DOI: 10.2507/36th.daaam.proceedings.004

CONCEPTUAL MODEL FOR MEASURING AND ANALYSING INNOVATION OBSOLESCENCE THROUGH HYBRID INTELLIGENCE

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This Publication has to be referred as: Georgieva, P[etya]; Topalova, I[rina]; Demirova, S[iyka] & Vasilev, I[liyan] (2025). Conceptual Model for Measuring and Analysing Innovation Obsolescence Through Hybrid Intelligence, Proceedings of the 36th DAAAM International Symposium, pp.0029-0038, B. Katalinic (Ed.), Published by DAAAM International, ISBN 978-3-902734-47-1, ISSN 1726-9679, Vienna, Austria
DOI: 10.2507/36th.daaam.proceedings.004

Abstract

This article presents a developed conceptual model, combining artificial intelligence and human experience to measure and analyse innovation obsolescence. By identifying key indicators and factors contributing to innovation obsolescence, a conceptual model was developed to assess the effectiveness of hybrid intelligence in detecting early signs of innovation obsolescence and supporting strategic decision-making. The hybrid model is based on machine learning with survey data focused on sales of computer devices on the Bulgarian market. In the study, the model was trained using two approaches - machine learning with a Random Forest algorithm and an MLP neural network, to compare the accuracy of the results in the test phase. The goal of the development is to provide insights and recommendations for manufacturers, retailers and policymakers on the management of innovation cycles and technological substitution in rapidly developing markets.

Keywords: Innovation Obsolescence; Hybrid Intelligence; AI-Human Collaboration; Bulgarian Market.

1. Introduction

According to an OECD (Organisation for Economic Cooperation and Development) report, systems innovation offers an integrated, multisectoral approach to addressing complex societal issues such as climate change, population aging, and resource depletion. This involves coordinated interventions across technological, social, market, and regulatory domains, promoting long-term, holistic solutions. Unlike traditional policies, systems innovation seeks to transform entire socio-technical systems-such as energy or healthcare-rather than focusing on isolated technologies or organizations [1].

Systems innovation requires collaboration among governments, businesses, civil society, and research institutions to achieve sustainable and resilient growth. It is a profound structural transformation that responds to disruptions or major breakthroughs by reshaping the components and architecture of systems. This approach transcends sectors and actors, integrating social, behavioural, and institutional change, and blending traditional innovation categories. Innovations often originate in niche technological areas and scale only when they align with broader societal needs and infrastructures. Understanding the obsolescence of systems innovation requires analysing complex transformations, enabling foresight and experimentation, and adapting strategies in times of uncertainty.

Multilevel perspective (MLP) studies [2] identify three levels:

The landscape developments layer represents macro-level trends and external pressures (e.g., climate change, societal values, and geopolitical shifts). Change here is slow and large-scale, but it can create "windows of opportunity" for innovation by putting pressure on the existing system. For example, global climate concerns are spurring the adoption of renewable energy.

The socio-technical system layer is the dominant system-existing norms, technologies, policies, infrastructure, market logics, and user practices. It is typically stable and resistant to change. Constant internal adjustments occur, but true transformation only occurs when pressure comes from above (the landscape) and below (niche innovations). Its subcomponents are markets/user preferences, science and technology, policy, and culture.

The technological niches layer represents sheltered spaces where radical innovations emerge. Innovations here are typically small-scale at first, but they are diverse, experimental, and dynamic. Through learning, communication, and development, niche innovations can grow and gain momentum. As these innovations mature and external pressures combine, they can disrupt or replace the system.

Time moves from left to right. Initially, niche innovations are isolated and experimental. As landscape pressures and system tensions increase, these niche innovations gain momentum. Eventually, a new configuration emerges, transforming the system- a shift in the socio-technical order. Once established, the new order influences future landscape developments, closing the cycle. [3]. Obsolescence management strategies are a set of proactive practices designed to mitigate risks related to innovation obsolescence throughout a product's lifecycle. These strategies incorporate innovation principles, particularly in the conceptual design phase, using model-based systems engineering to assess and respond to obsolescence risks early [4]. A modular, cross-sector framework categorizes strategies from suppliers to customers, highlighting critical obsolescence drivers and availability modelling techniques [5].

