Šanda, M, (2026). Extension of Model: Quality of Life Evaluation as Decision Support in Public Administration for Innovation and Regions Development. *Administratie si Management Public*, 47, 47-65. https://doi.org/10.24818/amp/2026.47-03

Extension of Model: Quality of Life Evaluation as Decision Support in Public Administration for Innovation and Regions Development

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Abstract: *This paper develops and evaluates an extension of a hybrid quality of life assessment framework for the 14 regions of Czechia, with a focus on decision support for regional development policy. The extension addresses two methodological dimensions: how indicators are identified and weighted, and how their information is aggregated into regional assessments. The original Wisdom of the Crowd approach uses respondents' suggestions, while the evolutionary principle iteratively refines indicator sets and the importance approach weights predefined indicators. The original evaluation methods, including fuzzy inference systems, the fuzzy technique for order preference by similarity to ideal solution, and case-based reasoning, are supplemented with rule-based reasoning and the analytic hierarchy process. The outputs are transformed into method-specific grant recommendations, aggregated across methods and approaches, and expressed as shares of regional capital expenditure. The results reveal recurring patterns of regional differentiation, but also meaningful differences across indicator approaches and evaluation methods. Under the evolutionary principle, cross-regional variation in scores obtained using fuzzy multi-criteria ranking, fuzzy inference systems, and case-based reasoning is lower than under the Wisdom of the Crowd approach. The overall recommended grant shares are highest for Ústí nad Labem (13.67%), Moravian-Silesian (13.33%) and Vysočina (12.33%), while Plzeň and Hradec Králové share the lowest recommended level (5.00% each). The analytic hierarchy process produces some markedly different regional orderings, indicating that methodological agreement should not be assumed. The study contributes a modular decision-support framework that makes alternative indicator-identification and evaluation strategies explicit and demonstrates their implications for resource-allocation recommendations. While the proposed architecture may be transferable to other complex variables, applications beyond regional quality of life assessment remain to be empirically validated.*

Keywords: quality of life, decision support, complex variables evaluation, regional development.

JEL: C69, I31, R58.

DOI: https://doi.org/10.24818/amp/2026.47-03

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Introduction

Quality of life (QL) is a multidimensional concept encompassing both subjective perceptions and objective living conditions. Its evaluation is relevant to public administration, particularly for identifying regional disparities, setting development priorities and supporting decisions on public resource allocation. However, regional assessments may be influenced by the selection and weighting of indicators as well as the evaluation methods employed. Šanda and Křupka (2018) introduced a hybrid framework for assessing QL across Czech regions at level 3 of the Nomenclature of Territorial Units for Statistics (NUTS 3). The model combined indicators identified through the Wisdom of the Crowd (WoC) approach with official statistical data and employed three evaluation methods: Fuzzy Inference System (FIS), fuzzy Technique for Order Preference by Similarity to Ideal Solution (fTOPSIS), and Case-Based Reasoning (CBR). The resulting assessments provided a basis for regional comparisons and grant allocation recommendations. Nevertheless, the original framework relied on a single indicator identification approach and a limited range of evaluation methods.

The present study extends this framework by introducing two additional approaches to indicator identification and weighting: the evolutionary principle (EP), based on iterative indicator confirmation, and the importance approach (IMP), which uses a predefined indicator set with explicitly assigned weights. Furthermore, Rule-Based Reasoning (RBR) and Analytic Hierarchy Process (AHP) are incorporated into the evaluation framework. The study compares the results of these three approaches across five evaluation methods and examines their implications for regional assessment and grant recommendations. Finally, it proposes a modular generalisation of the framework for evaluating other complex, multidimensional variables, while recognising that its applicability beyond QL requires further empirical validation.

1. Literature review

QL is widely understood as a multidimensional concept integrating subjective perceptions of well-being with objective economic, social, health and environmental conditions (Phillips, 2006; Rapley, 2003; Royuela *et al.*, 2010). Its assessment is particularly relevant to public administration, where regional comparisons can inform policy evaluation and development priorities while accounting for objective conditions and stakeholders' perspectives (Potluka, 2023). Previous studies have demonstrated the importance of combining objective and subjective dimensions when evaluating QL and regional disparities (Budowski *et al.*, 2016; Prakash *et al.*, 2016; von Wirth *et al.*, 2015).

Methodological approaches to multidimensional assessment include fuzzy logic, multi-criteria decision-making and knowledge-based reasoning. Fuzzy set theory provides tools for handling uncertainty and imprecision (Dubois & Prade, 1980; Zadeh, 1965), while recent research combines picture fuzzy sets with multicriteria techniques to assess objective and subjective QL dimensions (Reig-Mullor *et al.*,

2024). Established multi-criteria methods include TOPSIS and its fuzzy extension, as well as the Analytic Hierarchy Process (Chen, 2000; Hwang & Yoon, 1981; Saaty, 2004). Knowledge-based approaches include Case-Based Reasoning, which draws on previous cases (Aamodt & Plaza, 1994), and Rule-Based Reasoning, which applies explicit decision rules. A study of Slovak regions applied TOPSIS and the weighted sum method with three alternative weighting schemes, illustrating how different methodological configurations can be compared within regional QL assessment (Coronicova Hurajova & Hajduova, 2021).

