondary non-tertiary educ.	0.255***	0.244***	0.240***	0.211***	0.198***	0.269***
	[0.075]	[0.076]	[0.075]	[0.075]	[0.067]	[0.070]
"-" 5: Short-cycle tertiary education	0.346***	0.325***	0.328***	0.288***	0.276***	0.318***
	[0.059]	[0.061]	[0.061]	[0.061]	[0.058]	[0.065]
"-" 6: Bachelor's or equivalent level	0.480***	0.447***	0.454***	0.408***	0.394***	0.466***
	[0.063]	[0.064]	[0.064]	[0.064]	[0.058]	[0.064]
"-" 7: Master's or equivalent level	0.575***	0.534***	0.542***	0.492***	0.478***	0.544***
	[0.070]	[0.071]	[0.071]	[0.071]	[0.063]	[0.065]
"-" 8: Doctoral or equivalent level	0.534***	0.476***	0.488***	0.431***	0.414***	0.506***
	[0.080]	[0.079]	[0.078]	[0.078]	[0.073]	[0.081]
"-" 1: Primary education	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Employment status: Self-employed	0.050	0.014	0.021	-0.014	-0.011	-0.008
	[0.049]	[0.049]	[0.048]	[0.049]	[0.049]	[0.050]
"-": Employed	-0.065	-0.119***	-0.095**	-0.133***	-0.130***	-0.132***
	[0.042]	[0.043]	[0.041]	[0.043]	[0.041]	[0.041]
"-": Unemployed	0.014	0.015	0.011	0.011	0.012	0.011
	[0.044]	[0.044]	[0.044]	[0.045]	[0.046]	[0.046]
"-": Homemaker/looking after home	-0.107**	-0.125***	-0.125***	-0.115***	-0.112**	-0.097**
	[0.040]	[0.039]	[0.039]	[0.040]	[0.046]	[0.047]
"-": Other employed (prefer not to say)	0.109*	0.143**	0.120**	0.145**	0.143**	0.151***
	[0.055]	[0.056]	[0.055]	[0.055]	[0.057]	[0.058]
"-": Retired	-0.010	-0.038	-0.029	-0.053	-0.046	0.001
	[0.040]	[0.041]	[0.039]	[0.041]	[0.043]	[0.001]
"-": Student/pupil (full time)	0.205***	0.198***	0.190***	0.220***	0.218***	0.001
	[0.035]	[0.034]	[0.034]	[0.034]	[0.044]	[0.001]
"-": Inactive	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Income: Decile 10	–	0.208***	–	0.189***	0.191***	0.181***
		[0.031]		[0.030]	[0.023]	[0.027]
"-": Decile 9	–	0.179***	–	0.167***	0.170***	0.178***

		[0.031]		[0.030]	[0.028]	[0.033]
"-": Decile 8	–	0.136***	–	0.122***	0.125***	0.131***
		[0.033]		[0.033]	[0.029]	[0.035]
"-": Decile 7	–	0.133***	–	0.123***	0.125***	0.120***
		[0.027]		[0.027]	[0.028]	[0.030]
"-": Decile 6	–	0.091***	–	0.083***	0.089***	0.077**
		[0.027]		[0.026]	[0.026]	[0.032]
"-": Decile 5	–	0.073**	–	0.064**	0.069**	0.069**
		[0.031]		[0.030]	[0.026]	[0.033]
"-": Decile 4	–	0.069***	–	0.062**	0.069**	0.072**
		[0.025]		[0.025]	[0.027]	[0.032]
"-": Decile 3	–	0.050*	–	0.042	0.049*	0.052
		[0.029]		[0.029]	[0.029]	[0.038]
"-": Decile 2	–	0.024	–	0.020	0.025	0.015
		[0.025]		[0.024]	[0.025]	[0.032]
"-": Decile 1	–	0.017	–	0.017	0.025	0.029
		[0.021]		[0.020]	[0.022]	[0.030]
"-": Prefer not to say	–	*{Ref.}*	–	*{Ref.}*	*{Ref.}*	*{Ref.}*
Wealth: Decile 10	–	–	0.180***	–	–	–
			[0.037]			
"-": Decile 9	–	–	0.186***	–	–	–
			[0.036]			
"-": Decile 8	–	–	0.126***	–	–	–
			[0.030]			
"-": Decile 7	–	–	0.095***	–	–	–
			[0.028]			
"-": Decile 6	–	–	0.083***	–	–	–
			[0.028]			
"-": Decile 5	–	–	0.064**	–	–	–
			[0.031]			
"-": Decile 4	–	–	0.040	–	–	–
			[0.029]			
"-": Decile 3	–	–	0.044**	–	–	–
			[0.018]			
"-": Decile 2	–	–	0.004	–	–	–
			[0.024]			
"-": Decile 1	–	–	-0.038*	–	–	–
			[0.019]			
"-": Prefer not to say	–	–	*{Ref.}*	–	–	–
Number of distinct job task types	–	–	–	0.053***	0.053***	0.046***
				[0.004]	[0.004]	[0.004]
Country Fixed Effects	+	+	+	+	-	-
Regional Fixed Effects	–	–	–	–	+	+
% Gender Effect	6.65%	4.85%	5.29%	4.11%	4.17%	4.67%
Linear prediction	1.3902	1.3902	1.3902	1.3902	1.3902	1.3953
No. of Observations	29,872	29,872	29,872	29,872	29,872	21,564

Notes: The dependent variable is the media and information literacy index (0-3), with higher values indicating higher literacy levels. Columns (1)-(4) report OLS estimates with country fixed effects, starting with demographic controls (1) and then adding income, wealth, and job-task controls in (2)-(4). Column (5) replicates (4) with regional fixed effects and column (6) applies the regional fixed effects specification to the working-age sample. Robust standard errors are clustered at the country level in (1)-(4) and at the regional level in (5)-(6). ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4-6 reports OLS estimates for the Artificial Intelligence (AI) Literacy index (0-7) across six specifications. Across all specifications, men score higher on the AI literacy index relative to women (reference group). The male coefficient declines from 0.284 in the baseline model to around 0.183 in column (6) but remains statistically significant at the 1% level throughout. The table's "% Gender Effect" row indicates that this corresponds to roughly 8.0% higher predicted AI literacy relative to the reported linear prediction in baseline model in column (1) reaching to 5.11% in column (6). Respondents identifying as nonbinary also exhibit higher AI literacy than women, with coefficients between 0.500 and 0.629, consistently statistically significant at the 5% level, although estimates are less precise due to the smaller subgroup size.

By contrast, age does not appear to be correlated with AI literacy index. The linear age term is statistically insignificant in every column. Similarly, the squared term is generally insignificant, and only marginally negative and statistically significant at the 10% level in column (3). Overall, there is little evidence of a stable life-cycle profile in AI literacy once fixed effects and covariates are included. This result suggests that, conditional on the included controls and fixed effects, there is no evidence of systematic age differences in AI literacy.

Regarding marital status, being married, relative to being single (reference group), is strongly and consistently associated with lower AI literacy, ranging from 0.121 to 0.179 index points and is statistically significant at the 1% level in every specification. Widow/divorced status is similarly negative, from -0.119 to -0.191, statistically significant at the 5% level in columns (1)-(4) and at the 1% level in columns (5)-(6). Not reporting marital status ("unknown") is associated with an even larger deficit (from -0.281 to -0.351) and is statistically significant at the 1% level throughout. These patterns are highly stable across fixed-effect structures and sample restrictions.

The estimates reveal a strong and monotonic relationship between AI literacy and education attainment, relative to primary education (reference). Specifically, lower secondary education (ISCED 2) is positive but statistically insignificant in all columns. From upper secondary onwards, all coefficients are large and statistically significant at the 1% level in every specification. approximately 0.645-0.789 (upper secondary), 0.823-0.997 (post-secondary non-tertiary), 0.874-1.080 (short-cycle tertiary), 1.140-1.376 (bachelor's), 1.418-1.693 (master's), and 1.282-1.610 (doctoral). On a 0-7 scale, these magnitudes indicate substantial differences in AI literacy by educational attainment that remain robust to alternative fixed effects and the inclusion of income, wealth, and job-task controls.

Regarding employment status, relative to inactive respondents (reference), self-employment is weakly positively associated with AI literacy in the baseline model (0.160, statistically significant at the 10% level) but becomes statistically insignificant once income/wealth and job-task breadth are added and under regional fixed effects. Unemployment and homemaker status are statistically insignificant in all columns. A notable pattern concerns employment: the employed coefficient is statistically insignificant in columns (1)-(3). However, it becomes negative and statistically significant once job-task breadth is introduced and under regional fixed effects. This suggests that conditional on the number of job-task types (and other covariates), being employed (versus inactive) is associated with lower AI literacy. The "other employed (prefer not to say)" category is consistently positive from column (2) onward, with coefficient ranging from 0.227 to 0.271, and is statistically significant at the 5% level in columns (2)-(4), at the 1% level in column (5), and at the 5% level in column (6). Students/pupils show a large positive association in the full sample, with coefficient ranging from 0.571 to 0.673 and statistically significant at the 1% level, while in the working-age

specification in column (6) this category is essentially not informative, consistent with the sample restriction.

Income exhibits a strong and monotonic gradient relative to the reference category "prefer not to say." In columns (2), (4), (5), and (6), every income decile from 1 to 10 is positive and statistically significant, almost uniformly at the 1% level. The only exception is income decile 2 in column (6), which is statistically significant at the 5% level. Coefficients increase sharply toward the top of the distribution: the top income decile is around 0.518-0.578 (1% level), while even the bottom deciles are materially positive (e.g., decile 1 around 0.173-0.186, 1% level).

The wealth-decile coefficients, in column (3), shows a similarly pronounced gradient. Wealth deciles 3-10 are positive and statistically significant at the 1% level (top wealth decile 0.615), wealth decile 2 is positive (0.120) and statistically significant at the 10% level, and wealth decile 1 is small and statistically insignificant.

Finally, job-task breadth is one of the most robust predictors in the full specifications. Specifically, the number of distinct job task types is 0.176 in columns (4)-(5) and 0.159 in column (6), always statistically significant at the 1% level, implying that broader task exposure is strongly associated with higher AI literacy even after accounting for fixed effects and socioeconomic characteristics.

Overall, the results reveal a highly consistent set of associations. Specifically, AI literacy is strongly and positively related to educational attainment, income, wealth, and job-task breadth, while a robust male advantage persists across specifications. In contrast, age effects are not robust, and labour-market status effects are generally weak except for the negative employed coefficient that emerges once job-task breadth is controlled for. This pattern suggests that labour-market participation per se is not the key driver; rather, AI literacy appears to be more closely linked to socioeconomic resources and the nature of work, particularly exposure to diverse and potentially more complex tasks than to employment status alone.

Table 4-6: Artificial Intelligence (AI) literacy - OLS regression estimates

	Country fixed effects			Regional fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Gender: Male	0.284***	0.218***	0.218***	0.184***	0.186***	0.183***
	[0.031]	[0.032]	[0.028]	[0.031]	[0.028]	[0.031]
"-": Nonbinary	0.500**	0.538**	0.523**	0.587**	0.592**	0.629**
	[0.237]	[0.233]	[0.237]	[0.228]	[0.250]	[0.296]
"-": Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age of respondent	0.008	0.005	0.009	0.002	0.003	-0.010
	[0.008]	[0.008]	[0.008]	[0.008]	[0.007]	[0.009]
Age of respondent (squared)	-0.132	-0.110	-0.152*	-0.076	-0.081	0.077
	[0.080]	[0.078]	[0.078]	[0.078]	[0.066]	[0.099]
Marital status: Married	-0.121***	-0.159***	-0.166***	-0.179***	-0.167***	-0.166***
	[0.037]	[0.042]	[0.037]	[0.043]	[0.037]	[0.041]
"-": Widow/Divorced	-0.123**	-0.139**	-0.119**	-0.153**	-0.145***	-0.191***
	[0.057]	[0.058]	[0.057]	[0.058]	[0.050]	[0.063]
"-": Unknown	-0.281***	-0.316***	-0.313***	-0.331***	-0.323***	-0.351***
	[0.075]	[0.076]	[0.075]	[0.076]	[0.048]	[0.051]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
ISCED 2: Lower secondary education	0.135	0.127	0.127	0.093	0.063	0.133
	[0.105]	[0.105]	[0.107]	[0.104]	[0.104]	[0.111]
"-" 3: Upper secondary education	0.789***	0.752***	0.749***	0.668***	0.645***	0.727***
	[0.092]	[0.093]	[0.095]	[0.092]	[0.100]	[0.114]
"-" 4: Post-secondary non-tertiary educ.	0.997***	0.965***	0.942***	0.857***	0.823***	0.973***
	[0.128]	[0.130]	[0.128]	[0.125]	[0.119]	[0.130]
"-" 5: Short-cycle tertiary education	1.080***	1.020***	1.013***	0.899***	0.874***	0.942***
	[0.085]	[0.088]	[0.092]	[0.086]	[0.099]	[0.117]
"-" 6: Bachelor's or equivalent level	1.376***	1.290***	1.285***	1.163***	1.140***	1.269***
	[0.089]	[0.094]	[0.094]	[0.092]	[0.100]	[0.114]
"-" 7: Master's or equivalent level	1.693***	1.585***	1.579***	1.448***	1.418***	1.576***
	[0.103]	[0.109]	[0.105]	[0.107]	[0.104]	[0.119]
"-" 8: Doctoral or equivalent level	1.610***	1.462***	1.456***	1.314***	1.282***	1.475***
	[0.127]	[0.129]	[0.124]	[0.121]	[0.127]	[0.142]
"-" 1: Primary education	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Employment status: Self-employed	0.160*	0.075	0.071	-0.019	-0.019	-0.041
	[0.093]	[0.093]	[0.092]	[0.094]	[0.104]	[0.104]
"-": Employed	0.015	-0.126	-0.088	-0.171**	-0.173*	-0.190**
	[0.083]	[0.083]	[0.080]	[0.084]	[0.091]	[0.092]
"-": Unemployed	0.090	0.090	0.082	0.078	0.086	0.084
	[0.099]	[0.099]	[0.097]	[0.097]	[0.102]	[0.103]
"-": Homemaker/looking after home	0.009	-0.037	-0.052	-0.005	0.014	0.003
	[0.082]	[0.080]	[0.079]	[0.081]	[0.103]	[0.104]
"-": Other employed (prefer not to say)	0.177	0.265**	0.227**	0.269**	0.271***	0.265**
	[0.113]	[0.110]	[0.111]	[0.111]	[0.104]	[0.107]
"-": Retired	0.080	0.004	0.013	-0.044	-0.045	0.001
	[0.095]	[0.093]	[0.093]	[0.094]	[0.096]	[0.001]
"-": Student/pupil (full time)	0.612***	0.602***	0.571***	0.673***	0.673***	0.001
	[0.091]	[0.093]	[0.089]	[0.093]	[0.102]	[0.001]
"-": Inactive	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Income: Decile 10	–	0.578***	–	0.518***	0.525***	0.549***
		[0.072]		[0.071]	[0.055]	[0.056]
"-": Decile 9	–	0.531***	–	0.493***	0.499***	0.532***

		[0.068]		[0.066]	[0.055]	[0.060]
"-": Decile 8	–	0.532***	–	0.486***	0.494***	0.506***
		[0.060]		[0.058]	[0.055]	[0.059]
"-": Decile 7	–	0.409***	–	0.377***	0.387***	0.430***
		[0.065]		[0.063]	[0.053]	[0.061]
"-": Decile 6	–	0.346***	–	0.320***	0.331***	0.361***
		[0.060]		[0.057]	[0.055]	[0.063]
"-": Decile 5	–	0.361***	–	0.331***	0.347***	0.357***
		[0.060]		[0.058]	[0.056]	[0.067]
"-": Decile 4	–	0.275***	–	0.252***	0.258***	0.269***
		[0.055]		[0.053]	[0.054]	[0.071]
"-": Decile 3	–	0.184***	–	0.158***	0.172***	0.178***
		[0.056]		[0.055]	[0.047]	[0.061]
"-": Decile 2	–	0.140***	–	0.126***	0.144***	0.137**
		[0.048]		[0.045]	[0.049]	[0.062]
"-": Decile 1	–	0.173***	–	0.173***	0.186***	0.182***
		[0.049]		[0.048]	[0.043]	[0.057]
"-": Prefer not to say	–	*{Ref.}*	–	*{Ref.}*	*{Ref.}*	*{Ref.}*
Wealth: Decile 10	–	–	0.615***	–	–	–
			[0.057]			
"-": Decile 9	–	–	0.548***	–	–	–
			[0.073]			
"-": Decile 8	–	–	0.551***	–	–	–
			[0.058]			
"-": Decile 7	–	–	0.393***	–	–	–
			[0.071]			
"-": Decile 6	–	–	0.445***	–	–	–
			[0.054]			
"-": Decile 5	–	–	0.256***	–	–	–
			[0.055]			
"-": Decile 4	–	–	0.275***	–	–	–
			[0.057]			
"-": Decile 3	–	–	0.176***	–	–	–
			[0.045]			
"-": Decile 2	–	–	0.120*	–	–	–
			[0.067]			
"-": Decile 1	–	–	-0.026	–	–	–
			[0.055]			
"-": Prefer not to say	–	–	*{Ref.}*	–	–	–
Number of distinct job task types	–	–	–	0.176***	0.176***	0.159***
				[0.010]	[0.009]	[0.010]
Country Fixed Effects	+	+	+	+	-	-
Regional Fixed Effects	–	–	–	–	+	+
% Gender Effect	7.97%	6.11%	6.11%	5.16%	5.22%	5.11%
Linear prediction	3.5655	3.5655	3.5655	3.5655	3.5655	3.5820
No. of Observations	29,872	29,872	29,872	29,872	29,872	21,564

Notes: The dependent variable is the artificial intelligence (AI) literacy index (0-7), with higher values indicating higher literacy levels. Columns (1)-(4) report OLS estimates with country fixed effects, starting with demographic controls (1) and then adding income, wealth, and job-task controls in (2)-(4). Column (5) replicates (4) with regional fixed effects and column (6) applies the regional fixed effects specification to the working-age sample. Robust standard errors are clustered at the country level in (1)-(4) and at the regional level in (5)-(6). ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4-7 reports OLS estimates for the Data and Programming Literacy index (0-5) across six specifications. Across all specifications, men exhibit higher data and programming literacy than women (reference group). The male coefficient ranges from 0.251 to 0.337 index points and is statistically significant at the 1% level throughout. The magnitude decreases a bit as controls are added but remains economically meaningful. Consistent with this, the table's "% Gender Effect" declines from 12.12% in column (1) to 8.76% in the working-age regional fixed effects specification in column (6). By contrast, the coefficient for respondents identifying as nonbinary is negative (around -0.070 to -0.129) but statistically insignificant in every model, reflecting limited precision for this subgroup.

Age also appears to be correlated to data and programming literacy. The linear age term is negative and statistically significant at the 1% level in all columns (about -0.014 to -0.019 per year). The squared age term is positive but statistically insignificant throughout, indicating little evidence of a systematic nonlinear (U-shaped) age profile.

Regarding to marital status, being married, relative to being single (reference group), is associated with higher data and programming literacy in every specification, with coefficients between 0.061 and 0.110 that are statistically significant, typically at the 1% level, and at the 5% level in columns (2), (4), and (6). Widow/divorced status is generally statistically insignificant, with only one specification in column (3) showing a small positive association (0.057) that is statistically significant at the 10% level. Notably, respondents with unknown marital status consistently score higher than singles (about 0.089-0.123), and this association is statistically significant at the 1% level in all columns, suggesting that nonreporting of marital status is not random and is positively correlated with this literacy domain.

Estimates for education attainment levels, relative to primary education (reference group), exhibit a positive and monotonic relationship with data and programming literacy. Lower secondary education (ISCED 2) is negative but statistically insignificant in all models. From upper secondary onward, coefficients are uniformly positive and generally increase with attainment. Upper secondary education (ISCED 3) is statistically significant in columns (1)-(5) at the 5% or 10% level but becomes statistically insignificant in the working-age specification in column (6). Post-secondary non-tertiary education (ISCED 4) is consistently positive, ranging from 0.198 to 0.285 and statistically significant at the 5% level in most columns and at the 1% level in column (5). Short-cycle tertiary (ISCED 5), bachelor's (ISCED 6), master's (ISCED 7), and doctoral education (ISCED 8) are all large and statistically significant at the 1% level throughout, with coefficients ranging from 0.219 to 0.355 (short-cycle), from 0.368 to 0.531 (bachelor's), from 0.501to 0.676 (master's), and from 0.611 to 0.799 (doctoral).

Regarding employment status, relative to inactive respondents (reference), self-employment is positively associated with data and programming literacy in all specifications, with coefficients ranging from 0.143 to 0.277 and statistically significant at the 1% level throughout. Being employed exerts also positive coefficients, ranging from 0.177 to 0.326 and statistically significant at the 1% level in every specification. Being unemployed is also positively associated with coefficients ranging from 0.195 to 0.209 and statistically significant at the 1% level throughout. Homemaker/looking after home is positive but less robust: it is statistically significant at the 5% level in column (1) and at the 10% level in columns (3)-(6), but statistically insignificant in column (2). The "other employed (prefer not to say)" category is negative and statistically significant at the 10% level only in the baseline model (column (1)), becoming statistically insignificant thereafter. Retired respondents show a small positive association in some country fixed effects specifications, e.g., the coefficient is

significant at the 5% level in column (1) and at the 10% level in column (3), but insignificant in columns (2), (5) and, as expected, (6) which is the specification with the working-age sample restriction. Students/pupils have a large positive coefficient, ranging from 0.398 to 0.424, that is statistically significant at the 1% level in columns (1)-(5), but this category is essentially not informative in the working-age specification in column (6) consistent with the sample restriction.

Interestingly, income appears a non-linear relationship with data and programming literacy in columns (2), (4), (5) and (6). Higher income deciles 4-10 are consistently positive and statistically significant, typically at the 1% level, and at the 5% level for some middle deciles, with large effects at the top, e.g., coefficients ranging from 0.413 to 0.437 for decile 10, statistically significant at the 1% level. In contrast, lower income deciles do not uniformly predict higher literacy. Specifically, income decile 2 is negative and statistically significant at the 1% level in columns (2), (4), and (5), and at the 10% level in column (6). While deciles 1 and 3 are generally statistically insignificant, decile 1 becomes weakly negative and statistically significant at the 10% level in column (6).

The wealth included in column (3) shows a clearer positive gradient. From wealth decile 3 to decile10, coefficients are positive and statistically significant at the 1% level, while they are particularly sizeable in top deciles, e.g., 0.360 for the top wealth decile.

Finally, job-task breadth is positively related to data and programming literacy. Specifically, the number of distinct job task types exhibits a coefficient ranging from 0.060 to 0.063 and is statistically significant at the 1% level in columns (4)-(6). This indicate that broader task exposure is systematically linked to higher data and programming literacy even after conditioning on fixed effects and socioeconomic characteristics.

Overall, the estimates indicate that data and programming literacy is associated with being male, being younger, with higher educational attainment, higher income and wealth positions, and with broader task content in the main job. In addition, being either employed or self-employed is also positively related to data and programming literacy, while a positive association is also observed for unemployed respondents. This could reflect composition and selection effects, unemployed individuals in the sample may be disproportionately drawn from digitally intensive occupations or higher-skill segments and may also include recently displaced workers whose skills remain relatively strong, rather than indicating that unemployment itself increases data and programming literacy.

