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Review of Artificial Intelligence-Based Systems: Evaluation, Standards, and Methods

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Abstract

The rapid expansion of Artificial Intelligence (AI) technologies and algorithms in various industries necessitates a focus on protecting the public interest. Major economies have heavily invested in AI initiatives, underscoring the significance of these advancements. Ensuring the dependability and quality of these systems is crucial to mitigate potential risks stemming from AI failures. In response, there have been efforts to establish monitoring frameworks and evaluation standards for AI products.

This paper presents a comprehensive analysis of more than 200 standards and publications to identify quantitative and qualitative metrics for evaluating AI systems throughout development and operation stages. The study also examines the methodologies, AI evaluation, and standards associated with these assessment criteria. The findings emphasize the importance of implementing robust evaluation frameworks to ensure the safety and effectiveness of AI systems. By reviewing various metrics and standards, this research offers valuable insights for policymakers, regulators, and industry professionals aiming to enhance AI oversight and governance. Moreover, the study highlights the necessity of continuous monitoring and evaluation throughout the AI development process to address potential risks and challenges. By advocating transparency and accountability in AI practices, stakeholders can build trust and confidence in the deployment of these technologies.

Keywords Artificial Intelligence (AI), Standard, Trustworthy AI, AI evaluation, Evaluation Criteria

1. Introduction & background research

The dramatic increase in Artificial Intelligence (AI) capabilities has led to a wide range of innovations that can advance nearly every aspect of our society and economy—from business and healthcare to transportation and cybersecurity. AI technologies are often utilized to exert a beneficial effect by informing, advising or simplifying tasks [1]; [2]; [3]. Since these products and services are among the most sophisticated technologies available, many companies are engaged in research and development in this field. Due to the ever-increasing growth of AI technology, this technology is expected to make great contribution to the transformation of raw data and the improvement of business processes in the near future.

Up to now, there have many debates over AI failures. According to a 2019 IDC survey, "most organizations have reported AI failures in some of their projects, with a quarter having a failure rate of up to 50%. These failures have historically been a strong and compelling motivator for adequate software testing, and industry surveys suggest that AI is one of the most important trends for software testing [4]. Therefore, requirements for the production of AI products have been presented in the form of standards due to the importance of such systems and the high costs

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related to their failure [5].

Standardization of AI products is a catalyst, indicating that a number of prerequisites are defined during the production of AI products from defining specifications to providing and processing services in order to lay the basis of production. Standards and evaluations have a special role in creating a stable framework for AI, promoting the rapid transfer of technologies through research and playing a decisive role in the expansion of international markets [6]. Besides, the implementation of standards promotes profitability. For example, the production of AI-based systems based on standards has resulted in a profit of approximately 17,000,000 euros for Germany [7]. AI is evaluated using checklists based on standards. A comprehensive and detailed examination of AI systems can prevent possible accidents or other potentially undesirable consequences of AI systems as shown in the case of smart cities [8]. AI Along with standards, a number of criteria have been developed for the evaluation of an AI system. The evaluation criteria of AI systems are not limited to the measurement of accuracy and error but include the quality assessment of the AI system. These criteria are divided into functional and non-functional evaluation criteria. The former are specific tasks that a system should be able to perform and are related to the intended purpose of the system, which include things like input/output, processing, and data storage requirements [10] [11] [12]. On the other hand, non-functional criteria are constraints that specify how well the system should perform its functional tasks and how it must behave under different conditions, including such things as performance, scalability, security and usability [9].

In this paper, after examining more than 200 sources, we presented the evaluation methods of AI products for the first time according to both quantitative and qualitative criteria during the life cycle of AI products (data, hardware, software, and machine learning models). Through comprehensive evaluations across these four categories, stakeholders gain valuable insights into the strengths and weaknesses of AI-based systems. This facilitates improvements, advancements, and the development of more reliable and effective AI solutions) by reviewing standards, checklists and methods. Accordingly, we divided these criteria during the production life cycle of AI systems into evaluation methods as well as trustworthiness criteria. Trustworthiness AI evaluation is a process aimed at assessing and ensuring the reliable behavior and performance of AI. This process involves defining appropriate criteria and indicators for evaluating AI, designing and generating test samples, conducting tests, and analyzing the results. Ultimately, to enhance the trustworthiness of AI, necessary adjustments and optimizations can be made to the system. This process is crucial for ensuring confidence and dependability of AI in various applications. According to experts' opinion, the most important and prioritized criteria are as follows: 1) Transparency, explainability and interpretability [325]; [326]; [327]; 2) Safety and reliability [328]; [329]; [330]; 3) Bias [331]; [332]; 4) Robustness [333]; [334]; [335]; [336]; 5) Security [337]; [338]. Besides, specific testing methods have been presented for AI products section, including software, hardware, data, and machine learning methods.