Practical approaches include establishing interfaces with suppliers and project-level processes to anticipate and address obsolescence issues [6]. Lifecycle strategies can vary from start-ups may adopt iterative obsolescence for innovation quickly, growth stages tolerate chaotic obsolescence to scale, and mature companies often adopt planned obsolescence to maintain efficiency- strategies that can be aligned using tools such as the Global Innovation Map [7]. Planned obsolescence, while sometimes profit-driven, is under increasing scrutiny under consumer protection policies, particularly as accelerating innovation cycles and global competition shorten product lifetimes [8]. Overall, effective obsolescence management balances innovation, economic value, and lifecycle considerations to ensure long-term sustainability.

2. Research Methodology and Limitations:

The study applies a multi-layered methodological framework that combines conceptual modelling, empirical field research, and machine learning techniques within a hybrid intelligence paradigm (Fig.1). Despite demonstrating high accuracy in the test phase, the model is constrained by its reliance on a small dataset from five Bulgarian companies, the short validation interval of one month, and the use of survey-based inputs that may not fully reflect market dynamics. Furthermore, the predefined strategic categories limit flexibility, while the hybrid intelligence framework requires human interpretation that introduces subjectivity. These limitations suggest that further studies with larger datasets, extended observation periods, and diversified industries are necessary to enhance the generalizability and robustness of the model.

3. State of the Art

One research direction in the literature relates to technology readiness levels to identify key components and considerations for innovation. It provides a framework for assessing technology maturity and identifying critical components related to innovation. [9]. Other research trends emphasize the need for proactive, model-based approaches to assessing and predicting system obsolescence across the lifecycle of complex systems. Salas-Cordero [4] proposes a Model-Based Systems Engineering (MBSE) approach that integrates obsolescence risk assessment early in the conceptual design phase. This not only mitigates future risks but also balances obsolescence management with innovation strategies, viewing obsolescence and innovation as opposing but interconnected phenomena. In her work, Salas-Cordero introduces two key tools that support a structured assessment: The Obsolescence Measure (HoO) – a conceptual framework for identifying obsolescence factors in relation to a system architecture; system Obsolescence Criticality Analysis (SOCA) – a method for assigning an Obsolescence Criticality Index (OCI) to risks, enabling their prioritization for mitigation during the analysis phase. Trabelsi, I. [10] develop a quantitative mathematical model to predict component obsolescence. The model considers multiple influencing factors, such as technological change, supply chain dynamics, and market trends. Trabelsi [10] also applies Monte Carlo simulation to estimate the degree of system obsolescence (SOD) by analysing the obsolescence timelines of key components over a 30-year period. This simulation approach enables probabilistic risk estimation and long-term lifecycle forecasting. Finally, obsolescence management should begin in the early stages of design and be treated as a strategic activity linked to innovation.

