Shared Situation Awareness in the Globalised World

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Abstract: Well-developed and properly implemented concept of situation awareness (SA) improves decision-making at all levels of governance and management, especially when it comes to risky or emergent scenarios. The importance of SA increases with the level of uncertainty and dynamism of the surrounding environment, as well as with the number of external collaborators. The general complexity of such problems is high, and it is difficult to structure them in a directly applicable and interpretable way. Therefore, our goal was to discover whether it is possible to reasonably simplify, systemise and incorporate specific aspects of national and global dynamics into SA of both independent and collaborating organizations in order to formulate viable policies and plan development indicators with respect to external changes.

As the main result, this paper suggests a conceptual design of a qualitative model of organizational SA, composed of two major components, data, and knowledge. It internalizes the four key aspects of national performance, accompanied by two distinct resources of global changes. This input information was initially identified in terms of disjoint, internally well-structured and mutually unrelated national indexes, for which the historical time-series data were available. Adopted datasets were processed with supervised and unsupervised machine learning techniques, which discovered the most influential general and country-specific predictors of external and global changes. These variables and identified relational patterns served as a foundation for designing a qualitative dynamic model of SA in the form of a Causal loop diagram. Because of the predictive nature of the proposed model, its adopters can either directly follow its suggestions or continuously share their own indicators of quantitative availability and qualitative willingness towards external partners. Related comparative analyses of typical scenarios can discover possible asymmetric bottlenecks caused by national specifics and global disturbances, which could prematurely harm otherwise smooth bilateral collaboration.

Keywords: situation awareness, global dynamics, trust, knowledge-based modelling, machine learning

1. Introduction

Complete and valid awareness of the present situation, altogether with its appropriate contextual interpretation, are essential prerequisites for correct execution of any strategic decisions. Situation awareness (SA) is informally interpreted as “knowing what is going on around us”. Although such simplification is straightforward and apposite, more explicit formalization of this crucial phenomenon is unavoidable, especially in the organizational context. Thus, nowadays, frequently used and further developed models of SA are mainly based on findings, published in (Endsley, 1995). From the managerial perspective, SA is usually understood as a dynamic systemic model of structural and temporal evolution of continuously monitored internal and external environment, based on which individuals or groups make their decisions. A valid and applicable practical instance of SA can only be formed on the basis of reliable, secure, complete, available and domain-related data and information. Nevertheless, this generally applies to individuals, teams, organizations, or nations. However, the power of decision-makers on different strategic levels naturally differs in the scope, impact, range of collected data and derived information or type and form of adopted inferential models.

Such high-level structural interpretation has several so far entirely unresolved bottlenecks, which are addressed in this paper. The main problem is the overall complexity of full-range realistic SA, which needs to be reasonably simplified. The desirable effect was achieved with a hierarchical decomposition of SA altogether with its transparent internal representation and use of implementation methods and tools, reflecting the holistic and dynamic nature of SA. The general principle of the proposed hierarchy, consisting of data and knowledge levels, is outlined in Figure 1.

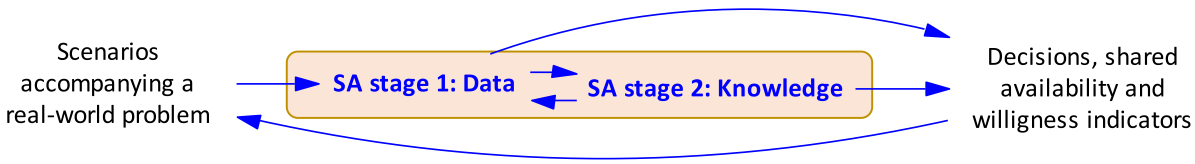

Figure 1: Schematic hierarchy of the proposed model of shareable situation awareness (SA).

According to this approach, effects of external dynamics are synthesised from the perceived data and information characterizing the current activities of market collaborators and competitors, completed with the behaviour of households, governmental regulations and global fluctuations. Incoming scenarios are interpreted in the context of internal preferences and after evaluating of possible consequences used for strategic decisions. In addition, this research claims that the specific way of SA implementation constitutes a level of perceived trust, reflecting the quality of internal relations as a long-term result of cumulative SA development. Moreover, an adjusted level of composite trustworthiness can be shared with external partners as am indicator of willingness to collaborate. All these interrelated factors are summarized in Figure 2.

