Collaborative Human-AI Decision-Making Systems

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Abstract

Advances in machine intelligence methods over the recent years are bringing the accuracy and confidence of AI systems to the level of regular human operator, and in a number of cases, exceeding it offering opportunities for improvements in the quality, performance and cost efficiency of decision-making systems. To address concerns and challenges in application of artificial systems in critical decision-making areas, the concept of collaborative human-AI decision-making system is proposed, aimed at utilizing the strengths of human and machine intelligent methods to maximize the performance in a cost-efficient process. It is demonstrated that multi-channel human-AI systems can have a number of advantages compared to conventional systems and produce significant improvements in both accuracy and performance. Applicability criteria of single and multiple stage decision-making systems are defined and discussed. It is demonstrated that collaborative human-AI decision-making systems have significant potential in improving quality and effectiveness of decisions in many areas of application.

Keywords

Artificial Intelligence, Decision-making systems, Multi-channel DMS

1. Introduction

The advances in machine intelligence methods and technologies over the recent years have brought the performance of machine systems in a number of tasks and areas of application to the level of regular human operator, human expert or exceeding it [1,2] including in critical domains as public security and health care [3, 4]. Artificial intelligent systems can offer a number of essential advantages, for example, by providing stable and consistent performance in 24×7 regime, not or less affected by personal, environmental and transient factors while having superior processing capacity with higher throughput and minimal processing times. These developments offer opportunities to improve both quality and performance of decision-making in a broad range of areas and applications by incorporating high performance machine intelligence systems [5].

However, introduction of such complex artificial intelligent systems in critical areas and applications including aviation; public safety and security; health care and others can be associated with essential challenges of its own, not in the least in the areas of public trust and confidence in critical decision-making systems that employ such components [6]. Internal operation and learning processes of complex machine systems such as deep neural networks commonly used in high accuracy image analysis are not very well understood and trusting them with essential decisions can be seen as risky and unwarranted by general public. For example, it has been noted that at times machine learning methods and algorithms can produce errors or non-intended outcomes that can be difficult to explain, evaluate and rectify [7, 8], emphasizing the need for robust verification and oversight of such systems particularly in the critical areas of application.

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Another driver for introduction of higher efficiency decision-making systems is the rising cost of errors in critical decision areas, for example the cost of diagnostic errors in primary healthcare system that has been found to contribute significantly to the overall cost of public healthcare [9, 10]. Similar trends were found in other areas where complex decisions are necessitated by the operational environment.

Often, the problem of decision making can be reduced to selection from the set of acceptable options [11]. Analysis of literature sources shows that an important problem at the stage making and making decisions is the coordination of decisions obtained from different sources [12]. For the reasons outlined earlier human expert remains an important the source of solutions. Methods of processing expert solutions were investigated extensively in the current research. In [13] the method of pairwise comparison of expert opinions was developed. Works [14, 15] considered fuzzy and other methods in processing expert assessments and established rules for producing collaborative solutions. Another group of works discussed methods for evaluating competence of experts [16-18].

On the other hand, methods of machine intelligence in application to decision-making in practical domains and applications include, clustering methods [19-21], methods of forecasting and regression [22-24] and classification and unsupervised learning [25-27] among others. The problem of search for an optimal decision can also be approached as "a game with nature", where a number of methods and criteria were developed [28-31]. The choice of criteria for decision-making usually rests with the decision maker and depends on such subjective characteristics as level of optimism, risk tolerance, etc. and objective factors describing the domain such as: confidence, risk tolerance, priority and importance of the decisions [32].

Taking into consideration challenges as well as the opportunities, an investigation and discussion of methods and strategies of safe and efficient application of machine intelligence technologies to decision-making problems in practical domains and applications with the objective to harness the advantages of human and machine intelligent systems to improve the quality and performance of resulting decisions without compromising safety and retaining full trust and confidence of the public in the system.

1.1. Human and AI Systems: Complementarity and Synergies

With human and AI decision-making systems having clear complementary strengths as illustrated in Table 1, the advances in machine intelligence methods over the recent years bringing the accuracy and confidence of decision to the level of regular human operator, and in a number of cases, exceeding it, provide both an opportunity and a foundation for introduction of Collaborative Human-AI decision-making systems (CHAI DMS) harnessing the synergy of strengths of human and machine intelligent systems and as a result, improving the performance in multiple domains and tasks of application in quality, confidence and capacity of decision-making system.

