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B-MIDIA: A Belief-Structure Multi-Criteria Decision Framework for Analyzing Citizens' Perceptions of Digital Technologies in the European Union

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Abstract

Digital technologies are reshaping economies, labor markets, social security systems, and societal well-being across the European Union, increasing the need for decision-support methods capable of systematically analyzing complex survey evidence. This study proposes B-MIDIA, a parametric extension of the belief-structure TOPSIS framework that integrates the MIDIA (Multi-Criteria Method Integrating Distances to Ideal and Anti-Ideal Points) aggregation mechanism with belief-structure-based multi-criteria decision analysis. The framework preserves the ordinal structure of survey responses and follows the standard belief-structure representation adopted in B-TOPSIS, in which uncertain ("Don't know") responses are incorporated into the evaluation through the normalization procedure. Using published country-level response distributions from Special Eurobarometer 554, the study evaluates public perceptions of recent digital technologies, including artificial intelligence (AI), across EU Member States in five domains: the economy, society, quality of life, current job, and social security benefits. Sensitivity analyses performed for alternative values of the aggregation parameter α, together with comparisons with the benchmark B-TOPSIS rankings, demonstrate the robustness of the proposed aggregation mechanism within the adopted belief-structure framework. Across most dimensions, Lithuania and Malta achieved the highest evaluations, whereas France, Italy, and Romania generally ranked among the lowest. Economic and employment-related evaluations formed the central perception structure and were strongly associated with quality-of-life assessments. The proposed framework extends the analytical capabilities of belief-structure TOPSIS by enabling systematic sensitivity analysis of aggregation assumptions while preserving methodological compatibility with the original framework.

Keywords: multi-criteria decision making; belief structure; B-MIDIA; B-TOPSIS; decision support systems; digital technologies

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1. Introduction

Digital innovations and AI-driven systems are increasingly reshaping economic productivity, organizational governance, employment structures, individual well-being, and social security systems [1–4]. These transformations extend beyond economic processes and affect normative and perceptual dimensions of society, raising concerns regarding fairness, autonomy, inequality, trust, and institutional responsibility [5,6]. As these technologies become more deeply embedded in socio-economic systems, understanding how citizens perceive their impacts is increasingly important for policy design, technology governance, and the development of human-centered digital transformation strategies [7,8].

Large-scale European surveys, including Special Eurobarometer 554 [9], provide extensive evidence on how citizens perceive the impact of digital technologies across five domains: economy, society, quality of life, current job, and social security benefits. Although AI is explicitly mentioned in the questionnaire, the survey does not distinguish perceptions of AI from other digital technologies. Therefore, this study examines citizens' perceptions of those technologies, with AI treated as an integral but not separately isolated component. Nevertheless, AI remains a highly visible aspect of contemporary digital transformation and provides an important context for interpreting the findings.

The responses are interpreted as reflecting citizens' perceptions of digital technologies and their role in contemporary digital transformation processes. Such insights are increasingly relevant for comparative policy evaluation, as public perceptions influence the acceptance, legitimacy, and implementation of digital technologies and AI-enabled systems. However, attitudes towards these technologies are multidimensional, context-dependent, and often characterized by uncertainty. Therefore, their analysis requires methodological approaches that preserve the ordinal response structure while enabling systematic analysis of the complete response distribution.

Questionnaire-based data provide a key empirical foundation in social science research for measuring attitudes, opinions, and behavioral perceptions [10–12]. Although ordinal scales retain ranking information, they lack metric properties [13,14]. Nevertheless, survey analyses frequently transform linguistic categories into numerical values and aggregate them using means or proportions, implicitly imposing cardinal assumptions and thereby simplifying the original ordinal response distribution.

Within multi-criteria decision-making (MCDM), numerous methods have been proposed for analyzing linguistic and ordinal survey data, including TOPSIS [15,16] with GDM2 [17], fuzzy-set methods [18–21], and intuitionistic fuzzy approaches [22–26]. These approaches differ in how ordinal survey information is represented and aggregated, as well as in how they handle uncertainty in respondents' evaluations. Belief-structure approaches [27–31] constitute one methodological stream that explicitly represents uncertain responses during the construction of the evaluation model. An additional challenge concerns responses such as "Don't Know", "Refused", or "No Answer" [32–34]. Particularly in the context of digital technologies, such responses may reflect limited familiarity, uncertainty, or insufficient evaluative confidence rather than simply missing information.

To address these limitations, recent studies have introduced the Belief Structure TOPSIS (B-TOPSIS) framework for analyzing ordinal survey data [26–31]. Belief-structure MCDM approaches provide a formal representation of such responses during the construction of the belief structure [27–30,35]. The resulting belief structures are evaluated using distances to positive and negative ideal solutions after application of the proportion of potential (POP) normalization procedure. This framework enables ordinal response distributions, including uncertain ("Don't know") responses, to be consistently incorporated into the belief-structure evaluation process. The proposed framework adopts this established belief representation and focuses instead on extending the aggregation stage of the decision process.

Although B-TOPSIS provides a coherent framework for representing ordinal survey responses and associated belief structures, its aggregation stage remains fixed and does not allow systematic investigation of how alternative aggregation assumptions influence final rankings. This limitation reduces the analytical flexibility of the framework, particularly when decision makers aim to evaluate ranking stability under different aggregation assumptions.

To overcome this limitation, the present study integrates the B-TOPSIS framework with the MIDIA (Multi-Criteria Method Integrating Distances to Ideal and Anti-Ideal

Points) approach [36–39]. MIDIA introduces the weighting parameter α [40,41], which determines the relative importance of proximity to the ideal solution and distance from the anti-ideal solution, analogously to the Hurwicz decision rule under uncertainty [42]. The resulting Belief Structure MIDIA (B-MIDIA) framework preserves the belief-based representation of survey responses and extends B-TOPSIS by modifying aggregation of the two distance components through the parameter α. Consequently, B-MIDIA can be interpreted as a parametric extension of the B-TOPSIS framework. Rather than modifying the established belief-structure representation or the POP normalization procedure, it introduces a parameterized aggregation mechanism that enables systematic sensitivity analysis while maintaining methodological comparability with previous B-TOPSIS studies.

Although public perceptions of digital technologies are frequently analyzed using averages, percentages, or conventional ranking procedures, such approaches may not fully preserve the ordinal nature of survey responses and often provide only limited treatment of uncertainty associated with non-response categories [43]. This limitation is particularly relevant in cross-country comparisons, where similar aggregate results may conceal substantially different response structures. Therefore, methods capable of preserving the ordinal response structure while consistently incorporating uncertain responses through an established belief-structure representation provide a valuable alternative for comparative analyses of public perceptions across the European Union.

This study assesses and compares public perceptions of digital technologies across EU Member States using data from Special Eurobarometer 554 and two belief-structure-based MCDM methods, namely B-TOPSIS and B-MIDIA. Accordingly, the study addresses the following empirical research questions:

RQ1. How do EU Member States differ in perceived impacts of digital technologies across the five analyzed domains: economy, society, quality of life, current job, and social security benefits?

RQ2. To what extent are country rankings sensitive to alternative aggregation settings within the B-MIDIA framework?

RQ3. To what extent does the balanced B-MIDIA specification ($\alpha = 0.5$) reproduce the benchmark rankings obtained using the B-TOPSIS method?

The proposed methodological framework is evaluated through comparison with the benchmark B-TOPSIS method and sensitivity analyses performed across alternative values of the aggregation parameter α.

This study makes two main contributions. From a methodological perspective, the study proposes B-MIDIA as a parametric extension of the B-TOPSIS framework by replacing the original aggregation stage with the MIDIA aggregation operator controlled by the parameter α. The proposed extension does not modify the established belief-structure representation or the POP normalization procedure. Instead, it introduces a parameterized aggregation mechanism that enables systematic sensitivity analysis while preserving methodological comparability with previous B-TOPSIS studies. Accordingly, the methodological contribution of this study should be interpreted as an extension of the aggregation mechanism rather than as a reformulation of the underlying belief-structure model or uncertainty representation.

From an empirical perspective, using published country-level response distributions from Special Eurobarometer 554 data [9], it provides a comparative assessment of citizens' perceptions of digital technologies across five domains in the EU-27.

The remainder of the paper is organized as follows. Section 2 reviews the literature on public perceptions of digital technologies and digital transformation, with particular attention to AI as one component of the broader technological landscape. Section 3 presents the data and the B-MIDIA methodology. Section 4 reports the empirical results,

including domain-specific analyses, sensitivity analysis, and cross-dimensional comparisons. Section 5 concludes by discussing the main findings, limitations, and directions for future research.

2. Literature Review: Public Perceptions of Digital Technologies Across Key Domains

Given the rapidly growing literature on digital technologies and digital transformation, this review focuses selectively on five domains from Special Eurobarometer 554: economy, society, quality of life, current job, and social security benefits. The review considers recent digital technologies broadly, including artificial intelligence as one important component of contemporary digital transformation. Rather than focusing exclusively on AI, this section examines how digital technologies are perceived across these five domains and provides the conceptual foundation for the empirical framework. Broader discussions of AI governance, public administration, or STS perspectives are beyond the scope of this study and are reserved for future research.

In the economic domain, digital technologies are widely recognized as important drivers of productivity growth and structural transformation [44]. Digitalization is increasingly recognized as a co-evolutionary process linking technological innovation, organizational change, and skills development across all sectors of the economy. The adoption and recombination of these technologies reshape production processes, influence labor demand, and affect productivity and inequality outcomes [45]. The digital economy has become a major engine of economic growth, transforming business models, market interactions, and access to goods and services.

Human capital and digital infrastructure are identified as key determinants of adoption [1], while AI has been shown to support economic growth but may intensify structural disparities within the EU [46]. Similarly, positive GDP effects have been reported, although with heterogeneous regional outcomes [47], and the role of institutional readiness and coordinated digital strategy has been emphasized [48,49].

Overall, the literature suggests that digital technologies enhance productivity while also raising concerns about inequality, labor disruption, and regional divergence, which likely shape public perceptions in this domain.

In the societal domain, the widespread deployment of digital technologies has intensified debates concerning governance, trust, and ethical legitimacy [50]. Digital transformation is increasingly understood as a broader societal shift driven by the growing importance of information processing, connectivity, and algorithmic decision-making. Beyond technological innovation itself, digitalization affects social institutions, communication patterns, governance structures, and citizen participation [51]. The societal consequences of these technologies reflect broader socio-economic and institutional conditions and are reflected in differences in inequality and progress toward sustainable development outcomes [52].

Previous studies indicate that acceptance of AI depends on transparency, accountability, and fairness [6], as well as normative principles such as responsibility and justice [5]. AI in public services may improve efficiency and accessibility, but also deepen exclusion, the digital divide, and algorithmic bias [2]. Public attitudes are strongly influenced by perceived risks, including opacity ("black box" effects), cybersecurity, and institutional trust [53]. Recent work further stresses the need for multi-stakeholder governance integrating ethical and institutional dimensions [54]. Recent European policy initiatives, including the AI Act, further illustrate the growing importance of transparency, accountability, and risk-based governance frameworks in shaping public trust towards AI systems [55]. Overall, public perceptions depend not only on performance but also on trust and perceived governance quality.

Regarding quality of life, digital technologies affect both work and everyday experience [56]. Digital inclusion and access to information and communication technologies have been shown to significantly influence quality of life by improving access to information, services, education, and social participation. Differences in digital access and usage may contribute to variations in perceived well-being across countries.

Human–AI collaboration may increase efficiency and autonomy, but also cognitive load and role ambiguity [57]. Job insecurity is a key channel linking technological change to well-being, affecting stress and psychological stability [58]. Beyond the workplace, AI-enabled services may improve convenience, accessibility, and personalization in everyday activities, thereby shaping individuals' overall assessment of quality of life [59]. AI influences users' sense of control and comfort in everyday interactions [59], while broader digitalization shapes access to services and life quality across Europe with notable cross-country differences [60]. Thus, perceptions combine benefits such as convenience with concerns about stress, uncertainty, and reduced control.

Digital technologies reshape work organization, task composition, and skill requirements. Digitalization is reshaping labor markets through changes in organizational practices, skill requirements, and the increasing integration of digital tools into everyday work processes. Rather than affecting employment solely through automation, digital technologies influence the composition of tasks, the demand for new competencies, and opportunities for continuous learning and adaptation [44].

These technologies increase demand for cognitive and analytical skills rather than simply replacing jobs [61], while also driving upskilling alongside displacement risks, especially for routine occupations [62,63]. Perceived risks of job displacement remain one of the most important determinants of employee attitudes towards AI adoption [62,63]. Algorithmic monitoring may improve productivity but increase stress and perceived surveillance [64]. AI in recruitment and HR improves efficiency but raises concerns about bias and opacity [65–67]. Overall, perceptions in this domain are shaped by job security, employability, and the fairness of algorithmic decision-making.

In social security and welfare systems, digital technologies enhance administrative efficiency in areas such as eligibility assessment and fraud detection [2,68]. The transition towards a digital economy creates both challenges and opportunities for social protection systems. Digitalization affects not only administrative processes but also the coverage, financing, and accessibility of social security programmes [69]. Emerging forms of digitally mediated work, including platform work, raise important questions regarding social protection rights, inclusion, and the capacity of welfare systems to adapt to changing labor-market conditions.

However, risks include exclusion errors, reduced discretion, and automation bias. Trust and legitimacy depend on transparency, accountability, and ethical alignment [5,6] as well as explainability and auditability of models [70–72]. Citizen trust is also strongly linked to fairness, data protection, and appeal mechanisms [55,71–73]. Thus, perceptions are closely tied to institutional trust and procedural justice.

Across all five domains—economy, society, quality of life, current job, and social security benefits—the literature consistently shows that digital technologies produce both enabling and disruptive effects. Productivity gains coexist with inequality risks, administrative efficiency with fairness concerns, and technological advancement with psychological and institutional uncertainty. Public attitudes towards these technologies are multidimensional and may differ substantially across countries.

However, existing comparative studies predominantly rely on descriptive statistics, averages, or proportions, which may not fully preserve the ordinal nature of survey responses. They typically provide limited treatment of uncertainty associated with non-response

categories. As a result, cross-country differences in the structure of perceptions may remain partially obscured. This methodological limitation motivates the application of belief-structure-based MCDM methods, namely B-TOPSIS and B-MIDIA. By representing survey responses through belief structures, these approaches offer a methodological framework for comparative analyses of citizens' perceptions of digital technologies across EU Member States.

3. Materials and Methods

3.1. Problem Description and Data Source

The empirical analysis uses published country-level response distributions from Special Eurobarometer 554: Artificial Intelligence and the Future of Work, conducted between 25 April and 22 May 2024 across the 27 EU Member States [9,74]. The survey was commissioned by the European Commission (DG EMPL) and implemented by the Verian Group.

The original Eurobarometer survey covered N = 26,415 respondents selected using a stratified sampling design to ensure cross-national comparability with respect to age, gender, education, region, and locality size. Data were collected through face-to-face interviews (CAPI) conducted in respondents' native languages. Detailed information on the survey design and implementation is available in the official Eurobarometer documentation [75,76]. The present study does not use individual-level respondent data. Instead, published aggregated country-level response distributions are used as the input data for the proposed B-TOPSIS and B-MIDIA analyses (see Tables A1–A5 in Appendix A).

The questionnaire consists of four thematic blocks, covering digital technologies, digital skills, AI in the workplace, and attitudes toward digitalization. This study uses five items (QB1.1–QB1.5) capturing perceived impacts of recent digital technologies in five dimensions [9,74]:

QB1. In your view, what impact do the most recent digital technologies, including Artificial Intelligence, currently have on:

QB1.1 The economy

QB1.2 Society

QB1.3 Your quality of life

QB1.4 Your current job

QB1.5 Social security benefits

Eurobarometer reports QB1.4 ("Your current job") in two variants: for the full sample of respondents (N = 26,415) and for respondents with a current occupation (QB1.4W; N = 14,146) [74]. In some tables and reports [9,74], these two specifications are not always clearly distinguished, which may lead to inconsistencies in reported results. In this study, QB1.4 is consistently defined using the full sample to ensure comparability across all QB1 items.

Response categories include: "A very positive impact", "A fairly positive impact", "A fairly negative impact", "A very negative impact", "Don't know enough about the most recent digital technologies (spontaneous response)", and "Don't know". The uncertainty-related categories are aggregated into a single "Total Don't know" category (see Appendix A, Tables A1–A5).

Eurobarometer 554 (2024) [9] forms part of a broader monitoring framework on digitalization and AI in the EU across different social and economic contexts, complemented by datasets such as OECD (2024) [77], ESENER (2024) [78], EWCS (2024) [79], and AIM-WORK (2024–2025) [80].

3.2. Belief Structure MIDIA (B-MIDIA) Approach for Ordinal Survey Data

3.2.1. Conceptual Background and Methodological Justification

The proposed Belief Structure MIDIA (B-MIDIA) framework integrates the MIDIA methodology [36–39] with the Belief Structure TOPSIS (B-TOPSIS) framework solutions [27–29,31], extending MIDIA to ordinal survey data represented by belief structures. This integration allows the simultaneous treatment of uncertainty and response dispersion while preserving the full distribution of survey responses.