Mardani *et al.* (2015) document the broad application of multi-criteria techniques across different decision-making contexts. The choice of evaluation method must be distinguished from the identification and weighting of indicators. Recent studies examine how alternative weighting techniques, including AHP, influence composite QL assessments at urban and regional scales (Bovkir *et al.*, 2023; Ustaoglu *et al.*, 2025). Such findings underline the importance of examining methodological choices jointly rather than treating one weighting strategy as definitive. Building on Šanda and Křupka (2018), the present study combines three indicator identification and weighting approaches with five evaluation methods and compares how their configurations affect regional assessments and indicative grant recommendations.

2. Research objectives

The study aims to extend the hybrid QL evaluation model introduced by Šanda and Křupka (2018) and examine how alternative approaches to indicator identification, weighting and evaluation influence regional assessments and indicative grant recommendations. It also explores the potential generalisation of the extended framework to other complex variables. To achieve this aim, four specific objectives are defined:

1. to extend the original QL evaluation model by incorporating two additional approaches: EP for iterative indicator identification and weighting, and IMP for weighting predefined indicators, alongside the original WoC approach;
2. to extend the evaluation framework by incorporating RBR and AHP alongside FIS, fTOPSIS and CBR, and to examine differences in regional assessments across these five methods under the WoC, EP and IMP approaches;
3. to apply the extended model to historical regional and survey data covering all 14 Czech NUTS 3 regions and derive indicative grant allocation recommendations from the resulting assessments;
4. to propose a conceptual generalisation of the extended framework for evaluating other complex, multidimensional variables, while acknowledging the need for further empirical validation beyond regional QL assessment.

3. Methodology

This section describes the methodology of the extended QL evaluation framework, including indicator identification, evaluation methods and their integration into a unified decision-support model. The original framework evaluated QL in Czech

NUTS 3 regions using indicators identified through the Wisdom of the Crowd approach and complemented by official statistics (Šanda & Křupka, 2018). Its main limitations were reliance on a single indicator identification approach, a restricted set of evaluation methods, and a focus on QL as a specific application. The extended model addresses these limitations by introducing alternative approaches to indicator identification and weighting, additional evaluation methods, and a modular architecture with potential applications beyond QL assessment.

3.1 Indicator identification and evaluation methods

Finding indicators is a critical phase in QL evaluation and other complex variables, as it determines which aspects of the phenomenon are assessed and how the model is structured. Rather than relying solely on predefined indicator sets, the extended model emphasises different approaches to finding indicators, reflecting varying degrees of openness, iteration and expert involvement. The underlying logic of these approaches differs and directly influences the composition of the indicators and the resulting evaluation outcomes. The WoC approach identifies QL indicators through respondents' open-ended suggestions rather than a predefined list. Their responses are consolidated into a collective indicator set reflecting perceived aspects of QL. This bottom-up approach captures subjective perspectives that may be overlooked by expert-defined indicators. Its implementation in the original model is described in Šanda and Křupka (2018).

The EP approach identifies QL indicators through an iterative process in which the indicator set is progressively refined based on respondents' feedback. Unlike the WoC approach, EP begins with an initial set of indicators that respondents review in successive iterations. They can confirm the relevance of existing indicators and propose modifications or additions. After each iteration, the indicator set is updated to incorporate newly suggested aspects, while the frequency of confirmation of individual indicators is recorded. These frequencies serve two purposes: they determine the relative weights of indicators and establish their ranking within the resulting indicator set. Consequently, EP combines iterative indicator identification with collective weighting, producing a structured and hierarchically ordered set of indicators without requiring the complete indicator list to be fixed in advance.

The IMP approach uses a predefined set of QL indicators, typically established based on expert knowledge, policy frameworks or existing analytical models. Unlike WoC and EP, the indicator set remains fixed throughout the evaluation process. Rather than identifying additional indicators, respondents assess the relative importance of those already selected. Their assessments are used to determine indicator weights, reflecting the perceived significance of individual aspects of QL. This approach separates indicator selection from importance assessment, maintaining a stable indicator structure while allowing differences in perceived relevance to be incorporated into the overall evaluation.

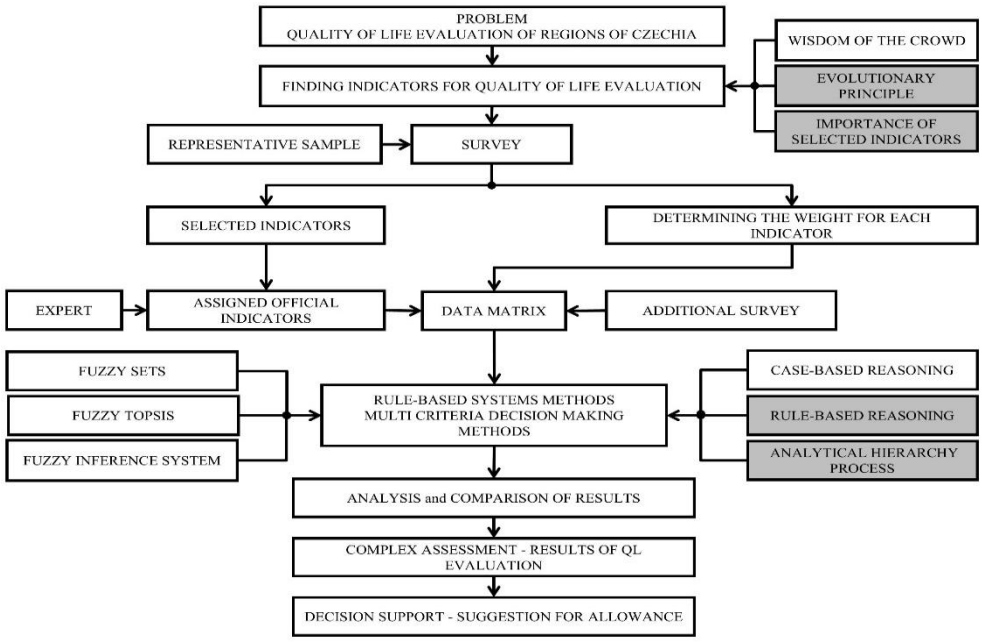
The evaluation phase employs five established methods: FIS, fTOPSIS, CBR, RBR and AHP. FIS, fTOPSIS and CBR were already applied in the original framework

(Šanda & Křupka, 2018), while RBR and AHP are incorporated in the extended model. All five methods are used to evaluate the regional QL outcomes under the WoC, EP and IMP approaches.