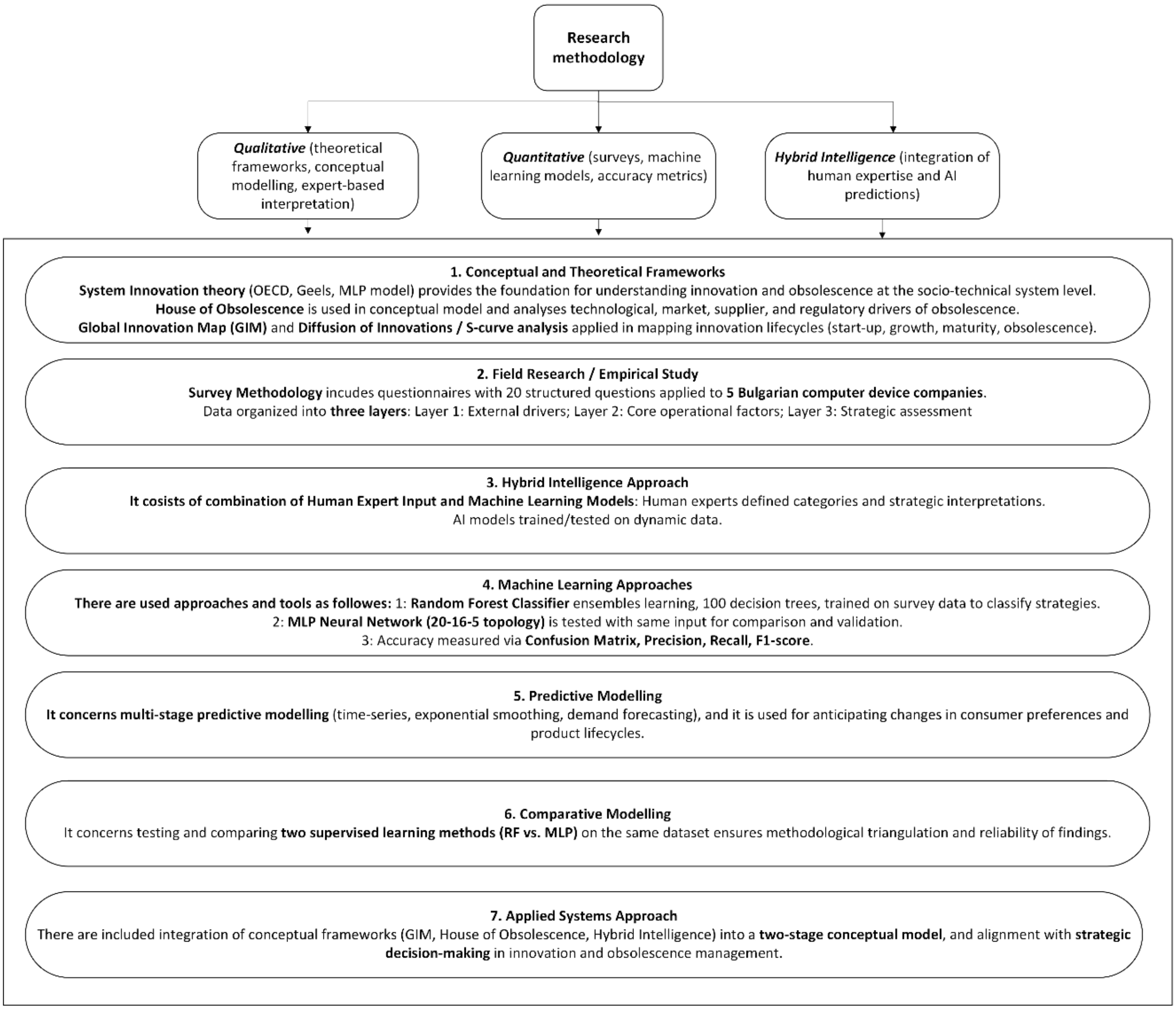


Fig. 1. Research methodology

Combining qualitative tools (such as HoO and SOCA) with quantitative models (such as Monte Carlo simulation) enhances foresight and decision-making. Integrating these models into the design and engineering processes supports more resilient and sustainable systems. The use of artificial neural networks (machine learning algorithms), applied to classify parts as active or obsolete with high accuracy, was discussed from Jennings et. al. (2016): "results have shown that machine learning algorithms (i.e., random forest, artificial neural networks, and support vector machines) can classify parts as active or obsolete with over 98% accuracy and predict obsolescence dates within a few months."[11].

The Random Forest method is a widely used machine learning algorithm that creates multiple decision trees during training and combines their results to improve prediction accuracy and robustness. It is particularly suitable for classifying components as active or obsolete and for modelling user behaviour, especially in contexts involving large amounts of data and complex, nonlinear relationships. Research shows that Random Forest, combined with other machine learning techniques such as artificial neural networks and support vector machines, can achieve classification accuracy exceeding 98% in distinguishing between active and obsolete parts. Additionally, this method can predict obsolescence timelines to within a few months of the actual date, making it a valuable tool for managing product lifecycles and planning maintenance or replacement schedules [12]. In addition to the Random Forest machine learning model, it is appropriate to compare the prediction accuracy with one of the classic neural network training models. For example, a neural network model of type Multi-Layer Perceptron (MLP) can be used to train and recognize/classify input data of the same type and format but dynamically changed over time.

The multi-stage predictive modelling approach is a methodology designed to capture the evolution of consumer preferences over time, particularly regarding product design. This approach supports design engineers in anticipating next-generation product features before they become widely adopted and potentially obsolete. This method operates in multiple stages, with each stage reflecting a different phase in the evolution of consumer preferences. A key component of this approach is the incorporation of time series analysis, specifically exponential smoothing, which is used to identify and predict emerging trends in product attributes.

The result is a dynamically evolving demand model that reflects changing consumer expectations, enabling proactive and informed product development decisions. This technique is particularly useful in rapidly changing markets, where staying ahead of consumer trends is critical to maintaining a competitive advantage and innovation relevance [13]. Hybrid intelligence is defined as the collaboration of human and machine intelligence to solve complex problems. It emphasizes conditional interdependence: tasks are divided among agents, but all contribute to a common goal. The outcome should be better than any one agent could achieve alone. Importantly, hybrid intelligence systems must continually learn and evolve through mutual interactions. These systems go beyond automation or human interaction models; they are dynamic, co-evolving systems [14].

