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Software engineering — Systems and software Quality Requirements and Evaluation (SQuaRE) — Quality model for AI systems

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Foreword

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This document was prepared by Joint Technical Committee ISO/IEC JTC 1, *Information technology*, Subcommittee SC 42, *Artificial intelligence*.

Any feedback or questions on this document should be directed to the user’s national standards body. A complete listing of these bodies can be found at www.iso.org/members.html and www.iec.ch/national-committees.

Introduction

High-quality software products and computer systems are crucial to stakeholders. Quality models, quality requirements, quality measurement, and quality evaluation are standardized within the International Standards on SQuaRE, see Annex A for further information.

AI systems require additional properties and characteristics of systems to be considered, and stakeholders have varied needs. AI systems have different properties and characteristics. For example, AI systems can:

— replace human decision-making;

— be based on noisy, or incomplete data;

— be probabilistic;

— adapt during operation.

According to ISO/IEC TR 24028,[2] trustworthiness has been understood and treated as both an ongoing organizational process as well as a non-functional requirement specifying emergent properties of a system — that is, a set of inherent characteristics with their attributes — within the context of quality of use as indicated in ISO/IEC 25010.

ISO/IEC TR 24028 discusses the applicability to AI systems of that have been developed for conventional software. According to ISO/IEC TR 24028, does not sufficiently address the data-driven unpredictable nature of AI systems. While considering the existing body of work, ISO/IEC TR 24028 identifies the need for developing new International Standards for AI systems that can go beyond the characteristics and requirements of conventional software development.

ISO/IEC TR 24028 contains a related discussion on different approaches to testing and evaluation of AI systems. It states that for testing of an AI system, modified versions of existing software and hardware verification and validation techniques are needed. It identifies several conceptual differences between many AI systems and conventional systems and concludes that “the ability of the [AI] system to achieve the planned and desired result ... may not always be measurable by conventional approaches to software testing”. Testing of AI systems is addressed in ISO/IEC TR 29119-11:2020.[3]

This document outlines an application-specific AI system extension to the SQuaRE quality model specified in ISO/IEC 25010.

AI systems perform tasks. One or more tasks can be defined for an AI system. Quality requirements can be specified for the evaluation of task fulfilment.

The quality model is considered from two perspectives, product quality as described in Clause 5 and quality in use in Clause 6. The relevance of these terms is explained, and links to other standardization deliverables (e.g. the ISO/IEC 24029 series[4][5]) are highlighted.

ISO/IEC 25012:2008[6] contains a model for data quality that is complementary to the model defined in this document. ISO/IEC 25012:2008 is being extended for AI systems by the ISO/IEC 5259 series.[7]

Software engineering — Systems and software Quality Requirements and Evaluation (SQuaRE) — Quality model for AI systems

1 Scope

This document outlines a quality model for AI systems and is an application-specific extension to the standards on SQuaRE. The characteristics and sub-characteristics detailed in the model provide consistent terminology for specifying, measuring and evaluating AI system quality. The characteristics and sub-characteristics detailed in the model also provide a set of quality characteristics against which stated quality requirements can be compared for completeness.

2 Normative references

The following documents are referred to in the text in such a way that some or all of their content constitutes requirements of this document. For dated references, only the edition cited applies. For undated references, the latest edition of the referenced document (including any amendments) applies.

ISO/IEC 25010:2011, *Systems and software engineering — Systems and software Quality Requirements and Evaluation (SQuaRE) — System and software quality models*

ISO/IEC 22989:2022, *Information technology — Artificial intelligence — Artificial intelligence concepts and terminology*

ISO/IEC 23053:2022, *Framework for Artificial Intelligence (AI) Systems Using Machine Learning (ML)*

3 Terms and definitions

For the purposes of this document, the terms and definitions given in ISO/IEC 22989:2022, ISO/IEC 23053:2022 and the following apply.

ISO and IEC maintain terminology databases for use in standardization at the following addresses:

— ISO Online browsing platform: available at https://www.iso.org/obp

— IEC Electropedia: available at https://www.electropedia.org/

3.1 General

3.1.1
measure, noun
variable to which a value is assigned as the result of measurement

Note 1 to entry: The term "measures" is used to refer collectively to base measures, derived measures, and indicators.