B-MIDIA adopts from B-TOPSIS the belief-structure representation of ordinal responses, the handling of incomplete information, and distance-based evaluation relative to positive and negative ideal solutions [27–29,31]. From MIDIA [36–39], it introduces a parametric aggregation mechanism controlled by $\alpha \in [0, 1]$ [36,37]. Unlike classical B-TOPSIS, the proposed approach introduces a scenario-sensitive aggregation stage, where α determines the relative importance of proximity to the ideal solution and remoteness from the anti-ideal solution. B-MIDIA combines belief-theoretic uncertainty modelling, ordinal distance evaluation, and parametric MIDIA aggregation. Unlike the original MIDIA framework [36–39], it applies an α-parameterized aggregation scheme directly to belief-structure measures derived from ordinal survey data.

In this study, the belief structure representation is applied at the aggregate level using observed survey response proportions. While classical Dempster–Shafer theory [81,82] defines belief masses as degrees of evidence, here they are operationalized as empirical response frequencies. Accordingly, the resulting "belief structures" should be interpreted as group-level response distributions rather than individual-level beliefs. This preserves the formal structure of belief-based modelling while acknowledging the observational nature of the data.

The proposed approach provides an effective framework for analyzing citizens' perceptions of digital technologies, accommodating ordinal-scale data while accounting for uncertainty in respondents' answers. Although presented for a single-item case, it can be readily extended to multi-item aggregation.

3.2.2. Procedure B-MIDIA for a Single Item

The Belief Structure MIDIA (B-MIDIA) procedure for ordinal survey data and a single item consists of the following steps:

Step 1. Definition of the Evaluation Problem

Let $O = \{O_1, O_2, \ldots O_m\}$ be a set of objects (e.g., countries) evaluated using an ordinal response scale with N categories $H_1, H_2, \ldots, H_N$, where H_k is more preferred than H_{k+1}. An additional category captures "Don't Know/No Answer/Refused" responses.

Step 2. Construction of Belief Structure Models

Each object O_i is represented by a Belief Structure model [27,28]:

$$BS(O_i) = \{(H_k; \beta_{ik}); k = 1, \ldots, N\} \quad (1)$$

where $\beta_{ik} = \frac{n_{ik}}{n_i}$ is the belief degree—i.e., n_{ik} is the number of respondents selecting grade H_k, n_i is the number of respondents who evaluated i-th object. The ignorance degree is defined as: $\beta_{iH} = 1 - \sum_{k=1}^{N} \beta_{ik}$.

This Belief Structure model can be written as a vector:

$$S_i = [\beta_{i1}, \beta_{i2}, \ldots \beta_{iN}]. \quad (2)$$

The degree of ignorance $\beta_{iH} = 1 - \sum_{k=1}^{N} \beta_{ik}$ captures the share of non-responses for i-th object $(i = 1, 2, \ldots m)$.

This step preserves the full distribution of responses and explicitly models hesitation.

Step 3. Normalization of Belief Structures

To ensure comparability and enable distance-based evaluation, the ignorance component is proportionally redistributed across observed response categories using the proportion of potential (POP) method [29,30]:

$$\bar{\beta}_{ik} = \beta_{ik} + \frac{\beta_{ik} \cdot \beta_{iH}}{\sum_{k=1}^{N} \beta_{ik}} \tag{3}$$

yielding normalized belief vector:

$$\bar{S}_i = [\bar{\beta}_{i1}, \bar{\beta}_{i2}, \ldots \bar{\beta}_{iN}] \tag{4}$$

where $\sum_{k=1}^{N} \bar{\beta}_{ik} = 1, k = 1, 2, \ldots, N$.

Step 4. Construct Utility Function and Similarity Matrix

Ordinal categories are embedded into a continuous scale: $U(H_i) \in [0, 1]$ with $U(H_1) = 1, U(H_N) = 0$, and strictly decreasing intermediate utilities, i.e., $U(H_{k+1}) < U(H_k)$ for $k = 1, 2, \ldots, N-1$.

Similarity between categories is defined as [27,28,31]:

$$\tilde{s}_{ij}(H_i, H_j) = 1 - |U(H_i) - U(H_j)|. \tag{5}$$

The resulting similarity matrix [27]:

$$\tilde{S} = [\tilde{s}_{ij}], \tag{6}$$

captures structural relationships between categories.

Step 5. Define Ideal and Anti-Ideal Belief Solutions

Positive Ideal Belief Solution PIBS is as follows:

$$A^+ = [1, \ldots, 0], \tag{7}$$

which means that 100% of respondents assign the highest grade H_1 to the object.

Negative Ideal Belief Solution NIBS is as follows:

$$A^- = [0, \ldots, 1], \tag{8}$$

which means that 100% of respondents assign the lowest grade H_N to the object.

Step 6. Computation of Separation Measures

The belief-based geometric distance between two structures PIBS and NIBS are defined [27,31].

In general, the belief distance between two normalized belief structures $\bar{S}_i, \bar{S}_j$ is defined as [27]:

$$dBS(\bar{S}_i \ \bar{S}_j) = \left(\frac{1}{2}(\bar{S}_i - \bar{S}_j)\tilde{S}(\bar{S}_i - \bar{S}_j)^T\right)^{\frac{1}{2}}. \tag{9}$$

Therefore, the distance from PIBS to the object O_i is calculated as:

$$D_i^+ = d_{BS}(\bar{S}_i, A^+) = \left(\frac{1}{2}(\bar{S}_i - A^+)\tilde{S}(\bar{S}_i - A^+)^T\right)^{\frac{1}{2}}. \tag{10}$$

Similarly, the distance from NIBS to the object O_i is calculated as:

$$D_i^- = d_{BS}(\bar{S}_i, A^-) = \left(\frac{1}{2}(\bar{S}_i - A^-)\tilde{S}(\bar{S}_i - A^-)^T\right)^{\frac{1}{2}}. \tag{11}$$

Both measures D_i^+ and D_i^- lie within the interval $[0,1]$.

Step 7. Construction of Partial Indices

The ideal proximity index is defined as:

$$DI_i = 1 - D_i^+. \tag{12}$$

Anti-Ideal proximity index is defined as:

$$DAI_i = D_i^- \tag{13}$$

Step 8. Aggregation Partial Indices

The final B-MIDIA measure is defined as:

$$D(\alpha)_i = \alpha\, DI_i + (1-\alpha)DAI_i, \tag{14}$$

where $\alpha \in [0,1]$.

We have $D(\alpha)_i \in [0,1]$. This convex combination integrates both perspectives: closeness to the ideal and remoteness from the anti-ideal. Varying α enables the assessment of ranking robustness under different aggregation settings. Lower values of α place greater emphasis on distance from the anti-ideal solution, whereas higher α prioritize proximity to the ideal solution. Extreme α reflects strongly ideal-oriented $(\alpha = 1)$ or anti-ideal-oriented $(\alpha = 0)$ aggregation attitudes. When $\alpha = 0.5$, the measure corresponds to a balanced evaluation.

Step 9. Rank alternatives

Sort $D(\alpha)_i$ in descending order. Higher values indicate better alternatives.

Step 10. Sensitivity analysis

Sensitivity analysis is performed to assess the robustness of rankings with respect to changes in the parameter α and utility values. The procedure may involve scenario analysis, varying one parameter while keeping the others fixed, or Monte Carlo simulation. The utility vector $(U = [U(H_1), \ldots, U(H_N)])$ can be perturbed within predefined intervals to reduce dependence on subjective utility assumptions. Repeated simulations generate alternative ranking distributions, which may be evaluated using stochastic dominance, statistical significance tests (see [29]), or Pearson and Spearman correlation coefficients.

Remark 1. *In this study, "Don't know" responses are initially treated as ignorance within the belief structure framework. To enable distance calculations, a normalization step is required [27,31] performed using the proportion of potential (POP) method [29]. This method redistributes the ignorance mass across observed response categories while preserving their relative proportions. Although normalization produces distributions suitable for computation, it is required to enable distance-based computations within the proposed framework and is therefore purely operational. It does not eliminate or alter uncertainty at the representation level, which remains encoded in the initial belief structure and is carried through the evaluation process.*

The present study adopts the belief-structure representation and POP normalization procedure used in previous B-TOPSIS studies to ensure methodological consistency with previous research and isolate the contribution of the proposed B-MIDIA aggregation mechanism. Alternative normalization procedures or approaches that explicitly preserve the uncertainty associated with "Don't know" responses may provide complementary insights and represent valuable directions for future methodological research.

Remark 2. *Although the above procedure is described for a single questionnaire item, the framework can be extended to multi-item aggregated analysis, based on the B-TOPSIS approach [28,29]. Thus,*

the proposed B–MIDIA framework offers a flexible and theoretically grounded tool for analyzing ordinal perception-based survey data under uncertainty.

3.2.3. Theoretical Properties of the B-MIDIA Measure

The following lemmas summarize the theoretical properties of the B-MIDIA framework introduced in Section 3.2.2. The notation and definitions of the normalized belief structures, belief distance, ideal and anti-ideal solutions, and partial indices DI_i, DAI_i, and the aggregation measure $D(\alpha)_i$ are the same as those introduced in the procedure above. The belief distance $d_{BS}(\bar{S}_i \bar{S}_j)$ for normalized belief structures follows Jiang et al. [27] (see Formula (8)), whereas the remaining properties are direct consequences of the proposed aggregation rule.

Lemma 1 (Properties inherited from the belief distance)**.** *The belief distance d_{BS} satisfies the following properties:*

1. $0 \leq d_{BS}(\bar{S}_i\, \bar{S}_j) \leq 1$;
2. $d_{BS}(\, A^+,\, A^-) = 1$;
3. $D_i^+,\, D_i^- \in [0,1]$;
4. $DI_i(A^+) = DAI_i(A^+) = 1$;
5. $DI_i(A^-) = DAI_i(A^-) = 0$.

Proof. Properties (1) and (2) follow directly from the normalized belief distance introduced by Jiang et al. [27], who proved that d_{BS} is a metric on the space of normalized belief structures. Property (3) follows from Equations (9) and (10), while properties (4) and (5) are immediate consequences of Equations (11) and (12). □

Lemma 2 (Properties of the B-MIDIA measure)**.** *For every object O_i we have the following:*

1. $\Delta_i := DAI_i - DI_i \geq 0$
2. $D_i(0) = DAI_i\,, \quad D_i\,(1) = DI_i$
3. $\max\limits_{\alpha} D(\alpha)_i - \min\limits_{\alpha} D(\alpha)_i = \Delta_i$
4. $D(\alpha)_i$ *is monotonically non-increasing on [0, 1].*

Proof. From Equations (11)–(13), $\Delta_i := D_i^+ + D_i^- - 1$. By the triangle inequality $D_i^+ + D_i^- \geq d_{BS}(A^+, A^-) = 1$ (Lemma 1), hence $\Delta_i \geq 0$. The remaining properties follow directly from Equation (13), which is an affine function of α. □

It is useful to clarify the relationship between B-MIDIA and B-TOPSIS at the level of individual alternatives. The proposed B-MIDIA index replaces the fixed B-TOPSIS aggregation with a controllable convex aggregation. The classical Belief TOPSIS index is defined as [27,28,83]:

$$BT_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{15}$$

where D_i^- represents the separation measure of the object O_i from the NIBS, and D_i^+ represents the separation measure of the object O_i from the PIBS, $i = 1, 2, \ldots, m$.

In particular, this can be shown by examining the structure of the partial distance components. The following lemma formalizes this connection.

Lemma 3. *For each object O_i the B-MIDIA evaluated at $\alpha = 0.5$ can be written as:*

$$D(0.5)_i = 0.5 + 0.5(D_i^- - D_i^+). \tag{16}$$

Moreover, B-TOPSIS and B-MIDIA for $\alpha = 0.5$ coincide for a given object O_i i.e.,

$$BT_i = D(0.5)_i \tag{17}$$

if and only if

$$D_i^- + D_i^+ = 1 \tag{18}$$

Proof. Substituting Equations (11) and (12) into Equation (13) with $\alpha = 0.5$ immediately gives

$$D(0.5)_i = 0.5DI_i + 0.5DAI_i = 0.5\left(1 - D_i^+\right) + 0.5D_i^- = 0.5 + 0.5\left(D_i^- - D_i^+\right)$$

which proves Equation (15).

Using the definition of the B-TOPSIS index (Equation (14)), the equality

$$BT_i = D(0.5)_i$$

holds if and only if

$$\frac{D_i^-}{D_i^- + D_i^+} = 0.5 + 0.5(D_i^- - D_i^+)$$

A straightforward algebraic transformation yields

$$D_i^- + D_i^+ = 1.$$

□

This equivalence holds at the level of individual objects and does not necessarily imply an identity across all objects simultaneously.

4. Results and Discussion

4.1. Analytical Strategy and Item-Level Evaluation Framework

In this section, we apply the B-MIDIA procedure described in Section 3 to the empirical data obtained from Special Eurobarometer 554 [9,74]. The analysis is conducted separately for each questionnaire item (QB1.1–QB1.5), corresponding to the five domains of digital technologies' impact: economy, society, quality of life, current job, and social security benefits.

This item-by-item modeling strategy preserves the conceptual distinctiveness of the analyzed domains while enabling direct comparison between the B-MIDIA ($D(\alpha)$) and B-TOPSIS (BT) measures. Sections 4.2–4.6 address RQ1 through domain-specific analyses, and RQ2 is examined through α-sensitivity and max–min analysis, whereas RQ3 is assessed using Pearson and Spearman correlations between B-MIDIA and B-TOPSIS rankings. To ensure comparability, the same analytical procedure is applied to all five dimensions.

First, survey responses are classified according to the ordinal evaluation scale: H_1 : A very positive impact, H_2 : A fairly positive impact, H_3 : A fairly negative impact, H_4 : A very negative impact. The categories "Don't know enough" and "Don't know" are combined into a single ignorance component. Using the empirical response distributions reported in Appendix A, Tables A1–A5, belief structures are subsequently constructed for each EU Member State and item. This yields a belief distribution vector (Formula (2)) preserving positive, negative, and uncertain responses. The belief structure vectors are normalized using Formula (3).

Next, ordinal categories are embedded into a continuous scale using the utility function [27,28]: $U(H_1) = 1$, $U(H_2) = 0.7$, $U(H_3) = 0.4, U(H_4) = 0$. These values are used to construct the similarity matrix $\tilde{S} = \begin{bmatrix} 1 & 0.7 & 0.4 & 0 \\ 0.7 & 1 & 0.7 & 0.3 \\ 0.4 & 0.7 & 1 & 0.6 \\ 0 & 0.3 & 0.6 & 1 \end{bmatrix}$ (Formulas (5) and (6)), which reflects ordinal proximity between evaluation categories. Distances from the Positive and Negative Ideal Belief Solutions are then calculated using the belief-based geometric distance measures (Formulas (9) and (10)). Finally, EU Member States are ranked using two aggregation approaches: the B-MIDIA index $D(\alpha)$ (Formulas (11)–(13)) and the benchmark B-TOPSIS closeness coefficient (Formula (14)).

In the empirical analysis, $D(\alpha)$ is computed for $\alpha \in \{0, 0.1, 0.2, \ldots, 1\}$, allowing a systematic examination of the sensitivity of country evaluations and rankings to different α specifications. Particular attention is given to the balanced specification ($\alpha = 0.5$), which assigns equal importance to proximity to the ideal solution and distance from the anti-ideal solution.

As established by Lemma 2, the observed monotonicity is a direct consequence of the MIDIA aggregation form and is independent of country-specific characteristics. Therefore, the main analytical focus is placed on the sensitivity amplitude Δ, which measures the responsiveness of the B-MIDIA evaluation to changes in the aggregation parameter α.

A sensitivity analysis of the adopted utility function is additionally performed for the $D(0.5)$ specification. Besides the baseline values $U(H_2) = 0.7$, $U(H_3) = 0.4$, alternative values within ± 0.1 are considered, resulting in nine utility-function variants defined by $U(H_2) \in \{0.6, 0.7, 0.8\}$ and $U(H_3) \in \{0.3, 0.4, 0.5\}$. Pearson and Spearman rank correlation coefficients are used to evaluate the stability of the obtained scores and rankings across alternative specifications.

The procedure yields five B-MIDIA measures ($DQ1(\alpha)$–$DQ5(\alpha)$) and five corresponding B-TOPSIS measures (BTQ1–BTQ5), one for each survey item. For simplicity, the utility parameterization is denoted as $DQk(0.5)(U(H_2), U(H_3))$, with $DQk(0.5)(0.7, 0.4)$ ($k = 1, 2, 3, 4, 5$) representing the baseline specification. Results for individual items are presented in Sections 4.2–4.6, while intercorrelations among the five dimensions based on $DQ1(\alpha)$–$DQ5(\alpha)$ are examined in Section 4.7.