3.2 Structure of the extended model

The extended framework integrates three approaches to indicator identification and weighting with five evaluation methods. As illustrated in Figure 1, the model follows a structured process from indicator selection annd data preparation to regional QL assessment and grant allocation recommendations.

Figure 1. Structure of the extended model for quality-of-life evaluation



Source: Authors' contribution based on Šanda and Křupka (2018).

Figure 1 illustrates the architecture of the extended model, with newly introduced components highlighted in grey. Following problem formulation, the WoC, EP or IMP approach determines how indicators are identified and weighted. Survey responses provide subjective inputs, while selected indicators are linked to official statistical measures with expert support. Where necessary, supplementary surveys provide data for indicators that cannot be quantified using official statistics. The resulting data matrix forms the basis for regional evaluation using FIS, fTOPSIS, CBR, RBR and AHP.

The evaluation methods produce regional assessments that are subsequently analysed and compared. Since these methods differ in their underlying principles and output scales, their results must be interpreted separately rather than treated as

directly interchangeable. The assessments are then translated into method-specific grant recommendations, which are aggregated to support decisions on regional resource allocation. By separating indicator identification, evaluation and decision support into distinct stages, the framework allows alternative methodological configurations to be compared while preserving a common analytical structure.

4. Data and indicators

The proposed framework combines survey-based inputs with official regional statistics to capture both subjective and objective dimensions of QL. Survey responses serve different purposes depending on the approach applied: identifying indicators through open-ended suggestions (WoC), iteratively confirming and refining indicator sets (EP), or assessing the importance of predefined indicators (IMP). The selected indicators are subsequently linked, where possible, to measurable variables from official statistical sources, covering socio-economic, environmental and infrastructural conditions. Where suitable statistical data are unavailable, supplementary data collection may be required. This distinction between indicator identification and empirical measurement is important: the former determines which dimensions of QL are assessed and how indicators are weighted, while the latter provides the regional observations used in the evaluation. Data availability and comparability therefore remain essential conditions for applying the framework consistently across regions.

To support interpretation, the indicators are organised into thematic areas representing distinct dimensions of QL. These areas provide an intermediate level between individual indicators and the overall assessment, allowing results to be examined by thematic domain as well as in aggregate. Since WoC, EP and IMP generate different indicator sets, their thematic structures may overlap without being fully equivalent. Comparing these structures therefore helps identify common dimensions and approach-specific differences in QL assessment.

4.1 Finding indicators using different approaches

The three indicator identification approaches produce indicator sets that differ in their composition, structure and weighting. The WoC approach captures a broad range of perceived QL dimensions, including well-being, transport and safety, environmental conditions, education, employment, leisure and health. The complete indicator set and its links to official statistical measures are documented in Šanda and Křupka (2018). The EP approach produces a progressively refined indicator set in which the frequency of confirmation or occurrence determines the relative weight and ranking of individual indicators. This makes it possible to distinguish widely supported aspects of QL from those receiving less collective attention. Table 1 lists EP indicators, weights, optimisation directions and thematic areas (CZK = Czech koruna; GDP = gross domestic product). In Tables 1 and 2, Area denotes thematic groups (B1-B8 for EP; C1-C7 for IMP), which are not necessarily equivalent across

approaches; Type indicates whether higher (max) or lower (min) indicator values are preferred.

Table 1: Indicators - Evolutionary principle

Sign	Official indicator (unit)	Weight	Type	Area
E_1	Good/very good self-rated health (% of population)	77.65%	max	B7
E_2	Crime index (reported crimes per 10,000 inhabitants)	76.46%	min	B2
E_3	Satisfaction, quality of life (% of population)	72.50%	max	B1
E_4	Residents per physician	63.40%	min	B7
E_5	Satisfaction with the future of children and descendants	61.42%	max	B1
E_6	Median gross monthly wage (CZK)	57.17%	max	B5
E_7	Environmental protection investment (thous. CZK per capita)	54.90%	max	B3
E_8	Family	50.94%	max	B1
E_9	Interpersonal relationships	47.08%	max	B1
E_{10}	Aggregate property price index (previous year = 100)	46.09%	max	B8
E_{11}	Social security – number of benefits paid (benefits per capita)	39.96%	max	B7
E_{12}	Friends	39.86%	max	B1
E_{13}	Monthly labour costs – social benefits (CZK/month per employee)	39.17%	max	B5
E_{14}	Cleanliness of streets in the city	38.87%	max	B8
E_{15}	Expenditure on research and development (million CZK per 1,000 inhabitants)	37.29%	max	B4
E_{16}	Degree of freedom	37.19%	max	B8
E_{17}	Unemployment rate (%)	33.14%	min	B5
E_{18}	Life optimism and life balance	32.34%	max	B1
E_{19}	Czech Sports Union units and clubs (per 1,000 inhabitants)	31.36%	max	B6
E_{20}	Physicians per capita (number of physicians per 1,000 inhabitants)	30.17%	max	B7
E_{21}	Humility and love among people	26.71%	max	B1
E_{22}	Municipal technical, cultural and sports facilities (% of municipalities equipped)	25.22%	max	B6
E_{23}	Length of railways, roads, motorways and waterways (km/km^2)	24.43%	max	B2
E_{24}	Education accessibility index (educational facilities per 1,000 inhabitants)	17.31%	max	B4
E_{25}	Love	17.11%	max	B1
E_{26}	Peace	14.05%	max	B8
E_{28}	Ecological stability coefficient (share of ecologically favourable vs. burdened areas)	2.97%	max	B3
E_{29}	Households managing income easily/very easily (%)	2.87%	max	B5
E_{30}	Emissions of pollutants - solids (t/km2)	1.88%	min	B3
E_{31}	Food price comparison (median of regional-to-national price ratios)	1.78%	min	B8
E_{32}	Housing starts per 1,000 inhabitants	1.68%	max	B6