Table 1
Strengths and synergies of Human, AI decision-making systems.

Decision-making system	Strength	Challenge
Human	High intelligence Associative capacity Anomaly detection Creativity	Influenced by environment Stability: stress, distraction, burnout Consistency: education, experience, competence
AI	Stability Consistency Speed, capacity, throughput Accuracy	Explainability Public perception Track record

However, as discussed earlier, introduction of decision-making systems based on, or with participation of machine intelligence methods and technologies needs to be cautious, based on comprehensively verified systems and technology as they deal with the issues of trust and confidence in machine-based technology by the general public that cannot be taken as assured [8].

The challenge therefore lies in creating collaborative human-machine intelligent decision-making methods, models and systems that are capable of combining the benefits and strengths of human and machine expertise, while minimizing their respective shortcomings and ensuring confidence and trust in the produced decisions.

2. Parallel Multi-Channel Decision-Making System

Consider a decision-making system that has multiple channels $C_1, ..., C_n$ and the final decision on an input X is obtained from decisions of the channels by a summation process described by a decision function D based on the decisions of the channels:

$$D(X) = D(c_1(X), c_2(X), .., c_n(X)) \tag{1}$$

In the general case, the decisions of the channels c_k can be of the following types:

- Categorical, with values in a certain set of valid values *V*.
- Numerical, integer, rational and other numerical types.
- Binary i.e. True or False value that will be assumed for illustration in the rest of this article.
- Other types, such as verbal, tokens, etc.

We will assume that the decision produced by a channel $C_k(X)$ on input X comprises a typed value $c(X)$ as defined above, and the confidence $A(X)$, measured by a factor in the range [0, 1].

Each decision-making channel C_k can be characterized by the following parameters: accuracy P_k and error E_k as combined measure of statistical errors of both types; and confidence, A_k. The goal of a multi-channel decision-making system is to maximize the accuracy of the decision function $D(X)$ and minimize the error on the trial set of inputs $\{ X \}$.

In addition to the decision function, a "conflict function" $C(X)$ is defined as measure of agreement or disagreement between decisions of channels on a given input:

$$C(X) = C(c_1(X), .., c_n(X)) \tag{2}$$

Together, the results of decision and conflict functions $D(X)$ and $C(X)$ for specific input evaluate how close the channels are to a common decision about the input.

Definition of decision functions are specific to the system. Several examples are provided below.

Logical decision function: in the simplest cases, the decision function can be defined as logical conjunction (AND) or logical disjunction (OR) of the channel decision. For example, a two-channel system with logical disjunction decision function has the accuracy and error that can be derived from the channel factors:

Confidence: the decision with the highest confidence among the channels is selected:

$$D(X) = c_k(X),\ A_k = max(A_1, .., A_n)$$

Ranked Confidence: the decision with the highest confidence taking into account ranks of the channels is selected:

$$D(X) = c_k(X),\ A_k = max(w_1 A_1, .., w_n A_n)$$

where w_k, weight or rank of the channel C_k.

Voting and Ranked Voting: the decision with the highest number of votes of confident channels is selected.

And a number of other strategies, as discussed in the following sections.

2.1. Two stage Multi-channel CHAI System with Expert Arbiter

An example of multi-channel Human-AI decision-making system in application to diagnostics of medical conditions was proposed in [33] whereas multi-stage decision-making systems were considered in [34]. The essential characteristic of such a system, that can be generalized to any number of channels is two-stage decision-making with an expert arbiter in case of conflict between the channels. The system operates as follows (**Figure 1**):

1. For a given input X, if no conflict has been detected between the channels based on the value of conflict function $D(X)$, the resulting decision is determined by the cumulative function $C(X)$.
2. If conflict is detected, $D(X) > 0$ the input with the decisions of channels is passed to the next, expert decision stage, $E(X)$ that is considered to be the final decision: $C(X) = E(X)$.
3. Finally, the expert decision can also be involved when an uncertainty or insufficient confidence was produced by some channels. This case can be considered as equivalent to a conflict in p.2.