Figure 1 summarizes the overall analytical framework, including sensitivity analysis with respect to the α parameter, utility-function robustness assessment, benchmarking against B-TOPSIS, and cross-dimensional correlation analysis.

4.2. Perceived Impact of Digital Technologies on the Economy in the EU Countries

The results of the $DQ1(\alpha)$ calculation for item QB1.1 are presented in Table 1.

As shown in Table 1, when $\alpha = 0$, scores range from 0.663 (Romania) to 0.817 (Lithuania), whereas for $\alpha = 1$, they range from 0.449 (France) to 0.606 (Lithuania). The EU27 aggregate follows the same pattern, declining from 0.721 to 0.505. The cross-country range changes only marginally, from 0.154 at $\alpha = 0$ to 0.157 at $\alpha = 1$, indicating that changes in α mainly modify the balance between the two partial components (DI and DAI) rather than the overall dispersion of country evaluations.

Consistent with Lemma 2, the observed amplitudes correspond exactly to the empirical range of $DQ1(\alpha)$ across the admissible α interval. The largest max–min amplitudes (Δ) are observed for Finland (0.258), Denmark (0.247), Sweden (0.242), the Netherlands (0.241), and Estonia (0.240), whereas Austria (0.161), Cyprus (0.176), Romania (0.179), Spain (0.184), and Ireland (0.190) exhibit the lowest values.

Table 1. $DQ1(\alpha)$ measure for EU countries under different values of α.

Country	$DQ1(\alpha)$ for Different Values of α											Δ = Max − Min	BTQ1
Coefficient α	**0.00**	**0.10**	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**		
EU27	0.721	0.699	0.678	0.656	0.635	0.613	0.592	0.570	0.549	0.527	0.505	0.216	0.593
Belgium (BE)	0.719	0.695	0.671	0.648	0.624	0.601	0.577	0.554	0.530	0.506	0.483	0.236	0.582
Bulgaria (BG)	0.757	0.734	0.712	0.689	0.667	0.644	0.622	0.599	0.577	0.554	0.532	0.225	0.618
Czechia (CZ)	0.741	0.720	0.699	0.679	0.658	0.638	0.617	0.596	0.576	0.555	0.535	0.206	0.614
Denmark (DK)	0.773	0.748	0.723	0.699	0.674	0.649	0.625	0.600	0.575	0.550	0.526	0.247	0.620
Germany (DE)	0.757	0.733	0.710	0.686	0.663	0.639	0.616	0.592	0.569	0.546	0.522	0.235	0.613
Estonia (EE)	0.788	0.764	0.740	0.716	0.692	0.668	0.644	0.620	0.596	0.572	0.548	0.240	0.636
Ireland (IE)	0.756	0.737	0.718	0.699	0.680	0.661	0.642	0.623	0.604	0.585	0.566	0.190	0.635
Greece (EL)	0.720	0.699	0.677	0.656	0.635	0.613	0.592	0.570	0.549	0.527	0.506	0.214	0.593
Spain (ES)	0.735	0.717	0.699	0.680	0.662	0.643	0.625	0.607	0.588	0.570	0.551	0.184	0.621
France (FR)	0.664	0.643	0.621	0.600	0.578	0.557	0.535	0.514	0.492	0.471	0.449	0.215	0.547
Croatia (HR)	0.739	0.719	0.699	0.679	0.659	0.639	0.619	0.599	0.579	0.559	0.539	0.200	0.616
Italy (IT)	0.707	0.683	0.660	0.636	0.613	0.589	0.566	0.542	0.518	0.495	0.471	0.236	0.572
Cyprus (CY)	0.722	0.705	0.687	0.669	0.652	0.634	0.617	0.599	0.582	0.564	0.546	0.176	0.614
Latvia (LV)	0.743	0.719	0.696	0.673	0.649	0.626	0.603	0.579	0.556	0.533	0.509	0.234	0.602
Lithuania (LT)	0.817	0.796	0.775	0.754	0.732	0.711	0.690	0.669	0.648	0.627	0.606	0.211	0.675
Luxembourg (LU)	0.737	0.717	0.698	0.678	0.659	0.639	0.619	0.600	0.580	0.561	0.541	0.196	0.616
Hungary (HU)	0.724	0.701	0.677	0.653	0.630	0.606	0.582	0.559	0.535	0.511	0.488	0.236	0.586
Malta (MT)	0.810	0.789	0.767	0.745	0.724	0.702	0.680	0.659	0.637	0.616	0.594	0.216	0.666
Netherlands (NL)	0.764	0.740	0.716	0.692	0.668	0.644	0.620	0.595	0.571	0.547	0.523	0.241	0.616
Austria (AT)	0.708	0.692	0.676	0.659	0.643	0.627	0.611	0.595	0.579	0.563	0.546	0.161	0.609
Poland (PL)	0.737	0.715	0.694	0.672	0.651	0.629	0.608	0.586	0.565	0.543	0.522	0.215	0.606
Portugal (PT)	0.738	0.715	0.691	0.668	0.644	0.621	0.597	0.574	0.550	0.527	0.503	0.235	0.598
Romania (RO)	0.663	0.645	0.627	0.609	0.591	0.573	0.556	0.538	0.520	0.502	0.484	0.179	0.562
Slovenia (SI)	0.779	0.756	0.734	0.712	0.689	0.667	0.645	0.622	0.600	0.577	0.555	0.224	0.636
Slovakia (SK)	0.765	0.745	0.724	0.704	0.684	0.663	0.643	0.623	0.603	0.582	0.562	0.203	0.636
Finland (FI)	0.784	0.759	0.733	0.707	0.681	0.655	0.629	0.603	0.577	0.551	0.526	0.258	0.623
Sweden (SE)	0.769	0.744	0.720	0.696	0.672	0.648	0.623	0.599	0.575	0.551	0.527	0.242	0.619

Note: Cell colours are displayed using conditional formatting. For $DQ1(\alpha)$ a yellow-to-green gradient is used, where yellow corresponds to lower values and green to higher values. For Δ = max − min, a red–white–blue gradient is applied, where red indicates the smallest differences, white indicates intermediate differences, and blue indicates the largest differences.

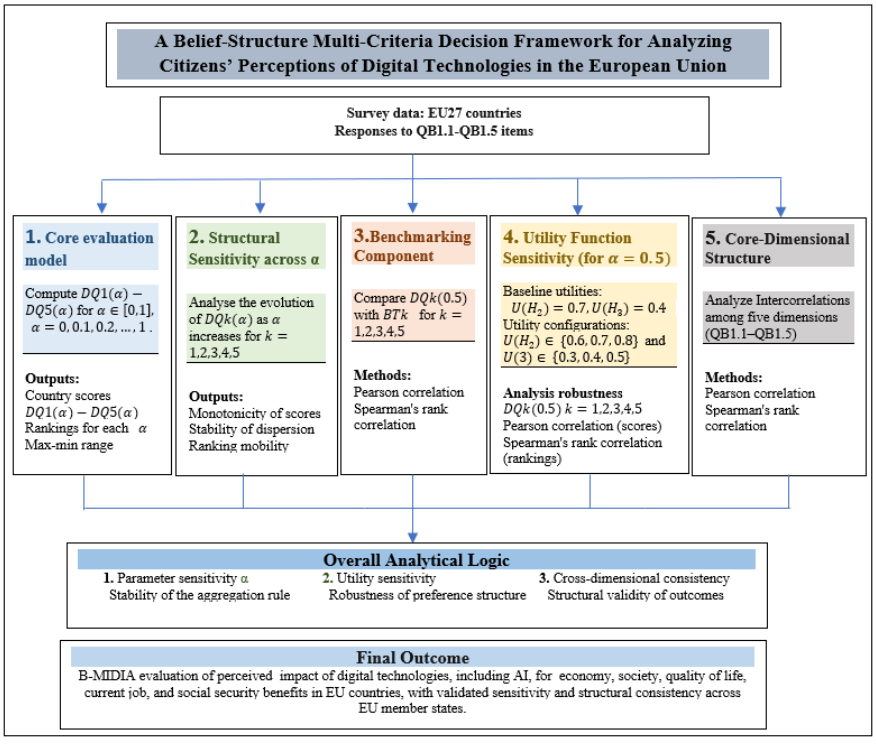

Figure 1. Research framework of the belief-structure multi-criteria decision framework for analyzing citizens' perceptions of digital technologies in the European Union.

Countries characterized by larger Δ generally lose positions as α increases, including Finland (4th–16th), Denmark (6th–15th), Sweden (7th–14th), and the Netherlands (9th–17th) (Figure A1, Appendix B). By contrast, countries with lower Δ improve their relative positions, notably Austria (24th–9th), Cyprus (21st–8th), Spain (19th–6th), and Ireland (12th–3rd) (Figure A1, Appendix B). At the extremes of the ranking, stability is substantially higher: Lithuania and Malta consistently occupy the top two positions across the entire range of α, while France remains at the lower end of the distribution.

Table A1 (Appendix A) indicates a predominantly positive response structure for QB1.1. In the EU27, around 50% of respondents selected the "fairly positive" category, while a further 12% reported a "very positive" evaluation. Negative assessments remain limited (23%), whereas "don't know" responses account for 15% and are consistently present across countries. Countries with higher Δ are characterized by a stronger concentration of responses in the "fairly positive" category and relatively few negative evaluations, whereas lower Δ values are associated with more balanced response distributions.

The BTQ1 results closely correspond to the B-MIDIA rankings, with Lithuania, Malta, Estonia, Slovenia, Slovakia, and Finland occupying the highest positions, while France, Romania, and Italy remain at the lower end (Table 1). Although the leading and trailing countries are clearly distinguishable, several adjacent countries in the ranking differ only marginally in their BTQ1 values. Therefore, these small numerical differences should be interpreted as reflecting broadly comparable levels of perceived economic impact rather than meaningful differences in country performance. The correspondence between the balanced B-MIDIA specification ($\alpha = 0.5$) and the B-TOPSIS benchmark is particularly strong, with Pearson and Spearman correlations equal to 0.997 and 0.980, respectively. The exceptionally high correspondence between the balanced B-MIDIA specification ($\alpha = 0.5$) and the B-TOPSIS benchmark is also consistent with the theoretical relationship established in Lemma 3. Pearson correlations also remain high for the extreme B-MIDIA specifications, reaching 0.913 for $DQ1(0)$ and 0.962 for $DQ1(1)$. The correlation between $DQ1(0)$ and $DQ1(1)$ equals 0.769, indicating that varying α affects relative country positions while preserving the overall structure of the rankings (Figure A2, Appendix B).

The sensitivity analysis of $DQ1(0.5)$ under alternative utility-function parameterizations is presented in Figure A3 (Appendix B). The highest values are obtained for $DQ1(0.5)(0.8, 0.5)$, whereas the lowest correspond to $DQ1(0.5)(0.6, 0.3)$. As expected, the baseline specification $DQ1(0.5)(0.7, 0.4)$ lies between these extremes. Nevertheless, country evaluations remain highly stable across utility variants, with Pearson correlations exceeding 0.957 and Spearman rank correlations exceeding 0.931. These results confirm the robustness of the $DQ1(0.5)$ ranking to reasonable modifications of the utility-function parameters.

Overall, Lithuania and Malta consistently report the most positive perceptions of the economic impact of digital technologies, whereas France, Romania, and Italy remain at the lower end of the ranking regardless of the α specification.

4.3. Perceived Impact of Digital Technologies on Society in the EU Countries

The results of the $DQ2(\alpha)$ calculation for item QB1.2 are presented in Table 2.

As predicted by the theoretical properties of B-MIDIA (Lemma 2), $DQ2(\alpha)$ decreases monotonically throughout the admissible α range. Table 2 shows that when $\alpha = 0$, scores range from 0.608 (France) to 0.761 (Lithuania), whereas for $\alpha = 1$, they range from 0.399 (France) to 0.561 (Lithuania). The EU27 aggregate follows the same pattern, declining from 0.680 to 0.471. The overall cross-country range changes only slightly, increasing from 0.153 to 0.162, indicating that differences between countries remain relatively stable despite alternative aggregation assumptions.

Table 2. $DQ2(\alpha)$ measure for EU countries under different values of α.

Country	$DQ2(\alpha)$ for Different Values of α											Δ = Max − Min	BTQ2
Coefficient α	**0.00**	**0.10**	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**		
EU27	0.680	0.659	0.638	0.617	0.596	0.575	0.554	0.533	0.513	0.492	0.471	0.209	0.562
Belgium (BE)	0.690	0.667	0.643	0.620	0.597	0.573	0.550	0.526	0.503	0.479	0.456	0.234	0.559
Bulgaria (BG)	0.735	0.713	0.691	0.669	0.648	0.626	0.604	0.582	0.560	0.538	0.516	0.219	0.603
Czechia (CZ)	0.648	0.627	0.607	0.587	0.566	0.546	0.526	0.505	0.485	0.465	0.444	0.204	0.538
Denmark (DK)	0.749	0.727	0.705	0.683	0.662	0.640	0.618	0.596	0.574	0.553	0.531	0.218	0.615
Germany (DE)	0.670	0.648	0.625	0.603	0.580	0.558	0.535	0.513	0.490	0.468	0.445	0.225	0.547
Estonia (EE)	0.760	0.738	0.717	0.695	0.674	0.653	0.631	0.610	0.589	0.567	0.546	0.214	0.626
Ireland (IE)	0.701	0.683	0.666	0.648	0.630	0.612	0.594	0.576	0.558	0.540	0.522	0.179	0.595
Greece (EL)	0.684	0.665	0.646	0.627	0.608	0.589	0.570	0.551	0.532	0.513	0.494	0.190	0.575
Spain (ES)	0.702	0.685	0.667	0.650	0.632	0.615	0.597	0.580	0.563	0.545	0.528	0.174	0.598
France (FR)	0.608	0.587	0.566	0.546	0.525	0.504	0.483	0.462	0.441	0.420	0.399	0.209	0.503
Croatia (HR)	0.690	0.671	0.652	0.634	0.615	0.597	0.578	0.559	0.541	0.522	0.504	0.186	0.582
Italy (IT)	0.705	0.683	0.660	0.637	0.615	0.592	0.570	0.547	0.524	0.502	0.479	0.226	0.575
Cyprus (CY)	0.683	0.666	0.650	0.633	0.617	0.600	0.583	0.567	0.550	0.533	0.517	0.166	0.586
Latvia (LV)	0.702	0.680	0.659	0.637	0.616	0.594	0.573	0.551	0.530	0.508	0.487	0.215	0.578
Lithuania (LT)	0.761	0.741	0.721	0.701	0.681	0.661	0.641	0.621	0.601	0.581	0.561	0.200	0.634
Luxembourg (LU)	0.672	0.654	0.636	0.617	0.599	0.581	0.563	0.544	0.526	0.508	0.490	0.182	0.568
Hungary (HU)	0.688	0.666	0.643	0.621	0.598	0.576	0.554	0.531	0.509	0.486	0.464	0.224	0.562
Malta (MT)	0.745	0.724	0.703	0.682	0.661	0.640	0.620	0.599	0.578	0.557	0.536	0.209	0.616
Netherlands (NL)	0.647	0.624	0.602	0.579	0.557	0.534	0.512	0.489	0.467	0.444	0.422	0.225	0.528
Austria (AT)	0.631	0.616	0.602	0.587	0.572	0.557	0.542	0.527	0.513	0.498	0.483	0.148	0.550
Poland (PL)	0.717	0.695	0.673	0.650	0.628	0.606	0.584	0.562	0.539	0.517	0.495	0.222	0.587
Portugal (PT)	0.725	0.704	0.682	0.661	0.639	0.617	0.596	0.574	0.552	0.531	0.509	0.216	0.596
Romania (RO)	0.656	0.639	0.621	0.603	0.586	0.568	0.550	0.533	0.515	0.497	0.480	0.176	0.558
Slovenia (SI)	0.625	0.606	0.587	0.568	0.550	0.531	0.512	0.494	0.475	0.456	0.437	0.188	0.526
Slovakia (SK)	0.706	0.688	0.669	0.650	0.632	0.613	0.595	0.576	0.558	0.539	0.521	0.185	0.596
Finland (FI)	0.746	0.720	0.695	0.669	0.643	0.618	0.592	0.566	0.540	0.515	0.489	0.257	0.594
Sweden (SE)	0.719	0.695	0.672	0.648	0.625	0.601	0.577	0.554	0.530	0.507	0.483	0.236	0.582

Note: Cell colours are displayed using conditional formatting. For $DQ2(\alpha)$ a yellow-to-green gradient is used, where yellow corresponds to lower values and green to higher values. For Δ = max − min, a red–white–blue gradient is applied, where red indicates the smallest differences, white indicates intermediate differences, and blue indicates the largest differences.