Sign	Official indicator (unit)	Weight	Type	Area
E_{33}	Regional capital expenditure (% of total expenditure)	1.58%	max	B8
E_{34}	Hospitals per 10,000 inhabitants	0.69%	max	B7
E_{35}	Average pension amount (CZK)	0.59%	max	B5
E_{36}	GDP per capita (thous. CZK per 1,000 inhabitants)	0.49%	max	B8

Source: Author's contribution

Following expert consultation, indicator E_{27} ("hope and belief in God") was excluded from the EP approach due to its sensitive nature and difficulties in defining an appropriate measurable indicator. In contrast to EP, the IMP approach uses a predefined indicator set and determines the relative importance of individual indicators through respondents' assessments. Table 2 presents the resulting indicators, their importance weights, optimization directions and thematic areas.

Table 2: Indicators – Importance

Sign	Official indicator (unit)	Weight	Type	Area
M_1	GDP per capita (thous. CZK per 1,000 inhabitants)	22.06%	max	C7
M_2	Average wage (CZK)	59.25%	max	C4
M_3	Unemployment rate (%)	50.45%	min	C4
M_4	Average property prices (CZK per m²)	29.67%	min	C7
M_5	Completed dwellings per 100 households	19.88%	max	C7
M_6	Crime index (number of reported crimes per 10,000 inhabitants)	49.75%	min	C1
M_7	Physicians (number of physicians per 1,000 inhabitants)	49.06%	max	C6
M_8	Healthcare facilities (number of facilities per 10,000 inhabitants)	46.59%	max	C6
M_9	Number of preschool children and primary and secondary school pupils (per 1,000 inhabitants)	19.98%	max	C3
M_{10}	Library loans per inhabitant	4.65%	max	C3
M_{11}	Average overnight stays per tourist (nights per tourist)	16.91%	max	C7
M_{12}	Life expectancy (years)	46.98%	max	C6
M_{13}	Households with internet access (% of households)	25.32%	max	C5
M_{14}	Share of tree-covered area (% of total area)	24.73%	max	C2
M_{15}	Population growth rate (total increase/population)	23.05%	max	C5
M_{16}	Number of economic entities (entities per inhabitant)	10.98%	max	C7
M_{17}	Average pension amount (CZK)	55.09%	max	C4
M_{18}	Ecological stability coefficient (share of ecologically favourable vs. burdened areas)	19.19%	max	C2
M_{19}	Share of agricultural land (share of agricultural area in total area)	23.84%	max	C2
M_{20}	Expenditure on research and development (million CZK per 1,000 inhabitants)	21.96%	max	C3
M_{21}	Researchers per 1,000 inhabitants	7.22%	max	C3
M_{22}	Employed residents with tertiary education (% of population)	14.14%	max	C3
M_{23}	Emissions of pollutants - solids (t/km2)	31.65%	min	C2

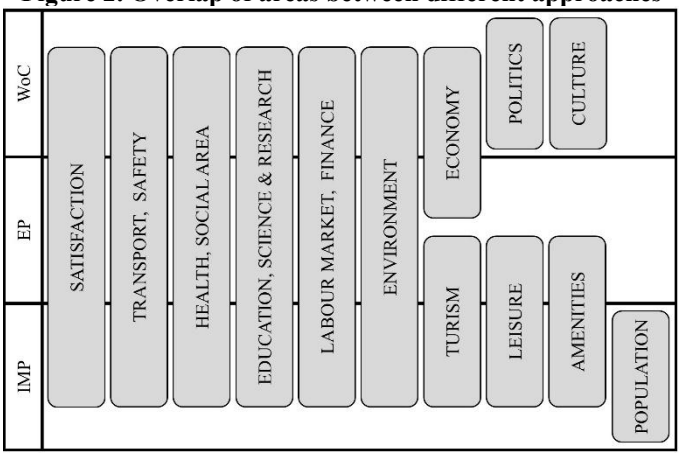
Sign	Official indicator (unit)	Weight	Type	Area
M_{24}	Population supplied by public water systems (%)	23.54%	max	C5
M_{25}	Population aged 65+ (% of population)	15.23%	min	C5
M_{26}	Job seekers (number of applicants per vacancy)	20.87%	min	C4
M_{27}	Registered vehicles (number of vehicles per inhabitant)	8.80%	min	C2
M_{28}	Traffic accidents (accidents per 1,000 inhabitants)	16.62%	min	C1
M_{29}	Nursing home beds per resident aged 65+	30.37%	max	C6