Table 4-7: Data and Programming Literacy - OLS regression estimates

	Country fixed effects			Regional fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Gender: Male	0.337***	0.280***	0.299***	0.268***	0.269***	0.251***
	[0.023]	[0.023]	[0.024]	[0.023]	[0.015]	[0.017]
"-": Nonbinary	-0.129	-0.100	-0.115	-0.083	-0.070	-0.122
	[0.128]	[0.126]	[0.125]	[0.126]	[0.137]	[0.156]
"-": Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age of respondent	-0.015***	-0.018***	-0.014***	-0.019***	-0.018***	-0.017***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.004]	[0.004]
Age of respondent (squared)	0.027	0.048	0.014	0.060	0.054	0.031
	[0.048]	[0.045]	[0.046]	[0.046]	[0.036]	[0.049]
Marital status: Married	0.110***	0.069**	0.084***	0.061**	0.063***	0.062**
	[0.031]	[0.026]	[0.030]	[0.026]	[0.020]	[0.024]
"-": Widow/Divorced	0.054	0.042	0.057*	0.037	0.039	0.042
	[0.033]	[0.031]	[0.032]	[0.031]	[0.033]	[0.046]
"-": Unknown	0.123***	0.095***	0.105***	0.089***	0.092***	0.100***
	[0.025]	[0.025]	[0.024]	[0.024]	[0.024]	[0.028]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
ISCED 2: Lower secondary education	-0.076	-0.069	-0.079	-0.081	-0.076	-0.119
	[0.085]	[0.084]	[0.083]	[0.085]	[0.068]	[0.076]
"-" 3: Upper secondary education	0.180**	0.163**	0.157*	0.133*	0.137**	0.084
	[0.078]	[0.078]	[0.077]	[0.078]	[0.060]	[0.063]
"-" 4: Post-secondary non-tertiary educ.	0.285**	0.265**	0.253**	0.227**	0.238***	0.198**
	[0.110]	[0.112]	[0.109]	[0.110]	[0.077]	[0.083]
"-" 5: Short-cycle tertiary education	0.355***	0.315***	0.317***	0.272***	0.279***	0.219***
	[0.086]	[0.087]	[0.084]	[0.086]	[0.066]	[0.070]
"-" 6: Bachelor's or equivalent level	0.531***	0.459***	0.478***	0.413***	0.416***	0.368***
	[0.080]	[0.080]	[0.079]	[0.080]	[0.062]	[0.069]
"-" 7: Master's or equivalent level	0.676***	0.582***	0.611***	0.533***	0.535***	0.501***
	[0.082]	[0.083]	[0.081]	[0.082]	[0.064]	[0.068]
"-" 8: Doctoral or equivalent level	0.799***	0.664***	0.710***	0.611***	0.624***	0.612***
	[0.093]	[0.088]	[0.089]	[0.086]	[0.075]	[0.082]
"-" 1: Primary education	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Employment status: Self-employed	0.277***	0.195***	0.226***	0.161***	0.158***	0.143***
	[0.048]	[0.047]	[0.046]	[0.050]	[0.052]	[0.053]
"-": Employed	0.326***	0.203***	0.267***	0.187***	0.182***	0.177***
	[0.043]	[0.043]	[0.040]	[0.045]	[0.043]	[0.043]
"-": Unemployed	0.206***	0.209***	0.200***	0.204***	0.197***	0.195***
	[0.051]	[0.050]	[0.049]	[0.049]	[0.051]	[0.051]
"-": Homemaker/looking after home	0.138**	0.094	0.104*	0.106*	0.096*	0.083*
	[0.057]	[0.055]	[0.054]	[0.056]	[0.049]	[0.049]
"-": Other employed (prefer not to say)	-0.122*	-0.045	-0.094	-0.044	-0.040	-0.034
	[0.072]	[0.073]	[0.070]	[0.072]	[0.064]	[0.064]
"-": Retired	0.142**	0.085	0.103*	0.068	0.066	0.001
	[0.055]	[0.052]	[0.052]	[0.053]	[0.048]	[0.001]
"-": Student/pupil (full time)	0.422***	0.399***	0.398***	0.424***	0.419***	0.001
	[0.052]	[0.052]	[0.051]	[0.051]	[0.049]	[0.001]
"-": Inactive	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Income: Decile 10	–	0.437***	–	0.415***	0.413***	0.414***
		[0.035]		[0.034]	[0.029]	[0.030]
"-": Decile 9	–	0.320***	–	0.306***	0.308***	0.314***

		[0.030]		[0.031]	[0.026]	[0.029]
"-": Decile 8	–	0.240***	–	0.224***	0.222***	0.233***
		[0.033]		[0.033]	[0.028]	[0.030]
"-": Decile 7	–	0.182***	–	0.171***	0.169***	0.155***
		[0.034]		[0.034]	[0.027]	[0.030]
"-": Decile 6	–	0.141***	–	0.132***	0.135***	0.136***
		[0.036]		[0.036]	[0.028]	[0.033]
"-": Decile 5	–	0.095***	–	0.084**	0.086***	0.088***
		[0.033]		[0.034]	[0.028]	[0.031]
"-": Decile 4	–	0.074**	–	0.065**	0.063**	0.071**
		[0.027]		[0.027]	[0.027]	[0.031]
"-": Decile 3	–	0.018	–	0.009	0.010	0.036
		[0.034]		[0.034]	[0.032]	[0.035]
"-": Decile 2	–	-0.077***	–	-0.082***	-0.079***	-0.054*
		[0.028]		[0.027]	[0.026]	[0.032]
"-": Decile 1	–	-0.040	–	-0.040	-0.038	-0.041*
		[0.026]		[0.025]	[0.025]	[0.024]
"-": Prefer not to say	–	*{Ref.}*	–	*{Ref.}*	*{Ref.}*	*{Ref.}*
Wealth: Decile 10	–	–	0.360***	–	–	–
			[0.052]			
"-": Decile 9	–	–	0.281***	–	–	–
			[0.033]			
"-": Decile 8	–	–	0.261***	–	–	–
			[0.034]			
"-": Decile 7	–	–	0.250***	–	–	–
			[0.027]			
"-": Decile 6	–	–	0.233***	–	–	–
			[0.032]			
"-": Decile 5	–	–	0.173***	–	–	–
			[0.033]			
"-": Decile 4	–	–	0.166***	–	–	–
			[0.034]			
"-": Decile 3	–	–	0.107***	–	–	–
			[0.031]			
"-": Decile 2	–	–	0.045	–	–	–
			[0.032]			
"-": Decile 1	–	–	-0.022	–	–	–
			[0.020]			
"-": Prefer not to say	–	–	*{Ref.}*	–	–	–
Number of distinct job task types	–	–	–	0.063***	0.063***	0.060***
				[0.005]	[0.005]	[0.005]
Country Fixed Effects	+	+	+	+	-	-
Regional Fixed Effects	–	–	–	–	+	+
% Gender Effect	12.12%	10.08%	10.77%	9.64%	9.68%	8.76%
Linear prediction	2.7790	2.7790	2.7790	2.7790	2.7790	2.8717
No. of Observations	29,872	29,872	29,872	29,872	29,872	21,564

Notes: The dependent variable is the data and programming literacy index (0-5), with higher values indicating higher competence. Columns (1)-(4) report OLS estimates with country fixed effects, starting with demographic controls (1) and then adding income, wealth, and job-task controls in (2)-(4). Column (5) replicates (4) with regional fixed effects and column (6) applies the regional fixed effects specification to the working-age sample. Robust standard errors are clustered at the country level in (1)-(4) and at the regional level in (5)-(6). ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4-8 reports OLS estimates for the Political Literacy index (0-3) across six specifications. Across all specifications, men exhibit higher data and programming literacy than women (reference group). The male coefficient ranges from 0.301 to 0.349 index points and is statistically significant at the 1% level throughout. Based on the table's "% Gender Effect" row, this corresponds to roughly 21% higher predicted political literacy for men relative to the reported linear prediction. The coefficient for respondents identifying as nonbinary is positive throughout but statistically insignificant in columns (1)-(5), while it becomes statistically significant at the 5% level in the working-age regional fixed effects specification in column (6).

Age effects are primarily captured by the quadratic term. The linear age term is generally small and statistically insignificant, while the squared age term is positive and statistically significant at the 1% level in most columns and at the 5% level in column (3). Taken together, these estimates indicate a convex age profile, with political literacy increasing more strongly at higher ages, rather than following a simple linear gradient.

Regarding marital status, being married, relative to being single (reference group) is not systematically related to political literacy, as the married coefficient is small and statistically insignificant in all columns. In contrast, widow/divorced respondents score lower than singles, with coefficients around -0.113 to -0.128 that are statistically significant at the 1% level throughout. The "unknown" marital-status category is also negative, becoming statistically significant once more controls are added in columns (2)-(5): significant at the 10% to 5% level, though it is statistically insignificant in columns (1) and (6).

Estimates for education attainment levels, relative to primary education (reference group), exhibit a positive and monotonic relationship with political literacy. Lower secondary education (ISCED 2) is positive but statistically insignificant across all specifications. From upper secondary onwards (ISCED 3 – ISCED 8), all coefficients are large, positive, and statistically significant at the 1% level in every column. Specifically, coefficients range from 0.287 to 0.340 (upper secondary), from 0.339 to 0.401 (post-secondary non-tertiary), from 0.366 to 0.446 (short-cycle tertiary), from 0.511 to 0.604 (bachelor's), from 0.627 to 0.738 (master's), and from 0.558 to 0.688 (doctoral). These magnitudes imply significant differences in political literacy by educational attainment, and they remain stable when moving from country to regional fixed effects and when restricting to working age.

Regarding employment status, significant coefficients in some categories appear in columns (1) to (3) but weaken once socioeconomic controls are introduced. Relative to inactive respondents (reference group), self-employment is positive and statistically significant in columns (1) to (3) , with coefficients ranging from 0.082 in columns (2) and (3), to 0.136 in column (1), but it becomes statistically insignificant when more controls are included in columns (3)-(6). Employment is also positive and statistically significant at the 1% level in the baseline model in column (1) but becomes statistically insignificant once income/wealth and job-task breadth are added, indicating that the baseline employment gap is largely accounted for by these covariates. Unemployment and the "other employed (prefer not to say)" category are statistically insignificant throughout. Homemaker/looking after home is negative in all columns and becomes statistically significant at the 10% to 5% level when income and wealth are included in columns (2)-(4) but turns insignificant under regional fixed effects and in the working-age model in columns (5) and (6). Retired respondents score higher than the inactive in several full-sample models with significant coefficients at the 1% level in column (1) and at the 10% level in columns (2), (3) and (5), but it turns insignificant once the full set of controls is included in column (4), and it is mechanically not informative in the working-age restriction in column (6). Students/pupils exhibit a large positive association in the full sample,

with coefficients ranging from 0.302 to 0.345, statistically significant at the 1% level in columns (1)-(5), but this category is likewise not informative in the working-age model column (6).

Income seems to be monotonically related to political literacy in columns (2), (4), (5) and (6). Relative to the reference category "prefer not to say", income deciles from 1 to 10 exerts positive coefficients and statistically significant at the 1% level, ranging from 0.142 - 0.180 in the bottom decile to 0.381 - 0.395 in the top decile. Taken together income coefficients an increased monotonic relationship between income and political literacy is observed.

Wealth deciles, included in column (3), show a similar upward gradient. Wealth deciles from 2 to 10 have positive and statistically significant coefficients at the 1% level. Even the bottom wealth decile 1 has a small positive (0.040) coefficient and statistically significant at the 10% level.

Finally, job-task breadth is also positively related to political literacy. The number of distinct tasks in the main job exerts a coefficient ranging from 0.038 to 0.040 that is statistically significant at the 1% level in columns (4)-(6). This indicates that broader task exposure is associated with higher political literacy even after controlling for fixed effects and socioeconomic characteristics.

Overall, the estimates reveal that the most that the robust patterns in political literacy are the male advantage, the strong education upward gradient, the negative association for widow/divorced respondents, and the pronounced income/wealth gradients, alongside a consistent positive relationship with job-task breadth. By contrast, differences by labour-market status (particularly being employed or self-employed) are not robust once income, wealth, and job-task characteristics are accounted for, suggesting that socioeconomic resources and task-related exposure explain much of the baseline association between employment and political literacy.

Table 4-8: Political Literacy - OLS regression estimates

	Country fixed effects			Regional fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Gender: Male	0.349***	0.308***	0.305***	0.301***	0.302***	0.309***
	[0.018]	[0.017]	[0.017]	[0.017]	[0.013]	[0.016]
"-": Nonbinary	0.148	0.179	0.164	0.191	0.204	0.312**
	[0.160]	[0.165]	[0.162]	[0.163]	[0.126]	[0.143]
"-": Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age of respondent	0.001	-0.001	0.001	-0.002	0.000	-0.006*
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.004]
Age of respondent (squared)	0.099***	0.111***	0.088**	0.119***	0.105***	0.178***
	[0.033]	[0.032]	[0.032]	[0.032]	[0.030]	[0.043]
Marital status: Married	0.007	-0.014	-0.020	-0.019	-0.017	0.004
	[0.018]	[0.019]	[0.018]	[0.019]	[0.018]	[0.020]
"-": Widow/Divorced	-0.114***	-0.125***	-0.113***	-0.128***	-0.125***	-0.114***
	[0.030]	[0.030]	[0.030]	[0.030]	[0.022]	[0.029]
"-": Unknown	-0.046	-0.068*	-0.069*	-0.071**	-0.060**	-0.032
	[0.035]	[0.035]	[0.035]	[0.034]	[0.024]	[0.026]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
ISCED 2: Lower secondary education	0.081	0.071	0.067	0.063	0.055	0.053
	[0.063]	[0.063]	[0.063]	[0.063]	[0.052]	[0.066]
"-" 3: Upper secondary education	0.340***	0.311***	0.307***	0.293***	0.287***	0.313***
	[0.051]	[0.053]	[0.053]	[0.053]	[0.045]	[0.055]
"-" 4: Post-secondary non-tertiary educ.	0.401***	0.376***	0.359***	0.352***	0.339***	0.361***
	[0.077]	[0.079]	[0.075]	[0.078]	[0.058]	[0.062]
"-" 5: Short-cycle tertiary education	0.446***	0.403***	0.396***	0.376***	0.373***	0.366***
	[0.052]	[0.053]	[0.053]	[0.052]	[0.050]	[0.062]
"-" 6: Bachelor's or equivalent level	0.604***	0.549***	0.543***	0.520***	0.511***	0.550***
	[0.055]	[0.057]	[0.055]	[0.057]	[0.047]	[0.053]
"-" 7: Master's or equivalent level	0.738***	0.672***	0.664***	0.640***	0.627***	0.675***
	[0.059]	[0.062]	[0.060]	[0.062]	[0.047]	[0.055]
"-" 8: Doctoral or equivalent level	0.688***	0.599***	0.589***	0.565***	0.558***	0.624***
	[0.105]	[0.104]	[0.103]	[0.103]	[0.063]	[0.075]
"-" 1: Primary education	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Employment status: Self-employed	0.136***	0.082**	0.082*	0.060	0.062	0.069
	[0.041]	[0.039]	[0.043]	[0.039]	[0.045]	[0.047]
"-": Employed	0.122***	0.032	0.056	0.022	0.025	0.027
	[0.041]	[0.039]	[0.041]	[0.039]	[0.040]	[0.042]
"-": Unemployed	0.029	0.032	0.022	0.029	0.022	0.018
	[0.038]	[0.039]	[0.040]	[0.040]	[0.048]	[0.048]
"-": Homemaker/looking after home	-0.057	-0.084*	-0.095**	-0.077*	-0.074	-0.070
	[0.045]	[0.044]	[0.045]	[0.044]	[0.049]	[0.049]
"-": Other employed (prefer not to say)	-0.024	0.035	0.012	0.036	0.034	0.025
	[0.055]	[0.055]	[0.052]	[0.055]	[0.056]	[0.059]
"-": Retired	0.144***	0.087*	0.097*	0.076	0.085*	0.001
	[0.047]	[0.045]	[0.048]	[0.045]	[0.044]	[0.001]
"-": Student/pupil (full time)	0.324***	0.327***	0.302***	0.343***	0.345***	0.001
	[0.057]	[0.056]	[0.058]	[0.057]	[0.052]	[0.001]
"-": Inactive	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Income: Decile 10	–	0.395***	–	0.381***	0.384***	0.387***
		[0.039]		[0.039]	[0.027]	[0.030]
"-": Decile 9	–	0.382***	–	0.373***	0.374***	0.381***

		[0.039]		[0.039]	[0.030]	[0.034]
"-": Decile 8	–	0.350***	–	0.340***	0.344***	0.346***
		[0.036]		[0.036]	[0.027]	[0.032]
"-": Decile 7	–	0.315***	–	0.308***	0.310***	0.302***
		[0.033]		[0.034]	[0.029]	[0.033]
"-": Decile 6	–	0.277***	–	0.271***	0.274***	0.286***
		[0.031]		[0.031]	[0.025]	[0.028]
"-": Decile 5	–	0.268***	–	0.261***	0.264***	0.248***
		[0.032]		[0.032]	[0.027]	[0.031]
"-": Decile 4	–	0.263***	–	0.258***	0.262***	0.265***
		[0.032]		[0.033]	[0.027]	[0.031]
"-": Decile 3	–	0.213***	–	0.207***	0.208***	0.203***
		[0.032]		[0.032]	[0.027]	[0.035]
"-": Decile 2	–	0.180***	–	0.177***	0.178***	0.204***
		[0.032]		[0.032]	[0.027]	[0.031]
"-": Decile 1	–	0.142***	–	0.142***	0.147***	0.180***
		[0.021]		[0.021]	[0.020]	[0.024]
"-": Prefer not to say	–	*{Ref.}*	–	*{Ref.}*	*{Ref.}*	*{Ref.}*
Wealth: Decile 10	–	–	0.396***	–	–	–
			[0.039]			
"-": Decile 9	–	–	0.357***	–	–	–
			[0.027]			
"-": Decile 8	–	–	0.361***	–	–	–
			[0.030]			
"-": Decile 7	–	–	0.320***	–	–	–
			[0.032]			
"-": Decile 6	–	–	0.281***	–	–	–
			[0.032]			
"-": Decile 5	–	–	0.269***	–	–	–
			[0.034]			
"-": Decile 4	–	–	0.222***	–	–	–
			[0.027]			
"-": Decile 3	–	–	0.178***	–	–	–
			[0.021]			
"-": Decile 2	–	–	0.146***	–	–	–
			[0.024]			
"-": Decile 1	–	–	0.040*	–	–	–
			[0.021]			
"-": Prefer not to say	–	–	*{Ref.}*	–	–	–
Number of distinct job task types	–	–	–	0.040***	0.040***	0.038***
				[0.004]	[0.004]	[0.005]
Country Fixed Effects	+	+	+	+	-	-
Regional Fixed Effects	–	–	–	–	+	+
% Gender Effect	21.04%	18.59%	18.40%	18.12%	18.17%	19.31%
Linear prediction	1.6592	1.6592	1.6592	1.6592	1.6592	1.5996
No. of Observations	29,872	29,872	29,872	29,872	29,872	21,564

Notes: The dependent variable is the political literacy index (0-3), with higher values indicating higher literacy levels. Columns (1)-(4) report OLS estimates with country fixed effects, starting with demographic controls (1) and then adding income, wealth, and job-task controls in (2)-(4). Column (5) replicates (4) with regional fixed effects and column (6) applies the regional fixed effects specification to the working-age sample. Robust standard errors are clustered at the country level in (1)-(4) and at the regional level in (5)-(6). ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4-9 reports OLS estimates for the Environmental Literacy index (0-3) across six specifications. Across all specifications, men display a positive association with environmental literacy than women (reference group). The male coefficient ranges from 0.129 to 0.153 index points and is statistically significant at the 1% level in every specification. The table's "% Gender Effect" indicates that this corresponds to approximately 7.3-8.7% higher predicted environmental literacy for men relative to the reported linear prediction. Respondents identifying as nonbinary also score higher than women with coefficients ranging from 0.236 to 0.288 which are statistically significant at the 1% level throughout, although estimates are less precise due to the smaller group size.

In contrast, age does not appear a systematic correlation with environmental literacy. Both the linear and squared age terms are statistically insignificant across all columns, providing no evidence of a robust lifecycle profile once fixed effects and controls are included.

Regarding marital status, being married and being widowed/divorced, relative to being single (reference group) is not related to environmental literacy, as both coefficients are small and statistically insignificant in all specifications. In contrast, he "marital status: unknown" category is consistently associated with lower environmental literacy (around -0.078 to -0.090) and is statistically significant at the 1% level in every column, indicating systematic differences for respondents who do not report marital status.

Estimates for education attainment levels exhibit a positive and monotonic relationship with environmental literacy. Relative to primary education (reference), lower secondary education (ISCED 2) is positive but statistically insignificant in all models. From upper secondary onwards (ISCED 3 – ISCED 8), coefficients are uniformly positive, sizeable, and statistically significant at the 1% level in every column. More specifically, about 0.164-0.196 (upper secondary), 0.203-0.239 (post-secondary non-tertiary), 0.233-0.266 (short-cycle tertiary), 0.289-0.339 (bachelor's), 0.343-0.400 (master's), and 0.325-0.399 (doctoral). These magnitudes imply significant differences in environmental literacy by educational attainment that remain very stable across fixed-effect structures and sample restrictions.

Regarding to employment status, most coefficients are small and statistically insignificant across specifications (self-employed, employed, unemployed, homemaker, and "other employed"). Two exceptions appear in the full-sample country fixed effects specification. First, retired respondents have a modest positive association in column (1), with coefficient of 0.071 and statistically significant at the 5% level. Second, students/pupils show a positive association in columns (1)-(5), with coefficients ranging from 0.197 to 0.214 and statistically significant at the 1% level. In the working-age specification in column (6), the coefficients for retired and student categories are essentially zero, consistent with these statuses being mechanically less relevant once the sample is restricted.

Income coefficients are slightly increasing across the distribution in columns (2), (4), (5) and (6). Relative to "prefer not to say" (reference group), the gradient is particularly pronounced at the top income deciles. Specifically, from income deciles 4 to 10 are all positive and statistically significant at the 1% level, ranging from 0.169 to 0.185 for the top decile. Lower income deciles show smaller but still positive associations, e.g., decile 3 is positive and statistically significant, decile 1 is positive and statistically significant, while decile 2 is generally statistically insignificant, becoming positive and significant only in the working-age model in column (6).

Wealth, included in column (3), exhibits a similar slightly upward gradient. Relative to "prefer not to say" (reference group), wealth deciles from 3 to 10 are positive and statistically significant, decile 3

at the 5% level, and deciles 4-10 at the 1% level. Whereas the bottom wealth deciles 1 and 2 are statistically insignificant.

Finally, job-task breadth is again positively associated with environmental literacy. The number of distinct job-tasks has a coefficient ranging from 0.017 to 0.018 and statistically significant at the 1% level in columns (4)-(6). This indicates that broader task exposure is associated with higher environmental literacy even conditional on fixed effects and socioeconomic characteristics.

Overall, some main results are consistent across specifications. The strongest patterns in environmental literacy are the male advantage, the strong education, income and wealth upward gradients, alongside a positive association with job scope. In contrast, there is no strong age pattern, and differences in labour market status are generally weak when socioeconomic resources and job characteristics are taken into account. This suggests that environmental literacy in this sample is more closely related to education and socioeconomic resources and (to a lesser extent) to job exposure, than to life-cycle age or employment status per se.

Table 4-9: Environmental Literacy - OLS regression estimates

	Country fixed effects			Regional fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Gender: Male	0.153***	0.132***	0.134***	0.129***	0.130***	0.138***
	[0.011]	[0.011]	[0.011]	[0.011]	[0.010]	[0.012]
"-": Nonbinary	0.236***	0.248***	0.244***	0.252***	0.255***	0.288***
	[0.063]	[0.065]	[0.064]	[0.064]	[0.088]	[0.098]
"-": Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age of respondent	0.003	0.003	0.004	0.002	0.002	-0.001
	[0.003]	[0.003]	[0.003]	[0.003]	[0.002]	[0.003]
Age of respondent (squared)	-0.025	-0.018	-0.033	-0.015	-0.018	0.025
	[0.031]	[0.030]	[0.030]	[0.030]	[0.025]	[0.036]
Marital status: Married	0.007	-0.006	-0.007	-0.008	-0.006	0.000
	[0.011]	[0.012]	[0.011]	[0.012]	[0.013]	[0.015]
"-": Widow/Divorced	-0.015	-0.020	-0.013	-0.021	-0.020	-0.010
	[0.020]	[0.020]	[0.019]	[0.020]	[0.021]	[0.025]
"-": Unknown	-0.078***	-0.089***	-0.088***	-0.090***	-0.090***	-0.085***
	[0.019]	[0.019]	[0.019]	[0.020]	[0.017]	[0.019]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
ISCED 2: Lower secondary education	0.051	0.050	0.050	0.047	0.041	0.011
	[0.043]	[0.043]	[0.043]	[0.043]	[0.042]	[0.058]
"-" 3: Upper secondary education	0.187***	0.176***	0.176***	0.168***	0.164***	0.196***
	[0.047]	[0.047]	[0.047]	[0.047]	[0.039]	[0.054]
"-" 4: Post-secondary non-tertiary educ.	0.231***	0.221***	0.214***	0.210***	0.203***	0.239***
	[0.065]	[0.064]	[0.064]	[0.064]	[0.046]	[0.065]
"-" 5: Short-cycle tertiary education	0.266***	0.248***	0.246***	0.236***	0.233***	0.250***
	[0.050]	[0.050]	[0.051]	[0.049]	[0.041]	[0.057]
"-" 6: Bachelor's or equivalent level	0.334***	0.307***	0.306***	0.294***	0.289***	0.339***
	[0.048]	[0.048]	[0.049]	[0.048]	[0.040]	[0.058]
"-" 7: Master's or equivalent level	0.398***	0.364***	0.363***	0.350***	0.343***	0.400***
	[0.048]	[0.049]	[0.049]	[0.049]	[0.040]	[0.055]
"-" 8: Doctoral or equivalent level	0.392***	0.344***	0.344***	0.330***	0.325***	0.399***
	[0.067]	[0.066]	[0.066]	[0.066]	[0.049]	[0.064]
"-" 1: Primary education	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Employment status: Self-employed	0.017	-0.010	-0.011	-0.019	-0.019	-0.031
	[0.029]	[0.029]	[0.030]	[0.029]	[0.035]	[0.034]
"-": Employed	0.042	-0.001	0.010	-0.006	-0.004	-0.018
	[0.031]	[0.031]	[0.032]	[0.031]	[0.031]	[0.031]
"-": Unemployed	0.013	0.013	0.009	0.012	0.011	0.007
	[0.036]	[0.036]	[0.036]	[0.035]	[0.035]	[0.036]
"-": Homemaker/looking after home	-0.030	-0.044	-0.048	-0.041	-0.038	-0.049
	[0.040]	[0.040]	[0.040]	[0.040]	[0.037]	[0.038]
"-": Other employed (prefer not to say)	0.044	0.071	0.059	0.071	0.075	0.073
	[0.054]	[0.054]	[0.053]	[0.054]	[0.047]	[0.048]
"-": Retired	0.071**	0.048	0.050	0.044	0.046	0.001
	[0.035]	[0.035]	[0.035]	[0.034]	[0.031]	[0.001]
"-": Student/pupil (full time)	0.211***	0.207***	0.197***	0.214***	0.209***	0.001
	[0.040]	[0.040]	[0.040]	[0.040]	[0.038]	[0.001]
"-": Inactive	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Income: Decile 10	–	0.185***	–	0.179***	0.182***	0.169***
		[0.024]		[0.024]	[0.020]	[0.022]
"-": Decile 9	–	0.161***	–	0.157***	0.160***	0.160***

		[0.021]		[0.021]	[0.020]	[0.023]
"-": Decile 8	–	0.144***	–	0.140***	0.139***	0.133***
		[0.023]		[0.023]	[0.021]	[0.025]
"-": Decile 7	–	0.111***	–	0.108***	0.112***	0.103***
		[0.022]		[0.022]	[0.020]	[0.023]
"-": Decile 6	–	0.094***	–	0.091***	0.094***	0.091***
		[0.020]		[0.019]	[0.023]	[0.026]
"-": Decile 5	–	0.117***	–	0.115***	0.117***	0.119***
		[0.023]		[0.023]	[0.021]	[0.026]
"-": Decile 4	–	0.072***	–	0.070***	0.071***	0.080***
		[0.020]		[0.020]	[0.020]	[0.026]
"-": Decile 3	–	0.056**	–	0.054**	0.059***	0.088***
		[0.026]		[0.026]	[0.022]	[0.029]
"-": Decile 2	–	0.030	–	0.029	0.033	0.052**
		[0.022]		[0.022]	[0.020]	[0.026]
"-": Decile 1	–	0.045**	–	0.045**	0.049**	0.041*
		[0.019]		[0.019]	[0.019]	[0.023]
"-": Prefer not to say	–	*{Ref.}*	–	*{Ref.}*	*{Ref.}*	*{Ref.}*
Wealth: Decile 10	–	–	0.184***	–	–	–
			[0.023]			
"-": Decile 9	–	–	0.154***	–	–	–
			[0.024]			
"-": Decile 8	–	–	0.128***	–	–	–
			[0.025]			
"-": Decile 7	–	–	0.118***	–	–	–
			[0.023]			
"-": Decile 6	–	–	0.107***	–	–	–
			[0.019]			
"-": Decile 5	–	–	0.114***	–	–	–
			[0.021]			
"-": Decile 4	–	–	0.092***	–	–	–
			[0.020]			
"-": Decile 3	–	–	0.044**	–	–	–
			[0.020]			
"-": Decile 2	–	–	0.011	–	–	–
			[0.017]			
"-": Decile 1	–	–	-0.019	–	–	–
			[0.018]			
"-": Prefer not to say	–	–	*{Ref.}*	–	–	–
Number of distinct job task types	–	–	–	0.017***	0.017***	0.018***
				[0.003]	[0.003]	[0.003]
Country Fixed Effects	+	+	+	+	-	-
Regional Fixed Effects	–	–	–	–	+	+
% Gender Effect	8.66%	7.47%	7.54%	7.28%	7.32%	7.82%
Linear prediction	1.7710	1.7710	1.7710	1.7710	1.7710	1.7587
No. of Observations	29,872	29,872	29,872	29,872	29,872	21,564

Notes: The dependent variable is the environmental literacy index (0-3), with higher values indicating higher literacy levels. Columns (1)-(4) report OLS estimates with country fixed effects, starting with demographic controls (1) and then adding income, wealth, and job-task controls in (2)-(4). Column (5) replicates (4) with regional fixed effects and column (6) applies the regional fixed effects specification to the working-age sample. Robust standard errors are clustered at the country level in (1)-(4) and at the regional level in (5)-(6). ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4-10 reports OLS estimates for the Sustainable Financial Literacy index (0-3) across six specifications. Relative to women (reference group), the male coefficient is small and not statistically significant in most specifications. Specifically, it is positive in the baseline specification (column 1) about 0.028 and statistically significant at the 10% level but becomes close to zero and statistically insignificant once income, wealth, and job-task controls are added as well as under regional fixed effects (columns 2-6). Consistent with this, the "% Gender Effect" is modest, about 1.2% in column (1) and essentially disappears in the richer specifications. For respondents identifying as nonbinary, the coefficient is positive in all models, roughly 0.14-0.26), but is only statistically significant at the 10% level in column (4) and in the working-age model in column (6), indicating suggestive but imprecisely estimated differences for this subgroup.

