From Features Engineering to Scenarios Engineering for Trustworthy AI: I&I, C&C, and V&V

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Artificial intelligence (AI)'s rapid development has produced a variety of state-of-the-art models and methods that rely on network architectures and features engineering. However, some AI approaches achieve high accurate results only at the expense of interpretability and reliability. These problems may easily lead to bad experiences, lower trust levels, and systematic or even catastrophic risks. This article introduces the theoretical framework of scenarios engineering for building trustworthy AI techniques. We propose six key dimensions, including intelligence and index, calibration and certification, and verification and validation to achieve more robust and trusting AI, and address issues for future research directions and applications along this direction.

At present, artificial intelligence (AI) is poised to fill a growing number of roles in modern society for a more sustainable and comfortable future with new ways of life.[1] However, every coin has two sides. For example, Tesla is reportedly facing a new investigation into its "Autopilot,"[2,3] by road safety authorities, after fatal injuries caused by AI. It is well known that the machine learning (especially deep learning) methods use large amounts of data to improve performance in different fields. In many cases, the network architectures and features engineering are used to figure the composition of the feature extraction function and the prediction function without extra specific action. Nevertheless, they are essentially the black box models created directly from data, resulting that even designers cannot clearly understand how variables are being combined to make predictions. As such, although deep-learning models can achieve high performance, their interpretability and reliability are often questioned and criticized.

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FEATURES ENGINEERING AND DEEP LEARNING

AI is considered to simulate human intelligence in a computer that is programmed to mimic human behavior and thinking. As the environment complexity increases, the gap between the AI,[4,5] to be modeled and their corresponding features (or data) become huge. Therefore, the handcrafted feature approach becomes less effective. In order to obtain better AI models, experts pay more attention to features of engineering and deep learning in the recent decade. Features engineering is the "art" of formulating useful features from existing data following the target to be learned, where the deep-learning model is used. It involves transforming data into forms that better relate to the underlying feature to be learned. The rapid development of AI has produced a variety of state-of-the-art models that rely on network architectures and features engineering. In general, features engineering can increase the value of existing data and improve the performance of deep-learning