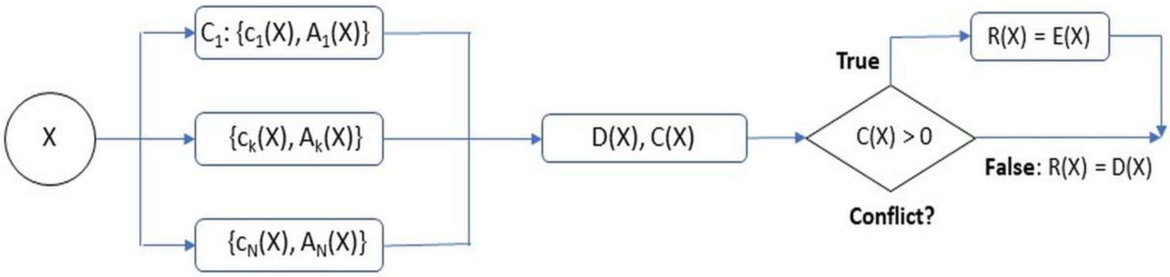

Figure 1. Two-stage CHAI system with an Expert Arbiter.

The logical sequence of the two-stage decision making model where $R(X)$ is the final decision on input X can be defined as:

X: $Ck(X)$, $D(X)$, $C(X)$
if $C(X) = 0$: | no conflict or uncertainty
  $R(X) = D(X)$
else if $C(X) > 0$: | conflict or uncertainty detected
  $R(X) = E(X, t_e)$

It is common to assume that the accuracy of the expert stage is superior to all of the channels: $P_e > P(C_k)$. Another essential parameter of a two-stage system is the second stage decision time factor t_e, measured as time from the last output of the first stage to the final decision of the expert stage. The discussion of criteria of applicability and effectiveness of two-stage CHAI systems is provided further in this section.

2.1.1. Advantages of Multi-channel CHAI Systems

Even relatively simple parallel system as multi-channel two-stage CHAI may have a number of important advantages over conventional single-channel decision-making models. As indicated by the results obtained with published accuracy benchmarks in medical diagnostics for a number of common conditions, employing a two-stage CHAI DMS with a human arbiter has the potential for improving the accuracy of the diagnostics up to and above 10% [33]. The gain can be achieved because, as pointed out earlier in Section 1.1, human and machine intelligence channels often have complementary strengths allowing to detect errors in several or all essential categories, such as inconsistency in performance for human operators; training bias in machine systems; and complex cases that require expert analysis.

Another essential advantage is efficiency and performance. If both human and machine channels are in agreement, the expert channel does not need to be activated. Additionally high operational efficiency of automated system and the fact that they can operate continuously in the 24×365 mode means that the incremental cost of producing the cumulative decision based on the results of the individual channels in a modern information system would be negligible.

Thirdly, the system allows to employ highly knowledgeable expert resources only for complex cases where higher level of expertise is warranted. Limited expert resources can be employed in a highly efficient distributed system on a regional or national level with remote access to all necessary data, tests and history.

Not in the least, the cost of deployment of a trained and verified in the related area of application multi-channel CHAI system can be minimal, comparable to that of a routine operation of installing or upgrading software while offering considerable value over time in improved quality of results.

Finally, further advantage of such an integrated system is that complex cases can be tracked to the outcome and eventually added to the training set increasing the quality of both human and machine decisions.

On the other hand, two stage CHAI DMS require certain time window, t_e for adjustment of the final decision in the scenario of conflict or uncertainty of the channels. In some cases, this is not a problem, but certain situations and / or environment may not allow even for a short window for the second stage decision. This case is considered in Section 2.2.

2.1.2. Applicability and Effectiveness Criteria

Parallel Human-AI DMS can be used when average accuracy of machine channel achieved that of a regular human operator. That condition is realized in the growing number of tasks and applications [8,9]:

$$P_m \geq P_h \quad (3)$$

where P_m, P_h the accuracy of machine and human operator, respectively.

It is also assumed, as commented earlier that the accuracy of the expert channel in the initial, parallel processing stage of the decision sequence is higher than that of either of the human or the machine channels in the parallel stage.

Finally, the time factor of the second stage decision t_e must be acceptable for the operational environment of the system T_{op}, i.e. $T_{op} \geq t_e$.

2.1.3. Evolution: Multi-Channel AI with Human Expert Arbiter

If the accuracy of machine channels achieves the level where it consistently exceeds that of a regular human operator (Chess, Go [1,2]) it may become a detriment to the overall performance of a parallel channel CHAI system due to high probability of regular false error scenarios. However, under the assumption that overall human control is still necessary for the system to maintain trust and integrity, the architecture of the system can be modified to maintain the performance and the ultimate human control. This can be achieved in a two-stage system with independently trained and verified machine channels in the first stage, with a human expert arbiter in case of conflict.