In contrast, age appears a non-linear relationship with sustainable financial literacy. The linear age term is positive and statistically significant at the 1% level in all specifications, while the squared term is negative and statistically significant at the 1% level in columns (1)-(5), implying an inverted-U relationship, implying that sustainable financial literacy increases with age at younger ages, but at a diminishing rate. In the working-age sample in column (6), the squared term is statistically insignificant, suggesting that the concavity is largely driven by older-age variation outside working age, with a more nearly monotonic increase within the working-age range.

Regarding marital status, being married and being widowed/divorced, relative to being single (reference group) is not related to sustainable financial literacy. Both married and widowed/divorced coefficients are small and statistically insignificant in all columns. In contrast, respondents with unknown marital status consistently exhibit lower sustainable financial literacy (approximately -0.084 to -0.103), with the effect statistically significant at the 5% level in columns (1)-(3) and at the 1% level in columns (4)-(6), pointing to systematic differences among non-respondents.

Estimates show that education attainment level is positively related to sustainable financial literacy. Relative to primary education, lower secondary (ISCED 2) has positive and statistically significant coefficients, ranging from 0.107 to 0.137. From upper secondary onward (ISCED 3 – ISCED 8), all coefficients are large and statistically significant at the 1% level across all specifications. More specifically, the coefficients' range is 0.328-0.368 (upper secondary), 0.428-0.504 (post-secondary non-tertiary), 0.394-0.456 (short-cycle tertiary), 0.529-0.601 (bachelor's), 0.592-0.672 (master's), and 0.498-0.591 (doctoral). These estimates indicate substantial and persistent differences in sustainable financial literacy by educational attainment.

Regarding employment status, relative to inactive respondents (reference group), self-employment and employment seems not to be associated with sustainable financial literacy, as both coefficients are small and statistically insignificant throughout. In contrast, unemployment is consistently associated with higher sustainable financial literacy (about 0.093-0.104) and is statistically significant at the 5% level in all columns. Homemaker/looking after home is negative in all specifications and becomes statistically significant at the 10% level in the working-age model (in column (6) but is otherwise statistically insignificant. The category "other employed (prefer not to say)" is positive and statistically significant at the 10% level in columns (2) and (4), and at the 5% level under regional fixed effects and in the working-age specification in columns (5)-(6), with coefficients 0,140-0.155. Retired respondents display positive coefficients across all specifications, from 0.125 significant at the 1% level in column (1), decreasing to 0.076, significant at the 10% level in columns (4)-(5). However, the coefficient is essentially zero in the working-age specification in column (6) which is mechanically consistent with the restriction. Students/pupils show a large

positive association as well, with coefficients ranging from 0.310 to 0.347 and statistically significant at the 1% level in columns (1)-(5) and similarly become non-informative in the working-age model.

Income seems to be positively related to sustainable financial literacy in columns (2), (4), (5) and (6). Relative to "prefer not to say" (reference group), the gradient is concentrated above the lower part of the distribution. Specifically, income deciles from 4 to 10 are positive and statistically significant at the 1% level in all specifications, rising from about 0.089-0.111 (decile 4) to roughly 0.172-0.202 at the top deciles (deciles 9-10). In contrast, income deciles 1 and 2 have small and statistically insignificant coefficients throughout, while decile 3 is generally statistically insignificant, becoming only weakly significant (10% level) under regional fixed effects in column (5).

Wealth deciles, included in column (3), show a similar pattern. Wealth deciles from 4 to 10 are positive and statistically significant, while the bottom of the distribution does not share this advantage. Specifically, wealth decile 1 is negative, about -0.072, and statistically significant at the 1% level, indicating lower sustainable financial literacy among the least-wealthy relative to the reference group.

Finally, job-task breadth is also positively related to sustainable financial literacy. The coefficient of the number of distinct job tasks ranges from 0.045 to 0.049 and is statistically significant at the 1% level in columns (4)-(6). This implies that broader task exposure is systematically associated with higher sustainable financial literacy even after accounting for fixed effects and socioeconomic resources.

Overall, some main results are consistent across specifications. Sustainable financial literacy is associated with inverted-U age profile, with educational attainment, higher income and wealth (particularly from the middle-to-upper distribution upward), and broader job-task exposure, while gender differences are small and not robust once controls are introduced. Marital status is largely unrelated, except for a persistent negative association among respondents with unknown marital status. Employment status effects are generally limited, with unemployment standing out as a stable positive correlate and with the full-sample advantages for students and retirees disappearing once attention is restricted to the working-age population

Table 4-10: Sustainable Financial Literacy - OLS regression estimates

	Country fixed effects			Regional fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Gender: Male	0.028*	0.003	0.005	-0.007	-0.006	-0.002
	[0.015]	[0.015]	[0.015]	[0.015]	[0.012]	[0.014]
"-": Nonbinary	0.142	0.160	0.151	0.174*	0.184	0.264*
	[0.100]	[0.104]	[0.102]	[0.100]	[0.123]	[0.135]
"-": Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age of respondent	0.019***	0.018***	0.020***	0.017***	0.017***	0.014***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.004]
Age of respondent (squared)	-0.115***	-0.108***	-0.127***	-0.099***	-0.101***	-0.055
	[0.029]	[0.029]	[0.029]	[0.029]	[0.028]	[0.040]
Marital status: Married	0.005	-0.011	-0.014	-0.016	-0.013	-0.016
	[0.019]	[0.020]	[0.019]	[0.021]	[0.017]	[0.019]
"-": Widow/Divorced	0.001	-0.005	0.004	-0.009	-0.007	-0.014
	[0.031]	[0.032]	[0.031]	[0.031]	[0.028]	[0.032]
"-": Unknown	-0.086**	-0.099**	-0.097**	-0.103***	-0.095***	-0.084***
	[0.036]	[0.036]	[0.035]	[0.036]	[0.024]	[0.026]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
ISCED 2: Lower secondary education	0.122**	0.121**	0.125**	0.112**	0.107*	0.137*
	[0.055]	[0.055]	[0.056]	[0.054]	[0.056]	[0.075]
"-" 3: Upper secondary education	0.364***	0.351***	0.355***	0.328***	0.327***	0.368***
	[0.062]	[0.062]	[0.063]	[0.061]	[0.055]	[0.076]
"-" 4: Post-secondary non-tertiary educ.	0.474***	0.461***	0.457***	0.430***	0.428***	0.504***
	[0.074]	[0.076]	[0.075]	[0.073]	[0.062]	[0.079]
"-" 5: Short-cycle tertiary education	0.456***	0.432***	0.434***	0.399***	0.394***	0.422***
	[0.061]	[0.061]	[0.063]	[0.061]	[0.056]	[0.076]
"-" 6: Bachelor's or equivalent level	0.601***	0.567***	0.569***	0.532***	0.529***	0.593***
	[0.059]	[0.061]	[0.061]	[0.060]	[0.054]	[0.073]
"-" 7: Master's or equivalent level	0.672***	0.631***	0.630***	0.593***	0.592***	0.663***
	[0.067]	[0.068]	[0.068]	[0.067]	[0.057]	[0.076]
"-" 8: Doctoral or equivalent level	0.591***	0.539***	0.534***	0.498***	0.501***	0.579***
	[0.086]	[0.087]	[0.085]	[0.086]	[0.068]	[0.092]
"-" 1: Primary education	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Employment status: Self-employed	0.051	0.011	0.013	-0.015	-0.022	-0.028
	[0.040]	[0.039]	[0.040]	[0.039]	[0.043]	[0.043]
"-": Employed	0.060	-0.003	0.020	-0.016	-0.017	-0.029
	[0.039]	[0.038]	[0.039]	[0.037]	[0.038]	[0.039]
"-": Unemployed	0.104**	0.104**	0.100**	0.100**	0.100**	0.093**
	[0.042]	[0.042]	[0.043]	[0.042]	[0.045]	[0.046]
"-": Homemaker/looking after home	-0.073	-0.094	-0.097	-0.085	-0.079	-0.093*
	[0.057]	[0.056]	[0.058]	[0.055]	[0.051]	[0.051]
"-": Other employed (prefer not to say)	0.097	0.139*	0.112	0.140*	0.152**	0.155**
	[0.069]	[0.069]	[0.070]	[0.069]	[0.059]	[0.062]
"-": Retired	0.125***	0.089**	0.101**	0.076*	0.076*	0.001
	[0.039]	[0.038]	[0.040]	[0.038]	[0.040]	[0.001]
"-": Student/pupil (full time)	0.331***	0.327***	0.310***	0.347***	0.342***	0.001
	[0.042]	[0.042]	[0.042]	[0.042]	[0.044]	[0.001]
"-": Inactive	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Income: Decile 10	–	0.189***	–	0.172***	0.172***	0.176***
		[0.032]		[0.033]	[0.025]	[0.027]
"-": Decile 9	–	0.194***	–	0.183***	0.187***	0.202***

		[0.031]		[0.030]	[0.023]	[0.026]
"-": Decile 8	–	0.165***	–	0.153***	0.151***	0.157***
		[0.034]		[0.034]	[0.027]	[0.029]
"-": Decile 7	–	0.140***	–	0.131***	0.130***	0.128***
		[0.026]		[0.026]	[0.025]	[0.029]
"-": Decile 6	–	0.134***	–	0.127***	0.130***	0.112***
		[0.032]		[0.032]	[0.025]	[0.029]
"-": Decile 5	–	0.122***	–	0.113***	0.115***	0.118***
		[0.032]		[0.031]	[0.028]	[0.034]
"-": Decile 4	–	0.111***	–	0.104***	0.109***	0.089**
		[0.034]		[0.034]	[0.028]	[0.035]
"-": Decile 3	–	0.044	–	0.037	0.046*	0.028
		[0.029]		[0.029]	[0.027]	[0.035]
"-": Decile 2	–	0.007	–	0.003	0.011	0.014
		[0.028]		[0.027]	[0.025]	[0.031]
"-": Decile 1	–	0.013	–	0.013	0.017	0.013
		[0.022]		[0.022]	[0.024]	[0.030]
"-": Prefer not to say	–	*{Ref.}*	–	*{Ref.}*	*{Ref.}*	*{Ref.}*
Wealth: Decile 10	–	–	0.221***	–	–	–
			[0.031]			
"-": Decile 9	–	–	0.181***	–	–	–
			[0.024]			
"-": Decile 8	–	–	0.158***	–	–	–
			[0.026]			
"-": Decile 7	–	–	0.101***	–	–	–
			[0.033]			
"-": Decile 6	–	–	0.117***	–	–	–
			[0.030]			
"-": Decile 5	–	–	0.072***	–	–	–
			[0.026]			
"-": Decile 4	–	–	0.061**	–	–	–
			[0.025]			
"-": Decile 3	–	–	0.027	–	–	–
			[0.021]			
"-": Decile 2	–	–	-0.025	–	–	–
			[0.025]			
"-": Decile 1	–	–	-0.072***	–	–	–
			[0.023]			
"-": Prefer not to say	–	–	*{Ref.}*	–	–	–
Number of distinct job task types	–	–	–	0.049***	0.049***	0.045***
				[0.004]	[0.004]	[0.005]
Country Fixed Effects	+	+	+	+	-	-
Regional Fixed Effects	–	–	–	–	+	+
% Gender Effect	1.22%	0.13%	0.20%	-0.29%	-0.24%	-0.09%
Linear prediction	2.2842	2.2842	2.2842	2.2842	2.2842	2.2415
No. of Observations	29,872	29,872	29,872	29,872	29,872	21,564

Notes: The dependent variable is the sustainable financial literacy index (0-3), with higher values indicating higher literacy levels. Columns (1)-(4) report OLS estimates with country fixed effects, starting with demographic controls (1) and then adding income, wealth, and job-task controls in (2)-(4). Column (5) replicates (4) with regional fixed effects and column (6) applies the regional fixed effects specification to the working-age sample. Robust standard errors are clustered at the country level in (1)-(4) and at the regional level in (5)-(6). ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4-11 reports OLS estimates for the Human Literacy index (0-3) across six specifications. Across all specifications, men score lower on the human literacy index relative to women (reference group). The male coefficient ranges from -0.083 to -0.127 index points and is statistically significant at the 1% level across all columns. Consistent with the table's "% Gender Effect" row, this implies a sizeable negative effect of roughly -7.8% to 12.1% relative to the reported linear prediction. The coefficient for respondents identifying as nonbinary is positive but statistically insignificant throughout, reflecting limited precision for this subgroup.

Age exhibits a non-linear, U-shaped, relationship with human literacy. The linear age term is negative and statistically significant at the 5% level in columns (1)-(3) and at the 1% level in columns (4)-(6). The squared term is positive and statistically significant at the 5% or 1% level in all columns. This pattern indicates that human literacy declines with age at younger ages but increases again at older ages, with the implied turning point falling around the early-to-mid 40s, given the typical scaling of the squared term.

Regarding marital status, being married, relative to being single (reference group), is associated with higher human literacy in all specifications, with coefficients between 0.058 and 0.084 that are statistically significant at the 1% level throughout. Widow/divorced respondents also display a positive association, with coefficients ranging from 0.043 to 0.056, which is statistically significant at the 5% level in columns (1) and (3), and at the 10% level in columns (2), (4), and (5). However, the coefficient becomes statistically insignificant in the working-age specification in column (6). The "marital status: unknown" category is likewise positive (0.046-0.068) and is generally statistically significant at the 5% or 10% level in columns (1)-(3) and (5)-(6), though it is statistically insignificant in column (4).

Education attainment level seems to be positively associated with human literacy. Relative to primary education (reference), lower secondary education (ISCED 2) is positive but statistically insignificant in every specification. From upper secondary onwards, coefficients are positive and typically increase with attainment level. Upper secondary education (ISCED 3) is positive and statistically significant in columns (1)-(5) but becomes statistically insignificant in the working-age model in column (6). Post-secondary non-tertiary education (ISCED 4) remains positive (0.136-0.210) and is statistically significant in all columns. Short-cycle tertiary and above (ISCED 5 – ISCED 8) appear a clear upward gradient: short-cycle tertiary (0.137-0.219), bachelor's (0.228-0.331), master's (0.282-0.403), and doctoral education (0.300-0.432) are all statistically significant at the 1% level across every specification, indicating large and stable differences in human literacy by higher educational attainment.

Regarding employment status, most categories indicate insignificant coefficients. Specifically, relative to inactive respondents (reference group), self-employment, employment, unemployment, homemaker status, and "other employed (prefer not to say)" are statistically insignificant throughout, with point estimates generally small. Retired respondents show a modest positive association only in the baseline model (column 1) which becomes statistically insignificant once additional covariates are introduced and under regional fixed effects. Students/pupils are consistently associated with higher human literacy in columns (1)-(5) but this category is effectively not informative in the working-age specification (column 6), as expected given the sample restriction.

Income is positively related to human literacy, with estimated coefficients increase monotonically across the income distribution, when income deciles are included in columns (2), (4), (5) and (6). Relative to the reference category "prefer not to say", all income deciles are positive and statistically

significant at the 1% level, rising from 0.079 to 0.081 in the bottom decile to around 0.298-0.331 in the top decile.

Wealth, included in column (3), shows a similar gradient. All wealth deciles from 1 to 10 appear positive and statistically significant coefficients at the 1% level, increasing from 0.067 (bottom wealth decile) to roughly 0.255-0.261 (top deciles), again relative to "prefer not to say."

Finally, as in the previous literacy indices, job-task breadth is related positively with human literacy. The number of distinct job tasks is 0.057-0.058 and statistically significant at the 1% level in columns (4)-(6), implying meaningful gains in human literacy for individuals whose work involves a wider set of tasks.

Overall, the results indicate that human literacy is lower for men, exhibits a U-shaped age profile, and is strongly increasing in education, especially from short-cycle tertiary upward. In addition, human literacy is related to monotonic gradients across both income and wealth deciles, while job-task breadth emerges as an additional correlate. In contrast, employment status categories, e.g., employed, self-employed, unemployed, is generally not a robust predictor once education and socioeconomic characteristics are accounted for, suggesting that human literacy in this domain is more closely connected to human capital and resources, and to exposure to diverse tasks, than to employment status alone.

Table 4-11: Human Literacy - OLS regression estimates

	Country fixed effects			Regional fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Gender: Male	-0.083***	-0.116***	-0.109***	-0.127***	-0.128***	-0.127***
	[0.013]	[0.012]	[0.013]	[0.012]	[0.012]	[0.013]
"-": Nonbinary	0.100	0.119	0.108	0.135	0.136	0.124
	[0.135]	[0.137]	[0.134]	[0.136]	[0.127]	[0.134]
"-": Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age of respondent	-0.007**	-0.008**	-0.006*	-0.009***	-0.009***	-0.016***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.004]
Age of respondent (squared)	0.078**	0.090***	0.074**	0.101***	0.098***	0.187***
	[0.034]	[0.032]	[0.033]	[0.033]	[0.030]	[0.046]
Marital status: Married	0.084***	0.065***	0.069***	0.058***	0.059***	0.058***
	[0.018]	[0.018]	[0.018]	[0.018]	[0.016]	[0.018]
"-": Widow/Divorced	0.056**	0.048*	0.054**	0.043*	0.044*	0.037
	[0.026]	[0.025]	[0.025]	[0.024]	[0.026]	[0.031]
"-": Unknown	0.068**	0.050*	0.054*	0.046	0.046**	0.054**
	[0.028]	[0.028]	[0.027]	[0.027]	[0.022]	[0.024]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
ISCED 2: Lower secondary education	0.041	0.037	0.031	0.026	0.026	0.015
	[0.053]	[0.054]	[0.054]	[0.054]	[0.052]	[0.066]
"-" 3: Upper secondary education	0.155***	0.138**	0.134**	0.110**	0.112**	0.093
	[0.053]	[0.053]	[0.054]	[0.053]	[0.048]	[0.059]
"-" 4: Post-secondary non-tertiary educ.	0.210***	0.196**	0.185**	0.161**	0.157**	0.136*
	[0.076]	[0.076]	[0.076]	[0.076]	[0.068]	[0.078]
"-" 5: Short-cycle tertiary education	0.219***	0.191***	0.191***	0.151***	0.153***	0.137**
	[0.052]	[0.054]	[0.054]	[0.053]	[0.052]	[0.067]
"-" 6: Bachelor's or equivalent level	0.331***	0.289***	0.295***	0.247***	0.246***	0.228***
	[0.053]	[0.054]	[0.055]	[0.053]	[0.051]	[0.061]
"-" 7: Master's or equivalent level	0.403***	0.349***	0.360***	0.303***	0.300***	0.282***
	[0.060]	[0.061]	[0.061]	[0.061]	[0.053]	[0.065]
"-" 8: Doctoral or equivalent level	0.432***	0.354***	0.376***	0.305***	0.300***	0.354***
	[0.070]	[0.071]	[0.070]	[0.070]	[0.076]	[0.086]
"-" 1: Primary education	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Employment status: Self-employed	0.067	0.027	0.039	-0.004	-0.002	-0.008
	[0.042]	[0.041]	[0.042]	[0.043]	[0.046]	[0.046]
"-": Employed	0.042	-0.020	0.008	-0.034	-0.034	-0.032
	[0.033]	[0.033]	[0.033]	[0.034]	[0.043]	[0.043]
"-": Unemployed	0.031	0.034	0.027	0.030	0.027	0.027
	[0.049]	[0.049]	[0.049]	[0.049]	[0.047]	[0.047]
"-": Homemaker/looking after home	-0.049	-0.068	-0.068	-0.057	-0.066	-0.059
	[0.044]	[0.042]	[0.042]	[0.043]	[0.050]	[0.051]
"-": Other employed (prefer not to say)	0.043	0.081	0.061	0.083	0.081	0.077
	[0.069]	[0.069]	[0.068]	[0.068]	[0.062]	[0.064]
"-": Retired	0.069*	0.034	0.044	0.018	0.019	0.001
	[0.034]	[0.034]	[0.034]	[0.034]	[0.045]	[0.001]
"-": Student/pupil (full time)	0.169***	0.165***	0.161***	0.188***	0.187***	0.001
	[0.038]	[0.038]	[0.038]	[0.039]	[0.048]	[0.001]
"-": Inactive	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Income: Decile 10	–	0.331***	–	0.311***	0.309***	0.298***
		[0.019]		[0.018]	[0.021]	[0.026]
"-": Decile 9	–	0.229***	–	0.217***	0.220***	0.221***

		[0.018]		[0.019]	[0.021]	[0.026]
"-": Decile 8	–	0.194***	–	0.179***	0.179***	0.143***
		[0.022]		[0.021]	[0.025]	[0.027]
"-": Decile 7	–	0.177***	–	0.167***	0.168***	0.166***
		[0.025]		[0.024]	[0.022]	[0.027]
"-": Decile 6	–	0.157***	–	0.148***	0.146***	0.133***
		[0.025]		[0.025]	[0.023]	[0.025]
"-": Decile 5	–	0.141***	–	0.131***	0.132***	0.153***
		[0.026]		[0.025]	[0.025]	[0.030]
"-": Decile 4	–	0.150***	–	0.143***	0.142***	0.152***
		[0.022]		[0.022]	[0.026]	[0.031]
"-": Decile 3	–	0.116***	–	0.108***	0.107***	0.124***
		[0.032]		[0.031]	[0.027]	[0.030]
"-": Decile 2	–	0.106***	–	0.102***	0.103***	0.112***
		[0.025]		[0.025]	[0.021]	[0.026]
"-": Decile 1	–	0.079***	–	0.079***	0.081***	0.080***
		[0.016]		[0.016]	[0.021]	[0.025]
"-": Prefer not to say	–	*{Ref.}*	–	*{Ref.}*	*{Ref.}*	*{Ref.}*
Wealth: Decile 10	–	–	0.261***	–	–	–
			[0.019]			
"-": Decile 9	–	–	0.255***	–	–	–
			[0.024]			
"-": Decile 8	–	–	0.182***	–	–	–
			[0.029]			
"-": Decile 7	–	–	0.172***	–	–	–
			[0.024]			
"-": Decile 6	–	–	0.184***	–	–	–
			[0.027]			
"-": Decile 5	–	–	0.152***	–	–	–
			[0.023]			
"-": Decile 4	–	–	0.157***	–	–	–
			[0.027]			
"-": Decile 3	–	–	0.123***	–	–	–
			[0.024]			
"-": Decile 2	–	–	0.125***	–	–	–
			[0.023]			
"-": Decile 1	–	–	0.067***	–	–	–
			[0.021]			
"-": Prefer not to say	–	–	*{Ref.}*	–	–	–
Number of distinct job task types	–	–	–	0.058***	0.058***	0.057***
				[0.004]	[0.003]	[0.004]
Country Fixed Effects	+	+	+	+	-	-
Regional Fixed Effects	–	–	–	–	+	+
% Gender Effect	-7.75%	-10.81%	-10.17%	-11.86%	-11.96%	-12.07%
Linear prediction	1.0719	1.0719	1.0719	1.0719	1.0719	1.0552
No. of Observations	29,872	29,872	29,872	29,872	29,872	21,564

Notes: The dependent variable is the human literacy index (0-3), with higher values indicating higher literacy levels. Columns (1)-(4) report OLS estimates with country fixed effects, starting with demographic controls (1) and then adding income, wealth, and job-task controls in (2)-(4). Column (5) replicates (4) with regional fixed effects and column (6) applies the regional fixed effects specification to the working-age sample. Robust standard errors are clustered at the country level in (1)-(4) and at the regional level in (5)-(6). ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4-12 reports OLS estimates for the Cultural Agility index (0-3) across six specifications. Across all specifications, men score lower on the cultural agility index relative to women (reference group). The male coefficient ranges from -0.045 to -0.078 index points and is statistically significant at the 1% level across all columns. Consistent with the table's "% Gender Effect" row, this implies a sizeable negative effect of roughly -4.3% to 7.6% relative to the reported linear prediction. The coefficient for respondents identifying as nonbinary is positive but statistically insignificant throughout, reflecting limited precision for this subgroup.