Source: Author's contribution

4.2 Thematic areas of indicators and their overlap

To examine the thematic structure of QL assessments, indicators identified through the WoC, EP and IMP approaches were grouped into conceptually related areas. These areas provide an intermediate level between individual indicators and overall evaluations, enabling comparisons of thematic coverage across approaches. Since each approach generates a different indicator set, the resulting thematic structures are not necessarily equivalent. The EP approach comprises eight thematic areas (B1-B8), while IMP includes seven (C1-C7); WoC retains the thematic structure established in the original model (Šanda & Křupka, 2018). Figure 2 illustrates the conceptual overlaps and differences between these structures. Importantly, thematic overlap indicates similarities in the dimensions assessed rather than identical indicators or weights.

Figure 2. Overlap of areas between different approaches



Source: Author's contribution

Figure 2 highlights both shared thematic dimensions and approach-specific differences in the representation of QL. The overlaps suggest that certain dimensions are captured across different indicator identification approaches, while other dimensions receive different emphasis depending on the approach applied. These differences are important for interpreting the subsequent regional assessments, as variations in evaluation outcomes may reflect not only the methods employed but

also the thematic composition of the indicator sets. The thematic structure therefore provides a basis for understanding how alternative approaches represent QL and influence decision-support outcomes.

5. Results: Case study of Czech NUTS 3 regions

This section presents the empirical application of the extended QL evaluation framework to all 14 Czech NUTS 3 regions. It compares regional assessments obtained using the WoC, EP and IMP approaches across five evaluation methods, examining differences associated with indicator identification, weighting and evaluation procedures. Particular attention is given to regional disparities, the consistency of assessment outcomes and their implications for grant allocation recommendations. The analysis thus demonstrates how alternative methodological configurations can inform regional decision support.

The empirical case study draws on regional data for 2016 and survey data collected in 2018. These historical data are used to demonstrate and compare the methodological configurations of the extended model rather than to provide a current assessment of regional QL. The empirical evaluation uses a regional data matrix covering all 14 Czech NUTS 3 regions. Indicators identified through the WoC, EP and IMP approaches were operationalised primarily using official statistical data and prepared according to the requirements of the individual evaluation methods. Where suitable statistical measures were unavailable for indicators identified through WoC, supplementary data collection was used to quantify previously defined indicators without introducing new dimensions. This procedure, established in the original model (Šanda & Křupka, 2018), provides a consistent basis for comparing regional assessments across the extended framework.

5.1 Results by approach

Tables 3-5 present the regional QL assessments obtained using the WoC, EP and IMP approaches across five evaluation methods. Since the methods employ different evaluation principles and output scales, their numerical results are not directly comparable. FIS and fTOPSIS express evaluation scores as percentages, while AHP produces relative preference weights. RBR uses a discrete scale from 1 (lowest) to 5 (highest), and CBR expresses similarity to reference cases as percentages. Comparisons should therefore focus primarily on regional differences and rankings within each method rather than on absolute values across methods.

Table 3 presents the QL evaluation results obtained using the WoC approach across individual evaluation methods.

Table 3: Results of individual methods – Wisdom of the Crowd

NUTS 3 region	fTOPSIS	FIS	AHP	RBR	CBR
Central Bohemian (STC)	62.46%	74.20%	5.81%	3	70.80%
Hradec Králové (KHK)	78.27%	76.89%	7.41%	4	74.95%
Karlovy Vary (KVA)	51.43%	65.78%	12.01%	3	61.52%
Liberec (LIB)	59.75%	74.21%	7.82%	3	65.85%
Moravian-Silesian (MSZ)	53.10%	64.80%	2.80%	3	55.97%
Olomouc (OLO)	62.38%	71.66%	3.79%	3	66.85%
Pardubice (PAK)	67.04%	75.30%	11.10%	4	72.85%
Plzeň (PLZ)	75.89%	76.31%	5.85%	4	73.88%
Prague (PRA)	60.06%	65.14%	19.48%	3	66.30%
South Bohemian (JHC)	61.69%	74.18%	3.57%	3	71.28%
South Moravian (JHM)	63.55%	72.51%	4.78%	3	68.12%
Ústí nad Labem (UST)	42.18%	58.46%	2.56%	2	58.78%
Vysočina (VYS)	58.16%	69.24%	3.73%	3	67.30%
Zlín (ZLN)	64.01%	75.64%	9.31%	4	69.63%

Source: Author's contribution

Hradec Králové and Plzeň achieve consistently high scores under fTOPSIS, FIS and CBR, whereas Ústí nad Labem and Moravian-Silesian generally perform less favourably. Prague ranks first under AHP but occupies considerably lower positions under fTOPSIS, FIS and CBR, highlighting differences in regional rankings across evaluation methods. Overall, fTOPSIS, FIS and CBR produce broadly similar patterns of regional differentiation, while AHP yields a different ordering. RBR provides coarser differentiation due to its discrete evaluation scale.
Table 4 presents the QL evaluation results obtained using the EP approach.