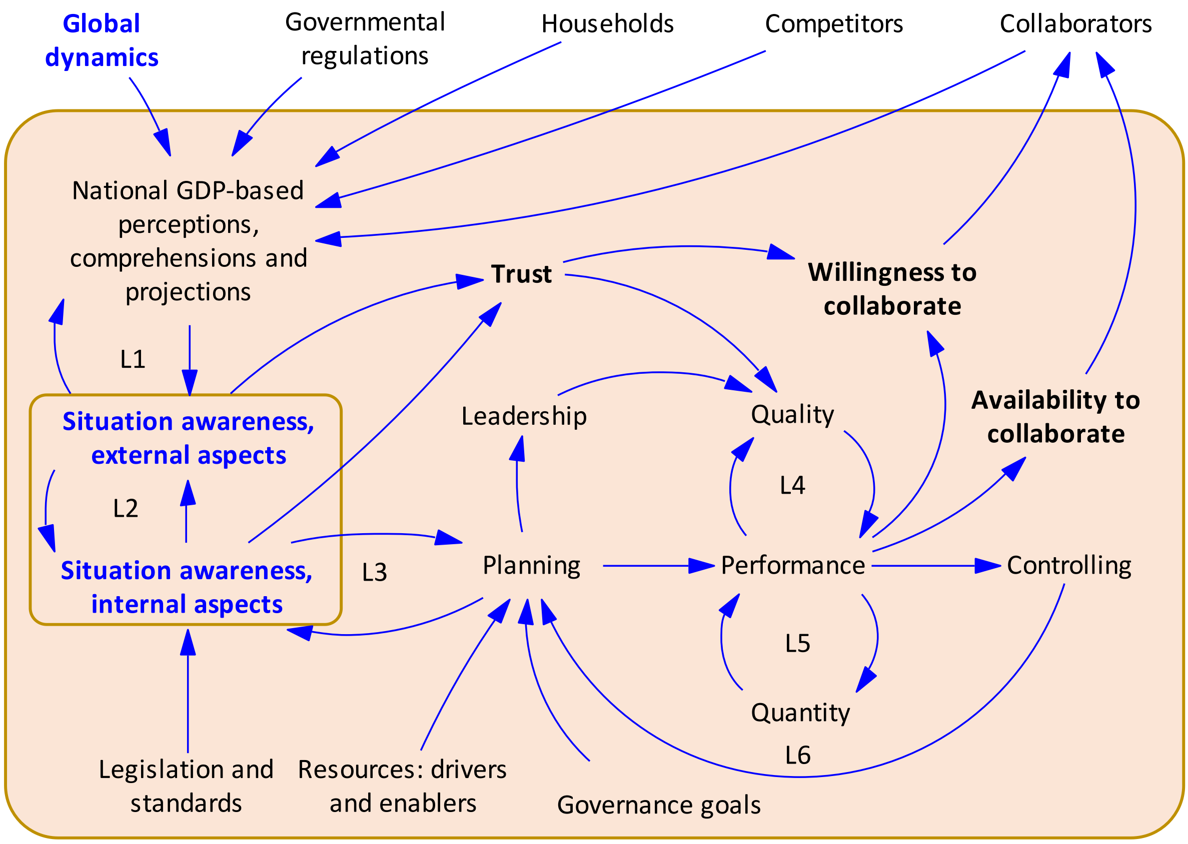

Figure 2: Schematic architecture of shared situation awareness.

The figure shows that SA model is split into two parts and developed through the loops L1 (improved comprehensions and projections) and L2 (higher inner cohesion of SA). The internal sector of SA is primarily used for planning (loop L3), achieving objectives (loops L4, L5) and managing performance of standard business cycles (loop L6). The external part of SA influences performance rather indirectly. However, it fundamentally contributes to the origination of shareable indicator of mutual trustworthiness. Although this dynamic diagram namely aims to provide an introductory overview, it can be used for indicative qualitative analysis of selected causes and effects with emphasis on the role of SA. For example, its conceptual incorporation to the organizational performance processes is shown in Figure 3, where parenthesis indicate the items, repeating inside the diagram.