In contrast, there is no robust age profile. Both the linear and squared age terms are statistically insignificant across all specifications.

Marital status is also not a systematic correlate. Being married, relative to being single (reference group), is associated with a small positive coefficient in the baseline model, about 0.023, which is statistically significant at the 10% level in column (1). However, it becomes statistically insignificant once income, wealth, and job-task controls are added and under regional fixed effects. Widow/divorced status and "unknown" marital status are statistically insignificant in every column.

Cultural agility displays a strong and monotonic education gradient relative to primary education (reference). Lower secondary education (ISCED 2) is positive (≈0.055–0.070) but statistically insignificant throughout. From upper secondary onwards, coefficients are uniformly positive and statistically significant at the 1% level in every specification: approximately 0.158–0.210 (upper secondary), 0.218–0.288 (post-secondary non-tertiary), 0.236–0.301 (short-cycle tertiary), 0.325–0.399 (bachelor's), 0.360–0.447 (master's), and 0.310–0.394 (doctoral). Given the 0–3 scale, these estimates imply sizeable and very robust differences in cultural agility by educational attainment, with magnitudes remaining substantial under regional fixed effects and in the working-age sample.

Education attainment level seems to be positively associated with cultural agility, showing monotonic positive gradient. Relative to primary education (reference), lower secondary education (ISCED 2) is positive but statistically insignificant throughout. From upper secondary onwards (ISCED 3 – ISCED 8), coefficients are positive and statistically significant at the 1% level in all columns. Specifically, the coefficients' range is approximately 0.158-0.210 (upper secondary), 0.218-0.288 (post-secondary non-tertiary), 0.236-0.301 (short-cycle tertiary), 0.325-0.399 (bachelor's), 0.360-0.447 (master's), and 0.310-0.394 (doctoral). These estimates imply sizeable differences in cultural agility by educational attainment, with magnitudes remaining substantial under regional fixed effects and in the working-age sample.

Regarding employment status, relative to inactive respondents (reference group), self-employment, employment, unemployment, and retirement are statistically insignificant in all specifications. Two categories stand out. First, homemakers/looking after home show lower cultural agility, with coefficients around -0.082 to -0.099 and statistically significant at the 5% level in columns (1)-(5), and remaining negative (-0.088) and statistically significant at the 10% level in the working-age model in column (6). Second, the "other employed (prefer not to say)" category is consistently negative and statistically significant at the 5% level in columns (1) and (3), and at the 10% level in columns (2), (4), (5), and (6). Students/pupils have a positive coefficient in the full sample (0.090–0.116) and statistically significant at the 5% level in columns (1)-(5) but are effectively non-informative in the working-age specification in column (6), consistent with the sample restriction.

Income is positively related to cultural agility with coefficients increasing slightly across the distribution in columns (2), (4), (5) and (6). This positive gradient is concentrated in the upper distribution. Specifically, income deciles 4-10 are positive and statistically significant at the 1% level

in all income specifications, with coefficients rising to about 0.145-0.170 in the top deciles. In contrast, income deciles 1-3 are generally statistically insignificant, although in the working-age model deciles 1 (0.048) and decile 2 (0.046) become positive and reach statistical significance at the 5% and 10% level, respectively.

Wealth, included in column (3), exhibits a similarly strong gradient. Relative to "prefer not to say" (reference group), wealth deciles from 2 to 10 are positive and statistically significant at the 1% level. Whereas the bottom wealth decile is close to zero (-0.009) and statistically insignificant.

Finally, job-task breadth is positively associated with cultural agility, although the estimated coefficients are smaller in magnitude than for most other literacy indices, indicating a more modest role of task variety in shaping cultural agility. Coefficients of the number of distinct job task types is 0.035-0.036 in columns (4)-(5) and 0.029 in column (6), are statistically significant at the 1% level, indicating that broader task exposure is systematically associated with higher cultural agility net of fixed effects and socioeconomic controls.

Overall, cultural agility is most strongly associated with an upward education gradient, pronounced income and wealth gradients (driven mainly by the middle-to-upper parts of the distributions) and a positive (albeit comparatively smaller) association with job-task breadth. Gender differences are also robust but operate in the opposite direction to several other literacy indices with men exhibit consistently lower cultural agility than women. By contrast, age and most employment status categories are not robust predictors once fixed effects and socioeconomic characteristics are accounted for.

Table 4-12: Cultural Agility - OLS regression estimates

	Country fixed effects			Regional fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Gender: Male	-0.045***	-0.065***	-0.063***	-0.072***	-0.071***	-0.078***
	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]	[0.015]
"-": Nonbinary	0.037	0.052	0.048	0.061	0.064	0.068
	[0.102]	[0.101]	[0.102]	[0.100]	[0.109]	[0.136]
"-": Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age of respondent	0.003	0.002	0.003	0.001	0.002	0.001
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]
Age of respondent (squared)	0.001	0.006	-0.007	0.012	0.006	0.025
	[0.024]	[0.024]	[0.024]	[0.023]	[0.026]	[0.039]
Marital status: Married	0.023*	0.011	0.011	0.007	0.010	0.010
	[0.013]	[0.013]	[0.013]	[0.013]	[0.014]	[0.017]
"-": Widow/Divorced	-0.002	-0.007	-0.001	-0.010	-0.007	0.007
	[0.022]	[0.022]	[0.022]	[0.022]	[0.024]	[0.029]
"-": Unknown	0.006	-0.004	-0.004	-0.007	-0.004	0.001
	[0.025]	[0.025]	[0.025]	[0.024]	[0.021]	[0.023]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
ISCED 2: Lower secondary education	0.070	0.069	0.065	0.062	0.059	0.055
	[0.051]	[0.052]	[0.052]	[0.053]	[0.052]	[0.057]
"-" 3: Upper secondary education	0.210***	0.199***	0.195***	0.182***	0.176***	0.158***
	[0.056]	[0.056]	[0.057]	[0.057]	[0.049]	[0.050]
"-" 4: Post-secondary non-tertiary educ.	0.288***	0.277***	0.269***	0.256***	0.254***	0.218***
	[0.060]	[0.060]	[0.060]	[0.061]	[0.059]	[0.066]
"-" 5: Short-cycle tertiary education	0.301***	0.282***	0.279***	0.258***	0.254***	0.236***
	[0.057]	[0.058]	[0.059]	[0.059]	[0.051]	[0.056]
"-" 6: Bachelor's or equivalent level	0.399***	0.372***	0.373***	0.347***	0.339***	0.325***
	[0.055]	[0.055]	[0.057]	[0.056]	[0.049]	[0.052]
"-" 7: Master's or equivalent level	0.447***	0.414***	0.415***	0.387***	0.379***	0.360***
	[0.058]	[0.059]	[0.061]	[0.061]	[0.051]	[0.055]
"-" 8: Doctoral or equivalent level	0.394***	0.352***	0.353***	0.322***	0.310***	0.349***
	[0.068]	[0.069]	[0.069]	[0.069]	[0.062]	[0.066]
"-" 1: Primary education	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Employment status: Self-employed	0.022	-0.009	-0.004	-0.028	-0.026	-0.006
	[0.030]	[0.030]	[0.029]	[0.031]	[0.037]	[0.038]
"-": Employed	0.020	-0.030	-0.011	-0.039	-0.039	-0.030
	[0.030]	[0.031]	[0.029]	[0.031]	[0.037]	[0.038]
"-": Unemployed	-0.042	-0.042	-0.046	-0.044	-0.037	-0.032
	[0.038]	[0.037]	[0.037]	[0.038]	[0.044]	[0.045]
"-": Homemaker/looking after home	-0.082**	-0.099**	-0.099**	-0.092**	-0.095**	-0.088*
	[0.039]	[0.038]	[0.038]	[0.039]	[0.046]	[0.046]
"-": Other employed (prefer not to say)	-0.121**	-0.087*	-0.106**	-0.087*	-0.093*	-0.094*
	[0.048]	[0.047]	[0.047]	[0.047]	[0.049]	[0.052]
"-": Retired	0.008	-0.021	-0.014	-0.030	-0.031	0.001
	[0.031]	[0.031]	[0.030]	[0.031]	[0.040]	[0.001]
"-": Student/pupil (full time)	0.101**	0.099**	0.090**	0.113**	0.116**	0.001
	[0.044]	[0.044]	[0.043]	[0.045]	[0.048]	[0.001]
"-": Inactive	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Income: Decile 10	–	0.161***	–	0.149***	0.145***	0.153***
		[0.020]		[0.020]	[0.021]	[0.024]
"-": Decile 9	–	0.157***	–	0.149***	0.146***	0.170***

		[0.019]		[0.019]	[0.022]	[0.025]
"-": Decile 8	–	0.131***	–	0.122***	0.123***	0.135***
		[0.021]		[0.021]	[0.022]	[0.024]
"-": Decile 7	–	0.122***	–	0.116***	0.117***	0.133***
		[0.028]		[0.027]	[0.024]	[0.026]
"-": Decile 6	–	0.122***	–	0.117***	0.120***	0.131***
		[0.022]		[0.021]	[0.020]	[0.021]
"-": Decile 5	–	0.104***	–	0.098***	0.103***	0.126***
		[0.023]		[0.022]	[0.024]	[0.030]
"-": Decile 4	–	0.103***	–	0.098***	0.102***	0.129***
		[0.027]		[0.027]	[0.025]	[0.028]
"-": Decile 3	–	0.026	–	0.021	0.029	0.037
		[0.023]		[0.024]	[0.023]	[0.026]
"-": Decile 2	–	0.027	–	0.024	0.029	0.046*
		[0.025]		[0.024]	[0.025]	[0.027]
"-": Decile 1	–	0.019	–	0.019	0.025	0.048**
		[0.018]		[0.019]	[0.020]	[0.024]
"-": Prefer not to say	–	*{Ref.}*	–	*{Ref.}*	*{Ref.}*	*{Ref.}*
Wealth: Decile 10	–	–	0.155***	–	–	–
			[0.023]			
"-": Decile 9	–	–	0.155***	–	–	–
			[0.022]			
"-": Decile 8	–	–	0.123***	–	–	–
			[0.021]			
"-": Decile 7	–	–	0.117***	–	–	–
			[0.022]			
"-": Decile 6	–	–	0.096***	–	–	–
			[0.028]			
"-": Decile 5	–	–	0.107***	–	–	–
			[0.024]			
"-": Decile 4	–	–	0.106***	–	–	–
			[0.018]			
"-": Decile 3	–	–	0.091***	–	–	–
			[0.022]			
"-": Decile 2	–	–	0.057***	–	–	–
			[0.021]			
"-": Decile 1	–	–	-0.009	–	–	–
			[0.021]			
"-": Prefer not to say	–	–	*{Ref.}*	–	–	–
Number of distinct job task types	–	–	–	0.035***	0.036***	0.029***
				[0.003]	[0.003]	[0.004]
Country Fixed Effects	+	+	+	+	-	-
Regional Fixed Effects	–	–	–	–	+	+
% Gender Effect	-4.36%	-6.31%	-6.06%	-6.96%	-6.81%	-7.60%
Linear prediction	1.0355	1.0355	1.0355	1.0355	1.0355	1.0272
No. of Observations	29,872	29,872	29,872	29,872	29,872	21,564

Notes: The dependent variable is the cultural agility index (0-3), with higher values indicating higher cultural agility. Columns (1)-(4) report OLS estimates with country fixed effects, starting with demographic controls (1) and then adding income, wealth, and job-task controls in (2)-(4). Column (5) replicates (4) with regional fixed effects and column (6) applies the regional fixed effects specification to the working-age sample. Robust standard errors are clustered at the country level in (1)-(4) and at the regional level in (5)-(6). ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

5. Literacies and Economic Resilience: Evidence from Labour Market and Financial Models

Having established the conceptual coherence and internal validity of the twelve literacy domains, the next step is to examine whether these literacies translate into tangible socio-economic advantages. This section investigates the extent to which different forms of literacy are associated with labour market resilience and financial/economic resilience. In doing so, it moves beyond descriptive patterns and correlation structures to assess whether literacies function as protective resources in contexts of economic uncertainty, technological change, and labour market volatility.

Resilience is understood here as the capacity to anticipate, adapt to, and recover from economic shocks. In the labour market domain, resilience encompasses adaptability to technological or organisational change, engagement in upskilling activities, and confidence in the ability to secure employment. In the financial domain, resilience reflects the ability to withstand income shocks, manage short-, medium-, and long-term financial strain, and maintain broader economic stability. Together, these dimensions capture both subjective and behavioural aspects of economic security.

The analysis addresses two central questions. First, do higher levels of literacy systematically predict stronger resilience outcomes? Second, are certain literacy domains more consequential than others? The twelve literacy constructs span economic, technological, civic, environmental, health, and interpersonal domains, allowing us to test whether resilience is primarily driven by technical skills, institutional knowledge, behavioural adaptability, or broader socio-cognitive competencies.

Importantly, the models include all literacy indices simultaneously, enabling a comparison of their relative explanatory power while accounting for overlap across domains. This approach allows us to identify whether specific literacies exert independent effects or whether resilience reflects a more generalised competence factor.

The results are presented in two parts. Section 5.1 examines labour market resilience and its components, while Section 5.2 focuses on financial and economic resilience across different time horizons. Together, these analyses provide a comprehensive assessment of how multidimensional literacy shapes individuals' capacity to navigate economic risk in contemporary European labour markets.

5.1 Literacies and Labour Market Resilience

This subsection examines whether and how the twelve literacy domains are associated with labour market resilience. The labour market resilience construct is operationalised as a composite index capturing individuals' capacity to adapt to labour market change. As detailed in the construction code, the index combines three distinct but complementary dimensions: adaptability to new technologies, processes, or work environments; engagement in upskilling and skill-improvement activities; and confidence in the ability to find work within one's field. The adaptability measure

reflects perceived behavioural flexibility in response to change, the upskilling measure captures active investment in human capital development, and the confidence measure reflects forward-looking labour market self-efficacy. Together, these components capture both behavioural and attitudinal aspects of labour market security and adjustment capacity.

The literacy measures are constructed as additive indices based on the number of correct responses to the respective survey questions within each domain. Each literacy index therefore reflects accumulated factual knowledge or competence in its domain, rather than a standardised latent factor score. The regression models estimate the association between these additive literacy scores and labour market resilience outcomes. The overall resilience index and its three sub-components are regressed simultaneously on all twelve literacy indices, allowing the coefficients to be interpreted as partial associations net of overlap across domains. The models additionally include a comprehensive set of socio-demographic and socio-economic controls, including age, gender, educational attainment, employment status, and country fixed effects. Standard errors are reported in brackets and statistical significance is indicated using conventional thresholds. This specification allows for a comparison of the relative contribution of each literacy domain while accounting for confounding characteristics and cross-country heterogeneity.

The results of Table 5-1 reveal a highly differentiated pattern of associations across literacy domains. The most striking finding concerns Data and Programming Literacy, which exhibits by far the largest coefficient in the model predicting overall labour market resilience. The association remains strong and statistically significant across adaptability, upskilling, and confidence. This suggests that computational and technical skills represent a particularly powerful form of transferable human capital in contemporary labour markets. Individuals with stronger data and programming competencies appear more adaptable to technological change, more likely to engage in skill development, and more confident in their employment prospects. The magnitude and consistency of these effects indicate that technical digital proficiency plays a central role in shaping resilience under conditions of ongoing technological transformation.

Digital Financial Literacy also shows a consistently positive association with overall labour market resilience and all three sub-dimensions. Although its magnitude is smaller than that of Data and Programming Literacy, its stability across outcomes suggests that digital fluency in financial contexts may reflect broader digital adaptability. Artificial Intelligence Literacy similarly predicts higher overall resilience and adaptability. However, it is negatively associated with confidence. One plausible interpretation is that individuals with greater knowledge of AI systems may be more aware of automation risks, which could temper their expectations regarding long-term job security even as their adaptability increases.

Interpersonal and adaptive competencies emerge as another important pillar of labour market resilience. Human Literacy displays strong and statistically significant associations with overall resilience and with each sub-component. Individuals scoring higher on measures of empathy, inclusive identity, and collaborative orientation are more adaptable, more engaged in upskilling, and more confident in their employment prospects. Cultural Agility follows a similar pattern, particularly with respect to adaptability and upskilling. These findings indicate that behavioural flexibility and

Table 5-1: The effect of literacies on labour market resilience

	Labour market resilience (1)	Adaptability score (2)	Upskilling score (3)	Confidence score (4)
Financial literacy	0.009	0.001	0.002	-0.003
	[0.012]	[0.005]	[0.006]	[0.005]
Retirement literacy	0.018	-0.009**	0.017**	0.001
	[0.014]	[0.004]	[0.008]	[0.007]
Health literacy	0.014	0.017***	-0.032***	0.009
	[0.014]	[0.003]	[0.007]	[0.007]
Digital financial literacy	0.115***	0.026***	0.041***	0.019***
	[0.013]	[0.004]	[0.008]	[0.006]
Media literacy	0.021**	0.014***	0.008	-0.002
	[0.010]	[0.004]	[0.006]	[0.005]
AI literacy	0.021***	0.004*	0.006	-0.010***
	[0.007]	[0.002]	[0.004]	[0.003]
Data and programming literacy	0.510***	0.189***	0.232***	0.099***
	[0.013]	[0.004]	[0.007]	[0.007]
Political literacy	0.041***	-0.010*	0.028***	0.002
	[0.013]	[0.005]	[0.006]	[0.005]
Environmental literacy	-0.001	0.001	0.003	-0.012*
	[0.014]	[0.005]	[0.008]	[0.006]
Sustainable finance literacy	-0.001	0.007	-0.024***	-0.007
	[0.011]	[0.005]	[0.006]	[0.006]
Human literacy	0.257***	0.066***	0.105***	0.075***
	[0.012]	[0.004]	[0.007]	[0.006]
Cultural agility	0.114***	0.018***	0.065***	0.006
	[0.011]	[0.004]	[0.006]	[0.004]
Self-employed	0.059	0.025*	0.039	0.021
	[0.045]	[0.014]	[0.026]	[0.021]
Unemployed	-0.505***	-0.02	-0.102***	-0.356***
	[0.054]	[0.016]	[0.027]	[0.024]
Inactive	-0.813***	-0.081***	-0.318***	-0.296***
	[0.060]	[0.022]	[0.036]	[0.035]
Homemaker	-0.125	-0.013	-0.130**	-0.015
	[0.083]	[0.030]	[0.053]	[0.045]
Retired	0.217***	0.043*	0.033	0.159***
	[0.067]	[0.022]	[0.046]	[0.037]
Student	0.587***	0.053*	0.276***	0.208***
	[0.088]	[0.026]	[0.050]	[0.051]
Male	-0.025	0.038***	-0.084***	0.027**
	[0.024]	[0.006]	[0.014]	[0.011]
LGBT+	0.234	-0.001	0.401***	0
	[0.188]	[0.083]	[0.120]	[0.103]
Age	0.007	-0.004	-0.005	0.006
	[0.008]	[0.004]	[0.006]	[0.004]
Age sq./1000	-0.179**	0.017	0.013	-0.096**

	[0.076]	[0.035]	[0.059]	[0.037]
Single	-0.204***	-0.047**	-0.080**	-0.058**
	[0.052]	[0.020]	[0.032]	[0.022]
Married	-0.086*	-0.026	-0.059**	-0.001
	[0.047]	[0.017]	[0.027]	[0.021]
Unknown marital status	0.029	-0.006	0.026	0.01
	[0.052]	[0.018]	[0.030]	[0.023]
ISCED 2: Lower secondary education	0.034	0.006	-0.062	0.045
	[0.106]	[0.041]	[0.059]	[0.051]
ISCED 3: Upper secondary education	0.246**	0.034	0.065	0.082**
	[0.096]	[0.040]	[0.052]	[0.040]
ISCED 4: Post-secondary non-tertiary	0.411***	0.06	0.149**	0.143***
	[0.121]	[0.044]	[0.061]	[0.052]
ISCED 5: Short-cycle tertiary education	0.383***	0.032	0.221***	0.074*
	[0.092]	[0.041]	[0.051]	[0.040]
ISCED 6: Bachelor's or equivalent level	0.337***	0.011	0.214***	0.046
	[0.089]	[0.041]	[0.046]	[0.038]
ISCED 7: Master's or equivalent level	0.449***	0.021	0.307***	0.063
	[0.093]	[0.040]	[0.049]	[0.040]
ISCED 8: Doctoral or equivalent level	0.498***	0.041	0.347***	0.038
	[0.088]	[0.045]	[0.053]	[0.042]
Age: 18-24	0.1	0.07	0.057	0.081
	[0.131]	[0.058]	[0.082]	[0.060]
Age: 25-34	0.077	0.069	-0.003	0.067
	[0.096]	[0.047]	[0.068]	[0.050]
Age: 35-44	0.013	0.032	-0.004	0.043
	[0.074]	[0.037]	[0.050]	[0.038]
Age: 45-54	0.005	0.021	0.036	-0.021
	[0.055]	[0.027]	[0.038]	[0.031]
Age: 55-64	-0.101**	0.005	-0.004	-0.095***
	[0.043]	[0.017]	[0.027]	[0.025]
Income decile 10	0.264***	0.031	0.036	0.125***
	[0.059]	[0.019]	[0.026]	[0.033]
Income decile 9	0.115**	0.002	0.012	0.013
	[0.048]	[0.016]	[0.027]	[0.026]
Income decile 8	0.129**	-0.007	0.008	0.043
	[0.050]	[0.018]	[0.026]	[0.029]
Income decile 7	0.06	-0.029*	-0.024	0.022
	[0.043]	[0.016]	[0.023]	[0.021]
Income decile 6	0.042	-0.039**	-0.035	0.014
	[0.053]	[0.014]	[0.027]	[0.027]
Income decile 5	0.065	-0.008	-0.017	-0.013
	[0.043]	[0.014]	[0.024]	[0.025]
Income decile 4	-0.021	-0.032*	-0.055**	-0.059**
	[0.046]	[0.016]	[0.023]	[0.027]
Income decile 3	-0.101*	-0.034**	-0.096***	-0.096***
	[0.052]	[0.015]	[0.030]	[0.029]

Income decile 2	-0.117**	-0.034*	-0.069**	-0.133***
	[0.053]	[0.018]	[0.032]	[0.025]
Income decile 1	-0.117***	-0.011	-0.081***	-0.136***
	[0.039]	[0.012]	[0.022]	[0.021]
Wealth decile 10	0.253***	0.009	0.077**	0.070***
	[0.047]	[0.012]	[0.035]	[0.022]
Wealth decile 9	0.300***	0.026	0.077**	0.085***
	[0.044]	[0.018]	[0.029]	[0.021]
Wealth decile 8	0.224***	0.009	0.076***	0.029
	[0.051]	[0.020]	[0.027]	[0.024]
Wealth decile 7	0.237***	0.006	0.081***	0.030*
	[0.035]	[0.014]	[0.025]	[0.018]
Wealth decile 6	0.212***	0.006	0.075**	0.01
	[0.053]	[0.015]	[0.034]	[0.019]
Wealth decile 5	0.208***	-0.006	0.095***	0.009
	[0.045]	[0.016]	[0.029]	[0.028]
Wealth decile 4	0.258***	0.019	0.090***	0.017
	[0.045]	[0.017]	[0.026]	[0.023]
Wealth decile 3	0.266***	0.025*	0.096***	0.029
	[0.051]	[0.015]	[0.026]	[0.025]
Wealth decile 2	0.251***	0.011	0.099***	0
	[0.040]	[0.013]	[0.027]	[0.019]
Wealth decile 1	0.166***	0.026*	0.054*	-0.040*
	[0.046]	[0.013]	[0.027]	[0.022]
Austria	-0.333***	-0.113***	-0.173***	0.045***
	[0.029]	[0.008]	[0.016]	[0.011]
Belgium	-0.671***	-0.296***	-0.212***	-0.107***
	[0.020]	[0.006]	[0.012]	[0.010]
Bulgaria	-0.344***	-0.092***	-0.110***	-0.138***
	[0.040]	[0.010]	[0.021]	[0.016]
Croatia	-0.329***	-0.115***	-0.132***	-0.077***
	[0.019]	[0.007]	[0.011]	[0.009]
Czechia	-0.599***	-0.185***	-0.132***	-0.243***
	[0.019]	[0.006]	[0.011]	[0.009]
Denmark	-0.667***	-0.158***	-0.306***	-0.044***
	[0.022]	[0.007]	[0.013]	[0.011]
Estonia	-0.309***	-0.137***	0.067***	-0.176***
	[0.016]	[0.005]	[0.010]	[0.009]
Finland	-0.827***	-0.276***	-0.106***	-0.343***
	[0.044]	[0.015]	[0.023]	[0.017]
France	-0.664***	-0.243***	-0.209***	-0.090***
	[0.020]	[0.005]	[0.013]	[0.008]
Germany	-0.532***	-0.098***	-0.246***	-0.054***
	[0.019]	[0.005]	[0.012]	[0.008]
Greece	-0.421***	-0.114***	-0.157***	-0.147***
	[0.042]	[0.012]	[0.024]	[0.017]
Hungary	-0.459***	-0.119***	-0.121***	-0.167***

	[0.020]	[0.006]	[0.014]	[0.008]
Ireland	-0.406***	-0.152***	-0.084***	-0.112***
	[0.045]	[0.013]	[0.023]	[0.018]
Italy	-0.802***	-0.202***	-0.139***	-0.367***
	[0.022]	[0.006]	[0.013]	[0.010]
Latvia	-0.503***	-0.221***	-0.066***	-0.219***
	[0.014]	[0.006]	[0.009]	[0.008]
Lithuania	-0.596***	-0.195***	-0.240***	-0.158***
	[0.015]	[0.005]	[0.009]	[0.008]
Luxembourg	-0.539***	-0.189***	-0.164***	-0.073***
	[0.044]	[0.014]	[0.023]	[0.016]
Malta	-0.446***	-0.185***	-0.128***	-0.067***
	[0.046]	[0.014]	[0.023]	[0.019]
Netherlands	-0.699***	-0.269***	-0.310***	-0.022*
	[0.020]	[0.006]	[0.013]	[0.011]
Poland	-1.080***	-0.297***	-0.282***	-0.411***
	[0.018]	[0.005]	[0.011]	[0.008]
Portugal	-0.387***	-0.119***	-0.049***	-0.171***
	[0.022]	[0.007]	[0.013]	[0.009]
Romania	-0.426***	-0.083***	-0.213***	-0.098***
	[0.020]	[0.006]	[0.012]	[0.008]
Slovakia	-0.703***	-0.223***	-0.221***	-0.247***
	[0.013]	[0.004]	[0.009]	[0.007]
Slovenia	-0.133***	-0.086***	-0.047***	0.025**
	[0.021]	[0.007]	[0.013]	[0.010]
Spain	-0.354***	-0.123***	-0.063***	-0.112***
	[0.021]	[0.006]	[0.013]	[0.010]
Sweden	-0.675***	-0.140***	-0.228***	-0.169***
	[0.020]	[0.006]	[0.011]	[0.010]
Serbia	-0.258***	-0.087***	-0.097***	-0.094***
	[0.020]	[0.005]	[0.011]	[0.009]
Switzerland	-0.463***	-0.106***	-0.138***	-0.115***
	[0.037]	[0.010]	[0.020]	[0.015]
Turkey	-0.272***	-0.185***	-0.013	-0.034***
	[0.024]	[0.008]	[0.014]	[0.010]
United Kingdom	-0.482***	-0.204***	-0.060***	-0.117***
	[0.019]	[0.006]	[0.012]	[0.009]
Constant	1.925***	0.761***	1.004***	0.834***
	[0.244]	[0.110]	[0.168]	[0.118]
Linear Prediction	3.7998	1.2443	1.6191	1.1261
No. of Observations	29,872	29,134	28,859	27,104
* p<0.10, ** p<0.05, *** p<0.01				

intercultural competence enhance individuals' ability to adjust to evolving work environments and diverse organisational contexts.