Table 4: Results of individual methods – Evolutionary principle

NUTS 3 region	fTOPSIS	FIS	AHP	RBR	CBR
STC	65.74%	71.01%	7.90%	3	69.93%
KHK	73.48%	73.09%	10.56%	4	73.27%
KVA	64.89%	69.15%	8.30%	3	69.00%
LIB	70.93%	76.34%	9.84%	4	74.86%
MSZ	67.48%	69.15%	3.45%	3	66.68%
OLO	59.23%	70.19%	1.85%	3	61.98%
PAK	68.19%	75.52%	8.46%	4	70.27%
PLZ	66.65%	76.70%	13.19%	4	71.57%
PRA	64.76%	68.81%	16.07%	3	68.30%
JHC	58.93%	74.70%	4.32%	3	67.61%
JHM	64.11%	75.40%	3.17%	4	69.41%
UST	57.24%	62.88%	3.22%	2	59.36%
VYS	56.44%	67.38%	3.36%	3	59.29%
ZLN	60.46%	72.06%	6.33%	3	68.31%

Source: Author's contribution

Compared with WoC, the EP produces a narrower range of regional scores under fTOPSIS, FIS and CBR. Liberec and Hradec Králové generally achieve higher evaluations, whereas Ústí nad Labem and Vysočina remain among the lower-ranked regions. Prague receives the highest AHP weight despite its lower positions under fTOPSIS, FIS and CBR, further illustrating method-specific differences in regional rankings. RBR provides less detailed differentiation due to its discrete evaluation scale.

Table 5 presents the QL evaluation results obtained using the IMP approach, which employs predefined indicators with explicitly assigned importance weights. Hradec Králové achieves the highest fTOPSIS score, while Plzeň ranks first under FIS. Prague ranks first under AHP and CBR but second lowest under FIS, illustrating substantial method-specific differences in regional assessments. These findings highlight the importance of interpreting regional rankings separately for each evaluation method.

Table 5: Results of individual methods – Importance

NUTS 3 region	fTOPSIS	FIS	AHP	RBR	CBR
STC	68.01%	74.61%	7.58%	4	71.73%
KHK	78.27%	73.89%	5.29%	3	68.90%
KVA	54.80%	63.57%	3.71%	3	60.78%
LIB	65.68%	69.50%	4.27%	3	66.74%
MSZ	63.68%	66.64%	3.38%	2	59.25%
OLO	61.20%	72.46%	4.21%	3	67.32%
PAK	62.45%	72.76%	3.81%	4	68.90%
PLZ	69.05%	77.50%	6.52%	4	69.47%
PRA	74.67%	66.16%	31.17%	4	73.03%
JHC	59.06%	75.85%	4.51%	3	66.05%
JHM	71.42%	71.35%	10.12%	4	68.61%
UST	60.71%	67.10%	6.26%	2	61.73%
VYS	57.34%	68.69%	4.66%	3	66.02%
ZLN	60.43%	74.91%	4.50%	4	67.58%

Source: Author's contribution

5.2 Cross-approach comparison

Tables 3-5 reveal both recurring patterns and differences across the WoC, EP and IMP approaches. Hradec Králové generally achieves favourable evaluations, whereas Ústí nad Labem and Moravian-Silesian frequently receive lower scores, although regional rankings depend on the evaluation method applied. Compared with WoC, the EP approach produces a narrower range of regional scores under fTOPSIS, FIS and CBR, indicating less pronounced regional differentiation under these methods. Differences across the three approaches also demonstrate the relevance of indicator identification and weighting, particularly for regions whose relative positions vary between assessments.

Differences between evaluation methods remain relevant even when broad patterns of regional differentiation are similar. In particular, AHP produces substantially different regional rankings for some regions compared with fTOPSIS, FIS and CBR. Since the methods also use different output scales, their results are interpreted separately and converted into method-specific grant recommendations before aggregation.

5.3 Suggestion for grant allocation as decision support

Building on Šanda and Křupka (2018), the extended model translates regional QL assessments into indicative grant allocation recommendations expressed as percentages of regional capital expenditure. In general, less favourable QL evaluations correspond to higher recommended grant shares. Grant recommendations follow the five-level conversion scale introduced by Šanda and Křupka (2018) (Table 5). For AHP, relative regional weights expressed as percentages are multiplied by the number of evaluated regions (14) before applying this scale. For RBR, evaluation levels from 1 to 5 correspond to recommended grant shares of 20%, 15%, 10%, 5% and 0%, respectively. The framework also allows thematic assessment results to inform the identification of priorities for targeted interventions. Tables 6-8 present the recommendations obtained under the WoC, EP and IMP approaches. For each approach, the aggregated recommendation (AGG) is calculated as the arithmetic mean of the five method-specific percentage recommendations. These outputs represent model-based recommendations rather than actual grant allocations.

Tables 6-8 reveal differences in grant recommendations across the three approaches. For example, Ústí nad Labem receives recommendations of 17% under WoC, 15% under EP and 9% under IMP, whereas Moravian-Silesian receives consistently high recommendations (14%, 12% and 14%, respectively). Table 9 combines these approach-specific recommendations using their arithmetic mean (AGG total), rounded to two decimal places. The indicative grant amounts are calculated by applying these rounded percentages to regional capital expenditure.