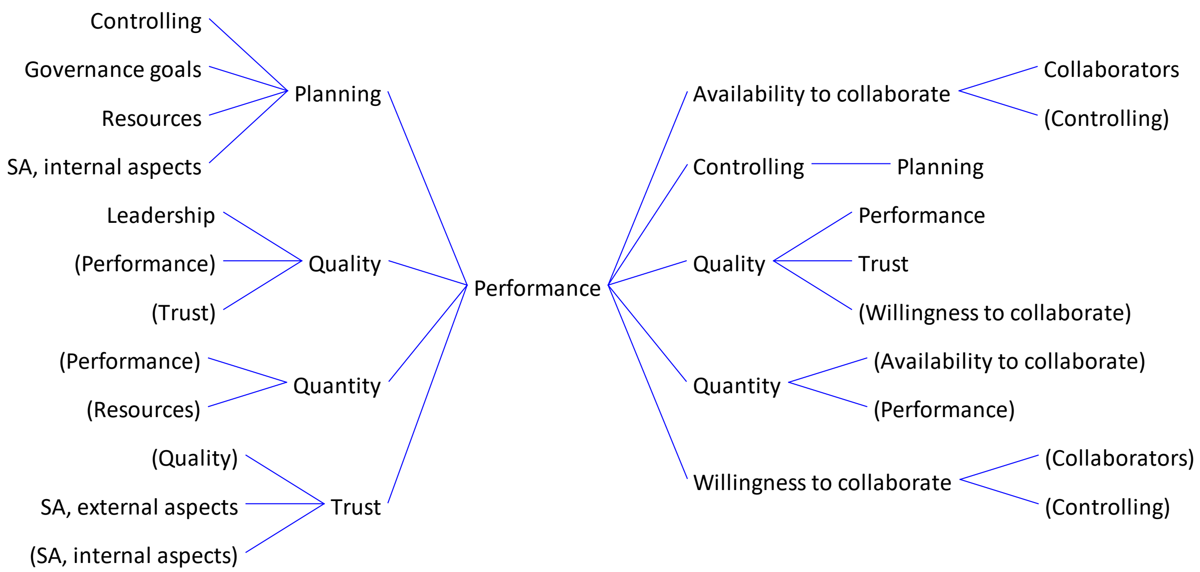

Figure 3: Partially unrolled set of *Performance* loops, showing the role of SA in the process of its creation.

The previous overview exhibited that the proposed architecture refers to a non-trivial transformation of continuously collected data and information into a compact and explainable form, applicable for decision-making support, especially at the tactical and strategic levels. From the organisational point of view, SA influences primarily processes with periods ranging from weeks to months. Thanks to their unevenly delayed causality, the conversion of perceived or measured facts into specific actions cannot be purely reflexive or predictive, but a broader contextual knowledge, combining both static and dynamic qualitative and quantitative aspects of the expected decision, is required. Usually, the presence of multistage causalities is mathematically solved by their representation with higher-order time-varying systems, where the highest derivative or difference determines the maximal achievable depth of history. However, non-linear systems with deep memory are analytically unsolvable, and their practically used numerical approximations may introduce additional computational errors. Thus, the development and updating of understandable and applicable organizational situational awareness should continuously integrate the gathered data into appropriate information and knowledge-based frameworks instead of utilization of purely mathematical formalisms.

The importance of SA was already mentioned already in The Art of War, dated to the 5th century BC. (Tzu, 2020) Several other authors have addressed the military aspects of situational awareness, whether on land, sea or air (Matthews *et al.*, 2001; Mittrick *et al.*, 2018; Murray *et al.*, 2010). The elements of rescue services perceive SA in a similar manner as armed forces (Arendtsen *et al.*, 2016; Garis *et al.*, 2015). Nevertheless SA also plays a crucial role in health care (Alhaider *et al.*, 2018; Cooper *et al.*, 2013; Qazi *et al.*, 2020). Moreover, a lack of situational awareness is reported as the main source of errors caused by the human factor (Endsley, 2015; Endsley and Garland, 2000). Therefore, the level of gradually maintained trust practically controls the real flow of available goods, services, and shared resources.

1.1 Individual and team models of situation awareness

The SA phenomenon is structurally characterised as a sequence of the following three subsequent decision-facilitating activities:

a) Temporal and spatial perception of the surrounding environment,
b) Comprehension of continuously collected data and information with respect to own performance,
c) Projection of derived conclusions to the future.

As situation awareness has a major impact on the organisational performance (Davies, 2016), it is crucial to measure it credibly. Consequently, number of recommendations suggesting how to quantify SA, were published. They typically concern the individual level of SA, however, a majority of them can be straightforwardly extended on the collaboration in teams. Purely personal metrics are based, e.g., on assessments of online reactions, prediction after freezing the inputs, self-assessment after the end of controlled or managed session, a posterior expert evaluation or a real impact of SA on overall performance. Actual methods and examples were described in (Gawron, 2019; Naderpour *et al.*, 2016; Nguyen *et al.*, 2019). For example, the SART (Situational Awareness Rating Technique) methodology, introduced in (Selcon *et al.*, 1991), works with the following categories:

a) Demand for attention, including environmental instability, variability, and complexity,
b) Supply of attention, considering emotional levels, free thinking capacity, concentration, and attention,
c) Degree of understanding of the environment, dependent on the quantity and quality of available information and knowledge.