Independent machine channels ensure that cases are evaluated to sufficient level of detail, and only if the channels are in agreement the decision of the first phase is accepted as final. Otherwise, if a conflict is detected between the decisions of channels, human expert makes the final decision with complete information about the case.

The applicability criteria of the multichannel AI with Expert Arbiter will be:

$$P_k = P(C_k) > P_h; \; P_e \geq P_k \quad (4)$$

where P_k, P_e the accuracy of the machine channels and expert channel, respectively; P_h: the accuracy of a regular human operator.

Such a system allows to maximize the quality of decisions made by individual channels while utilizing expert resources efficiently and effectively and retaining complete human control over critical decisions.

2.2. Single Stage Multi-Channel CHAI Systems

In some cases, even a short window for expert decision t_e cannot be allowed by the dynamics of the situation and / or operational environment. In these scenarios multi-channel CHAI model has to be adapted to produce decisions in a single pass within time allowance of the operational environment. This can be the case in dynamic operational environments dominated by automated processes, for example aviation; cyber-security; financial system and others. The diagram of a single-stage multi-channel DMS is shown in **Figure 2**.

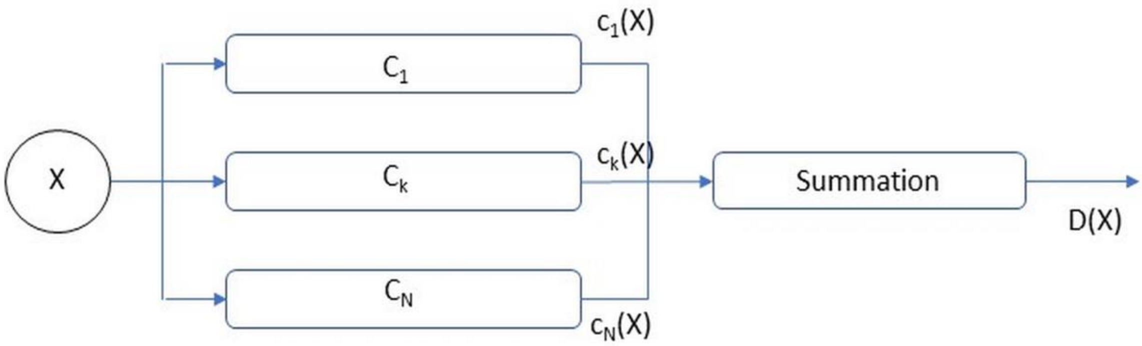

Figure 2. Single stage multi-channel CHAI DMS.

Let us consider application of a multi-channel CHAI system described in Section 2.1.2 above in a critical domain such as aviation or public security. It is clear that applicability of the system in these situations will be determined by the relationship of the time factor of the second stage decision t_e and the minimum time allowed by the situation, t_m. If the range of the former intersects with that of the minimum operational response time, i.e. for at least some X, $t_e \geq t_m$ it is clear that the second stage decision could not be used in such cases.

As before, let c_k, A_k be the decision and confidence of the k-th channel C_k. The essential objective of a single-stage DMS is then finding the decision function based on summation of partial channel decisions that:

1. Minimizes the error of the decision function D on the set of possible inputs $\{ X \}$; and
2. Can be achieved within a time window shorter than operational time, t_m.

As before, we will limit consideration to the case of binary channel decisions, $c_k = \{True; False\}$, $k = 1 .. N$; the cases with differently valued channel decisions (Section 2) can be considered in a similar manner.

A number of solutions can be proposed for single-stage decision functions $D(X)$, that include, among other possible definitions:

1. **Combined confidence**:

$$D = \begin{cases} True, \ if \displaystyle\sum_{i=1,n: C_i = True} A_i \geq \sum_{i=1,n: C_i = False} A_i; \\ False, \ otherwise. \end{cases}$$

The decision function is based on the sum of confidences of the channels that selected a decision, so that the decision with the highest confidence is selected.

2. **Difference of confidences**:

$$D = \begin{cases} True, \ if \displaystyle\max_{i=1,n: C_i = True} A_i - \max_{i=1,n: C_i = False} A_i \geq \Delta; \\ False, \ otherwise; \end{cases}$$

where $\Delta \in (-1, 1]$: const, confidence threshold.