The greatest values of Δ are obtained for Finland (0.257), Sweden (0.236), Belgium (0.234), Germany (0.225), and the Netherlands (0.225), whereas Austria (0.148), Cyprus (0.166), Spain (0.174), Romania (0.176), and Ireland (0.179) exhibit the lowest values. Countries exhibiting larger Δ values generally experienced a decline in their ranking positions as α increased, including Finland (4th–15th), Sweden (8th–17th), Italy (11th–20th), and Belgium (15th–22nd). By contrast, countries with lower Δ improve their relative positions, notably Cyprus (19th–8th), Spain (12th–5th), Ireland (14th–6th), and Austria (25th–18th) (Figure A4, Appendix B). At the extremes of the ranking, stability remains very high: Lithuania consistently occupies the first position, Estonia the second, while France remains last across the entire range of α.

Table A2 (Appendix A) indicates that perceptions of the societal impact of digital technologies are somewhat less positive than those related to their economic impact (QB1.1). Across the EU27, approximately 46% of respondents selected the "fairly positive" category and around 10% reported a "very positive" evaluation. Negative assessments account for approximately one-third of responses (33%), while "don't know" responses represent about 11% and display moderate variation across countries. Countries with higher Δ are generally characterized by a stronger concentration of positive evaluations and relatively limited negative responses, whereas lower Δ values are associated with more balanced response distributions.

The BTQ2 results are highly consistent with those obtained using the balanced B-MIDIA specification. Lithuania (0.634), Estonia (0.626), Malta (0.616), and Denmark (0.615) achieve the highest BTQ2 values, whereas France (0.503), Slovenia (0.526), and the Nether-

lands (0.528) remain at the lower end of the ranking (Table 2). The ranking is relatively compact, with several neighboring countries obtaining very similar BTQ2 values. Consequently, these countries should be regarded as exhibiting comparable perceptions of the societal impact of digital technologies. The correspondence between $DQ2(0.5)$ and BTQ2 is exceptionally strong, with Pearson and Spearman correlation coefficients equal to 0.999 and 0.992, respectively. Pearson correlations between BTQ2 and the extreme B-MIDIA specifications also remain very high, reaching 0.939 for $DQ2(0)$ and 0.962 for $DQ2(1)$. The Pearson correlation between $DQ2(0)$ and $DQ2(1)$ equals 0.810, indicating that varying α modifies relative country positions while preserving the overall ranking structure (Figure A5, Appendix B).

Figure A6 (Appendix B) presents the sensitivity of $DQ2(0.5)$ to alternative utility-function parameterizations. Although alternative utility functions affect the absolute $DQ2(0.5)$ values, the overall pattern of country evaluations remains highly stable. Pearson correlations exceed 0.969 and Spearman rank correlations exceed 0.949 across all utility-function variants, confirming the robustness of both the evaluation scores and the resulting country rankings.

Overall, Lithuania, Estonia, and Denmark consistently report the most positive perceptions of the societal impact of digital technologies, whereas France, Slovenia, and the Netherlands remain at the lower end of the ranking regardless of the α specification.

4.4. Perceived Impact of Digital Technologies on Quality of Life in the EU Countries

The results of the DQ3(α) calculation for item QB1.3 are presented in Table 3.

Table 3. $DQ3(\alpha)$ measure for EU countries under different values of α.

Country	$DQ3(\alpha)$ for Different Values of α											Δ = Max − Min	BTQ3
Coefficient α	**0.00**	**0.10**	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**		
EU27	0.719	0.697	0.676	0.654	0.633	0.611	0.589	0.568	0.546	0.525	0.503	0.216	0.591
Belgium (BE)	0.724	0.700	0.676	0.652	0.628	0.604	0.580	0.556	0.532	0.508	0.484	0.240	0.584
Bulgaria (BG)	0.741	0.719	0.698	0.677	0.656	0.635	0.613	0.592	0.571	0.550	0.529	0.212	0.611
Czechia (CZ)	0.702	0.681	0.659	0.638	0.617	0.596	0.575	0.553	0.532	0.511	0.490	0.212	0.579
Denmark (DK)	0.743	0.721	0.700	0.678	0.656	0.634	0.613	0.591	0.569	0.547	0.525	0.218	0.610
Germany (DE)	0.732	0.709	0.685	0.662	0.639	0.616	0.593	0.570	0.547	0.524	0.500	0.232	0.594
Estonia (EE)	0.773	0.751	0.728	0.705	0.683	0.660	0.637	0.615	0.592	0.569	0.547	0.226	0.630
Ireland (IE)	0.754	0.734	0.714	0.694	0.675	0.655	0.635	0.615	0.595	0.575	0.555	0.199	0.629
Greece (EL)	0.694	0.674	0.655	0.635	0.616	0.596	0.576	0.557	0.537	0.517	0.498	0.196	0.580
Spain (ES)	0.737	0.719	0.700	0.681	0.662	0.644	0.625	0.606	0.587	0.568	0.550	0.187	0.621
France (FR)	0.678	0.656	0.634	0.612	0.590	0.567	0.545	0.523	0.501	0.479	0.457	0.221	0.555
Croatia (HR)	0.728	0.708	0.688	0.667	0.647	0.627	0.606	0.586	0.566	0.545	0.525	0.203	0.605
Italy (IT)	0.699	0.677	0.655	0.632	0.610	0.587	0.565	0.542	0.520	0.497	0.475	0.224	0.571
Cyprus (CY)	0.712	0.694	0.676	0.657	0.639	0.620	0.602	0.583	0.565	0.546	0.528	0.184	0.601
Latvia (LV)	0.769	0.745	0.722	0.698	0.674	0.650	0.627	0.603	0.579	0.556	0.532	0.237	0.622
Lithuania (LT)	0.805	0.785	0.765	0.744	0.724	0.704	0.684	0.664	0.644	0.623	0.603	0.202	0.670
Luxembourg (LU)	0.740	0.719	0.698	0.678	0.657	0.636	0.616	0.595	0.574	0.554	0.533	0.207	0.613
Hungary (HU)	0.711	0.688	0.665	0.643	0.620	0.597	0.574	0.551	0.529	0.506	0.483	0.228	0.579
Malta (MT)	0.777	0.758	0.740	0.721	0.703	0.685	0.666	0.648	0.630	0.611	0.593	0.184	0.656
Netherlands (NL)	0.749	0.723	0.698	0.673	0.648	0.623	0.598	0.573	0.548	0.523	0.497	0.252	0.598
Austria (AT)	0.695	0.680	0.665	0.650	0.635	0.620	0.605	0.590	0.575	0.559	0.544	0.151	0.604
Poland (PL)	0.730	0.707	0.684	0.662	0.639	0.616	0.593	0.571	0.548	0.525	0.502	0.228	0.595
Portugal (PT)	0.727	0.705	0.684	0.662	0.641	0.620	0.598	0.577	0.555	0.534	0.512	0.215	0.598
Romania (RO)	0.668	0.650	0.632	0.613	0.595	0.577	0.558	0.540	0.521	0.503	0.485	0.183	0.565
Slovenia (SI)	0.721	0.699	0.678	0.656	0.635	0.613	0.592	0.570	0.549	0.528	0.506	0.215	0.593
Slovakia (SK)	0.736	0.715	0.694	0.673	0.652	0.632	0.611	0.590	0.569	0.548	0.528	0.208	0.609
Finland (FI)	0.757	0.733	0.708	0.684	0.659	0.635	0.610	0.586	0.561	0.537	0.512	0.245	0.608
Sweden (SE)	0.761	0.737	0.713	0.689	0.664	0.640	0.616	0.592	0.568	0.543	0.519	0.242	0.613

Note: Cell colours are displayed using conditional formatting. For $DQ3(\alpha)$ a yellow-to-green gradient is used, where yellow corresponds to lower values and green to higher values. For Δ = max − min, a red–white–blue gradient is applied, where red indicates the smallest differences, white indicates intermediate differences, and blue indicates the largest differences.

The quality-of-life dimension exhibits the same monotonic behavior predicted by the theoretical properties of the B-MIDIA measure. When $\alpha = 0$, scores range from 0.668 (Romania) to 0.805 (Lithuania), whereas for $\alpha = 1$, they range from 0.457 (France) to 0.603 (Lithuania). The EU27 aggregate follows the same pattern, declining from 0.719 to 0.503. Compared with QB1.1 and QB1.2, the overall cross-country dispersion remains relatively moderate, with the range increasing only slightly from 0.137 to 0.146.

The largest max–min amplitudes (Δ) are observed for the Netherlands (0.252), Finland (0.245), Sweden (0.242), Belgium (0.240), and Latvia (0.237), whereas Austria (0.151), Romania (0.183), Cyprus (0.184), Malta (0.184), and Spain (0.187) exhibit the lowest values.

Countries with higher Δ values tended to lose positions as α increased, including the Netherlands (8th–21st), Finland (6th–16th), Sweden (5th–14th), and Belgium (18th–24th). By contrast, countries with lower Δ improve their relative positions, notably Austria (24th–6th), Spain (12th–4th), Cyprus (20th–10th), and Ireland (7th–3rd) (Figure A7, Appendix B). At the top of the ranking, Lithuania and Malta consistently occupy the first two positions across the entire range of α. At the lower end, France remains last from $\alpha = 0.30$ onward, while Romania and Italy remain among the weakest-performing countries throughout the analysis.

Table A3 (Appendix A) indicates the most favorable response structure among all analyzed dimensions. Across the EU27, approximately 50% of respondents selected the "fairly positive" category, while around 12% reported a "very positive" evaluation. Negative assessments account for approximately 24% of responses, indicating a more favorable perception than in the previous dimensions. The distribution of responses across countries remains relatively homogeneous. Countries with higher Δ are generally characterized by a stronger concentration of positive responses, whereas lower Δ values are associated with more balanced response structures.

Once again, the empirical evidence demonstrates the close correspondence between the balanced B-MIDIA specification and B-TOPSIS predicted by Lemma 3. Lithuania (0.670), Malta (0.656), Estonia (0.630), Ireland (0.629), and Latvia (0.622) achieve the highest BTQ3 values, whereas France (0.555), Romania (0.565), and Italy (0.571) remain at the lower end of the ranking (Table 3). Only modest differences separate several neighboring countries in the BTQ3 ranking. Accordingly, the substantive interpretation should emphasize the overall ranking pattern rather than exact ordinal positions where score differences are minimal. The correspondence between $DQ3(0.5)$ and BTQ3 is very strong, with Pearson and Spearman correlation coefficients equal to 0.997 and 0.900, respectively. Pearson correlations between BTQ3 and the extreme B-MIDIA specifications remain high, reaching 0.901 for $DQ3(0)$ and 0.964 for $DQ3(1)$. The Pearson correlation between $DQ3(0)$ and $DQ3(1)$ equals 0.753, indicating that changes in α modify relative country positions to a somewhat greater extent than for QB1.2, while preserving the overall ranking structure (Figure A8, Appendix B).

The sensitivity analysis of $DQ3(0.5)$ under alternative utility-function parameterizations is presented in Figure A9 (Appendix B). Although alternative utility specifications affect the absolute $DQ3(0.5)$ values, the overall distribution of country evaluations remains highly stable. Pearson correlations exceed 0.954 and Spearman rank correlations exceed 0.926 across all utility-function variants, confirming the robustness of both the evaluation scores and the resulting rankings.

Overall, Lithuania and Malta consistently report the most positive perceptions of the impact of digital technologies on quality of life, whereas France, Romania, and Italy remain among the weakest-performing countries regardless of the α specification.

4.5. Perceived Impact of Digital Technologies on Your Current Job in the EU Countries

The results of the $DQ4(\alpha)$ calculation for item QB1.4 are presented in Table 4, while the rankings of EU countries are shown in Figure A10 (Appendix B).

Table 4. $DQ4(\alpha)$ measure for EU countries under different values of α.

Country	$DQ4(\alpha)$ for Different Values of α											Δ = Max − Min	BTQ4
Coefficient α	**0.00**	**0.10**	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**		
EU27	0.711	0.691	0.671	0.651	0.631	0.611	0.591	0.571	0.551	0.530	0.510	0.201	0.592
Belgium (BE)	0.712	0.690	0.668	0.645	0.623	0.601	0.579	0.557	0.534	0.512	0.490	0.222	0.583
Bulgaria (BG)	0.730	0.709	0.688	0.667	0.646	0.625	0.604	0.583	0.561	0.540	0.519	0.211	0.603
Czechia (CZ)	0.709	0.689	0.668	0.648	0.627	0.607	0.587	0.566	0.546	0.526	0.505	0.204	0.589
Denmark (DK)	0.731	0.713	0.695	0.677	0.660	0.642	0.624	0.606	0.588	0.571	0.553	0.178	0.620
Germany (DE)	0.730	0.709	0.688	0.667	0.646	0.624	0.603	0.582	0.561	0.540	0.518	0.212	0.603
Estonia (EE)	0.774	0.752	0.731	0.709	0.688	0.666	0.645	0.623	0.601	0.580	0.558	0.216	0.637
Ireland (IE)	0.740	0.722	0.705	0.687	0.670	0.652	0.635	0.617	0.600	0.582	0.565	0.175	0.630
Greece (EL)	0.715	0.695	0.676	0.657	0.637	0.618	0.599	0.579	0.560	0.541	0.521	0.194	0.599
Spain (ES)	0.724	0.708	0.692	0.676	0.660	0.644	0.628	0.612	0.596	0.580	0.564	0.160	0.624
France (FR)	0.688	0.667	0.646	0.625	0.604	0.583	0.562	0.540	0.519	0.498	0.477	0.211	0.568
Croatia (HR)	0.725	0.706	0.687	0.667	0.648	0.628	0.609	0.590	0.570	0.551	0.532	0.193	0.608
Italy (IT)	0.682	0.661	0.640	0.619	0.598	0.577	0.556	0.535	0.514	0.493	0.472	0.210	0.564
Cyprus (CY)	0.734	0.717	0.700	0.683	0.666	0.649	0.632	0.615	0.598	0.581	0.564	0.170	0.628
Latvia (LV)	0.754	0.733	0.711	0.690	0.669	0.647	0.626	0.604	0.583	0.562	0.540	0.214	0.621
Lithuania (LT)	0.810	0.791	0.771	0.752	0.732	0.713	0.693	0.674	0.654	0.635	0.615	0.195	0.678
Luxembourg (LU)	0.758	0.739	0.719	0.700	0.680	0.661	0.641	0.622	0.602	0.583	0.563	0.195	0.634
Hungary (HU)	0.707	0.686	0.664	0.642	0.621	0.599	0.577	0.555	0.534	0.512	0.490	0.217	0.581
Malta (MT)	0.816	0.798	0.780	0.762	0.743	0.725	0.707	0.689	0.671	0.653	0.635	0.181	0.691
Netherlands (NL)	0.772	0.750	0.728	0.706	0.684	0.662	0.640	0.618	0.595	0.573	0.551	0.221	0.632
Austria (AT)	0.703	0.688	0.674	0.659	0.645	0.630	0.616	0.601	0.587	0.572	0.558	0.145	0.614
Poland (PL)	0.719	0.699	0.678	0.657	0.636	0.616	0.595	0.574	0.553	0.533	0.512	0.207	0.596
Portugal (PT)	0.701	0.682	0.663	0.644	0.625	0.607	0.588	0.569	0.550	0.531	0.512	0.189	0.590
Romania (RO)	0.638	0.621	0.604	0.586	0.569	0.552	0.534	0.517	0.500	0.482	0.465	0.173	0.544
Slovenia (SI)	0.722	0.702	0.682	0.662	0.642	0.622	0.602	0.582	0.562	0.542	0.522	0.200	0.601
Slovakia (SK)	0.711	0.694	0.676	0.659	0.641	0.624	0.606	0.589	0.571	0.554	0.536	0.175	0.605
Finland (FI)	0.780	0.757	0.734	0.711	0.688	0.665	0.642	0.619	0.596	0.574	0.551	0.229	0.634
Sweden (SE)	0.776	0.756	0.736	0.717	0.697	0.678	0.658	0.639	0.619	0.600	0.580	0.196	0.649

Note: Cell colours are displayed using conditional formatting. For $DQ4(\alpha)$ a yellow-to-green gradient is used, where yellow corresponds to lower values and green to higher values. For Δ = max − min, a red–white–blue gradient is applied, where red indicates the smallest differences, white indicates intermediate differences, and blue indicates the largest differences.

The current-job dimension follows the theoretical behavior established for the B-MIDIA measure, with $DQ4(\alpha)$ decreasing monotonically as α increases. Table 4 shows that, when $\alpha = 0$, scores range from 0.638 (Romania) to 0.816 (Malta), whereas for $\alpha = 1$, they range from 0.465 (Romania) to 0.635 (Malta). The EU27 aggregate follows the same pattern, declining from 0.711 to 0.510. Cross-country dispersion changes only marginally, decreasing from 0.178 to 0.170, indicating a high degree of stability in the overall distribution of country evaluations.