The Observe-Orient-Decide-Act (OODA) is another living model for decision making in situations with large a number of quantitative inputs, such as cybersecurity, Internet of things or Industry 4.0. Nonetheless, OODA comes from the air force, where it was rather informally introduced in the late 1960s by Colonel J.R. Boyd. His concept attracted interest especially because of numerous incorporated feedbacks, producing richer internal dynamics in comparison with the traditional Endsley's model and adding the possibility of alternative feedforward propagation as well built-in preliminary testing features. These aspects were described and extended in (Luzwick, 2000; Lytvyn *et al.*, 2020; Noran and Bernus, 2018). Additionally, other structural frameworks for quantitative assessment of SA were presented by the following authors (Di Pace *et al.*, 2020; Fernández *et al.*, 2017; Kolbe *et al.*, 2017; Park *et al.*, 2017). In (Endsley and Jones, 2001) it was confirmed that individual models of SA could be straightforwardly generalized and efficiently adjusted for teamwork, so that their three-tier structure is further extended with an appropriate administrative, strategic and organisational context of the modelled matters. Related cases are described, e.g., in (Alhaider *et al.*, 2018, 2018; Guang and Chang, 2011; Salmon *et al.*, 2017). Therefore, the related team or organizational performance assessment techniques are based on joint problem-solving abilities concerning either theoretical tasks or practical situations, derived from real or simulated scenarios (Ganz *et al.*, 2015).

2. Methods

We followed the traditional modelling methodology proposed in (Mitroff, 1978), consisting of three further structured phases, problem identification, qualitative modelling, and model application. The summarized output of the first phase is in Figure 2 and proposes a simplistic system diagram of organizational SA, exposed to the basic set of external scenarios, including the global dynamics. Such structure could facilitate multidimensional decisions and early predict and mitigate impacts of sudden changes, control of which is out of scope of an organization. Moreover, its suggested representation is internally transparent and can be straightforwardly utilized for efficient networking. Such qualitative modelling represents the basis methodological platform of this research. It converts selected data, literature resources, expert, and domain knowledge into a two-stage decision-supporting model composed of data and knowledge.

The data-driven part of the model was created from appropriate national indexes of the first 21 OECD countries according to their GDP. In nontrivial process of their selection, we strived to identify a minimal set of indexes, disjointly and complementarily characterizing the majority of locally specific aspects concerning economy, population, and environment in the form of continuous time series between years 2014 and 2019: The reason for choice of such outdated interval was to avoid the pandemics-related fluctuations. Besides the yearly changing country-specific indexes, we as well calculated overall indexes of global dynamics as medians of all included countries, which remained constant for the given year. All dimensions of the resultant source data were normalized to interval <0,1> and split into two different tasks:

- Anonymised case-based reasoning (CBR), working with single records without named relations to source countries. Such analysis allows to identify the general key variables, patterns or their clusters in multidimensional feature space.
- Informed dynamic analysis (IDA), using two specific dynamic descriptors for each country, the normalized total difference and slope of linear approximation of every variable for the whole investigated period. Similar types of one-shot values were calculated also for the global indexes and used as country-specific constants.

For both tasks, we employed the following types of multidimensional analyses:

- Supervised dimensionality reduction (SUP), analysing the data multidimensional data set with respect to a priori defined target variable, which was an appropriate form of static or dynamic descriptor of GDP per capita. This technique can discover and quantify the most informative subset of target predictors, which shrinks the original dimensions and simplifies the problem.

- Unsupervised learning (UNSUP) discovers and analyses internal relations within the whole data set with equally rated variables. It typically results in a set of meaningful clusters of data or variables that needs to be personally evaluated and discussed. This technique was used predominantly for discovery of country-specific features.

All machine learning tasks were realized in the SAS Enterprise miner software environment. The StatExplore module with Gini tree-based selection criterion was applied for dimensionality reduction, and unsupervised analyses were performed with Variable Clustering node with default parameters. Detailed information regarding particular machine learning and pattern recognition methods can be found in (Bishop, 2007; Witten *et al.*, 2016). The data-driven model can be used either for immediate decisions, based on instant input-output mapping or for selecting the most important knowledge artefacts, useful for subsequent simplification and parametrization of the related knowledge-based model.