The rest of the paper is organized as follows. After the introduction, in the second section, the basics of research are presented, including importance of standardization and checklists. In the third section, methods are defined with an emphasis on the evaluation of AI-based systems (1- Hardware, 2- Software, 3- Data, and 4- Machine Learning models) and trustworthiness evaluation measurements. In the fourth section, summary and results are presented.

2. Research Fundamentals

In this section, before starting the main sections, necessary research background has been briefly reviewed. In section 2.1, the important role of standards in life cycle of AI-based products has been mentioned, and in section 2.2, the application of checklists in the evaluation of AI-based systems is presented.

2.1. The Importance of AI Standardization

Standards have become important indicators for measuring technology development rates. The culture of countries and regions as well as the formal rules of introducing products into the market are among the basic, supporting and guiding reasons for the standardization of AI. The important and key roles of AI standardization are presented in Table 1 [15].

2.2. The Importance of Artificial Intelligence Checklists

AI-based products are utilized in various applications, so that the trained model is accurate, fair, robust and resistant to attacks [13]. Systematic evaluation of AI-based products is done by checklists. AI-based product evaluation checklists include guidelines and criteria used by manufacturers and laboratory AI-based system assessors. By validating the information presented in the checklist, the evaluation laboratory provides a reliable, explainable and transparent product for all the stakeholders [14].

In Table 2, the three key roles of an AI-based system are presented. Each of these roles must provide the required documentation based on the specified task, and the documentation provided by the manufacturers is examined by the laboratory assessor.

Table 1. The Important Role of AI Standardization

The role of standardization in Artificial Intelligence	Standardization
• Facilitating and accelerating innovations in the field of artificial intelligence • Assisting in commercializing achievements in the field of artificial intelligence Furthermore, standardization can serve as a tool for strengthening technical accomplishments".	**The guiding role of standardization in technology innovation and support for industrial development.**
• Improving the quality of artificial intelligence products and services • Developing an integrated standard accompanied by methods for conducting necessary conformity Evaluation tests and evaluations	**Fast Realization of Innovation Universality**
• Increasing user safety • Protecting user rights • Adhering to human principles • Ensuring information security	
• Establishing fair and open ecosystems Currently, industry giants use methods such as open-source algorithms to create frameworks for deep learning and other ecosystems, which makes it more difficult to transfer user data. This requires unified standards for achieving collaboration and coordination between producers to prevent industry monopolies and user lock-ins, and to create fair and competitive industrial ecosystems.	

Table 2. Key roles of AI-based system

1. Ensuring testing and evaluation of the system according to established guidelines, criteria, and regulations. 2. Developing, deploying, and maintaining an AIsystem. 3. Making informed risk-reward decisions. 4. Responsible for operating and utilizing the algorithm. 5. Ensuring sustainable AIoperations.	Owner of AI
1. The algorithm owner is responsible for ensuring transparency, accountability, and ethicality of the algorithm. 2. Ensuring testing and evaluation of the algorithm's compliance with established guidelines, criteria, and regulations. 3. Documenting the algorithm's performance in documentation. 4. Monitoring, maintaining, and updating algorithms. 5. Making informed risk-reward decisions.	Algorithm Owner

3. Methods

The evaluation of AI-based systems is divided into four categories (Figure 1): 1- Hardware, 2- Software, 3- Data, and 4- Machine Learning models. In section 3.1, we will examine trustworthiness evaluation measurements in AI system life cycle. In sections 3.2 to 3.5, the four categories of AI based systems and evaluation of these methods are presented.