The largest max–min amplitudes (Δ) are observed for Finland (0.229), Belgium (0.222), the Netherlands (0.221), Hungary (0.217), and Estonia (0.216), whereas Austria (0.145), Spain (0.160), Cyprus (0.170), Ireland (0.175), and Slovakia (0.175) exhibit the lowest values. Greater Δ values were typically associated with declines in ranking positions, including Finland (3rd–12th), the Netherlands (6th–11th), and Belgium (19th–24th). By contrast, countries with lower Δ improve their relative positions, notably Austria (23rd–9th), Spain (15th–6th), Cyprus (10th–5th), Ireland (9th–4th), and Slovakia (20th–14th) (Figure A10, Appendix B). At the extremes of the ranking, stability remains particularly high. Malta and Lithuania consistently occupy the first two positions throughout the entire range of α, whereas Romania, Italy, and France remain at the lower end of the ranking.

Table A4 (Appendix A) reveals a more uncertain response structure than in the previous dimensions. Across the EU27, approximately 39% of respondents selected the "fairly positive" category and around 11% reported a "very positive" evaluation, while negative assessments account for approximately 20% of responses. The distinguishing feature of this dimension is the comparatively high share of "don't know" responses (approximately 30%), reflecting greater uncertainty regarding the impact of digital technologies on respondents' current jobs. Countries with higher Δ are generally characterized by a stronger concentration of positive evaluations, whereas lower Δ values are associated with more balanced or uncertainty-driven response distributions.

Together with the high agreement between $DQ4(0.5)$ and BTQ4, these results indicate that the theoretical properties established in Section 3 are preserved under empirical data. Malta (0.691), Lithuania (0.678), Sweden (0.649), Estonia (0.637), Luxembourg (0.634), and Finland (0.634) achieve the highest BTQ4 values, whereas Romania (0.544), Italy (0.564), and France (0.568) record the lowest scores (Table 4). Several countries cluster closely together in the BTQ4 ranking, indicating that neighboring positions often correspond to very similar evaluation scores. The correspondence between $DQ4(0.5)$ and BTQ4 is exceptionally strong, with Pearson and Spearman correlation coefficients equal to 0.998 and 0.993, respectively. Pearson correlations between BTQ4 and the extreme B-MIDIA specifications remain very high, reaching 0.947 for $DQ4(0)$ and 0.980 for $DQ4(1)$. The Pearson correlation between $DQ4(0)$ and $DQ4(1)$ equals 0.865, representing the highest value among all analyzed dimensions and indicating particularly strong structural stability of country evaluations (Figure A11, Appendix B).

Figure A12 (Appendix B) illustrates the robustness of $DQ4(0.5)$ under alternative utility-function parameterizations. While the choice of utility function influences the magnitude of $DQ4(0.5)$, it has only a limited impact on the relative ordering of countries. Pearson correlations exceed 0.954 and Spearman rank correlations exceed 0.923 across all utility-function variants, confirming the robustness of both the evaluation scores and the resulting rankings.

Overall, Malta and Lithuania consistently report the most positive perceptions of the impact of digital technologies on current jobs, whereas Romania, Italy, and France remain at the lower end of the ranking regardless of the α specification.

As a robustness check, the analysis for QB1.4W was repeated using only respondents who reported having a current occupation (Table A7, Appendix C). The resulting evaluation scores are slightly higher than those obtained for the full sample, suggesting that employed respondents perceive the impact of digital technologies on their jobs more positively. The proportion of "don't know" responses decreases substantially, ranging from 7% to 23%, compared with 22% to 44% in the full sample (Tables A4 and A6). Moreover, the Pearson correlation coefficient between $BTQ4$ and $BTQ4W$ equals 0.939, indicating a very strong association between the two measures.

The QB1.4 and QB1.4W specifications represent different target populations rather than alternative estimates of the same population. Therefore, QB1.4W is interpreted as a complementary robustness assessment addressing the applicability of the "current job" question among employed respondents. Despite differences in response distributions, the overall pattern of country rankings remains largely unchanged, with the highest- and lowest-ranked countries preserved across both analyses, confirming the stability of the main cross-country conclusions.

4.6. Perceived Impact of Digital Technologies on Social Security Benefits in the EU Countries

The results of the $DQ5(\alpha)$ calculation for item QB1.5 are presented in Table 5.

Table 5. $DQ5(\alpha)$ measure for EU countries under different values of α.

Country	$DQ5(\alpha)$ for Different Values of α											Δ = Max − Min	BTQ5
Coefficient α	**0.00**	**0.10**	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**		
EU27	0.719	0.699	0.679	0.659	0.639	0.619	0.599	0.579	0.559	0.539	0.519	0.199	0.599
Belgium (BE)	0.727	0.704	0.680	0.657	0.634	0.611	0.587	0.564	0.541	0.518	0.494	0.233	0.590
Bulgaria (BG)	0.780	0.758	0.735	0.713	0.691	0.668	0.646	0.623	0.601	0.578	0.556	0.224	0.637
Czechia (CZ)	0.725	0.704	0.683	0.662	0.641	0.619	0.598	0.577	0.556	0.535	0.513	0.212	0.599
Denmark (DK)	0.752	0.733	0.713	0.693	0.674	0.654	0.634	0.615	0.595	0.575	0.556	0.196	0.629
Germany (DE)	0.723	0.700	0.677	0.654	0.631	0.608	0.585	0.562	0.539	0.517	0.494	0.229	0.588
Estonia (EE)	0.773	0.752	0.731	0.711	0.690	0.669	0.648	0.627	0.607	0.586	0.565	0.208	0.640
Ireland (IE)	0.760	0.745	0.730	0.715	0.700	0.685	0.670	0.656	0.641	0.626	0.611	0.149	0.661
Greece (EL)	0.766	0.746	0.726	0.706	0.686	0.666	0.645	0.625	0.605	0.585	0.565	0.201	0.638
Spain (ES)	0.738	0.722	0.706	0.690	0.674	0.658	0.642	0.626	0.610	0.594	0.577	0.161	0.636
France (FR)	0.661	0.642	0.622	0.602	0.582	0.563	0.543	0.523	0.503	0.484	0.464	0.197	0.552
Croatia (HR)	0.746	0.727	0.708	0.689	0.670	0.651	0.632	0.614	0.595	0.576	0.557	0.189	0.627
Italy (IT)	0.727	0.705	0.683	0.661	0.639	0.617	0.595	0.573	0.551	0.529	0.507	0.220	0.596
Cyprus (CY)	0.730	0.714	0.698	0.682	0.666	0.650	0.634	0.618	0.602	0.586	0.570	0.160	0.629
Latvia (LV)	0.772	0.751	0.730	0.709	0.687	0.666	0.645	0.624	0.602	0.581	0.560	0.212	0.637
Lithuania (LT)	0.813	0.794	0.775	0.757	0.738	0.720	0.701	0.683	0.664	0.645	0.627	0.186	0.685
Luxembourg (LU)	0.766	0.746	0.726	0.706	0.686	0.665	0.645	0.625	0.605	0.585	0.565	0.201	0.638
Hungary (HU)	0.725	0.703	0.681	0.659	0.637	0.614	0.592	0.570	0.548	0.526	0.504	0.221	0.594
Malta (MT)	0.801	0.784	0.767	0.750	0.733	0.716	0.699	0.682	0.665	0.648	0.631	0.170	0.684
Netherlands (NL)	0.675	0.654	0.633	0.613	0.592	0.571	0.551	0.530	0.509	0.489	0.468	0.207	0.559
Austria (AT)	0.690	0.677	0.664	0.651	0.638	0.625	0.612	0.599	0.586	0.573	0.560	0.130	0.611
Poland (PL)	0.748	0.726	0.704	0.681	0.659	0.637	0.615	0.593	0.571	0.549	0.526	0.222	0.612
Portugal (PT)	0.760	0.737	0.714	0.691	0.668	0.645	0.622	0.598	0.575	0.552	0.529	0.231	0.618
Romania (RO)	0.696	0.676	0.657	0.637	0.618	0.598	0.579	0.559	0.540	0.520	0.501	0.195	0.582
Slovenia (SI)	0.758	0.737	0.716	0.696	0.675	0.654	0.633	0.613	0.592	0.571	0.551	0.207	0.628
Slovakia (SK)	0.758	0.736	0.714	0.692	0.670	0.648	0.626	0.604	0.582	0.560	0.538	0.220	0.621
Finland (FI)	0.764	0.743	0.722	0.701	0.680	0.659	0.638	0.618	0.597	0.576	0.555	0.209	0.632
Sweden (SE)	0.776	0.758	0.741	0.724	0.706	0.689	0.671	0.654	0.637	0.619	0.602	0.174	0.661

Note: Cell colours are displayed using conditional formatting. For $Q5(\alpha)$ a yellow-to-green gradient is used, where yellow corresponds to lower values and green to higher values. For Δ = max − min, a red–white–blue gradient is applied, where red indicates the smallest differences, white indicates intermediate differences, and blue indicates the largest differences.

The final dimension exhibits the same structural properties as the previous four dimensions, fully consistent with the theoretical properties MIDIA derived in Section 3.2.3. Table 5 shows that, when $\alpha = 0$, scores range from 0.661 (France) to 0.813 (Lithuania), whereas for $\alpha = 1$ they range from 0.464 (France) to 0.631 (Malta). The EU27 aggregate follows the same pattern, declining from 0.719 to 0.519. The overall cross-country range increases only slightly, from 0.152 to 0.167, indicating that differences between countries remain relatively stable despite changes in the aggregation parameter.

The highest Δ values are recorded for Belgium (0.233), Portugal (0.231), Germany (0.229), Bulgaria (0.224), Poland (0.222), Hungary (0.221), and Slovakia (0.220), whereas Austria (0.130), Ireland (0.149), Cyprus (0.160), Spain (0.161), and Malta (0.170) exhibit the lowest values. Countries characterized by larger Δ generally lose positions as α increases, whereas those with lower Δ improve their relative rankings. In particular, Finland declines from 9th to 15th owing to its comparatively higher sensitivity to α, while Ireland, Spain, and Cyprus move upward because of their relatively limited score reductions (Figure A13, Appendix B). At the top of the ranking, Lithuania and Malta consistently occupy the leading positions, with Lithuania ranking first for lower values of α and Malta becoming the highest-ranked country as α approaches 1. At the lower end of the ranking, France remains last throughout the entire range of α, while the Netherlands consistently belongs to the weakest-performing group.

Table A5 (Appendix A) indicates a predominantly positive yet relatively uncertainty-sensitive response structure. Across the EU27, approximately 48% of respondents selected the "fairly positive" category, and around 14% reported a "very positive" evaluation.

Negative assessments account for approximately 22% of responses, whereas "don't know" responses represent about 16%, indicating a moderate degree of uncertainty regarding the impact of digital technologies on social security and welfare-related services. Countries with higher Δ are generally characterized by a stronger concentration of positive evaluations and relatively low uncertainty, whereas lower Δ values are associated with more balanced or uncertainty-driven response distributions.

The BTQ5 results closely correspond to the balanced B-MIDIA specification. Lithuania (0.685) and Malta (0.684) achieve the highest BTQ5 values, followed by Ireland (0.661), Sweden (0.661), Estonia (0.640), Greece (0.638), and Luxembourg (0.638). France (0.552), the Netherlands (0.559), and Romania (0.582) remain at the lower end of the ranking (Table 5). The difference between the two highest-ranked countries is minimal, and similarly small differences are observed for several neighboring countries throughout the ranking. This indicates that adjacent positions frequently represent comparable levels of perceived impact. The correspondence between $DQ5(0.5)$ and BTQ5 is very strong, with Pearson and Spearman correlation coefficients equal to 0.997 and 0.902, respectively. Pearson correlations between BTQ5 and the extreme B-MIDIA specifications remain high, reaching 0.904 for $DQ5(0)$ and 0.977 for $DQ5(1)$. The Pearson correlation between $DQ5(0)$ and $DQ5(1)$ equals 0.794, indicating that changes in α influence relative country positions while preserving the overall ranking structure (Figure A14, Appendix B).

The sensitivity analysis of $DQ5(0.5)$ under alternative utility-function parameterizations is presented in Figure A15 (Appendix B). The utility specifications produce slight differences in the absolute values of $DQ5(0.5)$, but the resulting pattern of country evaluations remains remarkably stable. Pearson correlations exceed 0.968 and Spearman rank correlations exceed 0.944 across all utility-function variants, confirming the robustness of both the evaluation scores and the resulting rankings.

Overall, Lithuania and Malta consistently report the most positive perceptions of the impact of digital technologies on social security and welfare-related services, whereas France and the Netherlands remain at the lower end of the ranking regardless of the α specification.

4.7. Cross-Dimensional Correlation Structure

To further examine the multidimensional structure underlying these perceptions, the correlation matrix between the five TOPSIS-based dimensions (BTQ1–BTQ5) is presented in Table 6.

Table 6. Pearson and Spearman correlation rank coefficients between BTQ1–BTQ5 measures.

Pearson (r)	BTQ1	BTQ2	BTQ3	BTQ4	BTQ5	Spearman (ρ)	BTQ1	BTQ2	BTQ3	BTQ4	BTQ5
BTQ1	1.000					BTQ1	1.000				
BTQ2	0.595	1.000				BTQ2	0.579	1.000			
BTQ3	0.892	0.744	1.000			BTQ3	0.772	0.751	1.000		
BTQ4	0.860	0.556	0.907	1.000		BTQ4	0.778	0.537	0.875	1.000	
BTQ5	0.774	0.773	0.843	0.763	1.000	BTQ5	0.690	0.708	0.829	0.744	1.000

As shown in Table 6, the strongest association is observed between the country-level rankings for quality of life (BTQ3) and current job impact (BTQ4) (r = 0.907). This indicates that countries receiving higher evaluations in one of these dimensions also tend to receive high evaluations in the other. Strong associations are also observed between economic impact (BTQ1) and quality of life (r = 0.892), as well as between economic and job-related perceptions (r = 0.860). These results suggest that the corresponding country rankings exhibit similar patterns across these perception domains.

In contrast, the societal dimension (BTQ2) shows more moderate correlations with economic (r = 0.595) and job-related perceptions (r = 0.556), although its association with

quality of life remains higher (r = 0.744). This suggests that country rankings in the societal domain are related to, but not fully aligned with, rankings observed in the remaining dimensions. The social security dimension (BTQ5) is also strongly correlated with the remaining dimensions (r = 0.763–0.843), indicating that countries evaluated more positively in social security-related perceptions also tend to rank relatively highly in the other analyzed domains.

Spearman rank correlations reveal a similar pattern, with the strongest rank-based association observed between quality of life and job impact (ρ = 0.875), followed by quality of life and social security (ρ = 0.829) and economic impact and job impact (ρ = 0.778). The societal dimension remains the least strongly associated with the remaining dimensions (ρ = 0.537–0.579). The close agreement between the Pearson and Spearman coefficients suggests that the observed relationships are relatively stable and are not driven by a small number of extreme observations.

Overall, the results indicate that the five dimensions are not independent in terms of the obtained country-level rankings. Countries receiving relatively favorable evaluations in one perception domain tend to receive favorable evaluations in other domains as well, although the strength of these associations varies across dimensions. These findings should therefore be interpreted as relationships between country rankings derived from survey-based perceptions of citizens rather than as evidence of causal relationships between the underlying phenomena.

4.8. Comparison with Positive-Response-Based Rankings

In Special Eurobarometer 554: Artificial Intelligence and the Future of Work Report [76], country rankings are constructed using only the proportion of positive responses. While such measures are simple and intuitive, they neglect substantial information contained in the remaining response categories. In particular, they do not account for the ordinal structure of responses, the distribution of opinions across categories, or the presence of uncertainty reflected by non-substantive responses.

The belief-structure-based approach adopted in this study differs fundamentally from positive-response indicators. Rather than focusing exclusively on favorable evaluations, B-TOPSIS and B-MIDIA utilize the response information represented through belief structures. Countries with similar shares of positive responses may exhibit different rankings if their underlying response structures differ. Unlike positive-response indicators, the proposed framework is directly grounded in the theoretical properties established in Section 3, allowing both compensability (controlled by α) and response uncertainty to be incorporated into the aggregation process.

To assess the practical implications of this distinction, the rankings obtained using B-TOPSIS (Tables 1–5) were compared with rankings based solely on total positive responses (Tables A1–A5, Appendix A). Pearson and Spearman correlation coefficients were calculated separately for each domain. The obtained coefficients were as follows: Economy (Pearson = 0.827, Spearman = 0.794), Society (Pearson = 0.827, Spearman = 0.794), Quality of Life (Pearson = 0.698, Spearman = 0.566), Current Job (Pearson = 0.530, Spearman = 0.463), and Social Security Benefits (Pearson =0.748, Spearman = 0.618).

The degree of agreement between the two approaches varies across domains. Relatively strong correlations for Economy and Society suggest that rankings based on positive-response rates capture a substantial part of the information contained in the corresponding belief-structure rankings. In contrast, the noticeably lower correlations observed for Quality of Life, Current Job, and Social Security Benefits indicate that incorporating the complete response distribution, including neutral, negative, and uncertain responses, may lead to more substantial changes in country rankings.