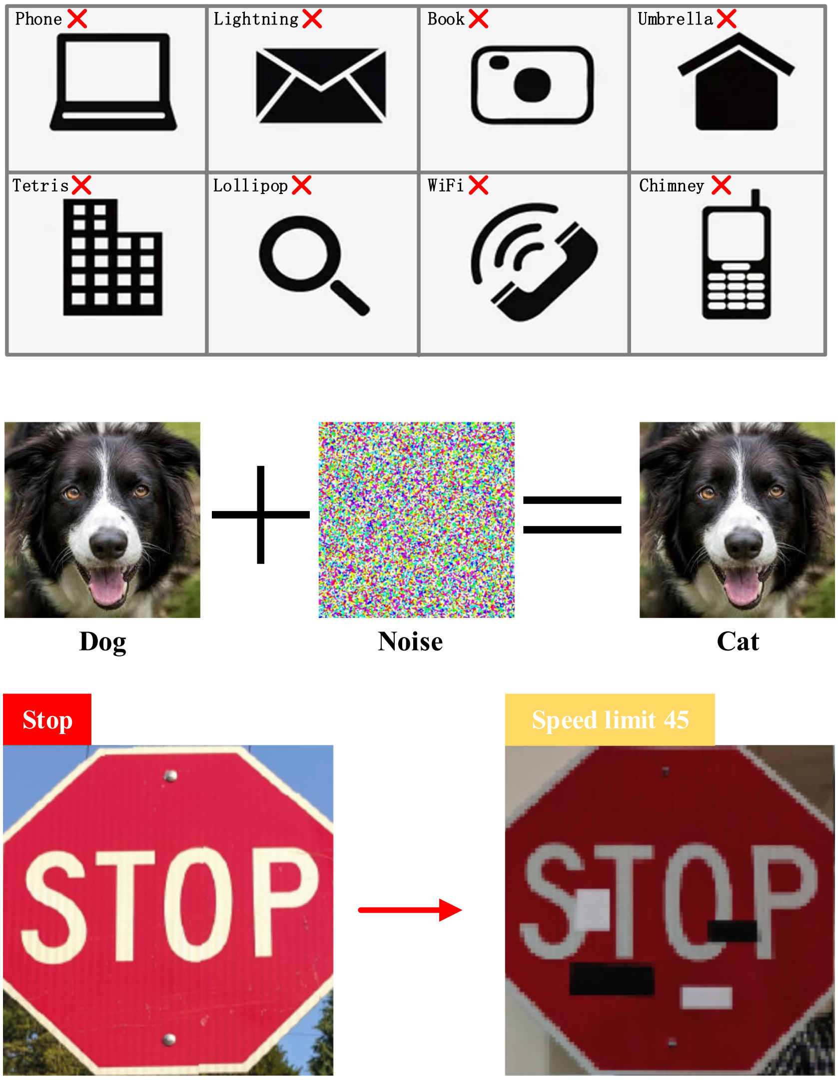

FIGURE 1. Examples of failure in AI.

models. However, using bad features may require you to build much more complex models to achieve the same level of performance.

Because deep learning has a good ability to model nonlinear phenomena, and its application is relatively simple. The goal of deep learning combined with features engineering is to simplify and speed up the data transformation while improving the accuracy of the AI models. However, anybody who has worked with deep learning[6,7,8] knows these systems occasionally make silly mistakes, as illustrated in Figure 1. For example, an intelligent vehicle observes a stop sign, but instead of slowing down, it speeds up into the busy road. An accident report later reveals that four small rectangles had been stuck to the face of the sign. These changes fooled the car's onboard AI into recognizing a "stop" sign as a "speed limit 45" sign. Then, the question is aroused that what are the reasons for this phenomenon? First, the massive data provided by features engineering have inconsistent data storage formats and organizational standards, which makes deep-learning models hard to obtain effective features. Second, most of the existing models only consider the performance in their field, without in-depth thinking about the reliability in terms of safety, security, and sustainability. Just like performance metrics, these goals also need to be evaluated, calibrated, and validated by corresponding metrics. The abovementioned defects can easily reduce the trust as well as cause systemic risk in deep-learning models.

With the abovementioned background, new questions come up: how to define and authorize trustworthiness, and how to quantitatively analyze[9] the causes when AI accidents, or undesired biases occur?

SE FOR TRUSTWORTHY AI

Needless to say, features engineering has played a fundamental role in the success of AI, which aims to extract the most suitable features from original data to achieve the best learning performance. As is well known by the research community, it is the quality of data/feature that determines the upper limit of machine learning, while models and algorithms are the only means to approximate that limit. However, things have changed in the context of deep learning. On the one hand, deep-learning models are often end-to-end where features engineering has been substantially weakened or ignored, replaced by input embedding, parameter tuning, and structure matching, etc. to the input. On the other hand, the flourishment of representation learning in recent years has shifted the research focus. Feature engineering has phased out substantially in the new era of learning, i.e., deep learning, instead, representation learning has become the focus, which partially does the job of feature engineering. However, while representation learning greatly extends the scope of features into a "latent" space, it reduces interpretability to humans.

Interpretability since the beginning has been an important area of deep learning, which represents the visibility that a human has into the working of the machine and serves as a key to data-driven AI. The notion of trust also depends not only on the visibility that a human has into the working of the machine, but also on the controllability of the learning features (or data) of the model. Experts are continuously looking for new ways to reach trustworthy AI that may guarantee their intelligence, calibration, and validation in complex environments. In this background, SE includes I&I, C&C, and V&V. I&I ensures the quality and trust. C&C ensures the result quality and some performance, such as security. V&V ensures the right operational flow and output. Overall, the process in an iteration is I&I –> C&C –> V&V, which is more consistent with general software/system engineering in our view.

SE is proposed to achieve trust in AI. Scenarios can be understood in many ways, either as a sequence of activities or as a branching structure of those activities. Besides, a scenario can be concrete or abstract, which means it can be real,[10] virtual, parallel,[11] or various intermediate options. For instance, scenarios can refer to molecules or atoms, and they can also describe either the whole world or the metaverse. Specifically, a single scenario can be represented in a variety of ways (e.g., text, natural language, databases, video, animation, history, and dreams), that is, anything that can or will happen. SE is defined as an integrated reflection of the scenarios and activities within a certain temporal and spatial range, where all actionable AI are encouraged to complete the design, certification, and verification. It aims at shaping the AI systems to be a form that is more relevant to the underlying scenario that will be learned and tested. Specifically, SE can be used throughout the AI life cycle to clarify the operation processes; to set goals (or index) for both experts and AI; to determine suitable model parameters after system testing; to provide a certification is issued by a third party; to validate user requirements before system specification begins; and to evaluate system design, performance, and function. The framework of the SE is depicted in Figure 2. In this way, AI needs to be thought of in a more nuanced way—continuously calibrate and verify its own dynamic functioning. In the next section, a journey toward the trustworthy AI is outlined based on SE with the help of I&I, C&C, and V&V .