Hybrid Intelligence (HI) represents a new and evolving paradigm, combining human cognitive abilities with AI systems to achieve superior problem-solving outcomes. Rather than seeking to replace human intelligence, HI emphasizes a collaborative partnership where each party compensates for the other's limitations. Human agents provide contextual awareness, ethical judgment, creativity, and emotional intelligence, while AI contributes speed, scalability, data processing power, and analytical accuracy [15] [16].

The literature emphasizes also the need to standardize the structure of hybrid systems and define governance frameworks that manage task allocation, data management, and incentive structures [17] [18]. The problem of the research is the high resource consumption and waste generation resulting from the production and sale of products (such as electronic devices). Measuring and analysing innovation obsolescence will support sustainable development and the application of circular economy principles. Research object is obsolescence of system innovations. The research aim is measuring and analysing system innovation obsolescence using hybrid intelligence with application in computer devices sales in Bulgaria. To address these issues, the subject of this research is to develop a machine learning-based methodology capable of forecasting obsolescence risk and product life cycle accurately while minimizing maintenance and upkeep of the forecasting system.

In this study, a hybrid supervised learning model was created to predict changes in recommended strategies based on dynamically changing input data. The hybridity of the proposed model lies in the integration between the predefined correspondence between the groups of combined input data and the desired recommended strategy. This first stage is determined by a human factor/expert. To standardize the structure of the proposed hybrid system, the second stage involves training two different well-known AI models with the prepared data. The third stage involves testing the two trained models with input data of the same type and format, but dynamically changed after a specified time, in order to correctly assign them to a specific strategy.

4. Description of the proposed conceptual system model

The diagram presents the first stage of the proposed conceptual model that integrates three key theoretical concepts: Global innovation map, the House of obsolescence, and Hybrid intelligence analysis, based on System innovation. It illustrates the interaction of these concepts in guiding strategic decision-making related to innovation obsolescence in dynamically evolving environments.

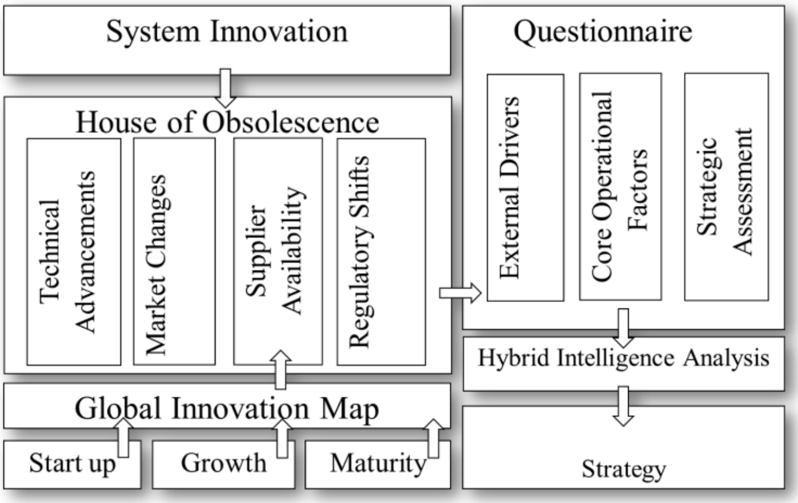


Fig. 2. First stage of the conceptual system model

4.1. System innovation block as the starting point

At the top of the diagram, System innovation captures the entire structure, focusing on a comprehensive, multi-sectoral transformation of socio-technical systems. This level establishes the premise that obsolescence and innovation should not be viewed as isolated phenomena, but rather as systemic processes embedded in evolving technological, economic, and organizational environments.

4.2. The House of obsolescence block: the multidimensional drivers behind the obsolescence of innovation

The concept of "House of obsolescence", which is based on working on the life cycle of innovation and technology turnover [19], includes four vertically aligned pillars:

- Technological developments: Refers to the pace and direction of technological progress that renders existing technologies obsolete.
- Market changes: Includes shifts in consumer demand, business models, and competitive dynamics.
- Supplier availability: Focuses on the continuity of supply of components and resources, highlighting the risks of dependency or disruption.
- Regulatory shifts: Includes legal, environmental, and political changes that enforce compliance and may lead to product or process obsolescence.

Together, these elements collectively define the obsolescence pressure affecting innovation.

4.3. Global innovation map block: mapping innovations throughout their lifecycle

The Global Innovation Map (GIM) is located below the "House of Obsolescence" and is derived from diffusion of innovation theory and S-curve analysis [20] Innovations are classified according to these stages:

- Start-up: Early-stage innovations, disruptive innovations, and niche innovations.
- Growth: Rapid expansion and market penetration.
- Maturity: Stable technologies with gradual improvement and increasing susceptibility to obsolescence.