[SOURCE: ISO/IEC/IEEE 15939:2017, 3.15]

3.1.2
measure, verb
make a measurement

[SOURCE: ISO/IEC 25010:2011, 4.4.6]

3.1.3
software quality measure
measure of internal software quality, external software quality or software quality in use

Note 1 to entry: Internal measure of software quality, external measure of software quality or software quality in use measure are described in the quality model in ISO/IEC 25010.

[SOURCE: ISO/IEC 25040:2011, 4.61]

3.1.4
risk treatment measure
protective measure
action or means to eliminate hazards or reduce risks

[SOURCE: ISO/IEC Guide 51:2014, 3.13, modified — change reduction to treatment.]

3.1.5
transparency
degree to which appropriate information about the AI system is communicated to relevant stakeholders

Note 1 to entry: Appropriate information for AI system transparency can include aspects such as features, components, procedures, measures, design goals, design choices and assumptions.

3.2 Product quality

3.2.1
user controllability
degree to which a user can appropriately intervene in an AI system's functioning in a timely manner

3.2.2
functional adaptability
degree to which an AI system can accurately acquire information from data, or the result of previous actions, and use that information in future predictions

3.2.3
functional correctness
degree to which a product or system provides the correct results with the needed degree of precision

Note 1 to entry: AI systems, and particularly those using machine learning models, do not usually provide functional correctness in all observed circumstances.

[SOURCE: ISO/IEC 25010:2011, 4.2.1.2, modified — Note to entry added.]

3.2.4
intervenability
degree to which an operator can intervene in an AI system's functioning in a timely manner to prevent harm or hazard

3.2.5
robustness
degree to which an AI system can maintain its level of functional correctness under any circumstances

3.3 Quality in use

3.3.1
societal and ethical risk mitigation
degree to which an AI system mitigates potential risk to society

Note 1 to entry: Societal and ethical risk mitigation includes accountability, fairness, transparency and explainability, professional responsibility, promotion of human value, privacy, human control of technology, community involvement and development, respect for the rule of law, respect for international norms of behaviour and labour practices.