The knowledge-based model is expressed in the form of a Causal loop diagram (CLD), which is a powerful tool for qualitative validation of dynamic hypotheses. Direction of causality of partial behaviour-determining features is marked with arrows, altogether with the polarity sign, marking their bilateral proportion. The total duration of closed arrow-wise loops denotes single business cycles, where the duration ranges from weeks to years. Individual loops are interlinked through common nodes, where their specific dynamics are superimposed in terms of the linking variable meaning (capacity, finances, people, quality etc.). Furthermore, the resultant structure allows to qualitatively analyse problem-related dynamic hypotheses, i.e., assumed time courses of selected variables. They are typically discussed concerning different scenarios, expressing typical configurations of internally uncontrollable events.

The significant advantage of CLD is the possibility of its conversion into the corresponding stock and flow diagram. This standard language of system dynamics can be computationally executed, and hitherto purely qualitative judgements can be completed with the quantitative outputs. Before the actual use, both proposed models were verified and validated, namely through individual and team expert assessments, supplemented with the unused data from processed global indexes. Key aspects of qualitative and quantitative modelling of complex dynamic socio-technical systems were thoroughly presented by (Forrester, 1961; Meadows and Wright, 2015; Morecroft, 2015; Sterman, 2014; Warren, 2008).

3. Results and discussion

3.1 Data-driven model

Source data sets characterizing internal and global dynamics were selected from the initially considered 12 indexes and compared from the following viewpoints: diversity, independence, transparency, structure, methodology, resource, and coverage. Every viewpoint was classified from 1 to 5 and the resulting total scores varied from 16 to 34. Consequently, the following five indexes with the highest rating were adopted for further processing:

a) Key aspects of national performance:
   - Democracy index (DEI), 34 points,
   - Environmental performance index (EPI): 33 points,
   - Global competitiveness index (GCI): 33 points,

b) Primary resources of global dynamics, indirectly reflecting, e.g., migration, terrorism, or climate change:
   - Reduced Human development index (HDI), where the Decent standards of living component was removed because its direct correspondence with the Gross domestic product (GDP): 33 points,
   - Reduced Multidimensional poverty index (MPI): 31 points. Although MPI partially overlaps with HDI, the former concerns only developing countries that do not belong to the set of 21 analysed OECD leaders and are considered to be the primary resource of global social disturbances.

The high-level internal structure of selected indexes and some related abbreviations are shown in Figure 4. For the data processing stage, composite values of global indexes were extended with the corresponding time-series of Gross domestic product per capita and Unemployment rate (UR). The case-based reasoning data included 120 11-dimensional records, and the set for informed dynamic analysis contained 20 28-dimensional records. Therefore, it is evident that the primary conclusions can be derived from a more extensive CBR set, whereas that IDA set requires a considerable reduction of dimensionality.