Table 6: Recommended for grant allocation - Wisdom of the Crowd

NUTS 3 region	fuzzy TOPSIS	FIS	AHP	RBR	CBR	AGG
STC	10%	5%	0%	10%	5%	6%
KHK	5%	5%	0%	5%	5%	4%
KVA	15%	10%	0%	10%	10%	9%
LIB	15%	5%	0%	10%	10%	8%
MSZ	15%	10%	20%	10%	15%	14%
OLO	10%	5%	15%	10%	10%	10%
PAK	10%	5%	0%	5%	5%	5%
PLZ	5%	5%	0%	5%	5%	4%
PRA	10%	10%	0%	10%	10%	8%
JHC	10%	5%	20%	10%	5%	10%
JHM	10%	5%	10%	10%	10%	9%

NUTS 3 region	fuzzy TOPSIS	FIS	AHP	RBR	CBR	AGG
UST	20%	15%	20%	15%	15%	17%
VYS	15%	10%	15%	10%	10%	12%
ZLN	10%	5%	0%	5%	10%	6%

Source: Author's contribution

Table 7: Recommended for grant allocation - Evolutionary principle

NUTS 3 region	fuzzy TOPSIS	FIS	AHP	RBR	CBR	AGG
STC	10%	5%	0%	10%	10%	7%
KHK	5%	5%	0%	5%	5%	4%
KVA	10%	10%	0%	10%	10%	8%
LIB	5%	5%	0%	5%	5%	4%
MSZ	10%	10%	20%	10%	10%	12%
OLO	15%	5%	20%	10%	10%	12%
PAK	10%	5%	0%	5%	5%	5%
PLZ	10%	5%	0%	5%	5%	5%
PRA	10%	10%	0%	10%	10%	8%
JHC	15%	5%	10%	10%	10%	10%
JHM	10%	5%	20%	5%	10%	10%
UST	15%	10%	20%	15%	15%	15%
VYS	15%	10%	20%	10%	15%	14%
ZLN	10%	5%	0%	10%	10%	7%

Source: Author's contribution

Table 8: Recommended for grant allocation - Importance

NUTS 3 region	fuzzy TOPSIS	FIS	AHP	RBR	CBR	AGG
STC	10%	5%	0%	5%	5%	5%
KHK	5%	5%	5%	10%	10%	7%
KVA	15%	10%	15%	10%	10%	12%
LIB	10%	10%	15%	10%	10%	11%
MSZ	10%	10%	20%	15%	15%	14%
OLO	10%	5%	15%	10%	10%	10%
PAK	10%	5%	15%	5%	10%	9%
PLZ	10%	5%	0%	5%	10%	6%
PRA	5%	10%	0%	5%	5%	5%
JHC	15%	5%	10%	10%	10%	10%
JHM	5%	5%	0%	5%	10%	5%
UST	10%	10%	0%	15%	10%	9%
VYS	15%	10%	10%	10%	10%	11%
ZLN	10%	5%	10%	5%	10%	8%

Source: Author's contribution

Table 9 distinguishes between the recommended grant share and the resulting absolute amount. The highest shares are assigned to Ústí nad Labem (13.67%),

Moravian-Silesian (13.33%) and Vysočina (12.33%). However, excluding Prague, South Moravia receives the largest indicative amount (approximately CZK 182 million), followed by Vysočina (CZK 176 million) and Moravian-Silesian (CZK 159 million). This difference reflects variation in regional capital expenditure and illustrates why percentage recommendations and monetary amounts should be interpreted jointly. The figures represent model-based recommendations rather than actual grant allocations or evidence of their effectiveness.

Unlike the original study by Šanda and Křupka (2018), which calculated indicative grant amounts using 10% of regional capital expenditure as the reference base, the present case study applies the recommended percentages to total regional capital expenditure.

Table 9: Recommended for grant allocation – total grant

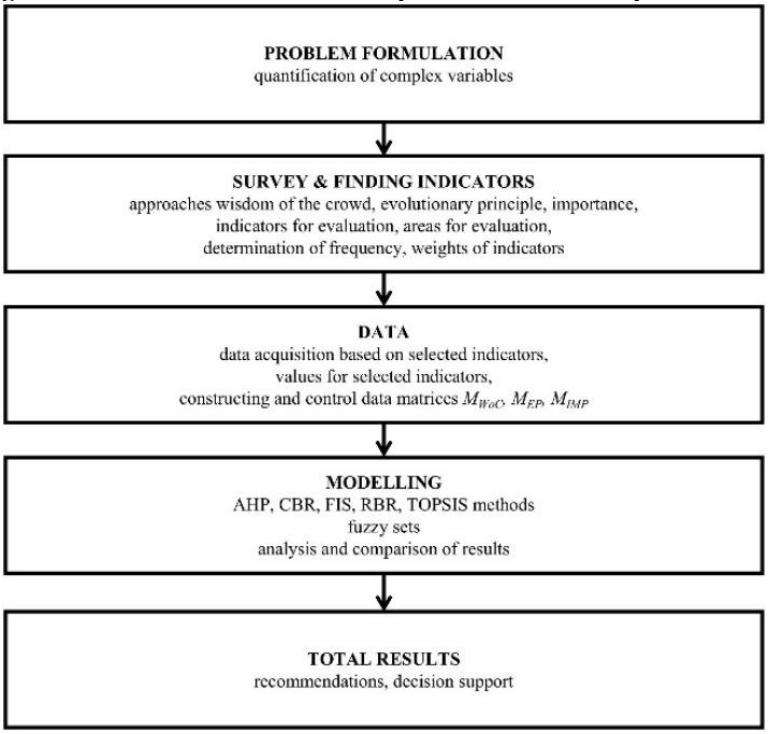
NUTS 3 region	WoC	EP	IMP	AGG total	Capital expenditure (thous. CZK)	Grant (thous. CZK)
STC	6%	7%	5%	6.00%	1,505,530	90,332
KHK	4%	4%	7%	5.00%	1,164,048	58,202
KVA	9%	8%	12%	9.67%	669,729	64,763
LIB	8%	4%	11%	7.67%	566,778	43,472
MSZ	14%	12%	14%	13.33%	1,192,562	158,969
OLO	10%	12%	10%	10.67%	1,147,991	122,491
PAK	5%	5%	9%	6.33%	870,110	55,078
PLZ	4%	5%	6%	5.00%	1,057,801	52,890
PRA	8%	8%	5%	7.00%	10,819,194	757,344
JHC	10%	10%	10%	10.00%	975,698	97,570
JHM	9%	10%	5%	8.00%	2,273,842	181,907
UST	17%	15%	9%	13.67%	921,511	125,971
VYS	12%	14%	11%	12.33%	1,426,220	175,853
ZLN	6%	7%	8%	7.00%	705,923	49,415