The reason for these differences can be illustrated by comparing countries with identical positive-response shares but different underlying response structures. For example, Czechia and Germany report the same proportion of positive evaluations regarding the impact of digital technologies on the economy (69%). However, the composition of these responses differs: Czechia has a higher share of "very positive" evaluations (17% vs. 13%) and a lower proportion of "Don't know" responses (9% vs. 14%) than Germany. Consequently, although both countries would receive the same position under a simple positive-response indicator, their belief structures represent different patterns of citizens' perceptions. The B-TOPSIS and B-MIDIA approaches capture these differences by considering the distribution of responses across categories rather than relying solely on aggregated positive shares.

The results indicate that although the rankings are positively associated, they are not identical, confirming that positive-response indicators capture only part of the information represented within the belief-structure framework. This suggests that reliance on positive-response rates alone may oversimplify public perceptions and obscure important differences in the structure of attitudes across countries. In particular, rankings based solely on positive responses ignore the distribution of neutral and negative evaluations as well as the uncertainty captured within the belief-structure framework.

These findings are consistent with previous studies comparing traditional aggregation approaches with belief-structure-based methods [28,30,31,35], which have shown that preserving the full response distribution can provide a more nuanced and informative representation of survey-based evaluations.

4.9. Key Empirical Findings

The empirical analysis provides several methodological and substantive findings regarding the proposed B-MIDIA framework and the perception of the impact of digital technologies across the European Union.

First, for every analyzed indicator, the B-MIDIA values decrease monotonically with increasing values of the aggregation parameter α, exactly as implied by the affine form of the proposed aggregation rule (Lemma 2). Although the absolute evaluation scores decline throughout the entire α interval, the overall dispersion of country evaluations remains remarkably stable. Consequently, changes in α influence mainly the relative ordering of countries rather than the general structure of the evaluation space. Despite noticeable ranking shifts within the middle part of the distributions, the highest- and lowest-ranked countries remain largely unaffected by changes in α. Lithuania and Malta consistently occupy the leading positions in most analysed dimensions, whereas France, Romania, and, depending on the analysed indicator, Italy or the Netherlands remain among the lowest-ranked countries. The empirical results, therefore, suggest that the proposed sensitivity analysis primarily affects intermediate-ranking countries, while preserving the overall ordering of the strongest and weakest performers.

Second, the sensitivity parameter Δ, introduced theoretically in Lemma 2, proves to be an informative measure of ranking robustness. As predicted by the theoretical relationship, countries characterized by larger Δ values consistently exhibit greater changes in ranking positions as α increases, whereas countries with lower Δ remain considerably more stable. This pattern appears systematically across all five analysed dimensions, indicating that Δ provides an interpretable measure of sensitivity to aggregation preferences rather than merely describing numerical variability.

The analysis of response distributions presented in Appendix A helps explain this behavior. Countries exhibiting larger Δ values are generally characterized by stronger concentrations of positive responses, particularly within the "fairly positive" category, whereas countries displaying lower Δ values tend to have more balanced response struc-

tures or relatively larger shares of "don't know" responses. Taken together, Δ captures not only mathematical sensitivity but also reflects important characteristics of the underlying response distributions, thereby providing an intuitive explanation for the observed ranking dynamics.

Third, across all five analyzed dimensions, the Pearson correlation coefficients between the balanced B-MIDIA specification ($\alpha = 0.5$) and B-TOPSIS exceed 0.99, while the corresponding Spearman rank correlations are similarly close to unity. These results demonstrate an almost perfect agreement not only in the obtained scores but also in the resulting country rankings. A comparison across different values of the parameter α further reveals that the balanced specification $(\alpha = 0.5)$ consistently exhibits the highest agreement with the B-TOPSIS benchmark. In contrast, the extreme specifications ($\alpha = 0$) and ($\alpha = 1$) produce lower, although still very high, correlations. This pattern suggests that differences between the aggregation methods become more pronounced at the boundary values of α, whereas intermediate values lead to highly consistent evaluations.

At the same time, several neighboring countries across all five dimensions exhibit only very small differences in evaluation B-TOPSIS scores. Consequently, the reported rankings should primarily be interpreted as descriptive summaries of relative country performance, with greater emphasis placed on broader ranking patterns than on exact ordinal positions where score differences are negligible.

The comparison with the belief-based TOPSIS benchmark provides strong empirical support for the theoretical relationship established in Lemma 3. Although the exact equivalence between B-MIDIA evaluated at $\alpha = 0.5$ and B-TOPSIS formally requires the condition $D_i^- + D_i^+ = 1$, for each alternative, the empirical evidence indicates that this relationship holds remarkably well in practice.

Fourth, the robustness analysis based on alternative utility-function parameterizations suggests that the proposed methodology is insensitive to reasonable modifications of the utility specification. Although different utility functions slightly affect the absolute values of the B-MIDIA indices, the resulting rankings remain highly stable across all analyzed dimensions. The consistently high Pearson and Spearman correlation coefficients confirm that the substantive conclusions do not depend on a particular choice of utility-function parameters.

In addition to demonstrating robustness with respect to utility-function specification, the proposed framework also provides insight into the sources of variability in the evaluation process. The MIDIA framework allows for disentangling three distinct sources of variation: (i) α-sensitivity driving ranking mobility, (ii) max–min sensitivity, measuring the range of evaluation values across the admissible α interval, and (iii) utility-function sensitivity affecting only level calibration. This decomposition facilitates a clearer interpretation of whether observed variation stems from changes in α, response structure, or utility-function specification.

Fifth, the empirical application reveals systematic differences in the perception of the impact of digital technologies across the analyzed domains. Across all five dimensions, responses are consistently skewed toward positive evaluations but differ in their degree of uncertainty and internal balance. The economy, society, and quality of life dimensions (QB1.1–QB1.3) exhibit relatively stable profiles with high shares of "fairly positive" responses and moderate uncertainty. The current-job dimension (QB1.4) differs from the others, with higher uncertainty and stronger fragmentation, while the social security dimension (QB1.5) is characterized by relatively high shares of positive responses, moderate uncertainty, and a more balanced response structure. Perceptions of the impact of digital technologies on the economy and quality of life are generally more positive than perceptions concerning society or employment, while assessments related to social security remain

relatively heterogeneous across Member States. Despite these differences, the general behavioral properties of the B-MIDIA framework remain remarkably consistent across all analyzed indicators.

Finally, the proposed B-MIDIA framework extends conventional belief-based multicriteria evaluation beyond the construction of a single composite ranking. Instead of providing only a single evaluation under fixed aggregation assumptions, the proposed method quantifies the robustness of rankings and identifies countries whose evaluations are particularly sensitive to aggregation preferences through the Δ parameter. At the same time, it preserves strong compatibility with the well-established B-TOPSIS approach.

Consequently, B-MIDIA offers both a theoretically grounded generalization of belief-based multicriteria analysis and a practical tool for robustness assessment in decision-making problems involving uncertain and ordinal information. These properties make B-MIDIA a useful methodological framework for comparative analyses involving subjective evaluations collected on ordinal response scales.

4.10. Policy Implications and Interpretation

The empirical findings reveal a coherent but uneven pattern of perceptions of recent digital technologies across EU Member States, with persistent differences observed between countries and substantial associations across the analyzed dimensions.

The observed stability of rankings at the top and bottom of the distribution suggests that cross-country differences in perceptions are relatively consistent within the analyzed dataset. These patterns are broadly in line with descriptive evidence from the Digital Economy and Society Index (DESI) [84], which reports persistent disparities in digital skills, infrastructure, and digital public services across Europe. However, it should be emphasized that the present analysis does not establish any statistical relationship or causal link between DESI and the B-MIDIA results.

The correlation analysis indicates that perceptions related to economic impacts and current jobs are more strongly associated with quality-of-life evaluations than with other dimensions. By contrast, the social and social-security dimensions exhibit somewhat weaker relationships, suggesting that these domains may be evaluated differently from economic, job-related, and quality-of-life perceptions.

From a policy perspective, the results are consistent with the broader literature on digital technologies and AI adoption, which highlights the importance of institutional capacity, regulatory quality, and public trust in shaping technology acceptance [71,85]. Previous studies also emphasize transparency, explainability, and perceived fairness as important factors influencing trust in digital systems [6], while European policy frameworks increasingly conceptualize digital transformation as a socio-technical process requiring governance, accountability, and ethical oversight [55,72].

Overall, the results indicate that perceptions of recent digital technologies differ systematically across EU countries and across policy domains. These findings support ongoing EU efforts to promote human-centric and trustworthy digital technologies while demonstrating systematic variation in country evaluations. Although the present study does not identify the determinants of these differences, future research could fruitfully explore their relationship with external structural indicators such as DESI, GDP, or digital skills measures.

5. Conclusions

This study proposes and empirically implements a belief-structure-based decision-support framework for assessing citizens' perceptions of digital technologies across EU Member States. By integrating B-TOPSIS with the MIDIA approach, the framework ad-

dresses a central challenge in ordinal survey analysis: how to preserve distributional information and uncertainty while producing coherent and comparable cross-country rankings. The proposed framework is intended to complement rather than replace the original B-TOPSIS methodology by providing an additional analytical perspective through parameterized aggregation.

The main contribution lies in extending the belief-structure framework by introducing a parametric aggregation mechanism based on the α parameter. This enables the systematic exploration of alternative decision perspectives, ranging from ideal- to anti-ideal-oriented aggregation, without imposing restrictive cardinal assumptions. Empirical results reveal a highly regular structure across all five evaluated domains. The $DQk(\alpha)$ ($k = 1, 2, \ldots, 5$) values decrease monotonically with increasing α, while the overall dispersion of country evaluations remains largely stable. This indicates that inequality patterns are preserved rather than fundamentally reshaped. Ranking variations are primarily concentrated in the middle of the distribution, whereas top- and bottom-ranked countries remain robust across specifications. The balanced specification ($\alpha = 0.5$) closely aligns with the B-TOPSIS benchmark, confirming the internal consistency of the proposed framework. At the same time, varying α provides additional insight into the stability of country rankings under alternative aggregation assumptions, extending the analytical capabilities beyond those offered by conventional B-TOPSIS or rankings based solely on positive-response shares.

Across dimensions, the results reveal a coherent yet clearly multidimensional structure of country-level perceptions of digital technologies in the EU. Economic, current-job, and quality-of-life evaluations form a central and strongly interconnected cluster, while societal and social-security dimensions provide complementary but partially distinct perspectives. High consistency between Pearson and Spearman correlations confirms the stability of these relationships across specifications.

From a broader perspective, the model contributes to the development of intelligent decision-support systems by demonstrating how ordinal and uncertain survey data can be transformed into explainable and analytically tractable information. The integration of belief structures and multi-criteria evaluation supports transparent and human-centred decision-making in complex socio-technical environments.

Despite its contributions, the study is limited by its cross-sectional design, which prevents the analysis of temporal dynamics in perceptions of digital technologies. The framework operates at the country level, thereby masking within-country differences related to demographic or socio-economic factors. In addition, results depend on predefined ordinal response categories, which constrain measurement flexibility. Finally, the α parameter should be interpreted as a modelling parameter used to explore alternative aggregation scenarios rather than an empirically estimated behavioral parameter.

Because the present analysis is based on published country-level response distributions rather than respondent-level microdata, uncertainty arising from sampling variability cannot be directly quantified. Consequently, the reported rankings should be interpreted primarily as descriptive comparative evaluations, and small differences between neighboring countries should not be interpreted as substantively meaningful.

Future research could extend the framework to longitudinal data in order to capture dynamic changes in perceptions of digital technologies and ranking stability over time. Multilevel extensions based on respondent-level data could incorporate individual sociodemographic characteristics while also enabling the application of alternative inferential procedures, such as bootstrap resampling and confidence-interval estimation, to assess ranking uncertainty and robustness.

The choice to retain the belief-structure representation and POP normalization procedure from previous B-TOPSIS studies was intended to ensure methodological comparability,

so that the impact of the proposed aggregation mechanism could be evaluated independently. Alternative normalization procedures or approaches that explicitly preserve the uncertainty associated with "Don't know" responses may provide complementary insights and represent valuable directions for future methodological research.

Further methodological developments may focus on alternative approaches to uncertainty modelling. In particular, future studies could compare different treatments of "Don't know" responses, including alternative redistribution and normalization procedures beyond the POP method, and explicit belief-mass representations. Such comparative analyses would provide deeper insights into how different assumptions regarding uncertainty propagation influence country rankings and decision outcomes.

Another promising direction concerns the extension of the aggregation framework itself. Future research may investigate alternative utility functions and aggregation operators, as well as empirical approaches to α calibration based on stakeholder preference elicitation, thereby moving beyond purely technical sensitivity analysis towards context-specific decision support. Hybrid and fuzzy belief-structure models may further enhance the representation of ambiguity and complex uncertainty in ordinal survey data. Future methodological studies may extend the benchmarking framework by comparing the proposed approach with additional descriptive indices and statistical models applied to ordinal survey data.

Finally, future studies could integrate the proposed framework with external explanatory variables, such as indicators of digital development, socio-economic conditions, institutional quality, or digital skills, to better understand the determinants of cross-country differences in public perceptions.

Beyond the present application, the proposed framework is readily transferable to other domains involving ordinal and uncertain data, including sustainability transitions, digital governance, and public health.

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Conflicts of Interest: The author declares no conflicts of interest.

Appendix A

Table A1. QB1.1. In your view, what impact do the most recent digital technologies, including Artificial Intelligence, currently have on: The economy.

Country	A Very Positive Impact	A Fairly Positive Impact	A Fairly Negative Impact	A Very Negative Impact	Don't Know	Total 'Positively'	Total 'Negatively'
EU27	12%	50%	18%	5%	15%	62%	23%
BE	9%	56%	20%	5%	10%	65%	25%
BG	13%	49%	12%	3%	23%	62%	15%

Table A1. *Cont.*

Country	A Very Positive Impact	A Fairly Positive Impact	A Fairly Negative Impact	A Very Negative Impact	Don't Know	Total 'Positively'	Total 'Negatively'
CZ	17%	52%	18%	4%	9%	69%	22%
DK	12%	55%	11%	2%	20%	67%	13%
DE	13%	56%	14%	3%	14%	69%	17%
EE	15%	56%	8%	2%	19%	71%	10%
IE	19%	46%	12%	4%	19%	65%	16%
EL	11%	53%	12%	7%	17%	64%	19%
ES	19%	46%	16%	5%	14%	65%	21%
FR	7%	41%	26%	7%	19%	48%	33%
HR	17%	51%	15%	5%	12%	68%	20%
IT	8%	53%	23%	5%	11%	61%	28%
CY	19%	47%	15%	7%	12%	66%	22%
LV	10%	47%	14%	3%	26%	57%	17%
LT	24%	53%	6%	1%	16%	77%	7%
LU	17%	49%	15%	5%	14%	66%	20%
HU	9%	52%	19%	4%	16%	61%	23%
MT	22%	53%	7%	1%	17%	75%	8%
NL	14%	60%	16%	2%	8%	74%	18%
AT	19%	42%	15%	8%	16%	61%	23%
PL	14%	54%	15%	5%	12%	68%	20%
PT	9%	45%	14%	3%	29%	54%	17%
RO	12%	39%	22%	9%	18%	51%	31%
SI	19%	59%	13%	2%	7%	78%	15%
SK	20%	52%	14%	3%	11%	72%	17%
FI	12%	58%	11%	1%	18%	70%	12%
SE	13%	56%	13%	2%	16%	69%	15%

Source: [9,74].

Table A2. QB1.2. In your view, what impact do the most recent digital technologies, including Artificial Intelligence, currently have on: Society.

Country	A Very Positive Impact	A Fairly Positive Impact	A Fairly Negative Impact	A Very Negative Impact	Don't Know	Total 'Positively'	Total 'Negatively'
EU27	10%	46%	26%	7%	11%	56%	33%
BE	7%	53%	27%	6%	7%	60%	33%
BG	12%	48%	15%	4%	21%	60%	19%
CZ	8%	45%	29%	10%	8%	53%	39%
DK	16%	54%	18%	3%	9%	70%	21%
DE	7%	43%	30%	6%	14%	50%	36%
EE	16%	50%	13%	3%	18%	66%	16%
IE	16%	43%	19%	7%	15%	59%	26%
EL	12%	47%	18%	9%	14%	59%	27%
ES	18%	43%	21%	7%	11%	61%	28%
FR	4%	39%	34%	12%	11%	43%	46%
HR	15%	43%	24%	7%	11%	58%	31%
IT	10%	52%	25%	5%	8%	62%	30%
CY	17%	45%	19%	10%	9%	62%	29%
LV	11%	42%	25%	4%	18%	53%	29%

Table A2. *Cont.*

Country	A Very Positive Impact	A Fairly Positive Impact	A Fairly Negative Impact	A Very Negative Impact	Don't Know	Total 'Positively'	Total 'Negatively'
LT	20%	51%	15%	3%	11%	71%	18%
LU	14%	44%	25%	9%	8%	58%	34%
HU	8%	48%	25%	6%	13%	56%	31%
MT	17%	50%	19%	3%	11%	67%	22%
NL	5%	47%	34%	9%	5%	52%	43%
AT	16%	35%	26%	13%	10%	51%	39%
PL	11%	52%	20%	5%	12%	63%	25%
PT	11%	44%	16%	4%	25%	55%	20%
RO	13%	37%	26%	9%	15%	50%	35%
SI	11%	36%	37%	11%	5%	47%	48%
SK	17%	48%	21%	7%	7%	65%	28%
FI	9%	59%	20%	2%	10%	68%	22%
SE	10%	55%	24%	4%	7%	65%	28%

Source: [9,74].