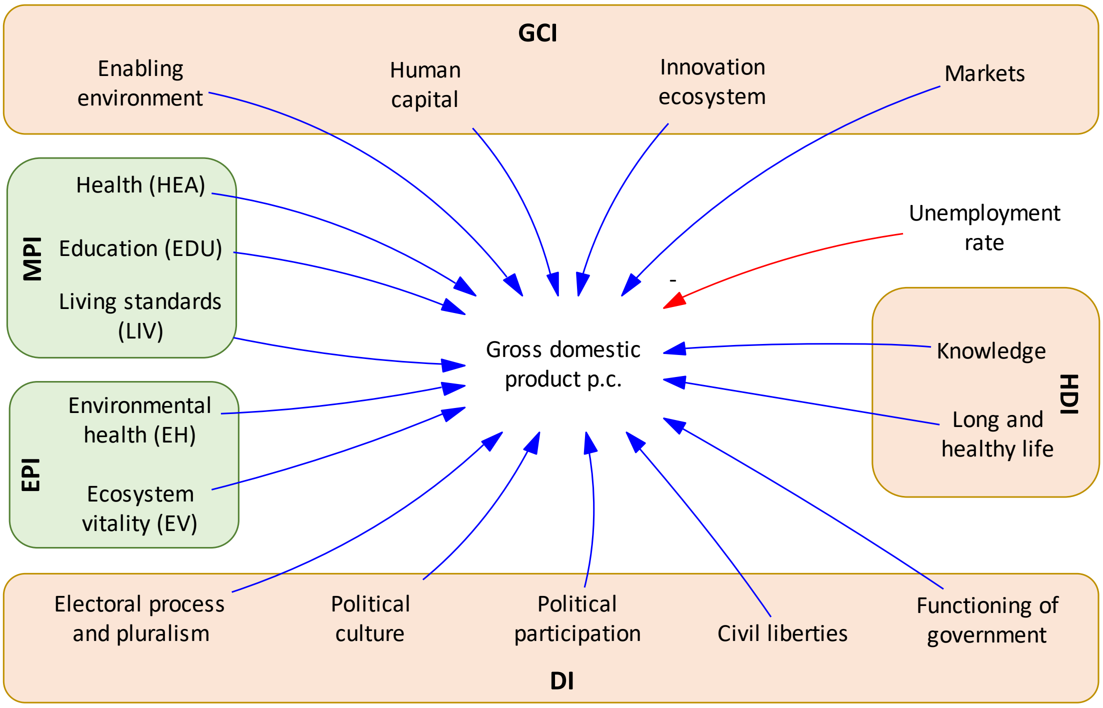

Figure 4: Internal structure of applied indexes.

The results of all applied machine-learning analyses are summarized in Table 1. Scope NAT indicates that the experiment marked *ID<number>* concerned primarily the national-level indexes DI, GCI, HDI and UR, while the columns marked with scope GLOB dealt with global indexes EPI and MPI. Both NAT and GLOB cases address all involved countries. To illustrate the ability of data mining in discovering the national-specific features, scopes CZ and GER, concerning the Czech Republic and Germany entirely, were also studied.

The anonymous case-based reasoning data processed with supervised dimensionality reduction (experiment ID1) identified approximately equally influencing indexes of Human development and Democracy as the most significant predictors of GDP at the steady level. The DI and HDI indexes were followed by mutually balanced contributions to Global competitiveness index and Unemployment rate, which had roughly one third impact compared to the previous pair. The overall power of global Environmental performance and Multidimensional poverty indexes was equally around 7% for each.

Moreover, as the considerably stronger national indexes suppressed the role of less influential global ones, we performed the same (CBR+SUP) analysis only for components of EPI and MPI (experiment ID2, scope GLOB), and results showed the dominance of EPI over MPI.

Experiments with Informed dynamic analysis data using the supervised dimensionality reduction (experiment ID3, IDA+SUP) initially found that the information values of differences and slopes of analysed predictors were equal, which allowed to concentrate only on slopes. Then the slope of the reduced Human development index was evaluated as the best internal predictor of GDP dynamics. Contributions of other indexes were found as inconclusive, partially because of the small size of the analysed data set. The same data-related limitation hold for independent supervised evaluation of global indexes and so the experiment ID4 was dropped completely.

Besides these generally valid chunks of knowledge, untargeted unsupervised learning (UNSUP) was capable of finding the desired county-sensitive features. Experiment ID5, processing static CBR data, reported the key differences between the Czech Republic (CZ) and Germany (GER). While CZ's steady level of GDP depends mostly on components of its HR and DEM indexes, in GER the UR plays this determining role. Moreover, IDA also indicated that the level of CZ's GDP is more sensitive to changes than GDP in GER. All static components of global indexes EPI and MPI were generally clustered with GCI without any country-specific bindings. This means that the effect of global dynamics for any country can be early recognized indirectly through GDI.

Additionally, such statement was also supported with experiment ID6 (UNSUP+IDA), which identified GCI as a common driver of dynamics changes for both countries. In this case, the influence of EPI and MPI was below the computational threshold.

Table 1: Ordered values of the most significant predictors for all performed machine learning tasks.

Learning approach	**Method and data**					
	Scope	Anonymous case-based reasoning (CBR) [normalized values of indexes]		Scope	Independent dynamic analysis (IDA) [slopes of indexes]	
Supervised (SUP)	NAT	ID1	HDI, DI, GCI, UR, EPI, MPI	NAT	ID3	HDI, *(DI, UR, GCI)*
	GLOB	ID2	EPI:EH,EV, MPI:EDU,HEA,LIV	GLOB	ID4	Not applicable
Unsupervised (UNSUP)	CZ	ID5	DI, HDI, UR	CZ	ID6	GCI, HDI
	GER		UR, HDI	GER		GCI

3.2 Knowledge-based model

As the next step, the system of introduced indexes was converted into the dynamic knowledge-based model. In accordance with the main goal of this research, the model formalized the joint influence of different resources of external dynamics, which was further integrated into the external part of an organizational SA model. Furthermore, this subsystem could valuably contribute to the formation of the overall trustworthiness level, shareable with external collaborators.