Source: Author's contribution

6. Generalization of the model: Quantification of complex variables

QL illustrates the challenges of quantifying complex, multidimensional variables that combine subjective perceptions with objective conditions. The extended framework addresses this challenge by separating indicator identification and weighting, data preparation, evaluation, and decision-support outputs. These stages form a modular structure that could also be adapted to other complex variables, as conceptually illustrated in Figure 3. However, applications beyond regional QL assessment would require separate empirical validation.

Figure 3. Generalized model for the quantification of complex variables



Source: Author's contribution

Figure 3 presents the generalised framework as a sequence of interconnected stages. The process begins with defining the complex variable and the purpose of its assessment. Relevant indicators are then identified and weighted using an appropriate approach, such as collective judgement or expert-based assessment. The selected indicators are operationalised through measurable variables, and the corresponding data are collected and organised into a data matrix. Suitable evaluation methods are subsequently applied to obtain partial and overall assessments. Finally, the results are interpreted and translated into outputs supporting comparison and decision-making. This structure separates the main methodological stages while allowing their specific implementation to reflect the nature of the evaluated phenomenon.

QL represents one empirical application of the generalised framework. The WoC, EP and IMP approaches illustrate alternative strategies for identifying and weighting indicators, while the subsequent stages of evaluation and aggregation follow a common conceptual structure. This modular architecture offers the potential for application to other multidimensional phenomena, including socio-economic, environmental and policy-related variables. However, transferring the framework to other domains would require appropriate indicators, relevant data sources, suitable evaluation methods and validation of the resulting assessments and decision rules.

Thus, the present study demonstrates the framework's application to regional QL, while its effectiveness in other contexts remains to be empirically established.

7. Discussion

The main methodological contribution of the extended framework lies in combining alternative approaches to indicator identification and weighting with multiple evaluation methods. The empirical results reveal both recurring patterns of regional differentiation and differences associated with the methodological configuration. Although broad regional patterns recur, AHP yields markedly different rankings for some regions, consistent with Cheng et al. (2026), who found that methodological choices can affect individual territorial rankings despite high overall agreement between QL measures. Furthermore, the narrower dispersion of regional scores under EP suggests that indicator identification and weighting can influence the apparent magnitude of regional disparities. These findings demonstrate the importance of distinguishing conclusions that remain consistent across methodological configurations from those that depend on specific analytical choices. Such distinctions are particularly relevant when evaluation results are used to support public resource allocation decisions.

Regional QL rankings can inform development priorities (Muthia et al., 2025); in the present framework, regional assessments are also translated into indicative grant recommendations. However, these recommendations should not be interpreted as estimates of actual funding needs or optimal grant amounts. Their practical application requires consideration of regional policy priorities, budgetary constraints and the feasibility of proposed interventions. The results also depend on the selection and weighting of indicators, data quality and the evaluation methods employed. Although combining multiple approaches enables the comparison of alternative assessments, it does not eliminate methodological uncertainty or subjectivity. Furthermore, the proposed grant recommendations have not been validated against the outcomes of implemented interventions. Future applications should therefore examine their practical effectiveness and test the framework in other regional or policy contexts.

8. Conclusions

This study extends the hybrid QL evaluation model introduced by Šanda and Křupka (2018) by integrating three approaches to indicator identification and weighting (WoC, EP and IMP) with five evaluation methods (FIS, fTOPSIS, CBR, RBR and AHP). The main methodological contribution lies in enabling alternative configurations to be examined within a common decision-support framework, thereby revealing how indicator selection, weighting and evaluation methods influence regional assessments.

The empirical application to historical data for all 14 Czech NUTS 3 regions demonstrates both recurring patterns and method-specific differences. The EP approach generally produces less dispersed regional scores than WoC under

fTOPSIS, FIS and CBR, while AHP yields substantially different rankings for certain regions. The aggregated grant recommendations identify Ústí nad Labem (13.67%), Moravian-Silesian (13.33%) and Vysočina (12.33%) as the regions with the highest recommended support, whereas Plzeň and Hradec Králové receive the lowest shares (5.00% each). These findings demonstrate how methodological choices can influence decision-support outcomes and highlight the value of comparing alternative evaluations before formulating regional development priorities.

Beyond regional QL assessment, the proposed framework offers a modular architecture for quantifying other multidimensional variables. However, its transferability remains a methodological proposition requiring empirical validation in other domains. Furthermore, the grant recommendations represent indicative model outputs rather than demonstrated optimal allocations. Future research should examine the framework's applicability to other complex phenomena, assess the sensitivity of aggregation procedures and evaluate the practical effectiveness of the resulting decision-support recommendations.

Conflict of Interest Statement

The author declares that there are no conflicts of interest.

Acknowledgment

Not the case.

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