INTELLIGENCE AND INDEX

As shown in Figure 3, SE is supported by the infrastructures of "6I," i.e., cognitive intelligence, parallel intelligence, crypto intelligence, federated intelligence, social intelligence, and ecological intelligence, and will be evaluated and measured by the indexes of "6I" for "6S" goals, i.e., safety index, security index, sustainability index, sensitivity index, service index, and smartness index. The intelligence of infrastructures and the indexes of "6S" goals together constitute "I&I" of SE.

Cognitive Intelligence: Its primary goal is to endow machines or systems with intelligent behaviors by exploiting how neural networks (real or artificial) receive and transform information, how the understandable knowledge is formed and represented, and how the responsive decision is made. Usually, analysis on such topics for human–machine hybrid systems concerns about the mental faculties, including language, perception, memory, attention, reasoning, and emotion. Typical analysis of cognitive intelligence spans many levels of the organization, ranging from learning, decision, logic, planning, and neural circuitry to modular brain organization. Ultimately, cognitive intelligence tries to understand and formulate the nature of intelligence with the hope that this will lead to better comprehension of the mind and a better construction of the machines/systems.

Parallel Intelligence: It provides an effective technology of making small data into Big Data and then refining Big Data into deep intelligence for specific tasks.[12] Parallel intelligence has three modes as follows:

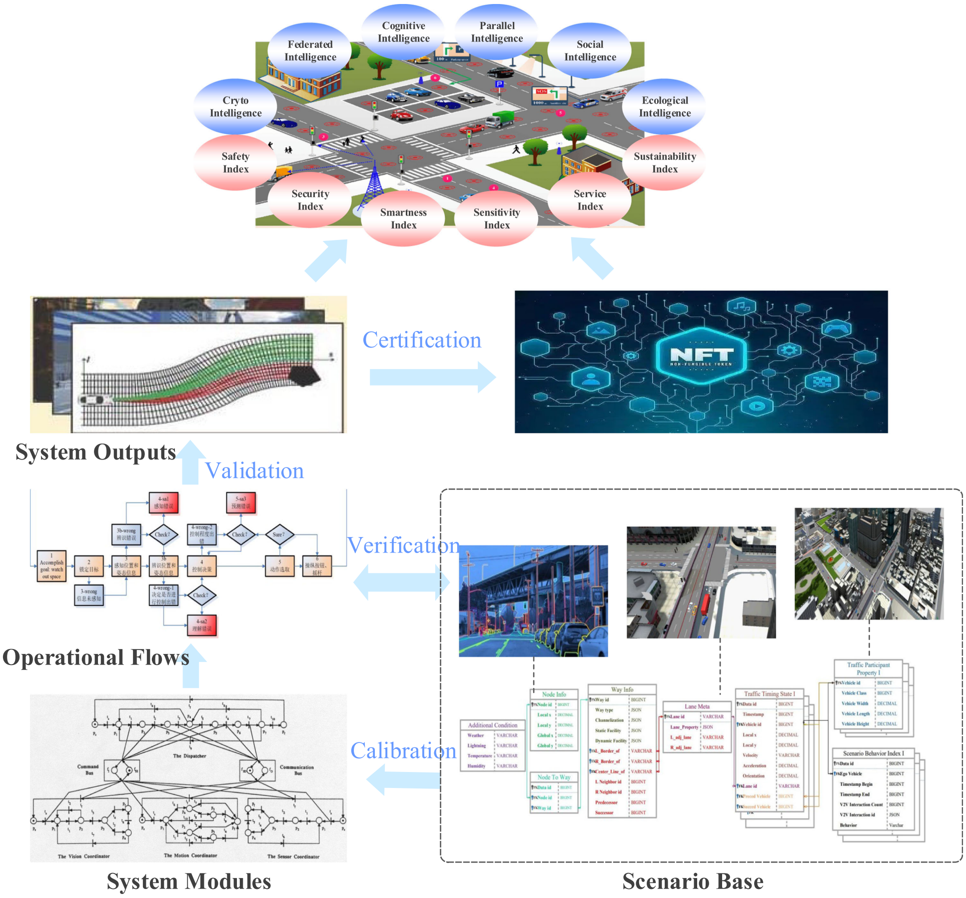

FIGURE 2. Overall framework of scenarios engineering (SE) is comprised of intelligence and index (I&I), calibration and certification (C&C), and verification and validation (V&V).