The core strength of qualitative dynamic modelling insists in its predictive character. This means that properly adjusted model of SA or any of its independent parts can generalize the past behavioural patterns and project their consequences into a reasonable time horizon. Thus, managers do not need to wait until an undesirable performance decrease happens, but can this situation efficiently anticipate. Such additional resilience minimizes possible losses, calms the institutional environment, as well as determines and stabilizes relations with external partners. Moreover, the proposed general framework can be further parametrized and refined to fulfil the explicit requirements concerning own or partnering countries and reliably express expected performance and trustworthiness of international collaborators.

The proposed subsystem, modelling the dynamics of national GDP as a part of organizational SA is shown in Figure 5. The amount of externally offered performance varies based on detected scenarios and their projected impacts because the total range of shareable resources is a cumulative function of both immediate availability and willingness. Although considerably reduced for publication purposes, this CLD contains 75 loops covering 2 to 12 variables.

The position of accordingly acting organization is marked with bold green lines. Red italics variables *Level of democracy, Import, Export, Markets* and *Quality of environment* are the prime entrances of global changes. The remaining ones have a national character and are under governmental control. Because of the complex cyclic nature of model behaviour, the difference between causes and effects occurs only in the initial conditions. Then it gradually dissolves into the compound dynamic of the whole system. Therefore, the properly parametrized superposition of loop effects in the merging nodes forms the desired course of dynamic hypothesis, evaluated with respect to the joint changes of adopted indexes.

Concerning the exemplary case of national differences and possible resulting collaboration rules between Czech and German companies, data mining found that the Czech partners should especially continuously monitor especially the German Unemployment rate, which is the best indirectly proportional predictor of the steady level of national GDP. This metric can be completed with the Global competitiveness index, which is more sensitive to GDP changes. In Figure 5, GCI is split into single components belonging to different loops and be analysed independently for more precise statements. On the other hand, German companies should follow Czech indexes of Democracy and Human development because their changes are tightly related to the fluctuations of local GDP. This binding is more robust than in case of Germany. GCI again provides additional CZ trust-related information. The related overall situation is generally characterised in Figure 6.