In contrast, institutional and policy-oriented literacies exhibit comparatively limited effects. Financial Literacy, Retirement Literacy, Environmental Literacy, and Sustainable Financial Literacy show weak or statistically insignificant associations with overall labour market resilience. While some isolated relationships appear-such as Retirement Literacy being positively associated with upskilling-their magnitudes are modest relative to technical and interpersonal literacies. This suggests that knowledge of financial systems, pension frameworks, or environmental governance does not directly translate into employment adaptability or labour market confidence. Such literacies may be more consequential in financial decision-making contexts rather than in employment adjustment processes.

Political Literacy and Media and Information Literacy display modest positive associations with overall resilience and, in some cases, adaptability or upskilling. These relationships may reflect the role of institutional awareness and information-processing capacity in identifying labour market opportunities or responding to structural changes. However, their explanatory power remains substantially smaller than that of digital-technical and interpersonal competencies.

The main messages emerging from the analysis are the following:

- Technical digital competencies, particularly Data and Programming Literacy, are the strongest predictors of labour market resilience across all dimensions.
- Digital Financial Literacy and AI Literacy contribute positively to adaptability and skill investment, though AI awareness may reduce employment confidence.
- Interpersonal competencies, captured by Human Literacy and Cultural Agility, play a substantial and independent role in shaping resilience.
- Institutional and policy-oriented literacies show limited direct relevance for labour market adaptability and employment confidence.
- Labour market resilience appears to be primarily driven by transferable skills and adaptive capacities rather than domain-specific knowledge of institutional frameworks.

5.2 Literacies and Financial and Economic Resilience

This subsection examines the association between the twelve literacy domains and financial as well as broader economic resilience. Financial resilience is operationalised using several complementary indicators constructed in the financial resilience do-file. These include: (i) overall financial resilience, reflecting respondents' ability to manage unexpected expenses; (ii) financial strain, capturing difficulty in covering basic living expenses; and (iii) short-, medium-, and long-term coping capacity, reflecting the ability to withstand financial shocks over different time horizons. In addition, an economic resilience index is constructed as a composite measure combining these financial coping dimensions into a broader indicator of structural household economic robustness.

While financial resilience captures immediate financial security, economic resilience reflects a more comprehensive capacity to absorb and adjust to economic shocks across time.

The regression models follow the same specification strategy as in Section 5.1. Each outcome is regressed on the full set of additive literacy indices, constructed as counts of correct responses within each domain, alongside socio-demographic controls and country fixed effects. The coefficients therefore represent partial associations between domain-specific knowledge and financial coping capacity, net of overlap across literacy domains.

The results in Table 5-2 indicate that financial resilience and economic resilience exhibit a broader and more distributed pattern of associations than labour market resilience. Financial Literacy emerges as the most consistent and direct predictor of financial resilience, financial strain reduction, and coping capacity across all time horizons. This confirms that core financial knowledge-such as understanding interest, inflation, and risk diversification-plays a central role in enabling households to manage shocks and maintain stability.

Retirement Literacy and Health Literacy also show significant positive associations across several financial coping dimensions. Their effects are smaller than those of Financial Literacy but remain consistent, suggesting that institutional knowledge and health-related understanding contribute to longer-term financial preparedness.

Digital Financial Literacy is particularly relevant for short- and medium-term coping capacity and for the broader economic resilience index. This suggests that digital fluency in managing financial tools may enhance households' ability to respond quickly to shocks and maintain structural financial stability. Artificial Intelligence Literacy shows strong associations with short-, medium-, and long-term resilience, though its relationship with overall financial resilience is weaker. This pattern may reflect forward-looking adjustment capacity rather than immediate financial conditions.

Unlike in the labour market models, Sustainable Financial Literacy and Environmental Literacy show positive and statistically significant associations with financial resilience indicators. This suggests that ESG-related awareness and environmental knowledge may correlate with more forward-looking financial behaviour and risk sensitivity.

Data and Programming Literacy presents a distinctive pattern. While its association with immediate financial resilience is limited, it strongly predicts the broader economic resilience index. This indicates that technical digital skills may contribute more to structural economic robustness-potentially through income capacity or occupational positioning-than to day-to-day financial management.

Human Literacy and Cultural Agility display consistent, though more moderate, associations across short-, medium-, and long-term resilience measures. These effects suggest that interpersonal and adaptive competencies may indirectly strengthen financial coping capacity, possibly through stronger social support networks or collaborative problem-solving mechanisms.

The main messages emerging from the analysis are the following:

- Financial Literacy is the most consistent and direct predictor of financial resilience and reduced financial strain.

- Retirement and Health Literacy contribute meaningfully to coping capacity across time horizons.
- Digital Financial and AI Literacy are particularly important for short- and medium-term adjustment.
- Sustainable and Environmental literacies are more relevant for financial resilience than for labour market resilience.
- Data and Programming Literacy strongly predicts broader economic resilience but is less central for immediate financial strain.
- Financial and economic resilience reflect a wider constellation of literacies than labour market resilience, combining domain-specific knowledge with digital and interpersonal competencies.

Table 5-2: The effect of literacies on financial and economic resilience

	Financial resilience (1)	Financial strain (2)	Short term resilience (3)	Medium term resilience (4)	Long term resilience (5)	Economic resilience (6)
Financial literacy	0.064***	-0.078***	0.040***	0.065***	0.045***	0.020**
	[0.010]	[0.008]	[0.007]	[0.007]	[0.006]	[0.009]
Retirement literacy	0.030***	-0.037***	0.030***	0.049***	0.034***	0.014*
	[0.009]	[0.007]	[0.005]	[0.008]	[0.007]	[0.007]
Health literacy	0.046***	-0.041***	0.018***	0.028***	0.022***	0.014*
	[0.010]	[0.009]	[0.007]	[0.009]	[0.007]	[0.008]
Digital financial literacy	0.012	-0.018**	0.041***	0.046***	0.037***	0.043***
	[0.008]	[0.008]	[0.006]	[0.007]	[0.006]	[0.008]
Media literacy	0.001	0.001	0.051***	0.068***	0.032***	0.012
	[0.007]	[0.007]	[0.006]	[0.005]	[0.007]	[0.007]
AI literacy	-0.003	-0.017***	0.079***	0.108***	0.082***	0.005
	[0.004]	[0.004]	[0.004]	[0.004]	[0.003]	[0.004]
Data and program. literacy	0.001	-0.013*	0.009**	0.023***	0.034***	0.215***
	[0.008]	[0.007]	[0.004]	[0.005]	[0.005]	[0.009]
Political literacy	0.005	-0.018**	0.029***	0.028***	0.023***	0.013
	[0.007]	[0.007]	[0.006]	[0.006]	[0.006]	[0.008]
Environmental literacy	0.028***	-0.025**	0.011*	0.015**	-0.005	0.004
	[0.010]	[0.009]	[0.006]	[0.007]	[0.007]	[0.008]
Sustainable finance literacy	0.050***	-0.032**	0.048***	0.073***	0.035***	0.006
	[0.014]	[0.012]	[0.006]	[0.006]	[0.007]	[0.008]
Human literacy	0.015	-0.019**	0.017***	0.020**	0.033***	0.136***
	[0.009]	[0.007]	[0.005]	[0.008]	[0.006]	[0.007]
Cultural agility	-0.011	-0.004	0.020***	0.048***	0.045***	0.029***
	[0.008]	[0.008]	[0.005]	[0.007]	[0.007]	[0.008]
Self-employed	-0.03	0.038*	-0.014	-0.072***	-0.039	0.03
	[0.031]	[0.022]	[0.021]	[0.020]	[0.024]	[0.029]
Unemployed	-0.358***	0.330***	-0.068***	-0.031	-0.038	-0.271***
	[0.041]	[0.040]	[0.024]	[0.034]	[0.035]	[0.033]
Inactive	-0.251***	0.208***	-0.089***	-0.142***	-0.121***	-0.312***

	[0.041]	[0.035]	[0.025]	[0.031]	[0.028]	[0.029]
Homemaker	0.07	-0.049	0.080***	0.024	0.064*	-0.063
	[0.054]	[0.044]	[0.028]	[0.040]	[0.035]	[0.043]
Retired	0.159***	-0.143***	0.047*	-0.031	0.008	0.121***
	[0.049]	[0.039]	[0.025]	[0.036]	[0.032]	[0.037]
Student	0.188***	-0.116**	0.128***	0.090*	0.052	0.216***
	[0.053]	[0.046]	[0.040]	[0.045]	[0.044]	[0.039]
Male	0.007	-0.038**	-0.033***	-0.026	0.021*	0.007
	[0.018]	[0.015]	[0.012]	[0.015]	[0.012]	[0.015]
LGBT+	-0.132	0.097	0.055	0.171	0.011	0.057
	[0.242]	[0.201]	[0.161]	[0.148]	[0.133]	[0.150]
Age	-0.017**	0.021***	-0.001	0.011*	0.003	-0.017**
	[0.009]	[0.007]	[0.005]	[0.007]	[0.005]	[0.006]
Age sq./1000	0.229***	-0.273***	-0.008	-0.155**	-0.061	0.116**
	[0.080]	[0.067]	[0.046]	[0.058]	[0.044]	[0.053]
Single	0.084**	-0.086***	-0.018	-0.062**	-0.034	-0.066**
	[0.037]	[0.030]	[0.021]	[0.024]	[0.032]	[0.025]
Married	0.100***	-0.103***	0.005	-0.015	-0.004	-0.023
	[0.027]	[0.018]	[0.021]	[0.021]	[0.022]	[0.025]
Unknown marital status	0.012	-0.037	0.013	-0.017	0.026	0.023
	[0.037]	[0.028]	[0.025]	[0.026]	[0.032]	[0.028]
ISCED 2: Lower secondary	-0.093	0.049	0.046	0.037	0.087*	-0.091
	[0.081]	[0.071]	[0.057]	[0.037]	[0.050]	[0.058]
ISCED 3: Upper secondary	-0.104	0.084	0.08	0.017	0.046	-0.021
	[0.074]	[0.068]	[0.052]	[0.033]	[0.044]	[0.054]
ISCED 4: Post-sec. non-tert.	-0.027	0.02	0.098	0.032	0.048	0.037
	[0.082]	[0.077]	[0.063]	[0.031]	[0.042]	[0.075]
ISCED 5: Short-cycle tertiary	-0.059	0.017	0.085	0.021	0.08	0.055
	[0.074]	[0.067]	[0.056]	[0.034]	[0.051]	[0.060]
ISCED 6: Bachelor's or equiv.	-0.048	0.01	0.100*	0.016	0.065	0.019
	[0.074]	[0.065]	[0.054]	[0.030]	[0.046]	[0.054]
ISCED 7: Master's or equiv.	0.001	-0.034	0.096*	0.037	0.062	0.114**
	[0.074]	[0.065]	[0.055]	[0.028]	[0.044]	[0.055]
ISCED 8: Doctoral or equiv.	-0.027	-0.01	0.069	-0.058	0.032	0.191***
	[0.073]	[0.070]	[0.064]	[0.041]	[0.053]	[0.062]
Age: 18-24	-0.019	-0.032	0.001	0.053	0.143**	-0.026
	[0.127]	[0.113]	[0.058]	[0.103]	[0.066]	[0.116]
Age: 25-34	-0.058	0.009	0.044	0.097	0.147**	-0.03
	[0.108]	[0.092]	[0.041]	[0.084]	[0.054]	[0.087]
Age: 35-44	-0.075	0.028	0.016	0.058	0.128***	-0.036
	[0.083]	[0.073]	[0.033]	[0.059]	[0.044]	[0.069]
Age: 45-54	-0.055	0.036	-0.022	0.03	0.082**	-0.007
	[0.058]	[0.054]	[0.028]	[0.044]	[0.032]	[0.048]
Age: 55-64	-0.051	0.021	-0.039*	0.016	0.073***	-0.054
	[0.041]	[0.037]	[0.021]	[0.031]	[0.022]	[0.035]
Income decile 10	0.192***	-0.218***	0.086***	0.112***	0.082***	0.196***
	[0.036]	[0.032]	[0.025]	[0.029]	[0.024]	[0.040]

Income decile 9	0.064	-0.116***	0.107***	0.163***	0.139***	0.074*
	[0.039]	[0.032]	[0.023]	[0.028]	[0.028]	[0.037]
Income decile 8	0.046	-0.070**	0.133***	0.162***	0.126***	0.051
	[0.035]	[0.027]	[0.024]	[0.024]	[0.023]	[0.037]
Income decile 7	-0.024	-0.012	0.133***	0.157***	0.124***	0.038
	[0.039]	[0.033]	[0.024]	[0.024]	[0.028]	[0.032]
Income decile 6	-0.079*	0.025	0.104***	0.160***	0.127***	-0.054
	[0.045]	[0.035]	[0.023]	[0.021]	[0.023]	[0.036]
Income decile 5	-0.193***	0.131***	0.116***	0.181***	0.138***	-0.05
	[0.051]	[0.039]	[0.018]	[0.023]	[0.026]	[0.032]
Income decile 4	-0.190***	0.122***	0.105***	0.129***	0.149***	-0.098***
	[0.043]	[0.037]	[0.027]	[0.021]	[0.025]	[0.033]
Income decile 3	-0.244***	0.184***	0.116***	0.124***	0.126***	-0.107***
	[0.040]	[0.035]	[0.025]	[0.023]	[0.026]	[0.032]
Income decile 2	-0.299***	0.238***	0.096***	0.131***	0.119***	-0.146***
	[0.056]	[0.047]	[0.020]	[0.023]	[0.026]	[0.034]
Income decile 1	-0.387***	0.328***	0.073***	0.084***	0.114***	-0.194***
	[0.044]	[0.038]	[0.026]	[0.021]	[0.021]	[0.027]
Wealth decile 10	0.197***	-0.250***	0.019	0.065**	0.117***	0.121***
	[0.031]	[0.030]	[0.023]	[0.024]	[0.026]	[0.033]
Wealth decile 9	0.157***	-0.191***	0.031	0.055	0.098**	0.126***
	[0.045]	[0.045]	[0.028]	[0.034]	[0.037]	[0.036]
Wealth decile 8	0.048	-0.123***	0.033	0.078**	0.131***	0.070**
	[0.049]	[0.040]	[0.025]	[0.032]	[0.027]	[0.034]
Wealth decile 7	-0.024	-0.07	0.056**	0.081***	0.150***	0.075***
	[0.043]	[0.044]	[0.023]	[0.027]	[0.025]	[0.026]
Wealth decile 6	-0.055	-0.036	0.060**	0.096***	0.141***	0.012
	[0.035]	[0.032]	[0.026]	[0.030]	[0.032]	[0.034]
Wealth decile 5	-0.062	-0.024	0.045	0.075***	0.145***	0.037
	[0.044]	[0.043]	[0.027]	[0.024]	[0.024]	[0.026]
Wealth decile 4	-0.131***	0.032	0.053**	0.082**	0.157***	0.035
	[0.041]	[0.036]	[0.023]	[0.030]	[0.024]	[0.033]
Wealth decile 3	-0.148***	0.057	0.051**	0.090***	0.130***	0.048
	[0.045]	[0.044]	[0.020]	[0.018]	[0.023]	[0.033]
Wealth decile 2	-0.249***	0.152***	0.061***	0.067***	0.141***	-0.007
	[0.046]	[0.040]	[0.020]	[0.023]	[0.020]	[0.031]
Wealth decile 1	-0.601***	0.487***	0.012	0.091***	0.112***	-0.158***
	[0.045]	[0.042]	[0.023]	[0.023]	[0.024]	[0.032]
Austria	0.299***	-0.445***	0.073***	0.085***	0.173***	-0.081***
	[0.026]	[0.022]	[0.012]	[0.014]	[0.017]	[0.016]
Belgium	0.447***	-0.424***	0.028***	-0.002	-0.094***	-0.259***
	[0.016]	[0.013]	[0.009]	[0.012]	[0.012]	[0.013]
Bulgaria	0.055	-0.03	0.063***	-0.006	-0.025	-0.222***
	[0.033]	[0.024]	[0.012]	[0.016]	[0.023]	[0.021]
Croatia	0.255***	-0.273***	0.132***	0.090***	0.053***	-0.192***
	[0.015]	[0.015]	[0.007]	[0.011]	[0.011]	[0.012]
Czechia	0.302***	-0.346***	0.163***	0.156***	0.097***	-0.198***

	[0.019]	[0.015]	[0.008]	[0.010]	[0.012]	[0.009]
Denmark	0.544***	-0.587***	0.071***	-0.131***	-0.002	-0.198***
	[0.017]	[0.015]	[0.010]	[0.015]	[0.012]	[0.013]
Estonia	0.169***	-0.228***	0.237***	0.190***	0.125***	-0.126***
	[0.011]	[0.011]	[0.007]	[0.010]	[0.010]	[0.010]
Finland	0.049	-0.221***	0.150***	0.275***	0.065**	-0.424***
	[0.035]	[0.026]	[0.015]	[0.019]	[0.025]	[0.024]
France	0.278***	-0.292***	0.069***	0.015	-0.072***	-0.305***
	[0.021]	[0.019]	[0.010]	[0.012]	[0.011]	[0.014]
Germany	0.331***	-0.443***	0.102***	-0.046***	0.089***	-0.209***
	[0.023]	[0.020]	[0.009]	[0.010]	[0.011]	[0.012]
Greece	-0.125***	0.078**	0.003	0.024	0.026	-0.326***
	[0.042]	[0.031]	[0.011]	[0.017]	[0.025]	[0.023]
Hungary	0.060***	-0.080***	0.080***	0.100***	0.033***	-0.245***
	[0.017]	[0.014]	[0.008]	[0.011]	[0.011]	[0.012]
Ireland	0.018	-0.141***	0.081***	-0.025	0.090***	-0.231***
	[0.039]	[0.029]	[0.018]	[0.022]	[0.029]	[0.022]
Italy	0.449***	-0.502***	0.047***	-0.125***	-0.041***	-0.282***
	[0.024]	[0.022]	[0.012]	[0.013]	[0.010]	[0.015]
Latvia	0.338***	-0.369***	0.139***	0.049***	0.076***	-0.215***
	[0.014]	[0.013]	[0.006]	[0.009]	[0.009]	[0.009]
Lithuania	0.607***	-0.640***	0.178***	0.128***	0.087***	-0.191***
	[0.010]	[0.009]	[0.007]	[0.009]	[0.008]	[0.009]
Luxembourg	0.363***	-0.459***	0.194***	0.128***	0.120***	-0.244***
	[0.036]	[0.027]	[0.016]	[0.018]	[0.025]	[0.023]
Malta	0.249***	-0.303***	0.138***	-0.113***	0.069**	-0.173***
	[0.036]	[0.026]	[0.015]	[0.017]	[0.028]	[0.023]
Netherlands	0.607***	-0.600***	0.005	-0.063***	-0.094***	-0.189***
	[0.022]	[0.020]	[0.010]	[0.014]	[0.013]	[0.013]
Poland	0.274***	-0.336***	0.056***	-0.039***	0.064***	-0.453***
	[0.019]	[0.017]	[0.008]	[0.010]	[0.011]	[0.011]
Portugal	0.243***	-0.297***	0.049***	0.080***	0.017	-0.168***
	[0.024]	[0.021]	[0.008]	[0.011]	[0.015]	[0.012]
Romania	0.151***	-0.063***	0.074***	-0.164***	-0.066***	-0.180***
	[0.019]	[0.016]	[0.008]	[0.010]	[0.014]	[0.010]
Slovakia	0.145***	-0.080***	0.077***	-0.034***	-0.102***	-0.364***
	[0.015]	[0.013]	[0.006]	[0.010]	[0.009]	[0.008]
Slovenia	0.305***	-0.381***	0.112***	0.017	0.097***	-0.017
	[0.019]	[0.018]	[0.009]	[0.012]	[0.012]	[0.012]
Spain	0.410***	-0.475***	0.074***	-0.065***	-0.001	-0.129***
	[0.022]	[0.020]	[0.010]	[0.013]	[0.012]	[0.018]
Sweden	0.215***	-0.330***	0.098***	-0.038***	0.100***	-0.279***
	[0.021]	[0.017]	[0.010]	[0.011]	[0.013]	[0.011]
Serbia	0.138***	-0.039***	0.163***	-0.178***	-0.076***	-0.142***
	[0.015]	[0.014]	[0.007]	[0.009]	[0.008]	[0.012]
Switzerland	0.228***	-0.349***	0.058***	0.084***	0.092***	-0.197***
	[0.028]	[0.022]	[0.012]	[0.016]	[0.022]	[0.019]

Turkey	-0.258***	0.075***	0.187***	-0.011	0.223***	-0.250***
	[0.019]	[0.015]	[0.009]	[0.011]	[0.012]	[0.016]
UnitedKingdom	0.309***	-0.343***	0.106***	-0.200***	-0.060***	-0.134***
	[0.018]	[0.017]	[0.010]	[0.010]	[0.010]	[0.011]
Constant	2.246***	1.491***	0.421***	0.027	0.017	2.273***
	[0.264]	[0.218]	[0.138]	[0.225]	[0.157]	[0.197]
Linear Prediction	2.403	1.0197	1.4551	1.5071	1.2337	2.498
No. of Observations	28,905	28,905	29,872	29,872	29,872	28,905
* p<0.10, ** p<0.05, *** p<0.01						

6. Literacies and Occupational Skill Architecture: Breadth, Diversification and Transferability

Section 6 shifts the focus from resilience outcomes to the occupational mechanisms that may underpin them. Rather than asking whether literacies are associated with labour market and financial resilience, we examine whether different literacy domains are linked to the skill content and skill architecture of individuals' primary jobs. The core idea is that literacies may matter not only because they shape behaviours and perceptions (e.g., upskilling or confidence), but also because they are associated with structural labour market positioning in occupations that differ in cognitive demands, digital intensity, automation exposure, and "greenness," as well as in how broad, diversified, and transferable their skill bundles are. This perspective provides a bridge between individual-level competences and the characteristics of jobs people hold, helping to clarify how literacy profiles relate to opportunities and vulnerabilities in changing labour markets.

To operationalise occupational skills in a harmonised and comparable way across countries, we combine respondents' self-reported primary occupation with an ISCO–ESCO linkage. Specifically, the survey provides 4-digit ISCO codes for respondents' current (or most recent) main job, which are then mapped to ESCO occupational skill profiles. These ESCO profiles describe the skills and competences typically associated with each occupation, enabling us to derive quantitative indicators of skill requirements at the occupation level. Based on this mapping and the construction procedures implemented in the attached do-file, we compute two complementary sets of outcomes. First, we derive six measures of skill intensity capturing the relative prominence of cognitive, digital, automation-related, green, physical, and social skill content in each respondent's primary occupation. Second, we derive indicators of skill architecture that summarise the structure of the occupational skill bundle, including measures of skill breadth, diversification, transferability (portability), and an overall skill portfolio index. We then estimate regression models linking additive literacy scores (constructed as counts of correct responses) to these occupation-level skill measures, controlling for socio-demographic characteristics and country fixed effects. The resulting estimates should be interpreted as associations between literacy profiles and occupational skill characteristics, offering evidence on how literacies align with different types of jobs and with skill bundles that may be more adaptable, diversified, or transferable across potential job transitions.