This map provides a temporal and contextual location of innovations in the market, helping organizations visualize the vulnerabilities of each stage with respect to obsolescence.

4.4. Questionnaire block: structured inputs for Hybrid intelligence analysis block

On the right of diagram, the questionnaire section divides user or expert input into three conceptual layers:

- External factors: macro-level forces, such as politics, climate change, or global economic trends.
- Core operational factors: internal process efficiency, technological integration, and organizational capabilities.
- Strategic assessment: A high-level assessment of the alignment between innovation objectives and external/internal conditions.

This analysis aligns with systems thinking approaches to diagnosis and supports data collection for HI analysis. For our research, 5 computer sales companies in Bulgaria were surveyed, and the respondents were asked 20 questions, grouped into Layer 1: External Drivers, Layer 2: Core Operational Factors and Layer 3: Strategic Assessment. According to the number of answers, A, B C and D categories were defined in each question group. The obtained results for two of the companies are shown in Table 1. The *combinations of Layer 1 (L1), Layer 2 (L2) and Layer 3 (L3),* together with *Detailed Interpretation of results by combinations of dominant Layer, Generalized obsolescence degree*, *Detailed Strategic Actions with Examples in Sales of Electronic Devices* and *Strategic Actions Summary*, are shown in Table 2.

	Q1-Q5	**Layer 1: External Drivers**				**Q6-Q11**	**Layer 2: Core Operational Factors**				**Q12-Q20**	**Layer 3: Strategic Assessment**			
Company 1		**A**	**B**	**C**	**D**		**A**	**B**	C	**D**		**A**	B	**C**	**D**
	Q1	52	15	12	7	Q6	54	16	10	6	Q12	51	19	13	3
	Q2	54	18	13	1	Q7	52	20	11	3	Q13	55	17	9	5
	Q3	62	12	10	2	Q8	65	9	7	5	Q14	61	13	10	2
	Q4	58	10	9	9	Q9	57	11	10	8	Q15	55	20	11	0
	Q5	71	9	6	0	Q10	69	11	4	2	Q16	73	7	4	2
						Q11	55	13	12	6	Q17	53	19	13	1
											Q18	72	10	2	2
											Q19	67	11	4	4
											Q20	68	12	5	1
Copmany 2	Q1	63	18	15	9	Q6	66	20	12	7	Q12	62	23	16	4
	Q2	66	22	16	1	Q7	63	24	13	4	Q13	67	21	11	6
	Q3	76	15	12	2	Q8	79	11	9	6	Q14	74	16	12	2
	Q4	71	12	11	11	Q9	70	13	12	10	Q15	67	24	13	0
	Q5	87	11	7	0	Q10	84	13	5	2	Q16	89	9	5	2
						Q11	46	26	2	31	Q17	52	23	30	0
											Q18	57	18	24	6
											Q19	58	24	6	17
											Q20	59	22	15	9