The function selects the decision if the best confidence among the channels that detected the condition exceeds that of those that did not detect it by a minimum value of a defined constant threshold (*confidence threshold*).

3. **Voting**:

Let

$$\chi(C_i) = \begin{cases} 1, \ if \ C_i = True; \\ 0, \ if \ C_i = False. \end{cases}$$

Then the decision function

$$D = \begin{cases} True, \ if \displaystyle\sum_{i=1}^{n} \chi(C_i) \geq \Delta; \\ False, \ otherwise; \end{cases}$$

where $\Delta \in (0, n]$: const, voting threshold.

The rule is based on the number of channels that detected the condition that has to exceed a defined constant threshold (*voting threshold*).

4. **Average confidence**:

Let the decision function, *D(X)* be:

$$D = \begin{cases} False,\ if\ \sum_{i=1}^{n} \chi(C_i) = 0; \\ True,\ if\ \sum_{i=1}^{n} \chi(C_i) = n; \\ True,\ if\ \dfrac{\sum_{i=\overline{1,n}: C_i = True} A_i}{\sum_{i=1}^{n} \chi(C_i)} \geq \dfrac{\sum_{i=\overline{1,n}: C_i = False} A_i}{n - \sum_{i=1}^{n} \chi(C_i)}; \\ False,\ otherwise. \end{cases}$$

This decision function detects the condition if the average confidence among the channels that detected it exceeds that of the channels that did not detect the condition.

Generally, the choice of the decision function depends on the specific task or application. To improve flexibility and versatility of the system, an option to pre-configure the system with a decision function from pre-defined standard set can be useful to support wide range of tasks and applications.

In most of considered standard decision functions confidence plays key role in choosing correct decision. Because appellation to second case is not available in this type of systems, confidence of the identified decision has to be sufficiently high, particularly in critical applications. We will return to further discussion of this question in Section 3.

2.3. Applicability Criteria

An important advantage of multi-channel AI systems is that they can be applied to tasks and applications with very short decision window (down to micro to milliseconds range), well beyond the range of capacity of a human operator. Essential criteria of their use in operational practice are:

1. Verified ability to achieve certain minimum threshold of accuracy P_{min} on a representative set of decisions.
2. Short operational time factor $T_{op} \leq t_e$
3. Sufficient level of confidence of the channels that can be measured by a minimum average confidence threshold A_{min} on a trial set of inputs $\{ X_{tr} \}$: $A_k \geq A_{min}$

As pointed out earlier, confidence is an essential factor in the decision that has to be considered in selection of specific decision function for the area of application.

3. Discussion

The analysis in the previous sections demonstrated that multi-channel human-AI systems can be effective in improving accuracy, cost and performance of decisions in many areas of application. Let us consider potential applications of CHAI DMS in critical areas such as aviation and public security. Applications in public health care were considered previously in [33].

A critical decision in a developing situation can be taken by the system based on combination of factors as: 1) operational time frame; 2) impact, or cost of wrong decision and 3) confidence of the decision produced by the system. For high-impact decisions such as in-flight issue or developing public security situation, the trade-off is between the response time and the confidence of the decision. In such scenarios two-stage systems with human expert arbiter have highest confidence, if operation time frame allows it. Note that the actual scale of the time frame is determined by the situation and can be different among the domains of application, from days in diagnostics, to minutes in operational flight control.

As was commented earlier, not all domains of application allow response time frames where human arbiter can be involved. An example can be a public information security situation or financial system, where action and response time can be measured in fractions of a second. In such situations, the response of an automated intelligent system such as multi-channel AI DMS discussed in Section 2.2 has to be determined by the confidence $A(X)$ that has to be above the minimal threshold of confidence A_{min} defined for a high-impact response.

As it cannot be ascertained with a practical system that every possible critical situation will produce a confident decision satisfying the condition of the minimum confidence, with exception cases that may include, for example, novel scenarios not encountered in training, a special, "default" scenario has to be defined as well for cases where DMS could not come to a decision with sufficient confidence within the operational timeframe. Such a scenario may constitute for example, "freezing" the situation at a safe level while triggering an alarm for immediate expert attention.

Applicability rules of single and two-stage collaborative DMS can be summarized in the following table:

Table 2
Applicability of Single and Two-Stage DMS.