6.1 The importance of occupational context

Skills are acquired, applied, and rewarded within occupational contexts. While individual skill endowments shape adaptability and performance, the way skills are developed and utilised depends critically on the tasks individuals perform, the technologies they interact with, and the organisational environments in which they work. As a result, understanding the relevance and

functioning of basic and transferable skills requires situating them within concrete occupational and task structures rather than treating them as abstract or context-free attributes.

Aggregated occupational categories, such as broad sectoral or major occupational groups, tend to obscure substantial variation in task content and skill requirements. This limitation is particularly salient in the context of the green and digital transitions and the diffusion of artificial intelligence, where exposure to technological change often varies more within occupations than between them. Two workers classified under the same broad occupational category may face very different task demands, levels of automation risk, and requirements for adaptation, depending on the specific activities they perform and the technologies embedded in their jobs.

To address this challenge, Task 5.2 employs detailed occupational classifications based on 4-digit ESCO occupations. This level of granularity allows for task-level differentiation and a more precise mapping between skills and occupational requirements. By linking individual-level measures of basic and transferable skills to detailed ESCO occupational groups, the analysis can contextualise skill profiles within the task environments in which they are applied, without conflating skill measurement with labour mobility or transition analysis.

The use of 4-digit ESCO occupations supports a more accurate assessment of how basic and transferable skills relate to job content, exposure to technological change, and emerging skill demands associated with green and digital transformations. While the identification of reskilling pathways and occupational transitions is addressed in subsequent tasks of the TRAILS project, notably Task 5.4, the role of ESCO in Task 5.2 is to provide an analytically robust framework for situating skills within real-world occupational structures. This approach strengthens the validity of the proposed skill classification and ensures its relevance for policy and research concerned with skills development in times of rapid economic and technological change.

6.2 Mapping respondents to 4-digit ISCO occupations

To place the TRAILS-I skill profiles in the job contexts where these skills are used and developed, we map respondents' free text questions about their occupation to ISCO-08 4-digit codes. The mapping is based on Heuristic Contextual Occupation Mapping (HCOM) which is a purpose-built approach that combines (i) multilingual semantic matching from open-text job descriptions with (ii) structured survey context on work activities and (iii) industry sector. The approach is designed for cross-country survey implementation, where free-text job titles and task descriptions are often short or vague and text-only coding can misclassify 4-digit occupations. The occupation linkage is used to place skills in their job context and support the proposed skills classification, not to study mobility, occupational distance, or job transitions.

The Heuristic Contextual Occupation Mapping (HCOM) draws on four occupation-related inputs collected in the TRAILS-I survey:

- Q1: Current (or most recent) main job title (open text).
- Q2: Description of main tasks and duties in the current (or most recent) job (open text).
- Q3: Self-reported work activities describing their job (multiple selections allowed).

- Q4: Industry sector of the company/organisation where the respondent works (single choice from a standardised list).

The key methodological choice is to treat Q3 and Q4 as contextual anchors that help recover the detail needed for 4-digit ISCO codes when Q1 and Q2 are vague (e.g., "manager", "consultant", "analyst") or provide insufficient task content. That is because using only the open-text job title and task description (Q1-Q2) is often not enough to code occupations accurately, as many respondents provide short or generic answers. For example, a title such as "Manager" with a brief description like "Managing daily operations" can refer to very different ISCO unit groups depending on the type of work and the sector. The mapping procedure therefore combines the semantic match from Q1-Q2 with additional context from respondents' selected work activities (Q3) and their industry sector (Q4), so that the assigned occupation reflects the most plausible task environment.

The Heuristic Contextual Occupation Mapping (HCOM) is implemented through a sequence of steps that combine information from respondents' open-text descriptions with structured indicators on tasks and sector. Below we outline the main steps of the approach, showing how candidate 4-digit ISCO codes are generated, refined using contextual information, and then selected through a transparent scoring rule.

Step 1: Textual input and multilingual semantic ensemble

The methodology first extracts the free-text responses describing the respondent's occupation. The open-text responses are combined into a single string (Q1+Q2). Then the concatenated text is processed using an ensemble of four multilingual sentence-transformer models:

- paraphrase-multilingual-MiniLM-L12-v2
- paraphrase-multilingual-mpnet-base-v2
- stsb-xlm-r-multilingual
- distiluse-base-multilingual-cased-v2

This multilingual ensemble avoids explicit translation and supports direct processing in the national languages of the countries covered by TRAILS-I (EU27, Türkiye, the UK, Switzerland, and Serbia). Each model compares the respondent text to the ESCO reference taxonomy and returns a Top-3 candidate pool of ISCO-08 4-digit codes. This yields the Semantic Score (S_{sem}) based on a normalized ratio of cosine similarities in order to be comparable with the contextual signals described below.

Step 2: Task-based activity scoring

To contextualize the semantic match, the methodology evaluates responses to Q3, which asks respondents to select one or more activity categories that best describe their job. Each option in Q3 is mapped to a predefined cluster of representative ISCO-08 4-digit codes that typically perform that type of work. Below are some examples of Activity-to-ISCO mapping:

```
# 1. Working with machines or tools
"Q3_1": ["7223", "7233", "8111", "8181", "8211"],

# 2. Interacting with clients or customers
"Q3_2": ["5221", "5223", "5244", "4221", "4226", "5113"],

# 3. Performing administrative or clerical tasks
"Q3_3": ["4110", "4120", "3341", "4311", "4416"],
```

```
# 4. Delivering care or support services
"Q3_4": ["2211", "2221", "3211", "5321", "5322", "2635"],

# 5. Teaching or training others
"Q3_5": ["2310", "2320", "2330", "2341", "2424"],

# 6. Conducting research or analysis
"Q3_6": ["2111", "2112", "2120", "2411", "2422", "2633"],

# 7. Operating vehicles or delivering goods
"Q3_7": ["8311", "8322", "8332", "8341", "9621"],

# 8. Coding, programming, or working with data
"Q3_8": ["2511", "2512", "2514", "2521", "2120", "3511"],

# 9. Selling or marketing products/services
"Q3_9": ["2431", "3322", "5223", "5241", "5243"],

# 10. Supervising or managing other workers
"Q3_10": ["1120", "1211", "1321", "1411", "3122"],

# 11. Creative or artistic production
"Q3_11": ["2161", "2162", "2641", "2651", "3431"],

# 12. Other, please specify:
"Q3_12": ["9112", "9211", "5412", "0110", "9622"]
```

Then the activity score (S_{act}) is calculated as the ratio of the respondent's selected activities that are consistent with a candidate ISCO code divided by the total number of activities selected by the respondent. This yields a normalized score in [0,1], where higher values indicate closer match between the candidate occupation and the reported task profile.

Step 3: Industry-sector alignment

The methodology also uses the respondent's reported industry sector (Q4) as an additional contextual check, reflecting that many occupations are more plausible in certain sectors than others. Sector-to-occupation mapping. Each of the 23 sector categories is linked to a set of typical ISCO-08 4-digit unit groups, which provides a sector-based plausibility benchmark for the candidate codes. Illustrative examples include:

```
# 1. Agriculture, forestry and fishing
"Q4_1": ["6111", "6112", "6121", "6210", "9211"],

# 3. Manufacturing
"Q4_3": ["1321", "3122", "8114", "8211", "7223"],

# 6. Construction
"Q4_6": ["7111", "7114", "7126", "3123", "1323"],

# 7. Wholesale and retail trade; repair of motor vehicles and motorcycles
"Q4_7": ["5221", "5222", "5223", "7231", "1420", "3322"],

# 8. Transportation and storage
"Q4_8": ["8332", "8341", "1324", "8322", "9621"],

# 9. Accommodation and food service activities
"Q4_9": ["1411", "1412", "5120", "5131", "9411"],
```

```
    # 10. Information and communication
    "Q4_10": ["2511", "2512", "2514", "1330", "3511"],

    # 11. Financial and insurance activities
    "Q4_11": ["2411", "2412", "1211", "3311", "4312"],

    # 15. Public administration and defence; compulsory social security
    "Q4_15": ["1111", "1112", "2422", "3359", "5412", "0110"],

    # 16. Education
    "Q4_16": ["2310", "2320", "2330", "2341", "5311"],

    # 17. Human health and social work activities
    "Q4_17": ["2211", "2212", "2221", "3221", "5321", "2635"],

    # 18. Arts, entertainment and recreation
    "Q4_18": ["2651", "2652", "2654", "3421", "3431"]
```

The resulting industry score (S_{ind}) is implemented as a simple bonus: candidates receive a value of *1* when the ISCO code is directly consistent with the typical occupational profile of the reported sector, and *0.3* when the candidate shares the same 1-digit ISCO major group as the sector profile (a partial but plausible alignment).

Step 4: Probabilistic integration and final assignment

Then for each candidate ISCO-08 4-digit code generated by the semantic ensemble, a composite probability score is calculated by weighting the semantic evidence the work activity (Q3) and the industry sector (Q4):

$$Score_{final} = (0.5 \cdot S_{sem}) + (0.3 \cdot S_{act}) + (0.2 \cdot S_{ind})$$

The final assigned occupation code (predicted ISCO) is the candidate with the highest $Score_{final}$. The weights are set so that the job-title and task text still matters most, while the reported work activities and industry sector provide additional structured context to help choose the right 4-digit code when the text is too general or ambiguous.

Step 5: Output structure for transparency and review

To ensure transparency and allow quality checks, the mapping procedure stores not only the final assigned ISCO-08 4-digit code (predicted_isco), but also a set of diagnostic outputs. Taken together, these diagnostics help distinguish high-confidence classifications, where the composite score is high and the contextual information confirms the semantic match, from cases where the additional context materially changes the ranking of candidate occupations. Thus, for each respondent the pipeline outputs the final prediction along with diagnostic indicators:

Table 6-1 : Output structure

Variable	Description	Example
predicted_isco	The final assigned ISCO-08 4-digit occupation code	2512
predicted_score	The final weighted composite score $\in [0, 1]$	0.647

top3_candidates	The top 3 ranked ISCO codes with their scores for uncertainty quantification.	[("2512", 0.647), ("2514", 0.592), ("2513", 0.521)]
all_candidates_count	The total number of distinct ISCO codes that entered the candidate pool	5 (indicates low ambiguity)
semantic_isco_rank1	The ISCO code from the #1 ranked semantic match *only* (baseline)	2512
semantic_score_rank1	The cosine similarity score of the top semantic match [0, 1]	0.823
prediction_change_from_semantic	Boolean flag indicating whether activity/industry evidence overrode the pure semantic prediction	False (signals agreed)

6.3 Operationalising Occupational Skill Content through the ISCO–ESCO Linkage

This section relies on a structured linkage between respondents' primary occupations and the European Skills, Competences, Qualifications and Occupations (ESCO) taxonomy. Each respondent reports a 4-digit ISCO code for their current (or most recent) main job. These ISCO codes are mapped to the corresponding ESCO occupational profiles, which provide a detailed list of skills and competences typically associated with each occupation. This mapping enables the transformation of survey-based occupational information into analytically tractable measures of occupational skill content.

The operationalisation of the ESCO taxonomy in this way is particularly important for contemporary labour market analysis. First, it allows researchers to move beyond coarse occupational classifications and instead analyse the underlying skill structure of jobs. This shift from occupations to skills reflects a growing recognition that technological change, digitalisation, and the green transition affect tasks and competences more directly than occupational titles. By quantifying the skill composition of jobs, we can more precisely identify which forms of literacy align with cognitively intensive, automation-resilient, green, or socially embedded occupations.

Second, this approach strengthens the integration of survey data with administrative and taxonomy-based labour market intelligence. ESCO provides a harmonised, pan-European skill classification framework, which makes it particularly well-suited for cross-country research such as the present study. By embedding survey respondents within the ESCO skill architecture, we bridge micro-level literacy measures with macro-level labour market structures.

Third, from a policy perspective, the operationalisation of ESCO skill profiles supports evidence-based workforce planning. Understanding how different literacy domains correlate with occupational skill intensities and transferability can inform education, training, and lifelong learning strategies. For example, identifying which literacies are associated with cognitively intensive or

green occupations can help target upskilling initiatives aligned with digital and sustainability transitions. Similarly, mapping literacies to skill transferability measures can inform active labour market policies aimed at facilitating mobility across occupations.

In sum, the ISCO–ESCO linkage provides the analytical backbone for Section 6. It enables a systematic and comparable assessment of how multidimensional literacies relate to the structural skill characteristics of jobs. Rather than relying solely on self-reported outcomes, this approach grounds the analysis in externally defined occupational skill architectures, thereby strengthening both the research validity and the policy relevance of the findings.

Using the ESCO skill taxonomy, we construct occupation-level indicators that capture the relative composition of skill requirements. For each ISCO–ESCO occupation, the total number of ESCO skills is first identified. Skill intensity measures are then computed as shares of total skills, allowing comparability across occupations with different absolute numbers of listed competences. Specifically:

- Digital intensity is defined as the share of digital skills relative to the total skill count.
- Cognitive intensity is defined as the combined share of thinking skills, knowledge skills, competence skills, and transversal skills.
- Social intensity is defined as the combined share of social skills, language skills, and self-management skills.
- Physical intensity is defined as the share of physical skills.
- Green intensity is defined as the share of environmentally related (green) skills.
- Automation exposure is constructed as a proxy for task routineness, calculated as physical intensity minus cognitive intensity. Higher values therefore indicate a more manual and less cognitively intensive skill structure, implying greater susceptibility to automation.

These measures capture the relative emphasis of different skill domains within each occupation, rather than absolute skill levels. As such, they allow us to examine how literacy profiles are associated with structurally different occupational skill bundles. Beyond intensity measures, the ISCO–ESCO linkage also enables the construction of broader skill architecture indicators. These include measures of skill breadth (the overall diversity of skill types within an occupation), skill diversification (the balance across skill domains), skill transferability (the degree of overlap between an occupation's skill set and those of other occupations), and a composite skill portfolio index summarising overall occupational robustness. Together, these variables capture not only what skills are required in an occupation, but also how flexible, diversified, and portable those skills are within the labour market.

The ISCO–ESCO linkage also enables a deeper structural analysis of occupational skill architecture. Specifically, it allows us to move beyond asking what type of skills dominate an occupation to asking how the full skill bundle is structured. This distinction is crucial for understanding labour market resilience, mobility, and long-term adaptability.

Using the detailed ESCO skill lists linked to each 4-digit ISCO occupation, we construct four complementary indicators capturing different dimensions of occupational skill structure.

- Skill breadth measures the overall diversity of skills embedded within an occupation. It captures the extent to which an occupation requires competences from multiple ESCO skill categories

rather than relying on a narrow, specialised skill set. Technically, breadth reflects the dispersion of skills across domains relative to the total number of skills associated with the occupation. Higher values indicate occupations with a wider range of skill requirements.

- Skill diversification captures the balance across skill domains. Whereas breadth reflects the number of different skills present, diversification captures how evenly skills are distributed across categories. An occupation that combines cognitive, digital, social, and green skills in relatively balanced proportions will display higher diversification than one dominated by a single skill cluster. This measure is conceptually related to entropy-based dispersion indices commonly used in industrial and portfolio analysis.
- Skill transferability (or portability) measures the extent to which an occupation's skill bundle overlaps with other occupations. This is computed by analysing the degree of shared ESCO skills between occupations within the taxonomy. Occupations with high overlap scores are characterised by skills that are widely demanded across the labour market, implying greater potential for mobility in the event of job displacement. Transferability therefore captures structural mobility potential embedded in the occupational skill profile.
- Finally, the skill portfolio index aggregates these dimensions into a composite measure of occupational robustness. It summarises breadth, diversification, and transferability into a single indicator reflecting how flexible, versatile, and mobile an occupation's skill architecture is within the broader labour market. Occupations with high portfolio scores are characterised by broad, balanced, and widely applicable skill bundles, while low scores reflect narrower and less transferable skill configurations.

The construction of these indicators demonstrates the analytical power of operationalising the ESCO taxonomy for labour market research. Rather than treating occupations as fixed and homogeneous categories, this approach allows us to quantify their internal skill composition and structural mobility potential. It enables researchers to link individual-level competences (literacies) to externally defined skill architectures, thereby distinguishing between behavioural resilience and structural occupational resilience.

From a data analytics perspective, this approach represents a shift toward skill-based labour market modelling. By leveraging ESCO's harmonised taxonomy, we can compute reproducible, cross-nationally comparable measures of occupational flexibility and transferability. This is particularly relevant in the context of digitalisation and the green transition, where task content and skill composition are more informative than occupational titles alone.

From a policy perspective, skill architecture measures provide valuable intelligence for workforce planning and lifelong learning strategies. Identifying which literacy domains are associated with occupations characterised by broader, more diversified, and more transferable skill bundles can inform targeted upskilling policies. It also allows policymakers to distinguish between occupations that are structurally robust and those that may require transition support in response to technological or environmental change.

In summary, the ISCO–ESCO linkage enables two complementary analytical layers in this section: first, an analysis of occupational skill intensity; and second, an analysis of occupational skill architecture. Together, these measures provide a structural lens through which the relationship between literacies and labour market positioning can be examined.

6.4 Literacies and Occupational Skill Intensity

Table 6.2 reports the estimated associations between the twelve literacy domains and the skill intensity profile of respondents' primary occupations, as derived from the ISCO–ESCO mapping. The six dependent variables capture the relative prominence of cognitive, digital, automation-related, green, physical, and social skills within each occupation. The coefficients therefore indicate whether individuals with higher literacy scores tend to be employed in occupations characterised by more analytically demanding, digitally intensive, automation-exposed, environmentally oriented, physically demanding, or socially intensive skill bundles.

A clear and consistent pattern emerges for technical digital literacies. Data and Programming Literacy exhibits by far the strongest associations across the skill intensity dimensions. It is strongly positively associated with cognitive intensity and digital intensity, and strongly negatively associated with automation exposure. This indicates that individuals with stronger technical and computational skills are disproportionately represented in occupations that rely heavily on analytical and digital competences while being less exposed to routine-task automation risks. At the same time, Data and Programming Literacy is negatively associated with social intensity, suggesting occupational sorting into analytically intensive rather than relationally intensive roles. This pattern reinforces the interpretation that technical digital literacy is closely aligned with structurally resilient, knowledge-intensive occupational profiles.

Artificial Intelligence Literacy displays a similar, though somewhat more moderate, pattern. It is positively associated with cognitive and digital intensity and negatively associated with automation exposure. The negative association with green intensity and social intensity suggests that AI-related knowledge is linked primarily to technologically oriented occupations rather than environmentally specialised or highly interpersonal roles. Together, these results indicate that technological literacies are systematically aligned with analytically demanding and digitally embedded occupational environments.

Financial, Retirement, and Health Literacies also show positive associations with cognitive intensity and negative associations with automation exposure, though their magnitudes are smaller. This suggests that broader knowledge-based literacies correlate with employment in occupations that require analytical reasoning and non-routine cognitive skills. The negative association with social intensity for Financial Literacy further indicates that financially literate individuals may be concentrated in more analytically structured roles rather than in socially intensive occupations.

In contrast, Human Literacy exhibits a markedly different pattern. It is negatively associated with cognitive and digital intensity and positively associated with social intensity. This indicates that individuals scoring higher on empathy, inclusiveness, and relational competence are more likely to be employed in occupations where interpersonal interaction is central. The positive association with automation exposure suggests that socially intensive occupations may simultaneously involve tasks that are less cognitive but more routine, potentially exposing them to certain forms of technological

substitution. This finding highlights an important distinction between analytically intensive and relationally intensive career tracks.

Table 6-2: Literacies and skill intensity on primary job

	Cognitive intensity (1)	Digital intensity (2)	Automation exposure (3)	Green intensity (4)	Physical intensity (5)	Social intensity (6)
Financial literacy	0.266***	-0.003	-0.263***	0.047*	0.003	-0.185***
	[0.048]	[0.003]	[0.048]	[0.026]	[0.004]	[0.040]
Retirement literacy	0.152***	-0.003	-0.158***	-0.031	-0.006*	-0.005
	[0.043]	[0.003]	[0.044]	[0.027]	[0.003]	[0.034]
Health literacy	0.109**	0.002	-0.113**	-0.066*	-0.005	-0.033
	[0.051]	[0.002]	[0.051]	[0.036]	[0.005]	[0.047]
Digital financial literacy	0.102**	0.001	-0.091**	-0.031	0.011***	-0.059*
	[0.039]	[0.002]	[0.039]	[0.025]	[0.003]	[0.035]
Media literacy	0.016	-0.001	-0.027	0.008	-0.011***	-0.009
	[0.050]	[0.001]	[0.051]	[0.023]	[0.004]	[0.041]
AI literacy	0.144***	0.004***	-0.145***	-0.032**	-0.001	-0.076***
	[0.019]	[0.001]	[0.020]	[0.012]	[0.002]	[0.018]
Data & program. literacy	0.459***	0.007***	-0.461***	-0.019	-0.002	-0.262***
	[0.047]	[0.002]	[0.047]	[0.023]	[0.003]	[0.035]
Political literacy	0.015	0.001	-0.023	0.026	-0.008**	0.006
	[0.045]	[0.002]	[0.046]	[0.024]	[0.003]	[0.036]
Environmental literacy	-0.03	0.002	0.029	0.056**	0.001	-0.03
	[0.062]	[0.002]	[0.062]	[0.023]	[0.004]	[0.042]
Sustain. finance literacy	0.001	-0.002	0.009	0.112***	0.010**	-0.084**
	[0.050]	[0.002]	[0.050]	[0.027]	[0.004]	[0.037]
Human literacy	-0.105***	-0.005***	0.093**	-0.035	-0.013***	0.123***
	[0.038]	[0.002]	[0.039]	[0.025]	[0.003]	[0.034]
Cultural agility	-0.013	0.002	0.01	-0.045*	-0.004	0.058
	[0.051]	[0.002]	[0.051]	[0.025]	[0.003]	[0.044]
Self-employed	-0.144	-0.019**	0.091	0.163	-0.053***	0.269*
	[0.175]	[0.007]	[0.178]	[0.151]	[0.012]	[0.140]
Unemployed	-1.286***	-0.012**	1.242***	-0.251*	-0.044**	1.362***
	[0.170]	[0.005]	[0.177]	[0.130]	[0.017]	[0.167]
Inactive	-1.212***	0.003	1.183***	-0.466***	-0.029	1.467***
	[0.219]	[0.009]	[0.216]	[0.116]	[0.024]	[0.179]
Homemaker	-0.847***	-0.022*	0.817***	-0.009	-0.03	0.54
	[0.295]	[0.012]	[0.285]	[0.165]	[0.028]	[0.340]
Retired	0.480*	-0.025*	-0.499*	0.131	-0.019	-0.466**
	[0.258]	[0.012]	[0.260]	[0.132]	[0.026]	[0.208]
Student	-1.391***	-0.025**	1.326***	-0.297*	-0.065**	1.201***
	[0.387]	[0.011]	[0.377]	[0.149]	[0.027]	[0.334]
Male	-0.571***	0.019***	0.723***	0.846***	0.152***	-0.560***
	[0.104]	[0.004]	[0.106]	[0.043]	[0.007]	[0.079]
LGBT+	0.119	0.001	-0.143	-0.196	-0.024	0.417
	[0.989]	[0.015]	[0.991]	[0.312]	[0.034]	[0.793]
Age	0.056	-0.002	-0.055	0.03	0.001	-0.067*

	[0.048]	[0.002]	[0.049]	[0.025]	[0.003]	[0.035]
Age sq./1000	-0.206	0.023	0.183	-0.331	-0.023	0.489
	[0.437]	[0.018]	[0.446]	[0.218]	[0.023]	[0.326]
Single	-0.194	0.006	0.204*	0.021	0.011	0.133
	[0.119]	[0.007]	[0.115]	[0.080]	[0.011]	[0.150]
Married	-0.346***	0.005	0.360***	0.123*	0.014	0.132
	[0.122]	[0.005]	[0.121]	[0.072]	[0.011]	[0.119]
Unknown marital status	-0.364**	0.008	0.367***	0.008	0.004	0.241*
	[0.134]	[0.006]	[0.130]	[0.083]	[0.012]	[0.139]
ISCED2: Lower secondary	0.406	0.008	-0.363	0.143	0.044	-0.614
	[0.387]	[0.006]	[0.385]	[0.257]	[0.026]	[0.400]
ISCED3: Upper secondary	1.016***	0.007	-1.037***	0.068	-0.021	-0.704*
	[0.357]	[0.007]	[0.353]	[0.228]	[0.030]	[0.359]
ISCED4: Postsec non-tert.	1.400***	0.026*	-1.436***	0.01	-0.036	-0.985***
	[0.433]	[0.015]	[0.441]	[0.306]	[0.034]	[0.337]
ISCED 5: Short-cycle tert.	1.580***	0.024**	-1.679***	-0.198	-0.099***	-0.648
	[0.371]	[0.010]	[0.368]	[0.244]	[0.033]	[0.386]
ISCED 6: Bachelor's or eq.	1.601***	0.015*	-1.728***	-0.147	-0.127***	-0.751**
	[0.329]	[0.008]	[0.326]	[0.237]	[0.028]	[0.327]
ISCED 7: Master's or eq.	1.666***	0.024**	-1.808***	-0.067	-0.142***	-0.962***
	[0.352]	[0.011]	[0.347]	[0.226]	[0.028]	[0.333]
ISCED 8: Doctoral or eq.	1.635***	0.098**	-1.772***	-0.051	-0.138***	-1.326***
	[0.390]	[0.046]	[0.394]	[0.333]	[0.033]	[0.377]
Age: 18-24	0.927	-0.03	-1.000	-0.166	-0.074	-0.293
	[0.703]	[0.030]	[0.708]	[0.371]	[0.048]	[0.520]
Age: 25-34	1.405***	-0.014	-1.437***	-0.07	-0.032	-0.781*
	[0.498]	[0.024]	[0.500]	[0.261]	[0.040]	[0.402]
Age: 35-44	0.969**	-0.015	-1.007**	-0.174	-0.039	-0.366
	[0.372]	[0.016]	[0.371]	[0.206]	[0.029]	[0.321]
Age: 45-54	0.443	-0.007	-0.477	-0.171	-0.033	-0.058
	[0.326]	[0.013]	[0.330]	[0.174]	[0.020]	[0.263]
Age: 55-64	0.376*	-0.003	-0.383*	-0.203**	-0.007	-0.112
	[0.206]	[0.008]	[0.211]	[0.096]	[0.014]	[0.197]
Income decile 10	0.301**	0.019	-0.302**	0.269***	-0.001	-0.472***
	[0.141]	[0.012]	[0.141]	[0.086]	[0.012]	[0.128]
Income decile 9	0.227	0.006	-0.219	0.175*	0.008	-0.408***
	[0.176]	[0.010]	[0.176]	[0.094]	[0.012]	[0.132]
Income decile 8	0.453**	0.004	-0.431**	0.246**	0.022*	-0.627***
	[0.191]	[0.010]	[0.193]	[0.102]	[0.013]	[0.185]
Income decile 7	0.269	0.007	-0.261	0.199**	0.009	-0.396**
	[0.187]	[0.009]	[0.190]	[0.082]	[0.016]	[0.168]
Income decile 6	0.373*	-0.008	-0.343	0.091	0.029*	-0.430**
	[0.215]	[0.011]	[0.221]	[0.090]	[0.017]	[0.161]
Income decile 5	0.481**	0.007	-0.440**	0.101	0.041**	-0.590***
	[0.209]	[0.009]	[0.212]	[0.085]	[0.015]	[0.171]