4 Abbreviated terms

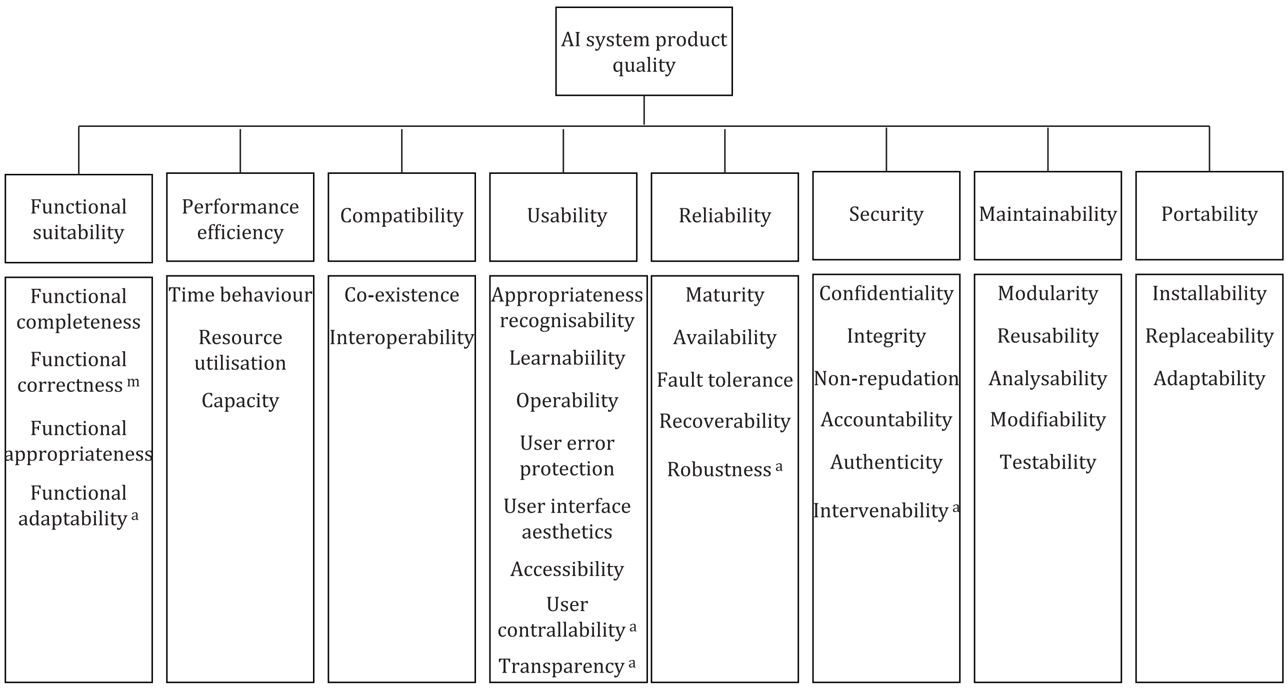
AI artificial intelligence

ML machine learning

5 Product quality model

5.1 General

An AI system product quality model is detailed in Figure 1. The model is based on a modified version of a general system model provided in ISO/IEC 25010. New and modified sub-characteristics are identified using a lettered footnote. Some of the sub-characteristics have different meanings or contexts as compared to the ISO/IEC 25010 model. The modifications, additions and differences are described in this clause. The unmodified original characteristics are part of the AI system product model and shall be interpreted in accordance with ISO/IEC 25010.



[a] New sub-characteristics.

[m] Modified sub-characteristics.

Figure 1 — AI system product quality model

Each of these modified or new sub-characteristics are listed in the remainder of this clause.

5.2 User controllability

User controllability is a new sub-characteristic of usability. User controllability is a property of an AI system such that a human or another external agent can intervene in its functioning in a timely manner. Enhanced controllability is helpful if unexpected behaviour cannot be completely avoided and that can lead to negative consequences.

User controllability is related to controllability, which is described in ISO/IEC 22989:2022, 5.12.

5.3 Functional adaptability

Functional adaptability is a new sub-characteristic of functional suitability. Functional adaptability of an AI system is the ability of the system to adapt itself to a changing dynamic environment it is deployed in. AI systems can learn from new training data, production data and the results of previous actions taken by the system. The concept of functional adaptability subsumes that of continuous learning, as defined in ISO/IEC 22989:2022, 5.11.9.2.

Continuous learning is not a mandatory requirement for functional adaptability. For example, a system that switches classification models based on events in its environment can also be considered functionally adaptive.

Functional adaptability in AI systems is unlike other quality characteristics as there are system specific consequences that cannot be interpreted using a straight-line linear scale (e.g. bad to good). Generally, higher functional adaptability can result in improvements for the outcomes enacted by AI systems.

For some systems, high functional adaptability can cause additional unhelpful outcomes to become more likely based on the system's previous choices. Weightings of a decision path with relatively high uncertainty, reinforced based on previous AI system decisions, can result in higher likelihood of unintended negative outcomes. In this fashion, functional adaptability can reinforce negative human cognitive biases.

While conventional algorithms usually produce the same result for the same set of inputs, AI systems, due to continuous learning, can exhibit different behaviour and therefore can produce different results.

5.4 Functional correctness

Functional correctness exists in ISO/IEC 25010. The AI system product quality model amends the description since AI systems, and particularly probabilistic ML methods, do not usually provide functional correctness because a certain error rate is expected in their outputs. Therefore, it is necessary to measure correctness and incorrectness carefully. Numerous measurements exist for these purposes in the context of ML methods and examples of these as applicable to a classification model can be found in ISO/IEC TS 4213.[11]

Additionally, there can be a trade-off between characteristics such as performance efficiency,[12] robustness[13] and functional correctness.

Annex C provides further information about why functional correctness is preferred to other terms such as the more general performance to describe the correctness of the model.

5.5 Robustness

Robustness is a new sub-characteristic of reliability. It is used to describe the ability of a system to maintain its level of functional correctness (see Annex C for discussion on the term performance) under any circumstances including:

— the presence of unseen, biased, adversarial or invalid data inputs;

— external interference;

— environmental conditions encompassing generalization, resilience, reliability;

— attributes related to the proper operation of the system as intended by its developers.