Decision-making system	Confidence $A > A_{min}$	$A \leq A_{min}$
Operational time $T_s \sim T_{op}$ or $T_s > T_{op}$	2-stage CHAI: default decision	2-stage CHAI: expert decision
$T_s < T_{op}$	Single stage multi-channel DMS: regular decision	Single stage DMS: special scenario

4. Conclusions

Rapid development of machine intelligence technologies offers opportunities for their applications to improve quality and performance of decision-making systems. In this work, models of collaborative decision making with participation of machine intelligence were studied. Two types of multi-channel decision-making systems were considered: two-stage system with an expert arbiter and single-stage multi-channel system with principal objective to improve accuracy and performance over conventional systems while retaining maximum human control over critical decisions.

Decision selection methods developed in the study take into account both the decisions and confidence of the channels that is essential in identification of optimal decisions in the critical cases and domains of application. An additional advantage of the proposed approach is the ability to configure decision rules in the pre-operational phase taking into account the context of the task and domain, as well as additional considerations of the decision maker. This approach allows to maximize flexibility of the system and employ it in a wide range of tasks and domains of application.

The proposed parallel multi-channel architecture combining human and machine expertise into a single synergetic system offers a number of essential advantages over conventional "single-chain" decision-making models, including:

- A significant improvement in overall accuracy of decisions.
- For two-stage systems, it does not introduce additional delays in the decision process due to high operational capacity of the machine intelligence channel, whereas for single-stage ones, offers significant improvement in performance.
- Flexibility: the system is highly adaptable and transferrable to different areas / domains of application.
- It allows optimal use of limited expert resources only in the situations that require expert attention.
- Is fully compatible with distributed, high-performance performance models of service delivery.
- Combines strengths and advantages of the human and machine intelligences for an optimal outcome.
- Allows to retain complete human control over critical decisions.

- With minimal incremental cost of development and implementation.

The essential benefit of incorporation of machine intelligence methods into decision-making systems is the ability to produce better decisions more efficiently in a broad range of tasks and applications. For these reasons it is expected that collaborative and synergetic human-machine intelligent systems, including of the type considered in this work, will be finding more applications in a wider range of tasks and domains with the potential of significant improvement in the quality, performance, reliability and efficiency of decisions in both everyday and critical tasks and applications.

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6. References

[1] F.-h. Hsu, Behind Deep Blue: building the computer that defeated the world chess champion. Princeton University Press, 2002.
[2] D. Silver, J. Shrittwieser K. Simonyan et al., Mastering the game of Go without human knowledge, Nature 550, 354–359 (2017).
[3] X. Liu, L. Faes L., A. Kale et al., A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: a systematic review and meta-analysis, The Lancet 1 (6), 271-297 (2019).
[4] N. Beau, B. S. Glicksberg, and A. J. Butte, A call for deep-learning healthcare, Nature medicine 25.1, 14-15 (2019).
[5] C. Jin, W. Chen, Y. Cao, Z. Xu, Z. Tan et al., Development and evaluation of an artificial intelligence system for COVID-19 diagnosis, Nature communications, 11(1), 1-14 (2020).
[6] W. Tongwen, L. Guan, Y. Zhang, A survey on application of artificial intelligence technology in power system stability assessment. Power System Technology 33.12, 60-65 (2009).
[7] J. Roberts, Thinking machines: the search for Artificial Intelligence, Distillations 2 (2), 14–23 (2016).
[8] O. Costopoulou, B. Delaney, C. Munro, Diagnostic difficulty and error in primary care – a systematic review. Oxford University Press (2008).
[9] W. Kondro, Canadian report quantifies cost of medical errors, The Lancet 363 (9426), 2059 (2004).
[10] M. Graber, The incidence of diagnostic error in medicine, BMJ Quality and Care 22 (2), 21 (2012).
[11] A. Alexander, M. Kumar, H. Walker, A decision theory perspective on complexity in performance measurement and management, International Journal of Operations & Production Management (2018).
[12] C. Fan, C. Zhang, A. Yahja, A. Mostafavi, Disaster City Digital Twin: A vision for integrating artificial and human intelligence for disaster management. International Journal of Information Management, 56, 102049 (2021).
[13] M. M. Salih, B. B. Zaidan, A. A. Zaidan, Fuzzy decision by opinion score method, Applied Soft Computing, *96*, 106595 (2020).
[14] K. Nehring, M. Pivato, The median rule in judgement aggregation. Economic Theory, 1-50 (2021).
[15] O. Mulesa, F. Geche, V. Voloshchuk, V. Buchok, and A. Batyuk, Information Technology for time series forecasting with considering fuzzy expert evaluations, 12th International scientific and technical conference “Computer Science and Information Technologies – CSIT 2017”, Lviv, Ukraine, 105–108 (2017).