Table 1. Questionnaire block with number of answers for two of the companies

Combinations from L1, L2, L3	Detailed Interpretation of results by combinations of dominant Layer	Generalized obscolenscence degree /GOD/	Detailed Strategic Actions with Examples in Sales of Electronic Devices	Strategic Actions Summary
AAA	Layer 1: High obsolescence risk or pressure (external/internal/strategic); Layer 2: High obsolescence risk or pressure (external/internal/strategic); Layer 3: High obsolescence risk or pressure (external/internal/strategic).	Critical obsolescence across all dimensions	Initiate an immediate redesign of outdated product lines. Allocate R&D resources toward developing next-generation PC components such as DDR5 RAM, PCIe 5.0 SSDs, and AI-accelerated GPUs. Collaborate with chipset manufacturers to ensure alignment with emerging hardware trends and address obsolescence across performance, compliance, and customer relevance.	**0** Immediate product redesign and innovation investment; initiate R&D programs
BBB	Layer 1: Moderate obsolescence signals or performance issues; Layer 2: Moderate obsolescence signals or performance issues; Layer 3: Moderate obsolescence signals or performance issues.	Moderate innovation pressure; partial stability	Focus on incremental updates to existing products, e.g., bundling popular mid-tier components (e.g., RTX 4060 with NVMe drives). Refine supply chain for efficiency and consider introducing co-branded configurations with OEMs. Monitor customer usage data and feedback to identify specific needs in gaming, productivity, or creator segments.	**1** Optimize operations; refresh outdated features and align product roadmap
CCC	Layer 1: Stable condition, but innovation may be lagging; Layer 2: Stable condition, but innovation may be lagging; Layer 3: Stable condition, but innovation may be lagging.	Stable but lagging in innovation	Conduct strategic foresight workshops to anticipate shifts in user preferences (e.g., demand for silent cooling systems or eco-packaging). Plan for the phased introduction of newer technologies in response to slow-moving legacy inventory. Enhance value proposition through warranty extensions, trade-in programs, or targeted marketing.	**2** Consider gradual innovation upgrades; monitor customer expectations
DDD	Layer 1: Low awareness or poor alignment – high risk if ignored; Layer 2: Low awareness or poor alignment – high risk if ignored; Layer 3: Low awareness or poor alignment – high risk if ignored.	Low awareness or poor strategic fit; high risk	Reassess product-market fit and ensure offerings align with both current regulations and technological standards (e.g., energy efficiency, RoHS compliance). Diversify supplier base to reduce exposure to component shortages and integrate real-time compliance monitoring tools. Rebuild customer trust through transparency and educational campaigns on product evolution.	**3** Improve strategic alignment; reassess compliance and vendor risks
ABC, ABD, ACB, ADC, BAC, BAD, BCD, BDA, CAB, CAD, DCB, DBC, DAC, CDB, DAB	Layer 1: High obsolescence risk or pressure (external/internal/strategic); Layer 2: Moderate obsolescence signals or performance issues; Layer 3: Stable condition, but innovation may be lagging.	Mixed signals; targeted improvements needed	Undertake a layered performance audit across marketing, operations, and product management functions. Deploy agile cycles for prototyping and testing updates in underperforming components. Engage B2B and enthusiast communities to crowdsource ideas and validate proposed adjustments.	**4** Conduct focused diagnostics; apply agile improvement plans in weak layers

Table 2. Answer combinations and proposed strategies

4.5. Hybrid intelligence analysis block: integration of human and machine thinking

Hybrid intelligence analysis block represents a pivotal moment in the synthesis process. Hybrid intelligence refers to the combination of machine learning models and human cognition to analyse, interpret, and help to predict innovation obsolescence [21]. It combines:

- Structured insights from the survey
- Quantified pressures from the obsolescence landscape
- Lifecycle positioning within the global innovation map

The analysis enables prediction of obsolescence risks, simulation of innovation trajectories, and optimization of strategic options.

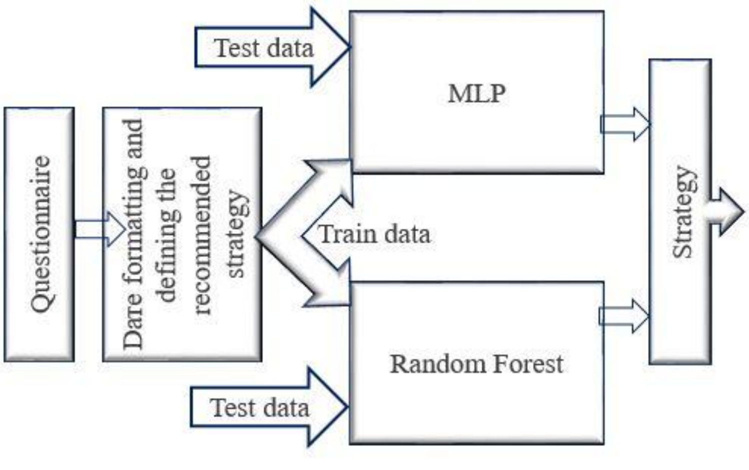


Fig. 3. Second stage of the conceptual system model - AI part of the Hybrid model

The second stage after collecting and formatting the answers to the questions, as given in Table 1, is to train the two models - Random Forest and a MLP neural network with the train data.

4.6. Strategy block: the convergent output

Essentially, the strategy emerges as a practical outcome of hybrid analysis. It may include different strategies [23, 24, 25]:

- Innovation renewal (reinvestment or re-pivot)
- Obsolescence planning
- Supplier diversification
- Regulatory compliance strategies

This last component represents the translation of complex system insights into organizational decision-making. In the test phase, the trained models are fed test data obtained after a survey with the same companies, but after one month. The system recognizes the data and classifies it into one of the five strategic categories. In this way, it responds adequately to dynamic changes in the respondents' answers.