The proper operation of a system is important for the security of the system and safety of its stakeholders in a given environment or context. Information about functional safety in the context of AI systems can be found in ISO/IEC TR 5469:—[1)].[14]

Robustness is discussed in ISO/IEC TR 24028:2020, 10.7,[2] and methods for assessment are described in ISO/IEC TR 24029-1[4] and defined in ISO/IEC 24029-2.[5]

5.6 Transparency

Transparency is sub-characteristic of usability in the product quality model and a sub-characteristic of satisfaction in the quality in use model.

It relates to the degree to which appropriate information about the AI system is communicated to stakeholders.

Transparency of AI systems can help potential users of AI systems to choose a system to fit their requirements, improving stakeholders' knowledge about the applicability and the limitations of an AI system, and assisting with the explainability of AI systems.

The transparency information can include a description of an AI system functionality, the system's decomposition, interfaces, ML models used, training data, verification and validation data, performance benchmarks, logs and the management practices of an organization responsible for the system.

Transparent AI systems document, log or display their internal processes using introspection tools and data files. The flow of data can be trackable at each step, with applied decisions, exceptions and rules documented. Log output can track processes in the pipeline as they permute data, as well as system level calls. Errors are logged explicitly, particularly in transform steps. Highly transparent AI systems can be built of well-documented subcomponents whose interfaces are explicitly described. The transparency of AI systems eases investigations of system malfunctions.

A system with low transparency has internal workings which are difficult to inspect externally. Unavailability of detailed processing records can impair testability and societal and ethical impact assessment and risk treatment.

Ultimately, transparency of AI systems contributes to establishing of trust, accountability and communication among stakeholders. Some aspects of transparency are discussed in ISO/IEC TR 24028:2020, 10.2.[2]

5.7 Intervenability

The extent of intervenability can be determined depending on the scenarios where the AI system can be used. The key to intervenability is to enable state observation and transition from an unsafe state to a safe state. Operability is the degree to which an AI system has attributes that enable operation and control, which emphasizes the importance of an AI system's user interface. Compared to operability, intervenability is more fundamental from a quality perspective and is intended to prevent an AI system from doing harm or hazard.

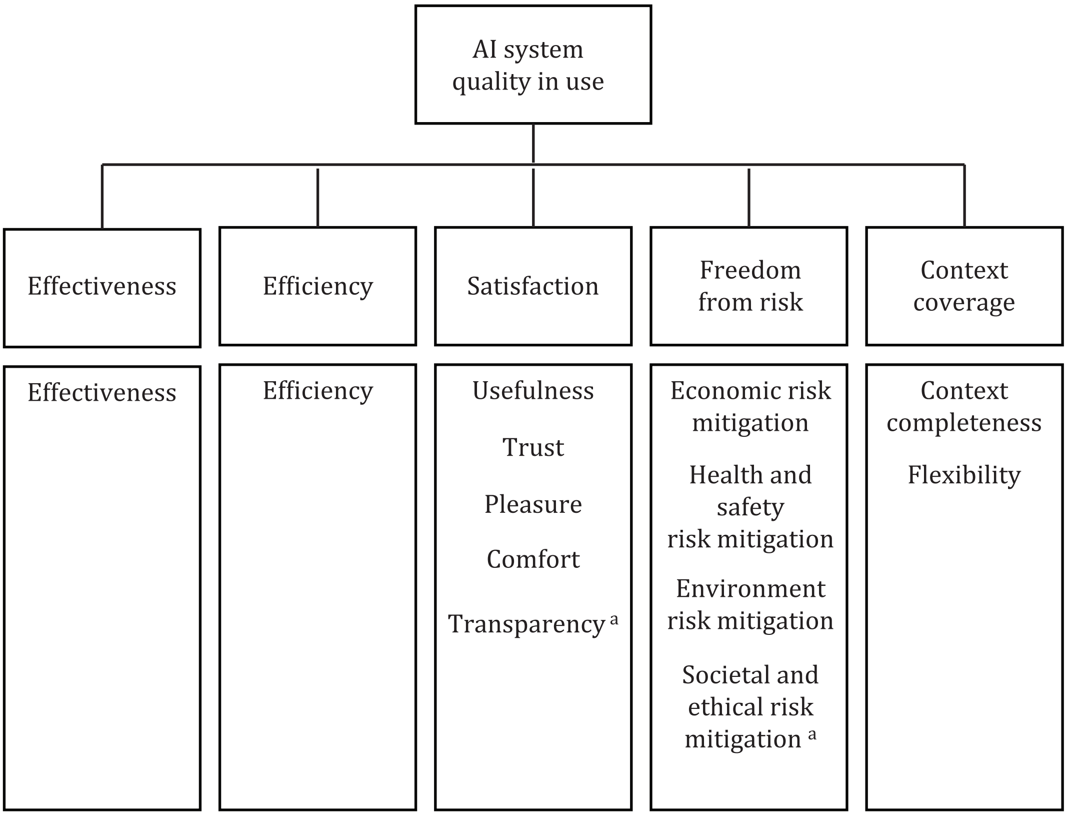
Intervenability is related to controllability, which is described in ISO/IEC 22989:2022, 5.15.5.