[16] H. Hnatiienko, V. Snytyuk, A posteriori determination of expert competence under uncertainty, Selected Papers of the XIX International Scientific and Practical Conference "Information Technologies and Security" (ITS 2019), 82–99 (2019).
[17] V. V. Tsyganok, S. V. Kadenko, and O. V. Andriichuk, Significance of expert competence consideration in group decision making using AHP, International Journal of Production Research 50.17, 4785-4792 (2021).
[18] M. Bohlouli, N. Mittas, G. Kakarontzas, T. Theodosiou, L. Angelis, M. Fathi, Competence assessment as an expert system for human resource management: A mathematical approach, Expert Systems with Applications, 70, 83-102 (2017).
[19] O. Mulesa, Design features of the information technology for the labor migrants group structure determination, Eastern-European Journal of Enterprise Technologies, 4/2 (76) 4–8 (2015) doi: 10.15587/1729-4061.2015.47204.
[20] A. Biloshchytskyi, A. Kuchansky, Yu. Andrashko, S. Biloshchytska, O. Kuzka, Ye. Shabala and T. Lyashchenko, A method for the identification of scientists' research areas based on cluster analysis of scientific publications, Eastern-European Journal of Enterprise Technologies, 5/2 (87) 4–11 (2017).
[21] S. Barak, T. Mokfi, Evaluation and selection of clustering methods using a hybrid group MCDM, Expert Systems with Applications, 138 (2019).
[22] L. Kirichenko, T. Radivilova, V. Bulakh, P. Zinchenko, and A. Saif Alghawli, Two approaches to machine learning classification of time series based on recurrence plots, 2020 IEEE 3rd International Conference on Data Stream Mining and Processing, DSMP-2020, 84–89 (2020).
[23] A. Kuchansky, A. Biloshchytskyi, S. Bronin, S. Biloshchytska, and Y. Andrashko, Use of the fractal analysis of non-stationary time series in mobile foreign exchange trading for M-Learning, Advances in Intelligent Systems and Computing, 1192 950–961 (2021).
[24] S. Makridakis, E. Spiliotis, V. Assimakopoulos, Statistical and Machine Learning forecasting methods: Concerns and ways forward, PloS one, 13(3) (2018).
[25] J. Schmidhuber, Deep learning in neural networks: an overview, Neural Networks, 61, 85–117 (2015).
[26] Z. Wang, S. Joshi, S. Savel'ev et al., Fully memristive neural networks for pattern classification with unsupervised learning, Nature Electronics, 1(2), 137-145 (2018).
[27] S. Dolgikh, Low-dimensional representations in unsupervised generative models, 20th International Conference Information Technologies – Applications and Theory (ITAT-2020) Slovakia, 2718 239–245 (2020).
[28] M. Baumann, M. Weil, J. F. Peters, N. Chibeles-Martins, and A. B. Moniz, A review of multi-criteria decision-making approaches for evaluating energy storage systems for grid applications, Renewable and Sustainable Energy Reviews, 107 516–534 (2019).
[29] L. Fei, Y. Deng, Multi-criteria decision making in Pythagorean fuzzy environment, Applied Intelligence, 50(2) 537–561 (2019).
[30] V. Ulansky, A. Raza, Generalization of minimax and maximin criteria in a game against nature for the case of a partial a priori uncertainty, Heliyon, 7(7) (2021).
[31] J. Newton, Evolutionary game theory: A renaissance, Games, 9(2), 31, (2018).
[32] Bavolar, J., & Bacikova-Sleskova, M. (2020). Decision-making styles and mental health—A person-oriented approach through clustering. *Journal of Behavioral Decision Making*, *33*(5), 629-642.
[33] S. Dolgikh, A robust model for integration of Artificial Intelligence methods in patient care, Proceedings of IDDM-2019 Lviv, Ukraine (2019).
[34] O. Mulesa, V. Snytyuk and I. Myronyuk, Optimal alternative selection models in a multi-stage decision-making process, EUREKA: Physics and Engineering, 6, 43–50 (2019).