Table A3. QB1.3. In your view, what impact do the most recent digital technologies, including Artificial Intelligence, currently have on: Your quality of life.

Country	A Very Positive Impact	A Fairly Positive Impact	A Fairly Negative Impact	A Very Negative Impact	Don't Know	Total 'Positively'	Total 'Negatively'
EU27	12%	50%	19%	5%	14%	62%	24%
BE	9%	59%	19%	5%	8%	68%	24%
BG	13%	46%	13%	4%	24%	59%	17%
CZ	12%	51%	24%	6%	7%	63%	30%
DK	14%	52%	15%	4%	15%	66%	19%
DE	11%	50%	20%	3%	16%	61%	23%
EE	15%	53%	9%	3%	20%	68%	12%
IE	18%	46%	15%	3%	18%	64%	18%
EL	12%	51%	16%	9%	12%	63%	25%
ES	19%	48%	16%	5%	12%	67%	21%
FR	7%	47%	24%	7%	15%	54%	31%
HR	15%	46%	19%	4%	16%	61%	23%
IT	9%	52%	23%	6%	10%	61%	29%
CY	17%	51%	16%	8%	8%	68%	24%
LV	13%	52%	12%	2%	21%	65%	14%
LT	24%	50%	9%	1%	16%	74%	10%
LU	16%	50%	17%	4%	13%	66%	21%
HU	9%	50%	20%	5%	16%	59%	25%
MT	25%	52%	10%	4%	9%	77%	14%
NL	10%	61%	17%	3%	9%	71%	20%
AT	19%	39%	15%	9%	18%	58%	24%
PL	11%	55%	16%	5%	13%	66%	21%
PT	11%	43%	15%	4%	27%	54%	19%
RO	12%	42%	22%	9%	15%	54%	31%
SI	13%	52%	20%	5%	10%	65%	25%
SK	16%	51%	19%	4%	10%	67%	23%
FI	11%	57%	13%	3%	16%	68%	16%
SE	13%	58%	16%	2%	11%	71%	18%

Source: [9,74].

Table A4. QB1.4. In your view, what impact do the most recent digital technologies, including Artificial Intelligence, currently have on: Your current job.

Country	A Very Positive Impact	A Fairly Positive Impact	A Fairly Negative Impact	A Very Negative Impact	Don't Know	Total 'Positively'	Total 'Negatively'
EU27	11%	39%	15%	5%	30%	50%	20%
BE	9%	46%	17%	5%	23%	55%	22%
BG	10%	38%	11%	4%	37%	48%	15%
CZ	11%	44%	15%	6%	24%	55%	21%
DK	16%	41%	10%	6%	27%	57%	16%
DE	11%	38%	15%	3%	33%	49%	18%
EE	12%	36%	7%	2%	43%	48%	9%
IE	15%	33%	10%	4%	38%	48%	14%
EL	10%	34%	10%	5%	41%	44%	15%
ES	18%	36%	12%	6%	28%	54%	18%
FR	6%	32%	13%	5%	44%	38%	18%
HR	14%	42%	14%	5%	25%	56%	19%
IT	8%	43%	19%	7%	23%	51%	26%
CY	17%	39%	9%	6%	29%	56%	15%
LV	11%	40%	6%	4%	39%	51%	10%
LT	18%	35%	5%	1%	41%	53%	6%
LU	17%	42%	12%	3%	26%	59%	15%
HU	9%	43%	17%	5%	26%	52%	22%
MT	22%	38%	3%	2%	35%	60%	5%
NL	15%	47%	11%	2%	25%	62%	13%
AT	17%	31%	12%	7%	33%	48%	19%
PL	12%	45%	16%	5%	22%	57%	21%
PT	10%	32%	13%	5%	40%	42%	18%
RO	10%	34%	22%	10%	24%	44%	32%
SI	13%	43%	15%	5%	24%	56%	20%
SK	16%	39%	16%	6%	23%	55%	22%
FI	13%	42%	10%	1%	34%	55%	11%
SE	18%	43%	8%	3%	28%	61%	11%

Source: [9,74].

Table A5. QB1.5. In your view, what impact do the most recent digital technologies, including Artificial Intelligence, currently have on: Social security benefits.

Country	A Very Positive Impact	A Fairly Positive Impact	A Fairly Negative Impact	A Very Negative Impact	Don't Know	Total 'Positively'	Total 'Negatively'
EU27	14%	48%	16%	6%	16%	62%	22%
BE	10%	56%	17%	5%	12%	66%	22%
BG	14%	45%	8%	2%	31%	59%	10%
CZ	13%	50%	17%	5%	15%	63%	22%
DK	18%	48%	13%	4%	17%	66%	17%
DE	9%	50%	15%	5%	21%	59%	20%
EE	16%	45%	8%	3%	28%	61%	11%
IE	25%	38%	10%	5%	22%	63%	15%
EL	18%	49%	9%	4%	20%	67%	13%
ES	24%	44%	15%	6%	11%	68%	21%
FR	9%	43%	23%	9%	16%	52%	32%

Table A5. *Cont.*

Country	A Very Positive Impact	A Fairly Positive Impact	A Fairly Negative Impact	A Very Negative Impact	Don't Know	Total 'Positively'	Total 'Negatively'
HR	18%	44%	14%	4%	20%	62%	18%
IT	12%	53%	17%	5%	13%	65%	22%
CY	22%	46%	11%	8%	13%	68%	19%
LV	16%	45%	11%	2%	26%	61%	13%
LT	28%	50%	6%	2%	14%	78%	8%
LU	20%	54%	11%	4%	11%	74%	15%
HU	11%	51%	16%	5%	17%	62%	21%
MT	29%	47%	7%	3%	14%	76%	10%
NL	9%	46%	23%	8%	14%	55%	31%
AT	21%	37%	11%	11%	20%	58%	22%
PL	14%	54%	14%	4%	14%	68%	18%
PT	11%	46%	9%	3%	31%	57%	12%
RO	12%	44%	18%	7%	19%	56%	25%
SI	18%	51%	15%	3%	13%	69%	18%
SK	14%	49%	12%	3%	22%	63%	15%
FI	17%	49%	12%	3%	19%	66%	15%
SE	27%	50%	11%	4%	8%	77%	15%

Source: [9,74].

Table A6. QB1.4W. In your view, what impact do the most recent digital technologies, including Artificial Intelligence, currently have on: Your current job (Base: Respondents who have a current occupation (N = 14,146).

Country	A Very Positive Impact	A Fairly Positive Impact	A Fairly Negative Impact	A Very Negative Impact	Don't Know	Total 'Positively'	Total 'Negatively'
EU27	15%	51%	17%	4%	13%	66%	21%
BE	11%	54%	18%	5%	12%	65%	23%
BG	13%	54%	10%	2%	21%	67%	12%
CZ	14%	56%	15%	4%	11%	70%	19%
DK	20%	51%	11%	4%	14%	71%	15%
DE	16%	49%	18%	3%	14%	65%	21%
EE	17%	51%	7%	2%	23%	68%	9%
IE	23%	43%	12%	4%	18%	66%	16%
EL	13%	50%	13%	6%	18%	63%	19%
ES	26%	47%	13%	3%	11%	73%	16%
FR	9%	48%	19%	4%	20%	57%	23%
HR	19%	50%	15%	3%	13%	69%	18%
IT	11%	54%	21%	4%	10%	65%	25%
CY	22%	52%	11%	6%	9%	74%	17%
LV	15%	56%	7%	2%	20%	71%	9%
LT	24%	52%	6%	0%	18%	76%	6%
LU	20%	50%	13%	3%	14%	70%	16%
HU	11%	53%	18%	4%	14%	64%	22%
MT	29%	56%	4%	3%	8%	85%	7%
NL	18%	57%	13%	3%	9%	75%	16%
AT	21%	45%	17%	4%	13%	66%	21%

Table A6. *Cont.*

Country	A Very Positive Impact	A Fairly Positive Impact	A Fairly Negative Impact	A Very Negative Impact	Don't Know	Total 'Positively'	Total 'Negatively'
PL	15%	54%	17%	4%	10%	69%	21%
PT	12%	44%	17%	7%	20%	56%	24%
RO	15%	46%	24%	8%	7%	61%	32%
SI	15%	59%	16%	2%	8%	74%	18%
SK	21%	48%	18%	3%	10%	69%	21%
FI	17%	58%	14%	1%	10%	75%	15%
SE	23%	55%	11%	3%	8%	78%	14%

Source: [9,74].

Appendix B. Additional Figures

Appendix B.1. Economy (DQ1)

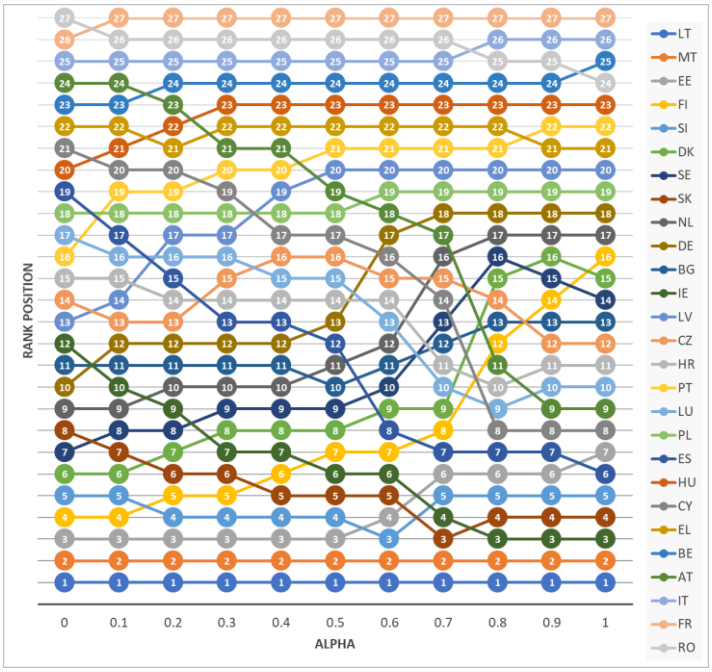

Figure A1. Rankings of EU countries based on the $DQ1(\alpha)$ measure for different values of α.

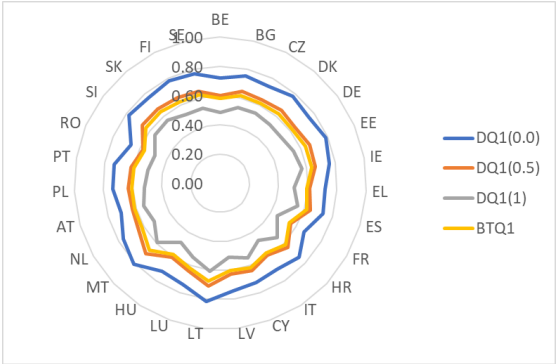

Figure A2. Radar chart of EU countries using $DQ1(0)$, $DQ1(0.5)$, $DQ1(1)$ and BTQ1 measures.

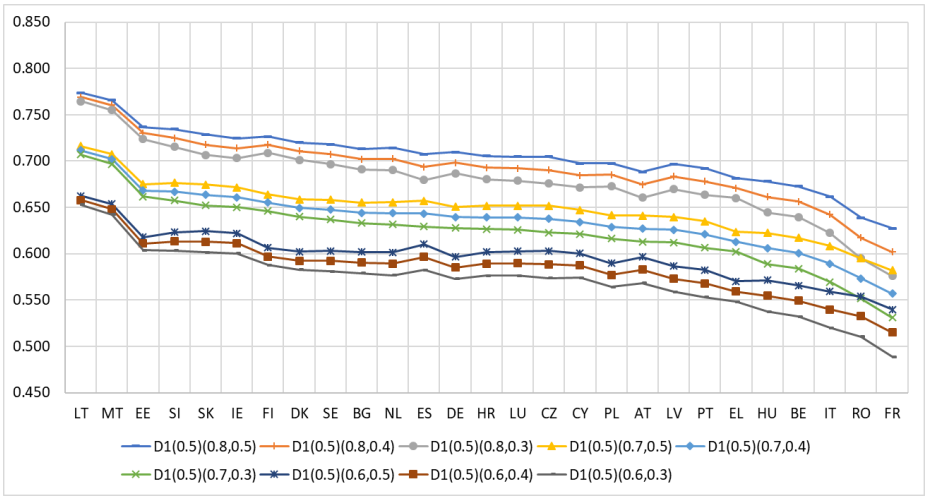

Figure A3. Relationship between $DQ1(0.5)$ values under different utility functions.

Appendix B.2. Society (DQ2)

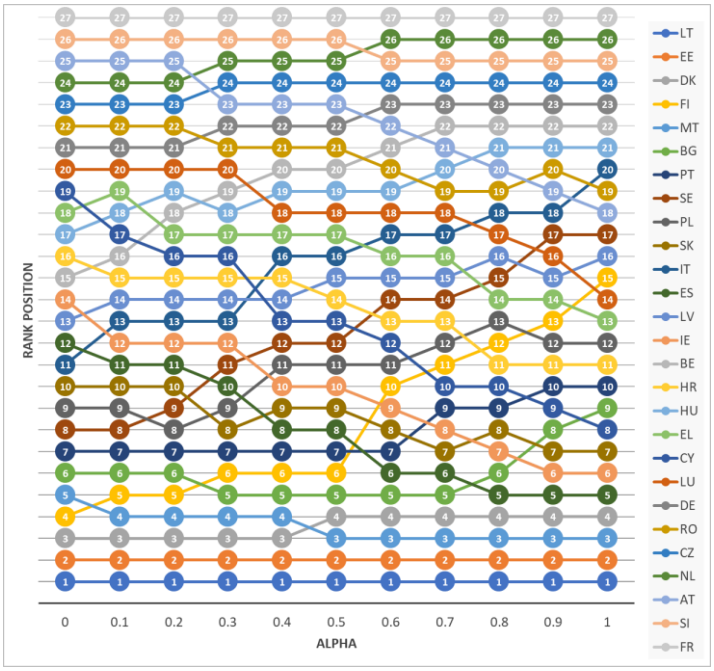

Figure A4. Rankings of EU countries based on the $DQ2(\alpha)$ measure for different values of α.

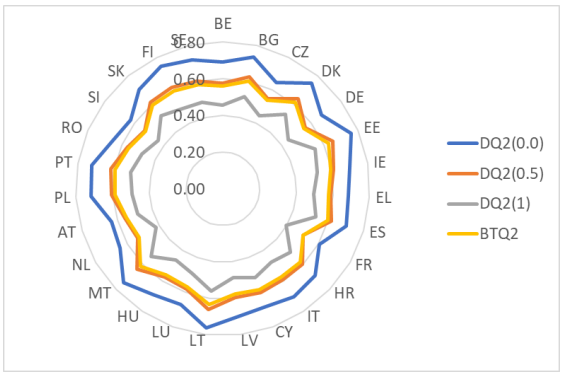

Figure A5. Radar chart of EU countries using $DQ2(0)$, $DQ2(0.5)$, $DQ2(1)$ and BTQ2 measures.

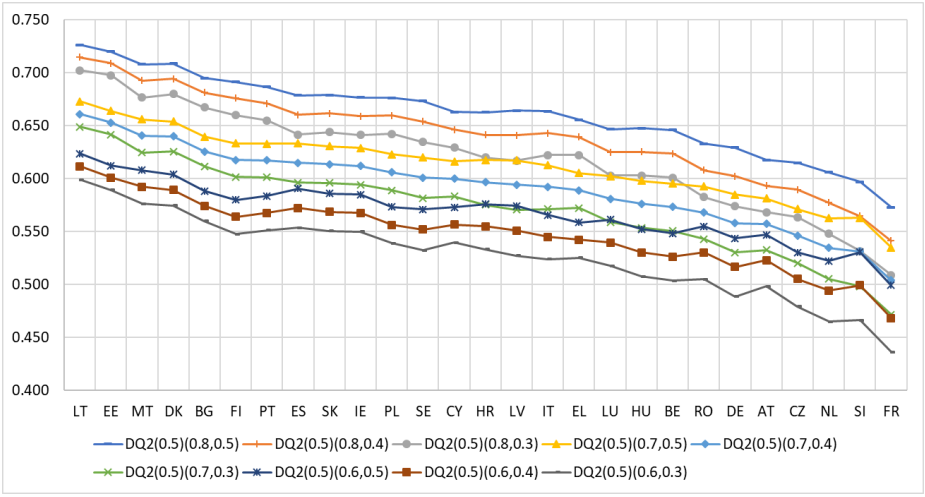

Figure A6. Relationship between $DQ2(0.5)$ values under different utility functions.