5. Experimental results

The Random Forest model was trained with 20 samples of each one combination, defined in Table 1 (AAA, BBB, CCC, DDD, ABC, ABD, ACB, ADC, etc.). To create the model, the *Collaboratory* cloud environment was used, with access to the necessary Python libraries [22]. # RandomForestClassifier was Initialized with n_estimators=100. This parameter specifies that the Random Forest will consist of 100 decision trees, where X_train variable represents the values of input parameters Q1… to Q20. Y_train variable represents the answer category - Strategy (0,1,2,3,4 in Table 2).

X = company_data[['Q1', 'Q2', 'Q3', 'Q4', 'Q5', 'Q6', 'Q7', 'Q8', 'Q9', 'Q10', 'Q11', 'Q12', 'Q13', 'Q14', 'Q15', 'Q16', 'Q17', 'Q18', 'Q19', 'Q20']]

Y = company_data ['Answer category']

rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)

Fitting the classifier to the training data

rf_classifier.fit(X_train, Y_train)

Test data were constituted as input data of the same type and format, but dynamically changed after a month, in order to correctly classify them to a specific strategy and evaluate if the input conditions (answer of questions) represent a dynamic change. The test set consists of 10 samples of each strategy 0 to 3, and 20 samples of strategy 4, as whole 60 test samples. They are chosen randomly and fed to the model input. The obtained confusion matrix represents, that 5 samples of strategy 4 (that is 5 combinations of answers) were changed and classified/transformed as strategy 0. And 1 sample of strategy 1 is classified as strategy 4. All other instances are classified without change compared to the training phase.

To determine whether the strategy should really change according to the model's decision, we need to consider the classical estimation parameters of the model's accuracy. Namely, these are the parameters „Precision“, „Recall“ and „F1-score“.

Real strategy categories	0 1 2 3 4
Classified in test phase 0	[[15 0 0 0 0]
1	[0 11 0 0 0]
2	[0 0 13 0 0]
3	[0 0 0 15 0]
4	[0 1 0 0 5]]

Table 3. Confusion matrix

As F1-score takes into account both precision and recall and is based on a balance of the two, it is more appropriate to calculate this parameter according to the given equation 1:

$$\mathrm{F1-score} = 2.\frac{\mathrm{preciscion.recall}}{\mathrm{preciscion+recall}} = \frac{\mathrm{TP}}{\mathrm{TP} + 1/2(\mathrm{FP}+\mathrm{FN})}, \quad (1)$$

Where:
True positives TP is an outcome where the model correctly predicts the positive strategy.
False positives FP is an outcome where the model incorrectly predicts the positive strategy.
False negatives FN is an outcome where the model incorrectly predicts the negative strategy.

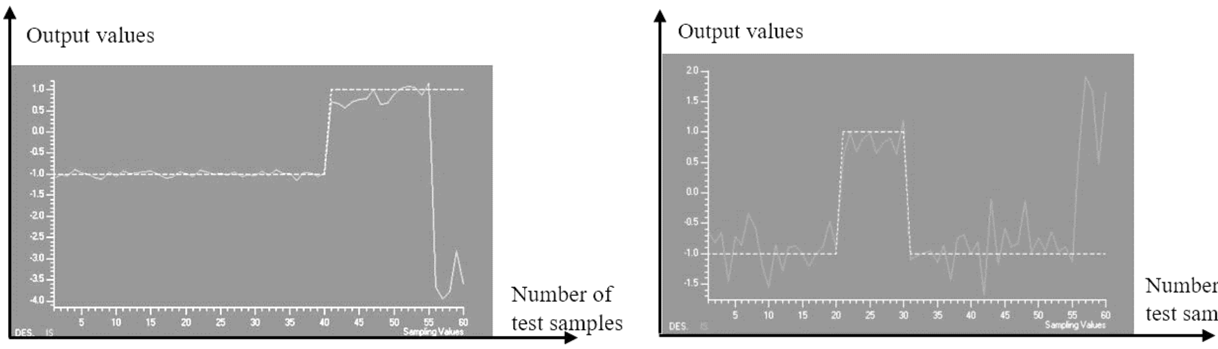
Strategy	Precision	Recall	F1-score	Test samples
0	1.00	1.00	1.00	15
1	0.92	1.00	0.96	11
2	1.00	1.00	1.00	13
3	1.00	1.00	1.00	15
4	1.00	0.9	0.95	6

Table 4. Accuracy results in test phase for the 5 defined strategies

The very high value of evaluation parameter F1-score, shows that we could consider the test results as recommendation for change in strategy for these 6 different classified samples (question answers one month later). To assess the accuracy of the created machine learning model, we trained a MLP neural network model with the same set of input data, with the following topology: 20 neurons in the input layer (associated with the 20 values of the number of answers for each of the 20 questions), 16 neurons in the hidden intermediate layer and 5 neurons in the output layer (corresponding to the 5 given strategies), i.e. MLP 20-16-5. The same train and test data sets were fed to the inputs in train and test phase.