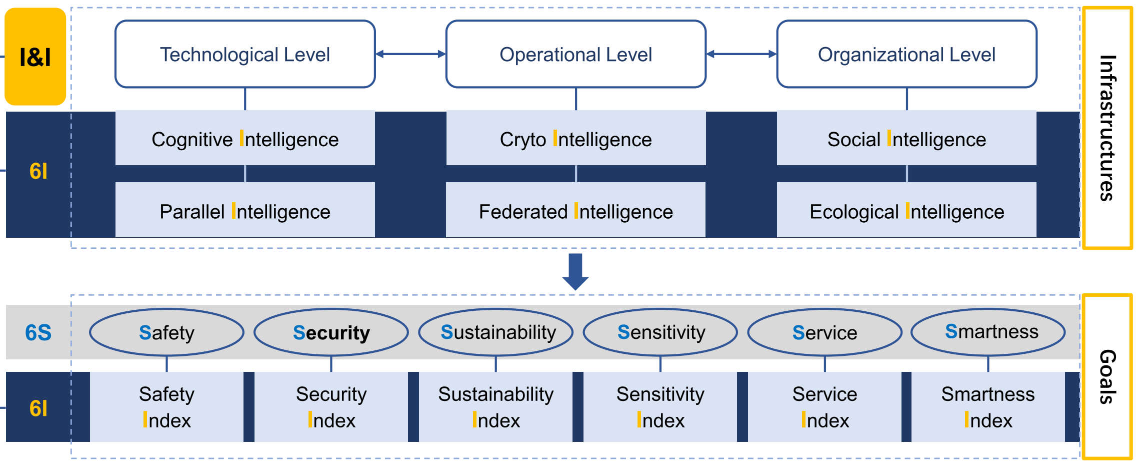

FIGURE 3. Infrastructures and Indexes of SE.

1) artificial systems are used to model real-world behaviors to conduct training and learning;
2) computational experiments are employed to validate and predict decision-making process and effects in artificial systems to conduct testing and validating; and
3) real-time decision-making and parallel execution of both real and artificial systems are accomplished to realize control and management.[13]

Crypto Intelligence: It aims to gather more resources and collect more wisdom in the trustless environment and generate trustable and reliable decision-making in real time on the premise of privacy preservation and data security.[14] Specifically, crypto intelligence is built on the basis of blockchain and under the structure of a decentralized autonomous organization (DAO), where federated data is the decision-making basis, smart contracts are the decision-making method and NFT is the decision-making incentive.[15,16,17]

Federated Intelligence: It transforms the individual intelligence of a single organization into federated intelligence for multiple organizations, so as to better optimize the decision-making of intelligent systems. Federated Intelligence is the group intelligence in the federated ecology driven by Big Data, AI, blockchain, etc.,[18,19] Federated ecology realizes data federalization through federated control, and service federalization through federated management, which are conducted under the support and constraints of federated contracts, federated consensus, federated incentives, and federated security.[20]

Social Intelligence: It mainly addresses the human-in-loop complex decision problems in cyber physical social systems (CPSS). CPSS takes social systems as its core and highlights the social behaviors and social relationships. Social intelligence can be achieved by modeling and analyzing social behaviors, capturing human social dynamics and social relationships, creating artificial social agents, using social learning and social cognition to analyze social phenomena, and finally generating social knowledge and managing social decisions.,[21,22]

Ecological Intelligence: It solves the complex tasks of intelligent systems with ecological thinking and science. It pays attention to the unity of individual, group, and community goals at the organizational level, the integration of natural, social, and cyber environments at the coordinational level, and the investigation of deep models, deep analytics, and deep management of ecologic systems, which will enable intelligent systems to move from rule enforcement legally to ecological enforcement ethically via ecological knowledge automation.[23]

The "6I" transforms the AI from feature-based elements, function, and engineering to scenario-based intelligent ecology, so as to realize "6S" goals for smart development and sustainability of intelligent systems: safety in the physical world, security in the cyber world, sustainability in the ecological world, sensitivity to individual needs, service for all, and smartness in all. For each goal of "6S" in SE, the corresponding indexes must be designed in line with the specific applications[24] and functions to evaluate and express it, which formulates another "6I": safety index, security index, sustainability index, sensitivity index, service index, and smartness index.