Appendix B.3. Quality of Life (DQ3)

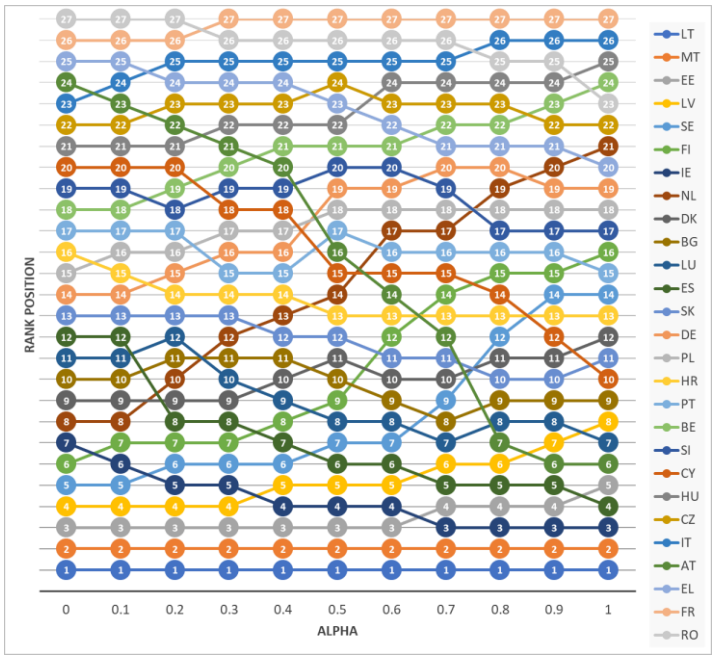

Figure A7. Rankings of EU countries based on the $DQ3(\alpha)$ measure for different values of α.

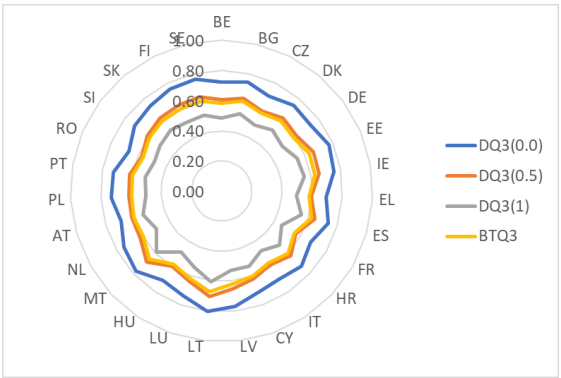

Figure A8. Radar chart of EU countries using $DQ3(0)$, $DQ3(0.5)$, $DQ3(1)$ and BTQ3 measures.

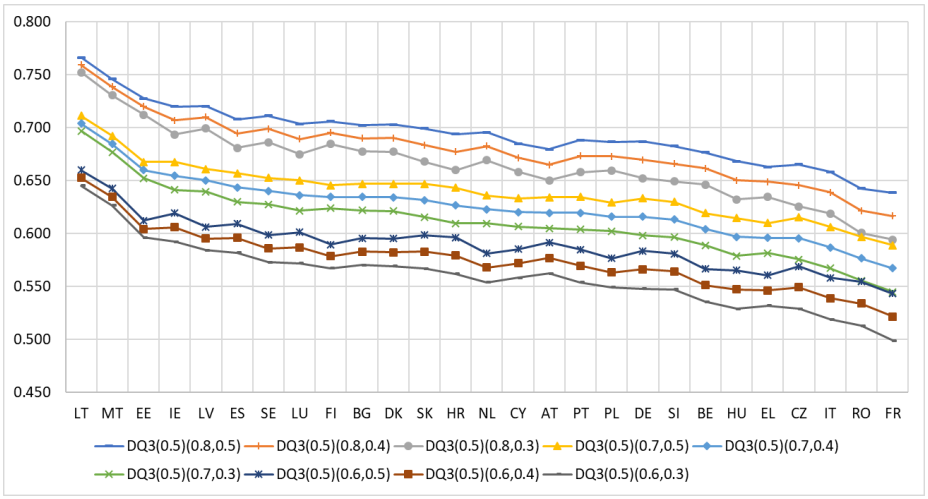

Figure A9. Relationship between $DQ3(0.5)$ values under different utility functions.

Appendix B.4. Current Job (DQ4)

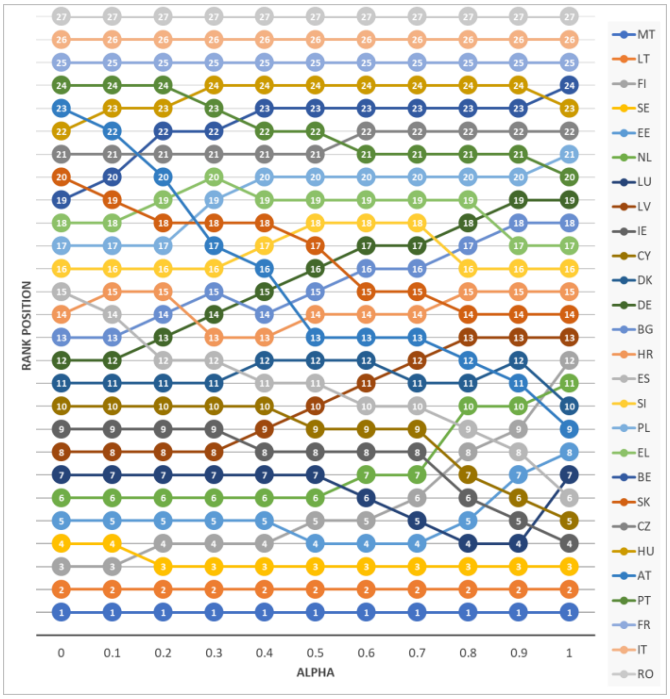

Figure A10. Rankings of EU countries based on the $DQ4(\alpha)$ measure for different values of α.

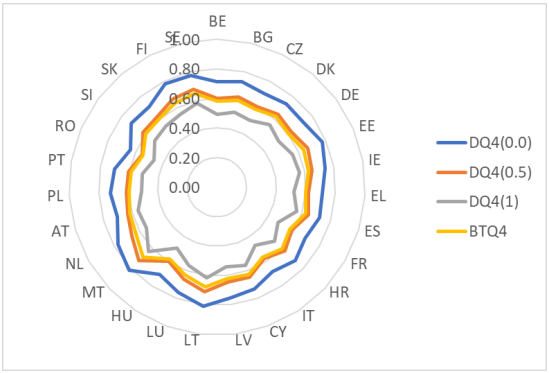

Figure A11. Radar chart of EU countries using $DQ4(0)$, $DQ4(0.5)$, $DQ4(1)$ and BTQ4 measures.

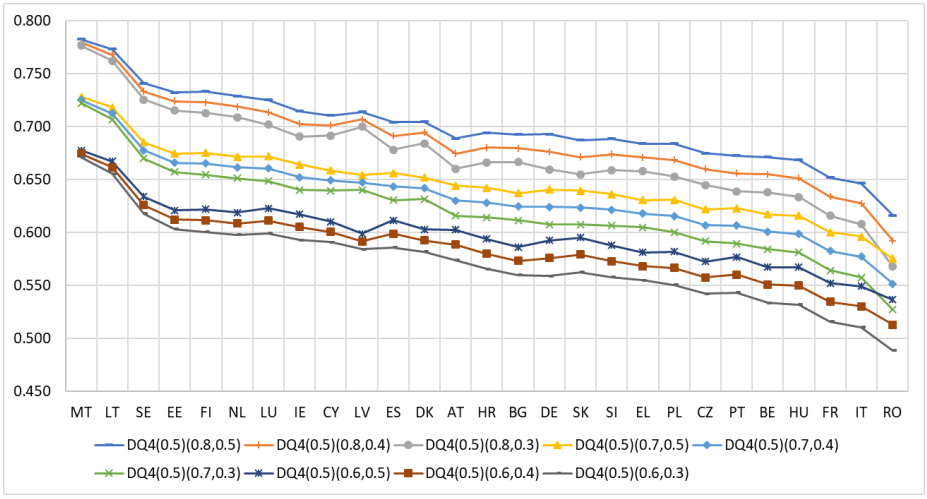

Figure A12. Relationship between $DQ4(0.5)$ values under different utility functions.

Appendix B.5. Social Security Benefits (DQ5)

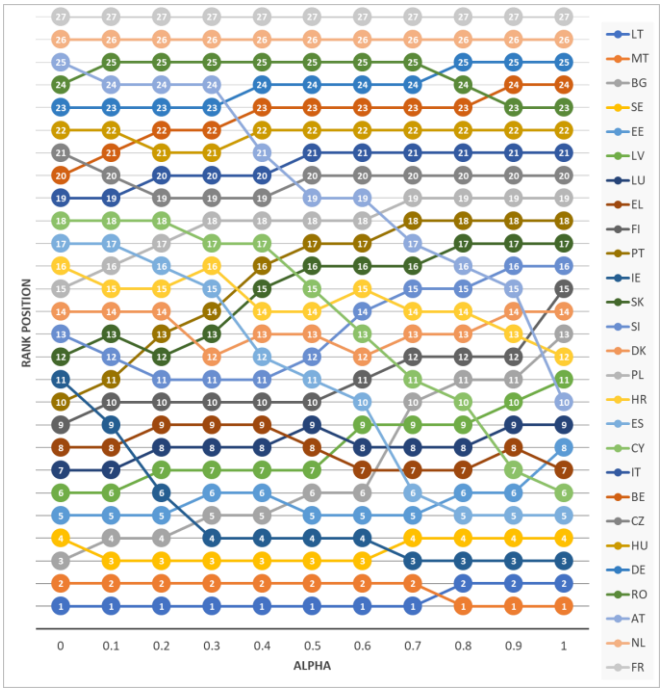

Figure A13. Rankings of EU countries based on the $DQ5(\alpha)$ measure for different values of α.

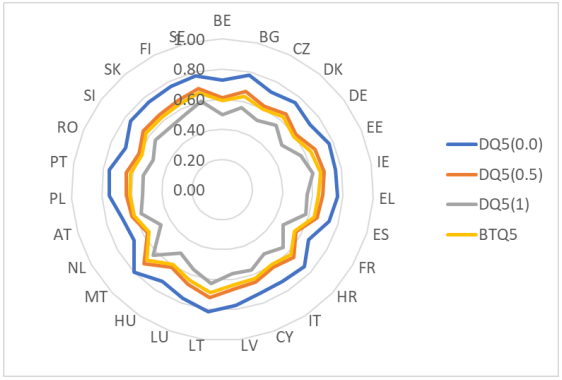

Figure A14. Radar chart of EU countries using $DQ5(0)$, $DQ5(0.5)$, $DQ5(1)$ and BTQ5 measures.

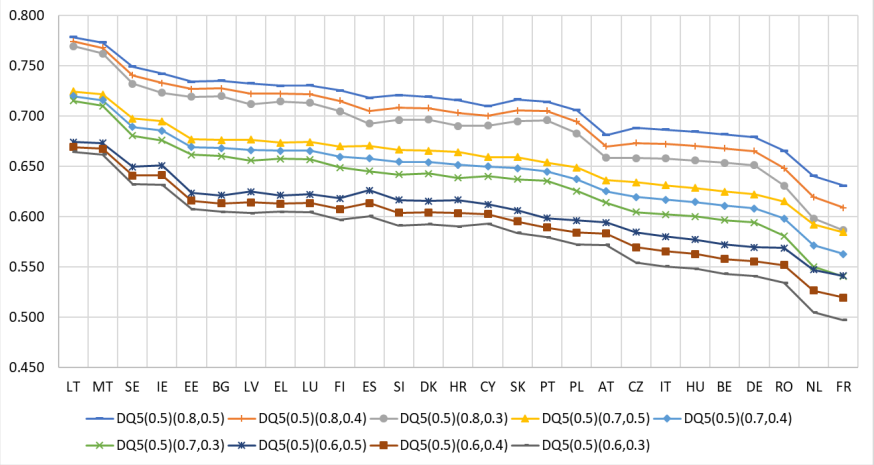

Figure A15. Relationship between $DQ5(0.5)$ values under different utility functions.

Appendix C

Table A7. $DQ4W(\alpha)$ measure for EU countries under different values of α.

Country	$DQ4W(\alpha)$ for Different Values of α											Δ = Max − Min	BTQ4W
Coefficient α	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1.0**		
EU27	0.739	0.717	0.696	0.675	0.654	0.633	0.612	0.590	0.569	0.548	0.527	0.212	0.610
Belgium (BE)	0.724	0.701	0.679	0.656	0.634	0.611	0.589	0.566	0.544	0.521	0.499	0.225	0.591
Bulgaria (BG)	0.777	0.753	0.729	0.704	0.680	0.656	0.632	0.607	0.583	0.559	0.535	0.242	0.625
Czechia (CZ)	0.747	0.725	0.702	0.680	0.657	0.635	0.613	0.590	0.568	0.545	0.523	0.224	0.610
Denmark (DK)	0.764	0.745	0.725	0.705	0.686	0.666	0.647	0.627	0.607	0.588	0.568	0.196	0.639
Germany (DE)	0.745	0.723	0.702	0.681	0.660	0.639	0.618	0.597	0.576	0.555	0.534	0.211	0.615
Estonia (EE)	0.793	0.770	0.748	0.725	0.703	0.680	0.658	0.635	0.613	0.591	0.568	0.224	0.647
Ireland (IE)	0.761	0.744	0.727	0.710	0.693	0.676	0.659	0.642	0.625	0.608	0.591	0.171	0.650
Greece (EL)	0.727	0.706	0.685	0.665	0.644	0.623	0.603	0.582	0.561	0.540	0.520	0.207	0.602
Spain (ES)	0.775	0.758	0.740	0.722	0.705	0.687	0.670	0.652	0.635	0.617	0.599	0.176	0.659
France (FR)	0.719	0.696	0.673	0.650	0.627	0.604	0.580	0.557	0.534	0.511	0.488	0.231	0.584
Croatia (HR)	0.759	0.739	0.718	0.698	0.678	0.658	0.638	0.617	0.597	0.577	0.557	0.202	0.631
Italy (IT)	0.725	0.702	0.679	0.656	0.633	0.610	0.587	0.564	0.541	0.518	0.495	0.230	0.590
Cyprus (CY)	0.752	0.733	0.715	0.697	0.679	0.661	0.643	0.625	0.607	0.588	0.570	0.181	0.636
Latvia (LV)	0.792	0.768	0.744	0.719	0.695	0.671	0.647	0.623	0.599	0.575	0.550	0.241	0.638
Lithuania (LT)	0.827	0.805	0.783	0.762	0.740	0.719	0.697	0.675	0.654	0.632	0.611	0.216	0.680
Luxembourg (LU)	0.767	0.747	0.727	0.707	0.687	0.667	0.647	0.627	0.607	0.587	0.567	0.200	0.639
Hungary (HU)	0.731	0.708	0.685	0.662	0.639	0.616	0.593	0.570	0.547	0.524	0.501	0.230	0.595
Malta (MT)	0.813	0.793	0.774	0.755	0.736	0.717	0.698	0.679	0.660	0.641	0.622	0.190	0.683
Netherlands (NL)	0.768	0.746	0.724	0.702	0.681	0.659	0.637	0.615	0.593	0.572	0.550	0.218	0.630
Austria (AT)	0.744	0.726	0.708	0.690	0.672	0.654	0.636	0.617	0.599	0.581	0.563	0.181	0.630
Poland (PL)	0.742	0.720	0.698	0.677	0.655	0.633	0.612	0.590	0.568	0.547	0.525	0.216	0.610
Portugal (PT)	0.698	0.678	0.659	0.639	0.620	0.600	0.581	0.562	0.542	0.523	0.503	0.195	0.584
Romania (RO)	0.686	0.668	0.649	0.631	0.612	0.593	0.575	0.556	0.538	0.519	0.500	0.186	0.579
Slovenia (SI)	0.765	0.741	0.718	0.694	0.670	0.647	0.623	0.600	0.576	0.553	0.529	0.236	0.619
Slovakia (SK)	0.753	0.733	0.714	0.695	0.676	0.657	0.637	0.618	0.599	0.580	0.561	0.192	0.631
Finland (FI)	0.781	0.758	0.734	0.711	0.687	0.664	0.640	0.617	0.593	0.570	0.546	0.235	0.633
Sweden (SE)	0.780	0.760	0.740	0.720	0.700	0.680	0.660	0.640	0.620	0.600	0.580	0.200	0.650

Base: Respondents who have a current occupation (N = 14,146). Note: Cell colours are displayed using conditional formatting. For $DQ4w(\alpha)$ a yellow-to-green gradient is used, where yellow corresponds to lower values and green to higher values. For Δ = max − min, a red–white–blue gradient is applied, where red indicates the smallest differences, white indicates intermediate differences, and blue indicates the largest differences.

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