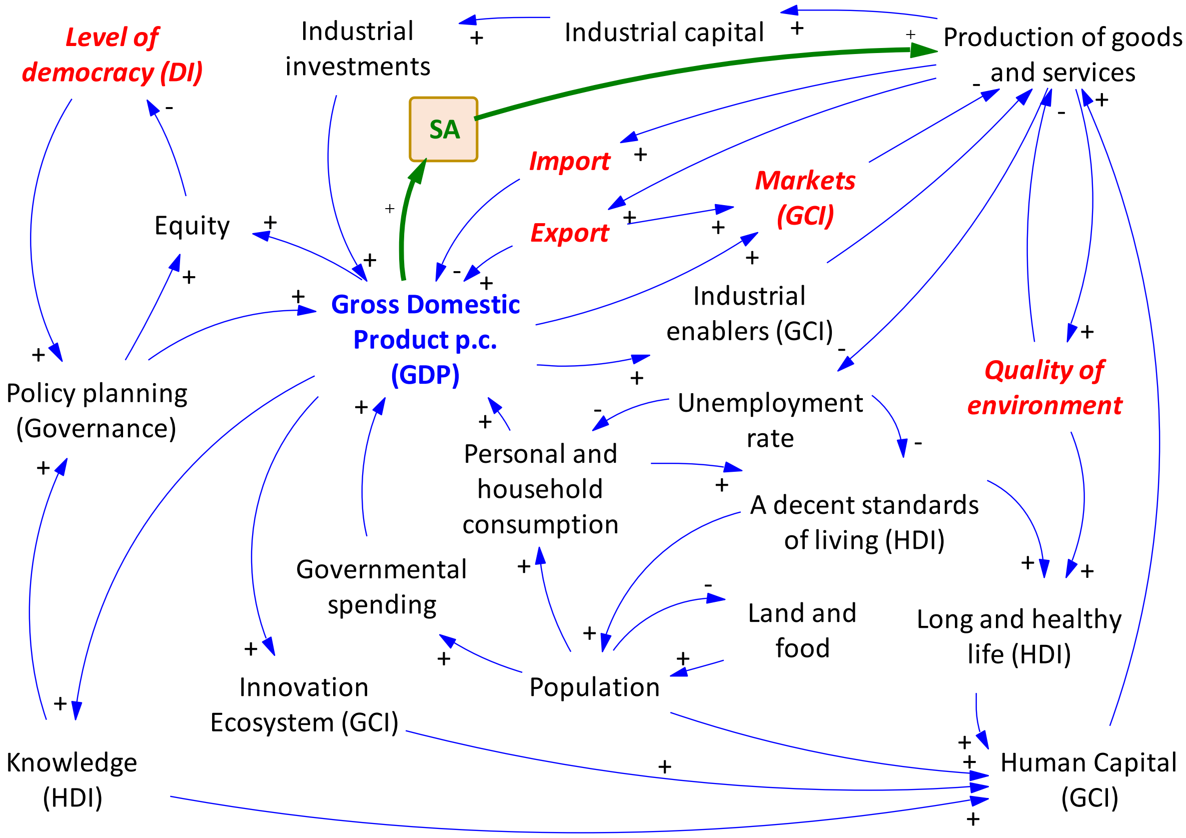

Figure 5: Causal loop diagram of the knowledge-based part of the external part of situation awareness model.

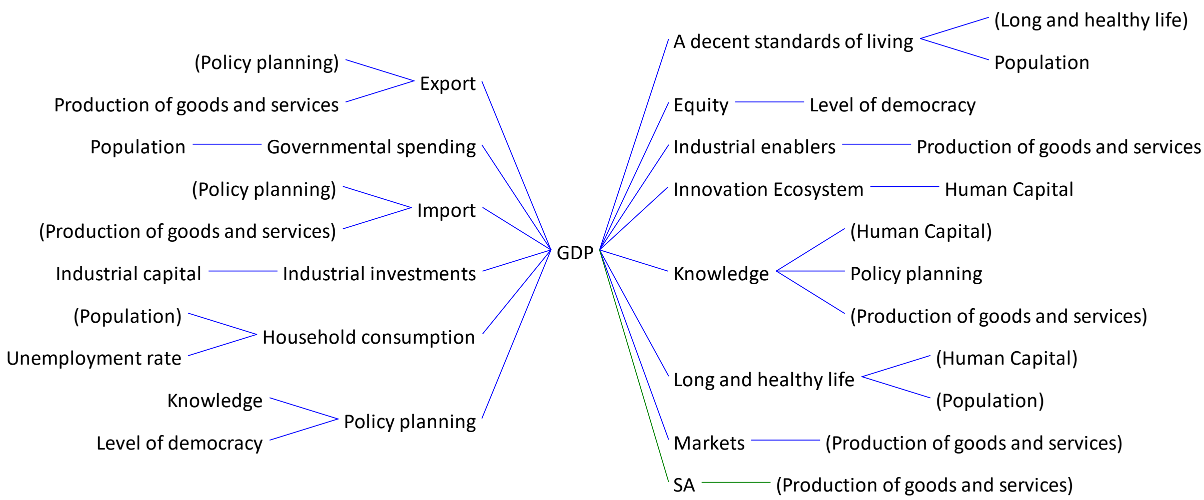

Figure 6: Partially unrolled set of cause and effects of *GDP* dynamics, including SA branch.

4. Conclusions

The positive role of well-structured and clearly formalized situation awareness on own performance and external collaboration was presented. Because of the inherent complexity of this matter, our research concentrated mainly on a single specific module, projecting nationally specific and global changes into the corresponding level of shared trustworthiness. Proper adoption of such platform increases organizational resilience and results in early anticipation and reflection of future movements. The presented model of situation awareness is based on information acquired from the set of complementary global indexes, preprocessed with different machine-learning tasks. These analyses identified leading predictors for static and dynamic changes of national GDP generated by national and global causes. Moreover, it was also found that the total direct impact of global changes during the analysed period was around 10%, which means that their slow changes are typically exposed indirectly, i.e., through the national indexes. Finally, the most emphasis from the static point of view must be given to internal components of Democracy and Human development indexes. Furthermore, for the majority of analysed well-developed countries, the role of Global competitiveness index and Unemployment rate is only secondary.

The structure of the resultant data-driven model was converted into the corresponding causal loop diagram. Determining loops of this complex oriented graph can be further analysed regarding the assumed dynamic hypotheses. Because of the complexity and multidimensionality of this problem, the current qualitative analysis represents a research limitation, which will be minimised with the conversion of CLD to its dual quantitative representation in the language of system dynamics.
We believe that holistic and transparent representation of shared situation awareness in the global environment, standardised at the level of source indexes, can help strategic decision-makers to define robust and resistant collaboration policies, capable to recognise possibly dangerous behavioural patterns in time and therefore minimise their impacts.

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