CALIBRATION AND CERTIFICATION

As stated previously, I&I provides a comprehensive evaluation goal and index for AI. For this, we need to rethink how to use these multidimensional evaluation indexes to guide and develop the intelligent and trustworthy AI. Calibration (also called estimation in some literature) of AI[27] refers to the identification of suitable values for model parameters so that the internal dynamics best fit the real world, as shown in Figure 4. Here, the "real world" in a quantitative way is often represented by empirical evidence gathered from case studies, inductive analyses, or more directly, by a set of expected intermediate states. In contrast with verification that aims to make sure a piece of equipment or subprocess is working according to the system's technical design specifications, the calibration goes deeper—to focus on the endogenous parameters of modules and components. For some complex systems, however, these parameters cannot be represented in an analytical form with state indicators. Thus, minimization of the aggregate distance between the model's intermediate and final outputs and the actually anticipated counterparts is a natural direction. The minimization may adopt trial-and-error processes in an emergent paradigm, which seems quite time-consuming. In our SE by contrast, the intermediate and final states are provided by well-designed scenarios as alluded to before. The calibration of SE can be represented as

$$\theta^* = \underset{\theta}{\operatorname{argmin}} \sum_{t=1}^{K} [y(t,\theta) - \hat{y}(t)]^T \cdot V \cdot [y(t,\theta) - \hat{y}(t)] \quad (1)$$

where $y(t,\theta) = [\,y_1(t,\theta) \quad \cdots \quad y_n(t,\theta)\,]^T$ and $|\,\hat{y}(t) = [\,\hat{y}_1(t) \quad \cdots \quad \hat{y}_n(t)\,]^T$ are the intermediate outputs of modules or components for test systems and elaborate scenarios in time step t. The positive symmetric matrix V represents the importance of each output. Clearly, the objective here is quadratic distance but it can be easily extended to other metrics as well.

A good calibration guarantees that the internal parameters of the system under test are at reasonable