1) Under preparation. Stage at the time of publication ISO/IEC CD TR 5469:2023.

6 Quality in use model

6.1 General

An AI system quality in use model is detailed in Figure 2. The model is based on a modified version of a general quality in use model provided in ISO/IEC 25010. New sub-characteristics are identified using a lettered footnote. Some of the sub-characteristics have different meanings or contexts as compared to the ISO/IEC 25010 model. The additions and differences are described in this clause. The unmodified characteristics are part of the quality in use model and shall be interpreted as defined in ISO/IEC 25010.



[a] New sub-characteristics.

Figure 2 — AI system quality in use model

6.2 Societal and ethical risk mitigation

Societal and ethical risk mitigation is a new sub-characteristic of freedom from risk.

ISO/IEC TR 24368:2022,[15] explores this topic and outlines the following themes:

— accountability;

— fairness and non-discrimination;

— transparency and explainability;

— professional responsibility;

— promotion of human values;

— privacy;

- safety and security;
- human control of technology;
- community involvement and development;
- human-centred design;
- respect for the rule of law;
- respect for international norms of behaviour;
- environmental sustainability;
- labour practices.

These themes should be considered along with the information in ISO/IEC TR 24368, with regard to the desirable characteristics of systems in order to mitigate societal and ethical risk.

Safety and security as well as sustainable environments are included within the existing SQuaRE characteristics health and safety risk mitigation, and environment risk mitigation, and therefore are not outlined in this document.

Annex B describes how a risk-based approach relates to a quality-based approach and quality models and, through examples, demonstrates how the two can be used in support of each other.

Bias, including in the context of fairness and non-discrimination, is described in ISO/IEC TR 24027.[16]

6.3 Transparency

Transparency is also a sub-characteristic of satisfaction in the product quality model. See 5.6 for further information.

Annex A
(informative)

SQuaRE

A.1 SQuaRE divisions

Figure A.1 (adapted from ISO/IEC 25000:2014[1]) illustrates the organization of the SQuaRE International Standards, further called divisions.

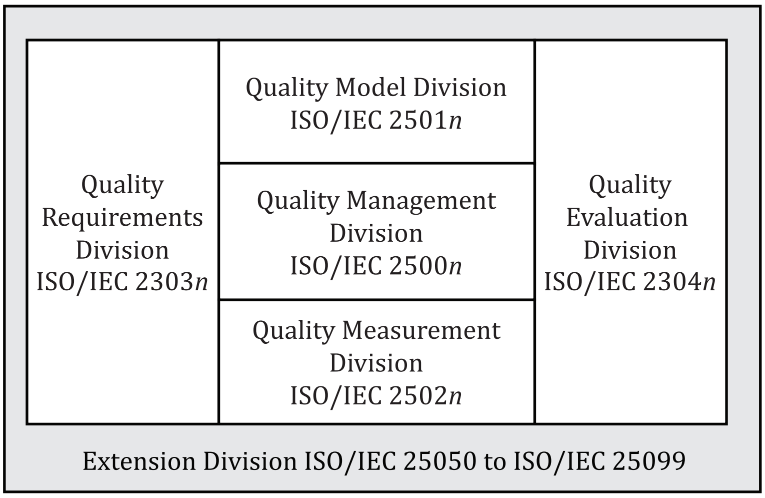


Figure A.1 — Organization of SQuaRE International Standards

The divisions within SQuaRE are:

— **ISO/IEC 2500*n* – Quality Management Division.** The International Standards that form this division define all common models, terms and definitions further referred to by all other International Standards relating to SQuaRE. The division also provides requirements and guidance for a supporting function that is responsible for the management of the requirements, specification and evaluation of software product quality.

— **ISO/IEC 2501*n* – Quality Model Division.** The International Standards that form this division present detailed quality models for computer systems and software products, quality in use and data. Practical guidance on the use of the quality models is also provided.

— **ISO/IEC 2502*n* – Quality Measurement Division.** The International Standards that form this division include a software product quality measurement reference model, mathematical definitions of software quality measures, and practical guidance for their application. Examples are given of internal and external measures for software quality and measures for quality in use. Quality Measure Elements (QME) forming foundations for these measures are defined and presented.

— **ISO/IEC 2503*n* – Quality Requirements Division.** The International Standards that form this division help specify quality requirements based on quality models and software quality measures. These quality requirements can be used in the process of quality requirements elicitation for a software product to be developed or as input for an evaluation process.

— **ISO/IEC 2504*n* – Quality Evaluation Division.** The International Standards that form this division provide requirements, recommendations and guidelines for software product evaluation, whether performed by evaluators, acquirers or developers. The support for documenting a measure as an Evaluation Module is also present.

— **ISO/IEC 25050 to ISO/IEC 25099 – SQuaRE Extension Division.** These International Standards currently include requirements for quality of Commercial Off-The-Shelf software and Common Industry Formats for usability reports, as well as for this document.

Annex B
(informative)

How a risk-based approach relates to a quality-based approach and quality models

B.1 General

Risk-based and quality-based approaches use two complementary methodologies to contribute to the specification of systems requirements, developing systems in accordance with the requirements and evaluating system functionality. In most cases a combined approach is necessary to cover all aspects of a specific system behaviour. The applicability and exact use of each methodology relies on many factors, including, but not limited to the maturity of technologies in use, the role of the system in the value chain, and the field of application. Such factors are taken into consideration when specifying product or regulatory requirements or a framework for the development and evaluation of a certain system in order to achieve practical results and appropriately manage customer or user expectations.

Using a quality model is most effective in situations where quantifiable or clearly qualifiable system-specific measures are established for all characteristics as well as for many sub-characteristics. For mature technologies in a context of a specific application field, the values of the measures can be specified as a part of the system requirements.

For new technologies or new applications, using a partial quality model can still be effective in high negative risk situations. In such cases, only the measure values for high negative risk sub-characteristics are specified and evaluated.

For new or evolving technologies, software quality measures are often subject to active research and collaboration between academia and industry.

A risk-based approach is better suited for situations where quantifiable measures are not established for many characteristics or important sub-characteristics. In addition, and by definition, a risk-based approach is uniquely suited to deal with unexpected events.

B.2 Relationship with other International Standards

ISO 31000[19] defines a risk management framework and process applicable to any kind of organization and any activity, including decision-making at all levels. ISO/IEC 23894[18] is based on ISO 31000; it customizes the risk management framework and process to managing risks to organizations and projects dealing with AI.

ISO/IEC 25010 defines two quality models. A product quality model contains characteristics and sub-characteristics of a software or a computer system. A quality in use model contains characteristics and sub-characteristics describing the interaction of a system with its environment. This can be viewed as a two-layered approach with the product quality properties providing the foundation for many of the properties demonstrated during the use of the product.