Income decile 4	0.330*	-0.008	-0.288	0.237**	0.042**	-0.671***
	[0.189]	[0.012]	[0.192]	[0.096]	[0.016]	[0.179]
Income decile 3	0.331	-0.012	-0.296	0.184*	0.035**	-0.580***
	[0.195]	[0.010]	[0.196]	[0.091]	[0.016]	[0.166]
Income decile 2	0.201	-0.013	-0.165	0.120	0.036***	-0.424**
	[0.195]	[0.010]	[0.196]	[0.095]	[0.012]	[0.158]
Income decile 1	-0.006	-0.011	0.023	0.146*	0.017	-0.323*
	[0.180]	[0.008]	[0.182]	[0.082]	[0.015]	[0.166]
Wealth decile 10	-0.217	-0.007	0.183	-0.141*	-0.034**	0.316**
	[0.153]	[0.009]	[0.159]	[0.079]	[0.014]	[0.120]
Wealth decile 9	-0.533***	0.004	0.533***	0.053	0.001	0.385***
	[0.184]	[0.010]	[0.191]	[0.098]	[0.020]	[0.134]
Wealth decile 8	-0.205	0.001	0.185	-0.077	-0.02	0.258*
	[0.178]	[0.010]	[0.177]	[0.110]	[0.012]	[0.138]
Wealth decile 7	-0.580***	-0.008	0.586***	0.263**	0.006	0.134
	[0.165]	[0.008]	[0.166]	[0.115]	[0.012]	[0.140]
Wealth decile 6	-0.400**	0.005	0.389**	0.054	-0.01	0.241*
	[0.156]	[0.010]	[0.157]	[0.087]	[0.009]	[0.137]
Wealth decile 5	-0.318*	0.003	0.294	-0.057	-0.024**	0.344**
	[0.187]	[0.009]	[0.188]	[0.082]	[0.011]	[0.148]
Wealth decile 4	-0.075	0.001	0.07	0.006	-0.005	0.035
	[0.188]	[0.006]	[0.188]	[0.096]	[0.013]	[0.138]
Wealth decile 3	-0.365**	0.006	0.355**	0.085	-0.009	0.133
	[0.151]	[0.008]	[0.152]	[0.087]	[0.011]	[0.116]
Wealth decile 2	-0.234	0.002	0.233	-0.022	-0.001	0.081
	[0.141]	[0.006]	[0.143]	[0.080]	[0.012]	[0.105]
Wealth decile 1	-0.485***	0.004	0.495***	0.098	0.01	0.174
	[0.161]	[0.006]	[0.161]	[0.083]	[0.011]	[0.148]
Austria	0.399***	0.024***	-0.422***	-0.151***	-0.022***	-0.258***
	[0.083]	[0.005]	[0.083]	[0.046]	[0.006]	[0.070]
Belgium	-0.087	0.011***	0.065	-0.163***	-0.022***	-0.061
	[0.053]	[0.003]	[0.052]	[0.045]	[0.004]	[0.059]
Bulgaria	0.083	0.017***	-0.021	0.039	0.062***	-0.491***
	[0.088]	[0.004]	[0.089]	[0.070]	[0.006]	[0.094]
Croatia	-0.093**	0.017***	0.111**	0.377***	0.018***	-0.536***
	[0.045]	[0.002]	[0.045]	[0.034]	[0.005]	[0.046]
Czechia	0.044	0.033***	0.041	0.235***	0.085***	-0.830***
	[0.088]	[0.003]	[0.087]	[0.042]	[0.006]	[0.077]
Denmark	0.039	0.025***	-0.056	-0.04	-0.017***	-0.409***
	[0.075]	[0.004]	[0.076]	[0.052]	[0.006]	[0.075]
Estonia	-0.216***	0.035***	0.266***	0.493***	0.051***	-0.596***
	[0.055]	[0.003]	[0.055]	[0.034]	[0.005]	[0.052]
Finland	0.360***	0.019***	-0.304***	0.084	0.056***	-0.691***
	[0.104]	[0.005]	[0.104]	[0.074]	[0.007]	[0.109]
France	-0.256***	0.005	0.255***	0.044	0.001	-0.048

	[0.060]	[0.004]	[0.058]	[0.046]	[0.006]	[0.076]
Germany	0.323***	0.031***	-0.343***	-0.061	-0.019***	-0.261***
	[0.067]	[0.004]	[0.066]	[0.041]	[0.006]	[0.074]
Greece	0.025	0.023***	0.025	0.057	0.050***	-0.345***
	[0.083]	[0.005]	[0.083]	[0.069]	[0.007]	[0.087]
Hungary	0.162*	0.029***	-0.127	0.063	0.035***	-0.490***
	[0.084]	[0.003]	[0.086]	[0.038]	[0.005]	[0.061]
Ireland	0.646***	0.009	-0.652***	-0.071	-0.006	-0.666***
	[0.102]	[0.006]	[0.104]	[0.089]	[0.008]	[0.098]
Italy	0.740***	0.012***	-0.768***	-0.275***	-0.028***	-0.277***
	[0.077]	[0.003]	[0.076]	[0.049]	[0.006]	[0.097]
Latvia	-0.108	0.024***	0.162**	0.402***	0.054***	-0.652***
	[0.073]	[0.003]	[0.072]	[0.034]	[0.004]	[0.050]
Lithuania	-0.114**	0.062***	0.146***	0.504***	0.031***	-0.669***
	[0.046]	[0.003]	[0.047]	[0.036]	[0.004]	[0.045]
Luxembourg	0.608***	0.044***	-0.653***	-0.461***	-0.045***	-0.217*
	[0.104]	[0.004]	[0.104]	[0.076]	[0.008]	[0.108]
Malta	1.215***	0.017***	-1.236***	-0.679***	-0.021**	-0.371***
	[0.111]	[0.005]	[0.113]	[0.090]	[0.010]	[0.120]
Netherlands	-0.183***	0.011**	0.157**	-0.263***	-0.025***	0.308***
	[0.062]	[0.005]	[0.062]	[0.050]	[0.005]	[0.075]
Poland	0.081	0.022***	-0.04	0.259***	0.041***	-0.379***
	[0.068]	[0.004]	[0.069]	[0.039]	[0.005]	[0.063]
Portugal	0.697***	0.025***	-0.699***	-0.07	-0.002	-0.818***
	[0.056]	[0.004]	[0.055]	[0.043]	[0.005]	[0.073]
Romania	-0.479***	0.032***	0.557***	0.295***	0.078***	-0.346***
	[0.067]	[0.004]	[0.067]	[0.043]	[0.005]	[0.064]
Slovakia	0.241***	0.019***	-0.161**	0.043	0.080***	-0.732***
	[0.060]	[0.004]	[0.061]	[0.034]	[0.006]	[0.060]
Slovenia	-0.149**	0.020***	0.178***	0.288***	0.029***	-0.605***
	[0.064]	[0.003]	[0.064]	[0.040]	[0.007]	[0.059]
Spain	-0.262***	0.001	0.269***	0.017	0.007	0.08
	[0.076]	[0.009]	[0.075]	[0.048]	[0.007]	[0.084]
Sweden	-0.365***	0.023***	0.363***	-0.145***	-0.001	-0.043
	[0.075]	[0.004]	[0.076]	[0.047]	[0.004]	[0.061]
Serbia	0.308***	0.025***	-0.290***	0.129***	0.018***	-0.721***
	[0.058]	[0.003]	[0.059]	[0.031]	[0.004]	[0.049]
Switzerland	0.169**	0.016***	-0.175**	-0.069	-0.006	-0.254***
	[0.080]	[0.005]	[0.079]	[0.059]	[0.005]	[0.074]
Turkey	-0.438***	0.025***	0.477***	0.111***	0.039***	-0.275***
	[0.068]	[0.004]	[0.068]	[0.038]	[0.005]	[0.065]
UnitedKingdom	0.540***	0.025***	-0.567***	-0.268***	-0.027***	-0.206***
	[0.061]	[0.005]	[0.061]	[0.045]	[0.005]	[0.062]
Constant	75.255***	0.052	-75.031***	1.117	0.225**	18.119***
	[1.509]	[0.065]	[1.525]	[0.786]	[0.097]	[1.061]

Linear Prediction	81.2119	0.0541	-81.017	2.1392	0.1949	13.3013
No. of Observations	29,776	29,776	29,776	29,776	29,776	29,776
* p<0.10, ** p<0.05, *** p<0.01						

Sustainable Financial Literacy and Environmental Literacy display positive associations with green intensity, indicating that ESG-related and environmental knowledge are aligned with occupations embedding environmentally relevant skills. Sustainable Financial Literacy is also positively associated with physical intensity and negatively associated with social intensity, suggesting that environmentally oriented occupations may combine technical, operational, and sustainability-related components rather than primarily interpersonal tasks.

Digital Financial Literacy shows a modest positive association with cognitive intensity and a negative association with automation exposure, but its strongest relationship appears with physical intensity. This may reflect occupational sorting into roles combining operational tasks with digital financial tools, though the magnitude remains smaller than that observed for core technical literacies.

Overall, the evidence suggests that literacies are systematically associated with distinct occupational skill profiles. Technical digital literacies align strongly with cognitive- and digital-intensive occupations that are less exposed to automation. Interpersonal literacies align with socially intensive occupations. ESG-related literacies align with greener skill profiles. These patterns indicate that literacy domains are not merely abstract competences but are embedded in structural labour market positioning, shaping the types of skill environments in which individuals are employed. The main findings from Table 6-2 can be summarised as follows:

- Data and Programming Literacy is the strongest predictor of occupational positioning in cognitively intensive and digitally intensive jobs, and is strongly associated with lower automation exposure.
- Artificial Intelligence Literacy shows a similar, though smaller, pattern: higher cognitive and digital intensity and lower automation exposure.
- Financial, Retirement, and Health Literacies are positively associated with cognitive intensity and negatively associated with automation exposure, suggesting alignment with non-routine analytical occupations.
- Human Literacy is positively associated with social intensity and negatively associated with cognitive and digital intensity, indicating sorting into relationally intensive roles.
- Sustainable Financial Literacy and Environmental Literacy are positively associated with green skill intensity, linking ESG-related knowledge to environmentally oriented occupations.
- Overall, technical digital literacies align with analytically intensive and structurally resilient occupational environments, whereas interpersonal literacies align with socially intensive roles, and ESG-related literacies align with greener skill profiles.

6.5 Literacies and Occupational Skill Architecture

Table 0.3 examines how literacy domains are associated not with the *type* of skills embedded in occupations, but with the broader structure of occupational skill bundles. The four dependent variables-skill breadth, skill diversification, skill transferability, and the composite skill portfolio index-capture different dimensions of occupational robustness and mobility potential. While the previous section focused on whether individuals are sorted into cognitively, digitally, socially, or environmentally intensive occupations, the present analysis investigates whether literacies are linked to occupations characterised by broader, more balanced, and more portable skill configurations.

A first striking result concerns Data and Programming Literacy. It exhibits strong positive associations with skill breadth, skill transferability, and the overall skill portfolio index. This indicates that individuals with stronger technical digital competencies are not only positioned in analytically intensive jobs, but also in occupations characterised by more diversified and portable skill bundles. The magnitude of the association with the composite portfolio index is particularly pronounced, reinforcing the interpretation that technical literacy aligns with structurally robust occupational profiles that offer mobility across job transitions.

Artificial Intelligence Literacy displays a similar, though more moderate, pattern. It is positively associated with skill breadth and strongly associated with the overall portfolio index. This suggests that AI-related knowledge correlates with occupational positioning in roles that combine multiple skill domains and embed a relatively versatile skill architecture. However, its weaker association with diversification and transferability indicates that its structural effects are less broad than those of core programming-related competencies.

Financial Literacy and Sustainable Financial Literacy also demonstrate meaningful structural associations. Financial Literacy is positively linked to skill breadth, transferability, and the portfolio index, suggesting that economically literate individuals tend to occupy roles with more widely applicable skill sets. Sustainable Financial Literacy shows positive associations across breadth, diversification, transferability, and the overall portfolio index, indicating that ESG-related knowledge aligns with structurally diversified occupational skill bundles. These findings imply that sustainability-oriented competencies may be embedded in occupations that integrate multiple skill domains and exhibit greater adaptability potential.

Political Literacy and Cultural Agility display more selective structural effects. Political Literacy is positively associated with skill diversification and transferability, suggesting that institutional awareness may align with occupations characterised by more balanced and mobile skill bundles. Cultural Agility is positively associated with diversification, transferability, and the portfolio index, indicating that intercultural competence may correlate with structurally flexible occupational roles, potentially due to their embedding in globally connected or cross-functional environments.

Table 6-3: Literacies and skill architecture

	Skill breadth (1)	Skill diversification (2)	Skill transferability (3)	Skill portfolio (4)
Financial literacy	0.029***	0.005	0.047***	0.151***
	[0.007]	[0.007]	[0.017]	[0.029]
Retirement literacy	0.003	0.005	0.007	0.049*
	[0.007]	[0.008]	[0.016]	[0.025]
Health literacy	-0.003	-0.004	0.005	0.044*
	[0.006]	[0.009]	[0.017]	[0.024]
Digital financial literacy	-0.002	0.001	0.001	0.035
	[0.007]	[0.006]	[0.015]	[0.028]
Media literacy	0.004	0.009	0.022	0.028
	[0.007]	[0.007]	[0.017]	[0.022]
AI literacy	0.009**	0.003	0.014	0.085***
	[0.004]	[0.004]	[0.009]	[0.012]
Data and programming literacy	0.046***	0.010	0.040***	0.261***
	[0.007]	[0.006]	[0.014]	[0.029]
Political literacy	-0.004	0.024***	0.035**	0.036
	[0.006]	[0.006]	[0.013]	[0.026]
Environmental literacy	0.021**	0.003	0.03	0.047
	[0.008]	[0.010]	[0.021]	[0.032]
Sustainable finance literacy	0.038***	0.019**	0.069***	0.099***
	[0.008]	[0.009]	[0.019]	[0.030]
Human literacy	-0.001	-0.004	-0.014	-0.066***
	[0.006]	[0.006]	[0.013]	[0.016]
Cultural agility	0.008	0.018**	0.039**	0.050*
	[0.007]	[0.008]	[0.017]	[0.027]
Self-employed	-0.138***	-0.097***	-0.270***	-0.516***
	[0.024]	[0.031]	[0.065]	[0.096]
Unemployed	-0.161***	0.002	-0.249***	-0.869***
	[0.033]	[0.036]	[0.075]	[0.129]
Inactive	-0.178***	0.049	-0.258***	-0.819***
	[0.037]	[0.036]	[0.066]	[0.129]
Homemaker	-0.194***	-0.162***	-0.510***	-1.057***
	[0.051]	[0.051]	[0.108]	[0.204]
Retired	0.014	-0.05	-0.017	0.069
	[0.047]	[0.048]	[0.098]	[0.138]
Student	-0.01	0.087	0.052	-0.493**
	[0.048]	[0.052]	[0.094]	[0.227]
Male	0.136***	0.114***	0.352***	0.346***
	[0.015]	[0.013]	[0.028]	[0.058]
LGBT+	-0.004	-0.042	-0.048	-0.007
	[0.105]	[0.106]	[0.199]	[0.392]
Age	-0.008	-0.018***	-0.028	-0.027
	[0.008]	[0.006]	[0.017]	[0.028]

Age sq./1000	0.094	0.158**	0.296*	0.408*
	[0.069]	[0.058]	[0.150]	[0.235]
Single	-0.033	0.02	-0.04	-0.116
	[0.028]	[0.022]	[0.059]	[0.092]
Married	0.017	0.045**	0.045	-0.035
	[0.021]	[0.018]	[0.048]	[0.074]
Unknown marital status	-0.014	0.03	0.009	-0.096
	[0.019]	[0.020]	[0.049]	[0.066]
ISCED 2: Lower secondary education	0.07	-0.055	0.127	0.352*
	[0.052]	[0.066]	[0.124]	[0.189]
ISCED 3: Upper secondary education	0.175***	0.022	0.314***	0.850***
	[0.053]	[0.048]	[0.095]	[0.191]
ISCED 4: Post-secondary non-tertiary	0.152***	0.031	0.339***	1.050***
	[0.052]	[0.064]	[0.114]	[0.193]
ISCED 5: Short-cycle tertiary education	0.226***	0.186***	0.514***	1.362***
	[0.054]	[0.047]	[0.105]	[0.209]
ISCED 6: Bachelor's or equivalent level	0.294***	0.259***	0.732***	1.629***
	[0.053]	[0.049]	[0.109]	[0.184]
ISCED 7: Master's or equivalent level	0.347***	0.347***	0.974***	1.978***
	[0.049]	[0.052]	[0.104]	[0.196]
ISCED 8: Doctoral or equivalent level	0.683***	0.499***	1.595***	3.193***
	[0.096]	[0.070]	[0.182]	[0.363]
Age: 18-24	-0.067	-0.195*	-0.286	-0.145
	[0.118]	[0.110]	[0.270]	[0.485]
Age: 25-34	0.01	-0.134	-0.023	0.402
	[0.088]	[0.087]	[0.201]	[0.354]
Age: 35-44	0.009	-0.073	-0.044	0.236
	[0.066]	[0.072]	[0.163]	[0.267]
Age: 45-54	0.038	-0.014	0.062	0.225
	[0.047]	[0.060]	[0.114]	[0.185]
Age: 55-64	0.002	-0.009	-0.004	0.113
	[0.033]	[0.040]	[0.079]	[0.121]
Income decile 10	0.094***	0.078**	0.165***	0.426***
	[0.024]	[0.029]	[0.055]	[0.092]
Income decile 9	0.095***	0.053*	0.181**	0.370***
	[0.030]	[0.030]	[0.074]	[0.087]
Income decile 8	0.082***	0.043	0.172***	0.415***
	[0.022]	[0.031]	[0.061]	[0.082]
Income decile 7	0.083**	0.009	0.130*	0.325***
	[0.031]	[0.030]	[0.069]	[0.114]
Income decile 6	0.038	-0.013	0.042	0.169*
	[0.032]	[0.034]	[0.078]	[0.093]
Income decile 5	0.009	-0.063**	-0.087*	0.098
	[0.025]	[0.027]	[0.050]	[0.091]
Income decile 4	0.010	-0.089**	-0.121*	-0.040
	[0.031]	[0.034]	[0.069]	[0.121]
Income decile 3	-0.006	-0.123***	-0.191**	-0.139

	[0.033]	[0.033]	[0.073]	[0.108]
Income decile 2	0.002	-0.124***	-0.170***	-0.155
	[0.033]	[0.027]	[0.061]	[0.112]
Income decile 1	-0.043	-0.132***	-0.224***	-0.313***
	[0.027]	[0.030]	[0.063]	[0.097]
Wealth decile 10	-0.007	0.025	0.012	-0.087
	[0.018]	[0.031]	[0.048]	[0.074]
Wealth decile 9	0.008	0.041	0.029	-0.124
	[0.041]	[0.038]	[0.091]	[0.135]
Wealth decile 8	-0.027	0.041	-0.007	-0.097
	[0.028]	[0.030]	[0.054]	[0.105]
Wealth decile 7	-0.029	0.049	-0.006	-0.255**
	[0.036]	[0.040]	[0.077]	[0.117]
Wealth decile 6	-0.061**	0.048	-0.035	-0.208**
	[0.025]	[0.030]	[0.051]	[0.100]
Wealth decile 5	0.012	0.066**	0.102*	0.023
	[0.020]	[0.027]	[0.054]	[0.088]
Wealth decile 4	-0.018	0.021	-0.014	-0.053
	[0.021]	[0.023]	[0.036]	[0.093]
Wealth decile 3	-0.016	0.029	0.011	-0.1
	[0.027]	[0.027]	[0.062]	[0.089]
Wealth decile 2	0.029	0.014	0.054	0.012
	[0.023]	[0.024]	[0.053]	[0.089]
Wealth decile 1	-0.024	0.058**	0.022	-0.148
	[0.023]	[0.026]	[0.055]	[0.110]
Austria	0.153***	0.053***	0.121***	0.495***
	[0.012]	[0.015]	[0.032]	[0.057]
Belgium	0.045***	0.027*	-0.047	0.014
	[0.012]	[0.013]	[0.029]	[0.039]
Bulgaria	0.118***	0.003	0.023	0.220***
	[0.011]	[0.010]	[0.024]	[0.045]
Croatia	0.097***	0.036***	0.116***	0.241***
	[0.012]	[0.011]	[0.028]	[0.039]
Czechia	0.167***	0.100***	0.256***	0.542***
	[0.014]	[0.015]	[0.037]	[0.055]
Denmark	0.153***	0.001	0.163***	0.420***
	[0.014]	[0.016]	[0.036]	[0.051]
Estonia	0.266***	0.153***	0.404***	0.717***
	[0.010]	[0.010]	[0.022]	[0.036]
Finland	0.122***	-0.087***	-0.098**	0.201***
	[0.016]	[0.016]	[0.036]	[0.062]
France	0.147***	0.029**	0.138***	0.218***
	[0.014]	[0.012]	[0.031]	[0.048]
Germany	0.132***	0.040***	0.042	0.396***
	[0.014]	[0.014]	[0.034]	[0.050]
Greece	0.085***	-0.113***	-0.142***	0.027
	[0.015]	[0.016]	[0.033]	[0.048]

Hungary	0.130***	0.044***	0.140***	0.423***
	[0.011]	[0.012]	[0.029]	[0.048]
Ireland	0.108***	-0.082***	-0.127***	0.226***
	[0.016]	[0.017]	[0.032]	[0.059]
Italy	0.132***	0.057***	0.098***	0.520***
	[0.017]	[0.012]	[0.032]	[0.058]
Latvia	0.200***	0.123***	0.318***	0.558***
	[0.011]	[0.011]	[0.027]	[0.042]
Lithuania	0.252***	0.095***	0.341***	0.773***
	[0.008]	[0.008]	[0.015]	[0.028]
Luxembourg	0.019	0.006	-0.076**	0.309***
	[0.016]	[0.015]	[0.037]	[0.061]
Malta	0.106***	0.095***	0.166***	0.734***
	[0.016]	[0.017]	[0.034]	[0.064]
Netherlands	0.060***	0.056***	-0.024	0.02
	[0.014]	[0.015]	[0.030]	[0.044]
Poland	0.194***	-0.011	0.031	0.323***
	[0.012]	[0.012]	[0.028]	[0.038]
Portugal	0.097***	-0.024*	-0.002	0.415***
	[0.012]	[0.012]	[0.027]	[0.044]
Romania	0.107***	0.045***	0.140***	0.191***
	[0.008]	[0.012]	[0.021]	[0.034]
Slovakia	0.136***	0.043***	0.069**	0.340***
	[0.009]	[0.011]	[0.026]	[0.035]
Slovenia	0.158***	0.090***	0.232***	0.409***
	[0.014]	[0.014]	[0.031]	[0.042]
Spain	0.051***	0.002	-0.031	-0.063
	[0.016]	[0.015]	[0.035]	[0.057]
Sweden	0.057***	0.078***	0.046	0.066
	[0.012]	[0.014]	[0.030]	[0.043]
Serbia	0.109***	0.042***	0.168***	0.467***
	[0.008]	[0.010]	[0.023]	[0.033]
Switzerland	0.132***	0.067***	0.081**	0.327***
	[0.014]	[0.016]	[0.036]	[0.054]
Turkey	0.083***	0.071***	0.056**	0.081**
	[0.009]	[0.010]	[0.022]	[0.034]
UnitedKingdom	0.104***	0.030**	-0.023	0.354***
	[0.010]	[0.014]	[0.025]	[0.038]
Constant	-0.582**	0.082	-0.708	-3.266***
	[0.260]	[0.191]	[0.561]	[1.009]
Linear Prediction	-0.0004	0.0008	-0.0008	-0.0063
No. of Observations	29,776	29,776	29,776	29,776
* p<0.10, ** p<0.05, *** p<0.01				

In contrast, Human Literacy shows a negative association with the overall skill portfolio index. While it was positively associated with social skill intensity in Table 0.2, here it appears linked to occupations with comparatively narrower or less transferable skill architectures. This likely reflects occupational sorting into socially intensive roles that rely heavily on relational competences but may not combine as many distinct skill domains or offer the same degree of structural portability as highly cognitive or digital occupations. Retirement, Health, Digital Financial, and Media Literacies display weaker or statistically insignificant relationships with most skill architecture measures. Their effects appear more domain-specific rather than structurally transformative in terms of occupational flexibility.