MLP Model Definition

```
model=Sequential()
model.add(Input(shape=(20,)))
model.add(Dense(16, activation='tanh')
model.add(Dense(5, activation='sigmoid'))
```



a) b)

Fig. 4. MLP output values: a/ output values of neuron 5 (strategy 4) when fed with 20 test instances of this strategy; b/ output values of neuron 2 (strategy 3) when fed with 10 test instances of this strategy

In the graphs in Figure 3, the dotted line represents the ideal values set in the training phase for the 5 neurons in the output layer, and the solid line represents the approximated values in the test phase. From the graphs in Figure 3, it can be seen that for 6 out of 20 test instances incorrect classifications are obtained - for strategy 4. That is, the number of transformed strategies for the test data obtained after one month coincides with that obtained with the Random Forest model. This is a prerequisite for considering that the methodology can claim standardization in terms of the adequacy of prescriptions for change in business strategy.

6. Conclusion and feature work

What is new in this study that distinguishes it from similar studies discussed at the beginning of the article?

- Bringing the concept of innovation to the system level in the context of innovation obsolescence.
- Studying the obsolescence of the elements of systemic innovation.
- Recommendations for strategies that are based on information about the system in which the innovation operates. In this way, the innovation can be positioned in terms of its effect on the system.
- Using Random Forest and MLP in the context of tracking innovation obsolescence.

Finally, the model represents a systems-oriented approach to managing innovation obsolescence. It presents a multidimensional, lifecycle-aware, and intelligence-enhanced model, where each theoretical component (innovation management, business architecture, and hybrid intelligence) plays a role in guiding flexible and informed innovation strategies. This integrative logic aligns well with contemporary frameworks in strategic innovation management, particularly in high-speed sectors such as electronics, software, and advanced manufacturing. Using field research, a framework was developed to measure and analyse innovation obsolescence, and a survey was developed to survey the opinions of five companies deal with Computer devices sales, from different regions in Bulgaria.

The survey was conducted over three days, and the data was used to train the AI. One month later, the survey was repeated, and the data was used to test the AI model and predict the change in strategies. In this study, a hybrid supervised learning model was created to predict changes in recommended strategies based on dynamically changing input data. The hybridity of the proposed model lies in the integration between the predefined by a human specialist correspondence between the groups of combined input data and the desired recommended strategy. Training and testing two different supervised learning models with the same input data is a prerequisite for comparing results and confirming the correctness of the choice of transformed strategy. The system recognizes the data and classifies it into one of the five strategic categories. In this way, it responds adequately to dynamic changes in the respondents' answers. An advantage of the model is the possibility of repeated re-training with different survey results, in order to build different strategies in other business sectors. Submitting data in the test phase with survey results obtained after different periods of time, leads to automated dynamic change in recommendations for changing strategies.

Research contribution concerns development of an innovative conceptual model that combines hybrid intelligence (human expertise and artificial intelligence) for innovation obsolescence analysis, applied to a real market (computer sales in Bulgaria); integration of three theoretical frameworks: Global Innovation Map, House of Obsolescence, Layered model for strategic assessment through questionnaires. The technical contributions of the research are creation and training of two machine learning models: Random Forest and MLP neural network, used to predict and classify strategies for dealing with innovation obsolescence. Use of dynamic input data collected over different time periods to validate the adaptability and accuracy of the models. Practical contribution concerns conducting a field study among 5 real companies engaged in the sale of computer devices, through 20 questions in three layers of assessment; deriving strategies that organizations can undertake: innovative renewal, planned obsolescence, supplier diversification, strategic regulatory compliance, etc. Conceptual and methodological contributions are defining hybrid intelligence as a strategic tool that combines human expert thinking with predictive analytics; forming a basis for standardization that allows the methodology to be applied across industries and adapted to the specifics of the sector.

As a future development of the method, it is planned to test it with survey data from more companies from different industries. For the analysis of predictions and recommendations for changes in strategies, the test can be further developed with data after different time periods, to establish the aging time of innovations according to the type of industry, the volume of commercial activity, etc.

7. Acknowledgments

Acknowledgements for the support of the Research Project № 3O-340/10.04.2025, of the *University of Telecommunications and Post* titled "A conceptual model for analysing innovation obsolescence through hybrid intelligence".

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