“Freedom from risk” is identified as one of the quality characteristics under the quality in use model. Its sub-characteristics are called “risk mitigations” and correspond to common high-level societal concerns about economy, health, safety, environment, and ethics. In comparison, according to the risk-based approach, the essential societal properties related to economy, health, safety, environment, and ethics are called “objectives”. Furthermore, in a risk-based approach, objectives are not limited to societal considerations. They include all relevant engineering considerations, for example, those related to system security, reliability, and transparency. Subsequently, for each identified objective, potential risks are identified and mitigated by applying selected risk treatment measures or “controls”. Therefore, each relevant property (societal, system, etc.) can be expressed both in terms of characteristics and in terms of objectives.

B.3 Comparison of approaches

The main challenge of specifying or evaluating systems using a quality-based approach alone is that quality sub-characteristics are often not specific enough and do not directly correspond to accepted qualifying or quantifying measures.[19]

Looking at "fairness" as an AI system quality model sub-characteristic, being "fair" can carry drastically different meanings across different application areas and systems with different purpose.[16] No single fairness measure exists to measure a system "fairness". Moreover, the availability and maturity of fairness measures depends on the system type and the technology used. For example, fairness measures for classification systems are better understood than fairness measures for reinforcement learning systems.

The risk-based approach allows the specification and assessment of objectives, including those for which no direct measures are available, by shifting the task to a set of new objectives. These objectives do not necessarily have corresponding measures. In a risk-based approach, potential negative effects, sometimes referred to as repercussions or consequences, are identified and quantified or qualified. As a part of risk treatment, risk sources leading to negative repercussions are examined, and risk treatment measures to reduce (or eliminate) the risk sources are selected. An iterative process of selection and implementation of risk treatment measures and the assessment of the residual risk continues until the risk is reduced to an acceptable level (as specified in the system requirements).

In comparison to the two defined quality models, risk management is a multi-layered top-down approach. This means that risk treatment measures (or "controls") at one layer selected by a risk management process become the objectives of a risk management process at a layer below. In turn, these new objectives correspond to a set of different sub-characteristics, for which software quality measures or their values can be available or not.

Assuming that "fairness" was stated as one of the AI system requirements, as a result of risk assessment, the following potential risks sources were identified:

— lack of experience in the application field;

— biased training data.

The selected mitigation risk treatment measures (or "controls") included:

— a functional specification review by experts in the application field;

— reducing selection bias in the training data using appropriate data quality methods.

The next layer of objectives is:

— implementing the experts' review recommendations;

— keeping the data bias at an acceptable level as specified using selected statistical measures of data quality.

The risk-based approach can also assist with developing new software quality measures. It can be used to assess the behaviour or the value of a new measure under various conditions and risk levels as a function of existing "proxy" measures.

Suppose that in the process of requirements specification for an AI classification system used for people hiring, Demographic Parity and Equality of Opportunity[16] have been identified as suitable measures for judging a system's fairness. Nevertheless, currently no sufficient experience exists to determine the required measure's values. In such a situation, the risk-based approach will still allow the implementation of the AI system by identifying the appropriate risk mitigation risk treatment measures and assessing their results.

Subsequently, experience from the system deployment and the collected data will help to find the correlation between the levels of risk and the optimal measure values. This knowledge can then be used for the specification of similar systems in the future.

In conclusion, using a risk-based approach increases flexibility in specifying requirements. System characteristics and sub-characteristics in the quality-based approach correspond to high-level objectives in the risk-based approach. Each system property can be expressed both in terms of characteristics and in terms of objectives. Risk-based approach allows the specification, implementation, and verification of system behaviour for objectives, including those for which software quality measures are not available or their values are not specified. In addition, the risk-based approach can assist with establishing suitable values for new measures.

Annex C
(informative)

Performance

The term performance is used differently in the field of software and systems engineering, compared to the field of artificial intelligence.[20]

Within the field of software and systems engineering, performance typically means how fast a certain piece of software executes and how efficient it is. These aspects fall under the existing SQuaRE characteristic performance efficiency.

Within the field of artificial intelligence, performance typically means how well a certain AI system performs the intended tasks. Performance of intended tasks of an AI system can be measured by determining suitable evaluation measures that are relevant to the type of AI system. For example, ISO/IEC TS 4213[11] specifies methodologies for assessing ML classification performance.

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