Taken together, the results indicate that not all literacies are equally associated with structurally robust occupational skill configurations. The main findings from Table 0.3 can be summarised as follows:

- Data and Programming Literacy is the strongest predictor of occupational skill breadth, transferability, and overall portfolio robustness.
- Artificial Intelligence Literacy is positively associated with skill breadth and portfolio strength, though less strongly with diversification and transferability.
- Financial and Sustainable Financial Literacies are positively linked to broader and more transferable occupational skill bundles.
- Political Literacy and Cultural Agility contribute to skill diversification and transferability.
- Human Literacy, while associated with socially intensive occupations, is negatively associated with overall skill portfolio robustness.
- Overall, technical and sustainability-related literacies are most strongly aligned with structurally diversified and portable occupational skill architectures.

7. Structural Implications for Skills Policy, Education and Workforce Development

Deliverable 5.2 demonstrates that multidimensional literacies are unevenly distributed across countries, regions, and population groups-and that these differences carry structural consequences for resilience and occupational positioning. The descriptive maps and regional analyses reveal persistent territorial disparities across Europe. Northern and parts of Western Europe tend to exhibit higher average levels of digital, AI, financial, and sustainable finance literacies, while several Southern and Eastern European regions fall into lower distribution classes across multiple domains. At the same time, significant within-country variation is visible at NUTS-2 level, indicating that literacy gaps are not purely national but also regional.

These territorial patterns are compounded by demographic inequalities. Across literacy domains, younger cohorts tend to perform more strongly in digital and AI-related literacies, while older cohorts often display lower digital-technical scores but in some cases higher financial or institutional knowledge. Educational attainment is a strong and consistent predictor across almost all literacy domains, reinforcing the cumulative nature of skill acquisition. Income gradients are also visible, particularly in financial, digital, and sustainable finance literacies. Gender differences appear in selected domains, especially in technical digital literacies and financial knowledge, suggesting persistent structural imbalances in access to certain competence areas.

These regional and demographic disparities matter because the econometric evidence shows that literacies are systematically associated with labour market resilience, financial stability, and structurally robust occupational skill architectures. Regions and population groups with lower levels of technical digital literacy are more likely to face higher automation exposure and lower occupational transferability. Groups with weaker financial literacy display lower financial resilience and higher financial strain. Areas with lower sustainability-related literacies may be less well positioned for participation in green skill-intensive occupations.

The evidence reveals differentiated structural functions across literacy domains. Technical digital literacies-particularly Data and Programming Literacy and AI Literacy-are strongly associated with cognitively intensive, digitally embedded, and automation-resilient occupations. They also align with broader and more transferable skill portfolios. Financial literacy is central for household resilience and economic stability. Sustainable and environmental literacies align with green skill intensity and diversified occupational architectures. Interpersonal literacies such as Human Literacy and Cultural Agility support labour market adaptability and social skill intensity, though they are less associated with highly diversified technical portfolios.

These findings imply that education and training frameworks must be reoriented toward multidimensional literacy integration. Rather than treating digital skills, financial education, sustainability awareness, and interpersonal competences as separate policy tracks, they should be understood as complementary components of structurally resilient skill architectures.

The findings therefore suggest that literacy gaps translate into structural labour market inequalities. Differences in literacy levels are not merely educational indicators; they shape exposure to automation, occupational mobility potential, and financial vulnerability. From a policy perspective, this underscores the importance of embedding literacy development within territorial cohesion strategies, education reform, and targeted reskilling initiatives.

The remainder of this section synthesises the structural implications of these findings for education systems, vocational training frameworks, and lifelong learning policies. It argues that multidimensional literacy development must become a central pillar of European workforce strategy-particularly in regions and demographic groups where current literacy gaps risk reinforcing economic divergence.

7.1 Curriculum Reform: Embedding Multidimensional Literacies Across Education Levels

The findings suggest that early and tertiary education systems should embed literacy development in a systematic and cumulative manner. Technical digital competencies, including computational thinking and AI awareness, are strongly linked to both labour market resilience and structurally robust occupational profiles. This indicates that digital-technical literacy should not remain confined to specialised ICT tracks but should become a transversal competence across disciplines.

Similarly, financial literacy should be strengthened as a foundational component of general education. The strong association between financial literacy and household economic resilience highlights its relevance not only for employability but for economic stability and social inclusion. Integrating financial competence into secondary education curricula can therefore serve both economic and social policy objectives.

Sustainability-related literacies also require deeper integration. The alignment between sustainable finance literacy and greener occupational skill profiles suggests that ESG-related knowledge should be mainstreamed into business, economics, engineering, and vocational programmes. As the green transition accelerates, embedding environmental literacy across curricula can support workforce alignment with evolving labour market demands.

Importantly, interpersonal competences should not be overlooked. Human Literacy and Cultural Agility significantly predict labour market adaptability. Education systems should therefore continue to prioritise collaborative learning, intercultural competence, and socio-emotional skills, particularly in increasingly diverse labour markets.

From a policy standpoint, this implies:

- Embedding digital-technical literacy as a transversal competence across educational pathways.
- Integrating financial literacy into core curricula at secondary and tertiary levels.
- Mainstreaming sustainability literacy across disciplines in alignment with Green Deal objectives.
- Strengthening socio-emotional and intercultural competences as core employability skills.

7.2 Vocational Education and Training (VET): From Occupational Narrowness to Skill Architecture

The ISCO–ESCO analysis demonstrates that technical digital literacies are associated not only with employment in specific occupations, but with broader and more transferable occupational skill architectures. Individuals with stronger Data and Programming Literacy or AI Literacy are disproportionately positioned in occupations characterised by higher cognitive intensity, lower automation exposure, greater skill breadth, and stronger transferability across job families. This finding has significant implications for vocational education and training (VET) systems, which in many Member States remain strongly organised around narrowly defined occupational standards and qualification profiles.

Traditional VET systems have historically prioritised occupation-specific competence development, often structured around fixed professional pathways. While this model has supported high levels of occupational specialisation and employer alignment, the empirical evidence presented in this deliverable suggests that narrow specialisation may limit structural mobility in an era defined by digital transformation and rapid technological change. Occupations characterised by narrow skill portfolios and low diversification are more vulnerable to automation exposure and less adaptable to labour market shocks. By contrast, literacy combinations that enhance cognitive and digital intensity are systematically associated with occupations that embed broader, more diversified, and more portable skill bundles.

These findings point to the need for a gradual reorientation of VET frameworks from occupation-bound training models toward portfolio-oriented competence development. Rather than preparing learners exclusively for one narrowly defined occupational role, VET systems should enable the accumulation of transferable skill modules that increase mobility potential across related occupational clusters. This is particularly relevant in regions where automation exposure is higher or where industrial restructuring is underway.

In practical terms, this implies several strategic adjustments:

- Digital modules should be embedded across all vocational tracks, not limited to ICT or technology-specific occupations. Even traditionally manual or service-oriented roles increasingly require digital interfaces, data handling, and platform-based coordination.

Embedding digital fluency as a transversal component can reduce automation exposure and enhance cognitive task intensity across sectors.

- Green and sustainability competences should be systematically integrated into technical, construction, manufacturing, and industrial training programmes. The evidence linking sustainability-related literacies to green skill intensity suggests that VET systems can proactively align learners with emerging environmentally oriented occupational profiles.
- Financial and entrepreneurial literacy should be incorporated into vocational curricula to strengthen long-term economic resilience. Particularly for self-employed workers, SMEs, and sectors with cyclical volatility, financial competence enhances structural coping capacity.
- Cross-functional and interdisciplinary training approaches should be encouraged to increase skill diversification. For example, combining technical training with communication, project management, or digital analytics modules can expand occupational portability and reduce structural lock-in.
- Interpersonal and intercultural competences should be integrated into vocational pathways, particularly in service-intensive sectors and increasingly globalised production networks.

Policy instruments can support this structural shift. Micro-credentials, stackable certifications, and modular qualification frameworks enable learners to accumulate competences incrementally and flexibly across their careers. Recognition of prior learning (RPL) systems can facilitate the formal validation of transversal literacies acquired outside formal education. Sectoral skills alliances and regional skills ecosystems can align VET provision with evolving ESCO-based skill architectures.

Importantly, this reform agenda also has a territorial dimension. Regions with lower average digital or technical literacy levels-identified in the descriptive mapping of this deliverable-may face greater structural vulnerability if VET systems remain narrowly specialised. Targeted investment in digital modules and modularised qualification pathways can therefore function as a cohesion instrument, reducing regional disparities in skill architecture robustness.

In sum, the evidence suggests that future-oriented VET systems should be designed not only to meet current occupational standards but to enhance learners' long-term mobility and adaptability. By aligning vocational training frameworks with diversified and transferable skill architectures, policymakers can strengthen structural labour market resilience in the face of digitalisation, automation, and the green transition.

7.3 Lifelong Learning and Workforce Transition Policy

The differentiated effects of literacy domains on labour market and financial resilience underscore the central role of adult education and reskilling systems in shaping long-term workforce adaptability. As technological transformation accelerates-through automation, artificial intelligence, platformisation, and the green transition-mid-career transitions are likely to become more frequent and less predictable. Workers will increasingly need to reconfigure their skill portfolios rather than rely on static occupational pathways. The evidence presented in this

deliverable suggests that literacy profiles significantly influence individuals' structural positioning within this evolving landscape.

Technical digital literacies-particularly Data and Programming Literacy and AI Literacy-are strongly associated with cognitively intensive and automation-resilient occupational environments. Individuals lacking these competences are more likely to be embedded in occupations with higher automation exposure and narrower skill architectures. This implies that reskilling policies targeting digital-technical competences are not merely productivity-enhancing measures but structural resilience instruments. At the same time, financial literacy emerges as a crucial determinant of household coping capacity, reducing financial strain and improving short-, medium-, and long-term resilience. In periods of economic volatility, insufficient financial literacy can amplify vulnerability even when employment is maintained.

These findings imply that lifelong learning strategies must adopt a differentiated and targeted approach. Rather than generic training provision, adult education systems should align closely with structural labour market intelligence and demographic risk profiles. In particular:

- Reskilling programmes should prioritise data literacy, programming foundations, and AI-related competencies, especially for mid-career workers in occupations with high automation exposure. Modular digital upskilling pathways can support gradual competence accumulation without requiring full occupational requalification.
- Financial literacy interventions should target vulnerable demographic groups, including low-income households, older workers, and those in precarious employment. Strengthening financial capability can reduce economic strain during transition periods and enhance resilience to income shocks.
- Sustainability and green literacy development should be aligned with sectoral transition strategies. As industries decarbonise and environmental regulations tighten, workers in energy, construction, transport, and manufacturing sectors will require updated sustainability-related competences.
- Interpersonal, adaptive, and intercultural skill training should support employability in service-intensive and socially embedded sectors. These competences remain critical in health, education, care, and hospitality sectors, where automation substitution is more limited but relational complexity is high.

Importantly, the ESCO-based skill architecture analysis provides a powerful analytical tool for guiding adult learning investments. By identifying occupations characterised by narrow skill portfolios, low diversification, and limited transferability, policymakers can detect structural risk zones within the labour market. Training resources can then be strategically directed toward workers in these occupations, facilitating proactive transition pathways rather than reactive displacement responses.

Skill transferability indicators are particularly valuable in this context. Workers embedded in occupations with high skill overlap across job families may require only incremental upskilling to transition into adjacent roles. In contrast, workers in highly specialised and low-transferability occupations may require more comprehensive retraining programmes. Integrating such indicators

into public employment services and regional skills forecasting systems can significantly enhance the efficiency of reskilling strategies.

The territorial dimension is equally important. Regions identified in this deliverable as having lower average levels of digital and technical literacies may face compounded structural risks if their workforce is concentrated in automation-exposed occupations. Lifelong learning strategies should therefore be embedded within regional development and cohesion frameworks, ensuring that literacy gaps do not translate into persistent regional divergence.

Finally, adult learning policies must address participation barriers. Lower-skilled individuals and older workers-groups often displaying lower literacy scores in digital and AI domains-are also less likely to participate in training programmes. Incentive mechanisms, flexible delivery models (including blended and online formats), recognition of prior learning, and employer co-investment schemes will be essential to avoid reinforcing existing inequalities.

In sum, lifelong learning systems must evolve from reactive retraining instruments to proactive skill architecture development strategies. By aligning reskilling investments with literacy profiles and ESCO-based structural labour market intelligence, policymakers can strengthen both individual resilience and systemic adaptability in the face of ongoing digital and green transformations.

7.4 Integrating Skill Intelligence into Policy Design

One of the most significant contributions of this deliverable is methodological and strategic. By operationalising the ESCO taxonomy and linking it to survey-based literacy measures, we demonstrate how micro-level competence data can be systematically integrated with occupation-level skill architectures. This approach moves beyond traditional descriptive labour market analysis and offers a replicable framework for embedding skill intelligence into policy design.

The ISCO–ESCO linkage allows us to map individual literacy profiles onto externally defined occupational skill structures. This enables the identification of structural relationships between literacy domains and occupational characteristics such as cognitive intensity, automation exposure, green skill content, and skill transferability. Crucially, it allows policymakers to distinguish between behavioural resilience (e.g., confidence, upskilling behaviour) and structural resilience (e.g., employment in occupations with broad and transferable skill portfolios).

For policymakers, this implies that skill-based analytics should complement-and in some cases replace-traditional occupation-based statistics. Conventional labour market indicators often rely on broad occupational classifications that obscure underlying task composition and skill structures. However, technological change affects tasks and competences more directly than job titles. A skill-based analytical approach provides more granular insight into which workers are structurally exposed to automation, which occupations are aligned with green transitions, and which skill bundles enable cross-occupational mobility.

Embedding such intelligence into policy design can significantly improve targeting and effectiveness. For example:

- Active labour market policies can use automation exposure and transferability indicators to identify workers in structurally vulnerable occupations and prioritise proactive reskilling pathways.
- Training subsidies and voucher schemes can be aligned with occupations exhibiting narrow or low-diversification skill architectures, thereby enhancing long-term mobility rather than short-term placement outcomes.
- Education reform initiatives can incorporate skill breadth and cognitive intensity metrics to assess whether curricula align with future-oriented occupational structures.
- Regional development strategies can use ESCO-based skill analytics to detect territorial mismatches between workforce literacy profiles and emerging sectoral demands.

Furthermore, integrating ESCO-based skill intelligence supports better coordination between education systems, employment services, and industrial policy. Sectoral transition plans-particularly in digitalisation and decarbonisation-can be grounded in empirical assessments of skill architectures rather than static occupational projections. This is particularly relevant for the European Green Deal and Digital Decade objectives, where skill transformation is a central pillar.

The approach also enhances monitoring and evaluation capacity. By linking literacy profiles to occupational skill metrics, policymakers can assess whether investments in digital literacy, sustainability education, or financial competence translate into structural improvements in skill positioning and transferability. This creates the foundation for evidence-based feedback loops between policy implementation and labour market outcomes.

Importantly, skill intelligence systems should be embedded within national and regional governance structures. Public employment services, regional skills councils, and social partners can use ESCO-derived indicators to anticipate structural risks and coordinate targeted interventions. The use of harmonised European taxonomies such as ESCO ensures cross-country comparability, facilitating benchmarking and mutual learning across Member States.

Finally, the integration of micro-level literacy data with macro-level skill architectures strengthens the coherence of European skills policy. It aligns survey evidence, occupational intelligence, and strategic workforce planning within a unified analytical framework. In doing so, it supports the transition from reactive labour market management toward proactive, data-driven skills governance.

In sum, the operationalisation of ESCO within this deliverable demonstrates that skill intelligence can move from abstract taxonomy to actionable policy instrument. By embedding skill architecture analytics into education reform, VET modernisation, and lifelong learning strategies, policymakers can design more precise, future-oriented, and structurally resilient workforce development policies.

7.5 Strategic Outlook

The findings of Deliverable 5.2 support a fundamental shift from occupation-centred to skill-centred education and labour market policy. Traditional labour market governance has largely been organised around occupational classifications, employment rates, and sectoral projections. However, the evidence presented in this deliverable demonstrates that resilience, mobility, and structural adaptability are shaped less by job titles and more by the composition, breadth, and transferability of individuals' skill portfolios.

In a context defined by rapid digitalisation, automation, demographic change, and the green transition, employment status alone is no longer a sufficient indicator of security. Workers embedded in narrowly specialised or automation-exposed skill architectures may remain employed in the short term but face heightened structural vulnerability. Conversely, individuals possessing diversified, cognitively intensive, digitally embedded, and transferable skill bundles are better positioned to adapt to technological shifts, sectoral restructuring, and cross-occupational mobility. Resilience therefore emerges not simply as a labour market outcome but as a function of multidimensional literacy development and structural skill architecture.

The territorial and demographic evidence further reinforces this conclusion. Regions and population groups displaying lower levels of digital-technical literacy are more likely to be concentrated in occupations with higher automation exposure and lower transferability. Educational attainment and income gradients amplify these structural divides. Without strategic intervention, literacy gaps risk translating into persistent regional and socio-economic inequalities in labour market resilience. A skill-centred strategy is therefore not only an economic imperative but also a cohesion and inclusion imperative.

A forward-looking European skills strategy should therefore:

- Promote multidimensional literacy development across the life course, integrating digital-technical, financial, sustainability, and interpersonal competences into coherent frameworks rather than isolated policy streams.
- Enhance skill breadth, diversification, and transferability by supporting modular, stackable, and cross-occupational training pathways that strengthen long-term mobility potential.
- Align education, VET, and lifelong learning systems with the structural requirements of digital and green transitions, ensuring that literacy development anticipates emerging skill architectures rather than reacting to displacement.
- Integrate socio-emotional and intercultural competences into employability and workforce development frameworks, recognising their role in adaptability and social cohesion.
- Embed ESCO-based skill analytics and evidence-driven skill intelligence into policy planning, monitoring, and evaluation processes at national and regional levels.

Such a strategy requires coordinated governance across education ministries, labour market institutions, regional authorities, and social partners. It also requires sustained investment in adult learning systems, targeted support for vulnerable groups, and continuous updating of curricula in response to evolving skill taxonomies.

In sum, literacies matter structurally. They shape financial stability, labour market resilience, occupational positioning, and mobility potential. By operationalising a multidimensional literacy architecture and linking it to skill-based labour market intelligence, Deliverable 5.2 provides an empirical foundation for more precise and forward-looking workforce policy. Education and training systems that recognise and institutionalise this multidimensional approach will be better equipped to support inclusive, sustainable, and regionally balanced labour market transitions across Europe.

8. Concluding remarks

Deliverable 5.2 represents a major milestone in the implementation of Task 5.2: *"Towards a new classification of basic and transferable skills in the era of the green and digital transformation."* As specified in the TRAILS proposal, Task 5.2 initiates a substantive innovation in the classification, measurement, and empirical analysis of often neglected basic and transferable skills. The present deliverable operationalises this ambition by developing and validating new literacy constructs, generating novel EU-wide evidence through TRAILS Survey I, and embedding these constructs within a skill-based labour market analytical framework.

At its core, Deliverable 5.2 advances a new multidimensional classification of basic and transferable skills. Moving beyond traditional narrow definitions of literacy or occupational skill categories, the analysis introduces and empirically validates a broader set of literacies, including financial, retirement, health and medical, digital financial, media and information, artificial intelligence, data and programming, political, environmental, sustainable finance, human literacy, and cultural agility.

This classification responds directly to the conceptual gap identified in the TRAILS proposal: that several foundational competences-particularly those relevant for digital transformation, financial resilience, sustainability, and social cohesion-remain under-measured and under-integrated into labour market and education policy frameworks. By constructing additive literacy indices, testing their internal coherence, and analysing their inter-relationships, this deliverable establishes a systematic empirical foundation for these domains.

The findings provide evidence on:

- Their levels across EU countries and regions,
- Their demographic determinants,
- Their inter-relationships and potential common drivers,
- Their associations with labour market and financial resilience,
- Their alignment with occupational skill architectures derived from ESCO.

This integrated approach marks a departure from the current state of the art, which often treats such literacies as isolated thematic areas rather than as structurally embedded components of skill portfolios. TRAILS Survey I constitutes a foundational empirical pillar of this innovation. It provides harmonised, cross-country data enabling the measurement of newly operationalised literacy domains across the EU. The survey allows for:

- Mapping territorial and regional disparities,
- Identifying demographic gaps (e.g. by age, gender, education, income),

- Estimating associations with resilience outcomes,
- Linking literacy profiles to occupation-level skill architectures.

Importantly, TRAILS Survey I enables the integration of micro-level behavioural and competence data with macro-level labour market intelligence through the ISCO–ESCO linkage. This methodological integration is one of the central contributions of Deliverable 5.2. By operationalising the ESCO taxonomy and mapping literacy profiles onto occupational skill intensities and architectures, the deliverable bridges survey-based measurement with externally validated skill taxonomies. This approach provides a replicable analytical framework that can be extended in future survey waves and policy monitoring exercises.

The results confirm that the newly defined literacies are neither redundant nor trivial. They display meaningful variation across countries and demographic groups, and they are systematically associated with:

- Labour market adaptability and upskilling behaviour,
- Financial resilience and economic coping capacity,
- Occupational cognitive intensity and automation exposure,
- Skill breadth, diversification, and transferability.

In doing so, the analysis sheds light on basic and transferable skills that have historically received less systematic empirical attention. Low levels of financial, digital, sustainability, and data-related literacies are shown to correlate with higher vulnerability, both economically and structurally. These vulnerabilities disproportionately affect certain population groups-including lower-educated individuals, some regional clusters, and specific demographic segments-thus reinforcing the cohesion relevance of this work.

The findings also contribute to ongoing debates regarding whether such literacies are independent domains or whether they are influenced by common behavioural or cultural factors, including overconfidence, present-biased preferences, or other socio-cultural predispositions. While causal pathways remain outside the scope of this deliverable, the inter-correlation analysis provides a necessary first empirical basis for further exploration.

Deliverable 5.2 provides empirical support for the concept of “robot-proof education and training” (Aoun, 2017). The analysis demonstrates that literacy domains-particularly technical digital literacies-are associated with lower automation exposure and broader occupational skill portfolios. This suggests that education and training systems oriented toward multidimensional literacy development can contribute to structurally resilient labour market positioning.

Moreover, by embedding literacy analysis within ESCO-based occupational architectures, this deliverable contributes to a more future-oriented labour market analysis framework. Rather than relying exclusively on occupational projections, it shifts the focus to skill

composition, transferability, and diversification-dimensions that are more directly relevant in contexts of automation and technological restructuring.

This skill-centred analytical lens provides a robust foundation for designing forward-looking education, VET, and lifelong learning policies aligned with the green and digital transitions.

While Deliverable 5.2 makes significant advances, it is important to clarify its scope limits.

- First, the analysis is observational and cross-sectional. While strong associations are identified between literacies and resilience or occupational structures, causal inference is beyond the scope of this deliverable.
- Second, the literacy indices are additive measures based on correct responses. Although internal coherence and statistical validity are examined, further refinement and experimental validation of measurement instruments will enhance precision.
- Third, while occupational skill architectures are derived from ESCO mappings, actual task content may vary within occupations across firms and regions. The analysis therefore captures structural tendencies rather than individual-level task variation.

These limitations are not weaknesses but define the boundaries of Task 5.2. They also provide the rationale for the subsequent tasks within Work Package 5. Deliverable 5.2 lays the conceptual and empirical groundwork for the next stages of analysis within Work Package 5. TRAILS Survey II will significantly extend and refine the analytical framework established in this deliverable. While TRAILS Survey I provided the foundational measurement of multidimensional literacies and enabled their linkage to occupational skill architectures through 4-digit ISCO–ESCO mapping, Survey II will move further into detailed skills and training measurement. In particular, it will allow the approximation of 6-digit ISCO classifications, thereby substantially narrowing occupational categories and enabling more granular mapping of skill portfolios. This increased occupational precision will reduce heterogeneity within broad job families and enhance the accuracy of ESCO-based skill architecture indicators.

In addition, the integration of detailed NACE sectoral codes at the individual level will enable a richer analysis of sector-specific skill configurations and training exposure. The combined use of fine-grained occupational (6-digit ISCO) and sectoral (NACE) information will allow TRAILS to capture not only the skill content of jobs, but also the industrial context within which those skills are deployed. This will strengthen the capacity to analyse sectoral transitions, green restructuring processes, and digital transformation pathways.

TRAILS Survey II's enhanced focus on training participation, skill acquisition pathways, and competence updating will further allow the project to move from structural association analysis toward dynamic skill development analysis. It will enable a closer examination of how individuals build, adjust, and diversify their skill portfolios over time, and how training interventions interact with occupational mobility and resilience outcomes.

Together, TRAILS Survey I and II establish a uniquely integrated framework for analysing basic and transferable skills in the era of digitalisation and green transformation. Survey I provides the baseline literacy architecture and structural associations. Survey II enhances granularity, training measurement, and sectoral contextualisation. This sequential design ensures that TRAILS moves progressively from classification innovation (Task 5.2), to measurement refinement (Task 5.3), to detailed portfolio and mobility analysis (Task 5.4), thereby building a cumulative and forward-looking evidence base for robot-proof education and future-oriented labour market policy in Europe.

In conclusion, Deliverable 5.2 fulfils the ambition set out in Task 5.2 by initiating a major innovation in the classification and empirical analysis of basic and transferable skills. It provides a robust empirical foundation for robot-proof education, future-oriented labour market analysis, and evidence-based policy design. It establishes the methodological infrastructure for subsequent refinement and mobility analysis, and it positions TRAILS Survey I as a cornerstone of a broader, multi-wave research agenda supporting inclusive and sustainable skill development in Europe.

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