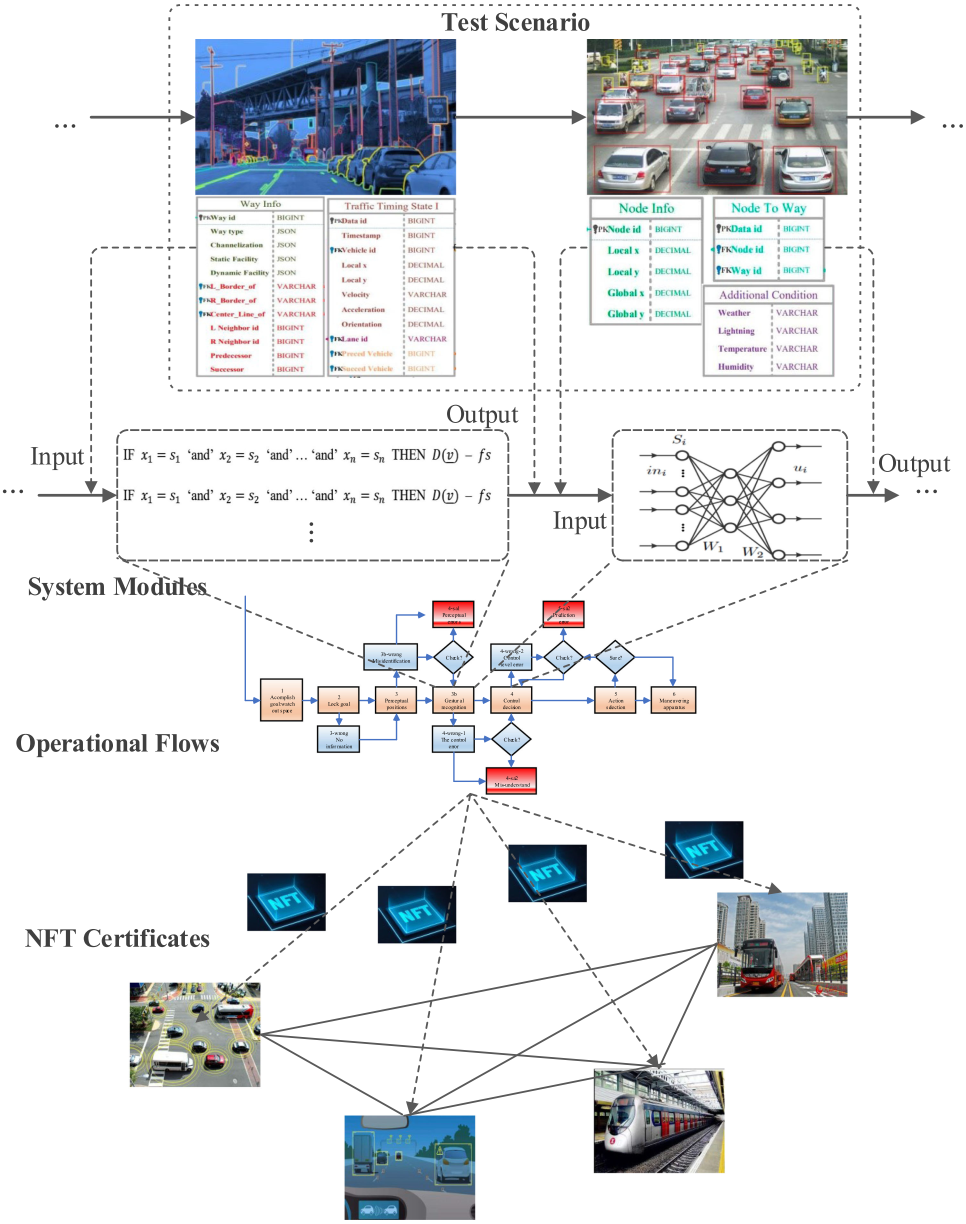

FIGURE 4. C&C of SE.

levels. It ensures the designed functions are implemented and the desired output is achieved. To prove that the calibrated system has corresponding technical performances and services as designed, certification would be issued for a third-party (users or integrator) check. As a formal attestation or confirmation of certain characteristics of actionable AI, the certification needs to meet certain requirements in the following.

- It is not perishable and easy to preserve since some systems are designed for several decades. In this sense, digital certification is an ideal candidate.
- It is globally unique so that any two systems of the same class would be distinguished clearly.

Based on the abovementioned criteria, if the certification is eligible, the certificate will be granted. The nonfungible token (NFT)[28] residing in blockchain can be used to issue calibration certificates, taking its advantage of scarcity and indivisibility. The NFT-based certificate can be rooted from the inherent knowledge,

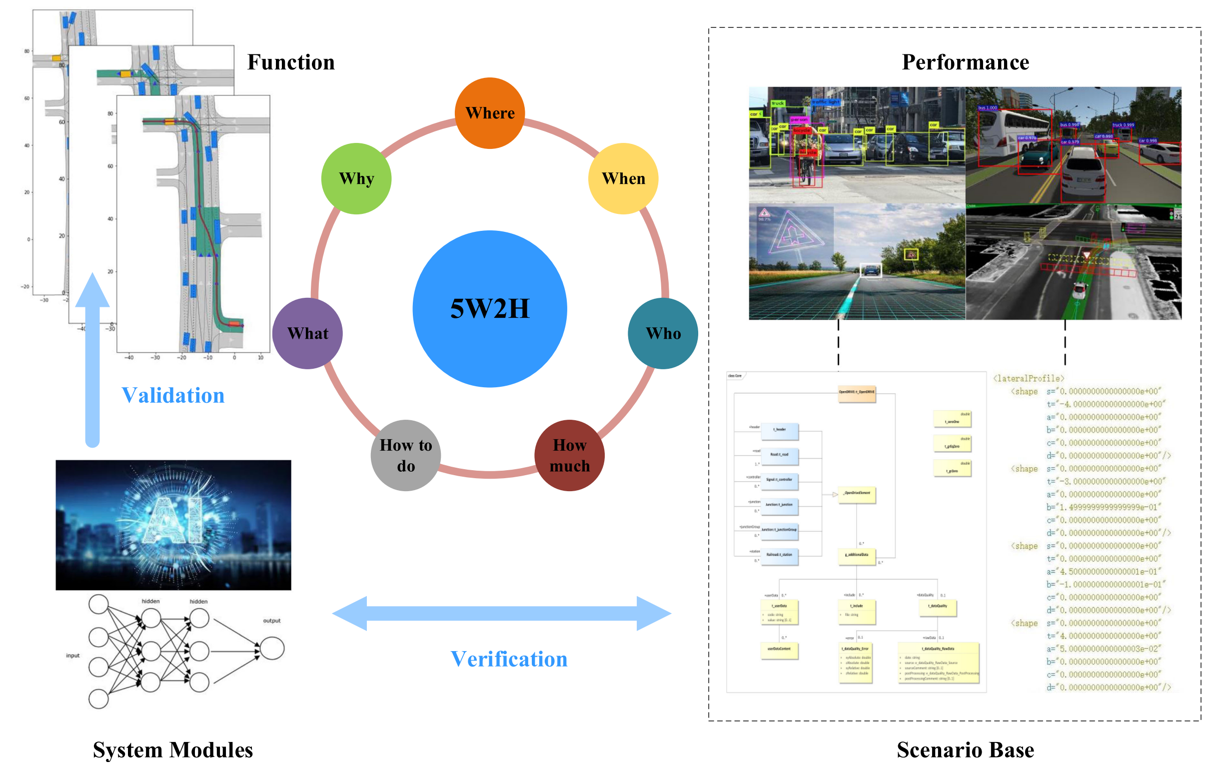

FIGURE 5. V&V of SE.

capability, and contribution in the intelligent systems, and represented by the nontransferring reputation endorsement or transferring economic tokens.

VERIFICATION AND VALIDATION

When trying to create a general AI, the 5W2H analysis[25] is used to support the entire process of V&V. Here, 5W2H represents the first letters of the seven questions asked by professional evaluators using this process, which include: What (problem or goal)? Why (achieving this goal is important)? Where (setting or platform)? When (timeline)? Who (team members)? How (necessary steps)? How much (costs for each phase)? This analysis method is helpful to collect relevant activities, so as to construct the SE more effectively.

In SE (see Figure 5), verification[26] is a process that accesses the performance of the AI, equipment, and engineering toward the intelligent service. It includes all activities related to the production of high-quality AI, such as design analysis, program testing, system inspection, specification analysis, and so on. Verification is a relatively objective process, in that if the various processes and documents are expressed precisely enough, no subjective judgment should be needed in order to verify the system. For instance, during the system design and predevelopment phases, verification procedures involve modeling or simulating a portion, or the entirety, of a product, service, or system, followed by an analysis of the modeling results. In the postdevelopment phase, verification procedures involve regularly repeating practical or critical tests to ensure that the product, service, or system continuously meets practical requirements or specifications. Verification can be carried out at any time during the design, development, and production of AI, that is, throughout the product life cycle. This is often an internal process. It is sometimes said that verification can be expressed by the query “Are you building the AI right?” “Building the AI right” checks that the performance is correctly implemented by the system.

Validation is a process in which product (AI) functions actually meet customer requirements. Validation is done at the end of the development process and takes place after the verification step. It can discover and locate abnormal data, functions, and services, so as to enhance the user experience. As such, validation can create feedbacks to assist the functionality improvement of trustworthy AI. For a new process of developing AI, validation may include predicting faults or gaps that could result in an invalid or incomplete system. In addition, validation procedures include functional tests specifically designed to ensure that existing functional tests are compatible. In particular, the user-defined validation requirements can be used as a basis for determining the development or validation process for the environment, service, or system. In simple words, the test execution which we do in our daily lives is actually the validation activity which includes environmental testing, function testing, service testing, system testing, etc. Meanwhile, validation can be represented as "Are you building the right AI?" "Building the right AI" refers back to the user-defined functional requirements.

CONCLUSION

This article presents the theoretical framework of SE, which represents the visibility, interpretability, and reliability that a human has in the working of intelligent systems and serves to realize trustworthy AI. The SE consists of I&I, C&C, and V&V. I&I shift the AI from feature-based elements, functions, and engineering to scenario-based intelligent ecology. Moreover, the calibration guarantees that the internal parameters of the system under test are at reasonable levels, and certification would be issued for the third-party recognition after calibration. Finally, V&V are used to effectively evaluate the performance and function of the AI. In the future, the evolution of SE can help to develop the DAO Systems,[29] metaverses, robotics, and blockchain for a trustworthy and sustainable AI world.

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