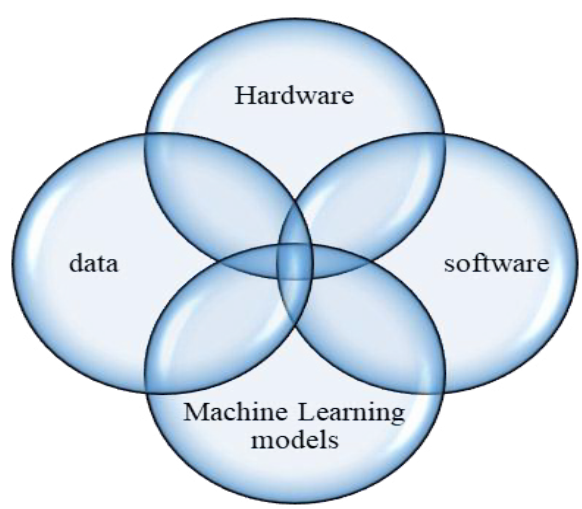

Fig 1. AI system Layers

3.1. Trustworthiness Evaluation Measures in AI system Life Cycle

AI system life cycle provides people with a suitable framework that can guide them towards their goal. The main role of AI system life cycle is to distribute the development of AI project into different phases so that the development becomes easier and clearly understandable, and the phases should be more specific to effectively achieve the best possible output. In general, architecture of the production cycle of AI-based products includes seven phases as follows: 1) Conceptualization; 2) Design and development; 3) Validation and verification; 4) Deployment; 5) Operations and monitoring, 6) Re-evaluation; and 7) Completion of operations.

Quantitative and qualitative assessments are used to test and evaluate the performance of AI software. The former

Table 3. Checklist of AI

Ethical Quality model AI	Robust AI	Legal AI
1. Technical 2. Non-technical	1. Human agency and oversight 2. Technical robustness and safety 3. Privacy preservation and data governance 4. Transparency 5. Diversity 6. Non-discrimination and fairness 7. Environmental and societal well-being 8. Accountability	• Explainability • Fairness • Respect for human autonomy • Prevention of harm

is evaluation based on system code testing and implementation methods and the latter is divided into several categories, which are the subsets of risk evaluation criteria and reliability measurement as follows: 1) Transparency, explainability and interpretability; 2) Safety and reliability; 3) Bias; 4) Sustainability; 5) Security, which should be checked to measure the trustworthiness of AI systems. To achieve these goals, the architecture shown in Figure 2 was taken into account in this paper to review the standards, checklists, and evaluation criteria. This architecture performs development review operations in phases 2-6; transparency and explainability, security and privacy review operations in phases 2-7; risk management and governance operations in phases 1-7.

Also, by reviewing the papers and standards, the checklists of this field have been presented in detail in Table 3.

3.1.1. Transparency and Explainability

The complexity of AI-based systems can lead to problems in understanding for both users and developers. This "understanding" can generally be considered in terms of clarity, interpretability and explainability of a system as follows:

-Transparency- The level of access to the algorithm and data used by the system based on AI ;

-Interpretability- The level of understanding of the way the underlying technology works;

-Explainability- The level of understanding how the AI-based system reached a certain result .

By reviewing the papers and standards, in Table 4 and Figures 3 and 4, the standards and methods of this field have been examined in detail [14], [17], [18], [242], [243], [244], [245], [246], [247], [248], [249], [250], [251], [252].

Evaluation methods related to explainability are important for assessing the transparency and interpretability of machine learning models. Two common subcategories of evaluation methods for explainability are explainable modeling and posthoc explanation .

Explainable modeling involves designing and developing machine learning models that are inherently interpretable. This can involve using simpler algorithms that are more transparent, incorporating human-readable features, or providing a clear understanding of the decision-making process within the model .

Posthoc explanation methods, on the other hand, involve explaining the decisions made by a complex machine learning model after it has already been trained. This can include techniques such as feature importance analysis, local explanation methods (e.g. LIME or SHAP), or generating text or visual explanations to justify model predictions.

3.1.2. Security and Privacy

AI-based systems are expanding and developing, and they are used in many fields as a significant alternative to traditional methods. However, due to the high complexity and extensive potentials that these systems provide, the security and privacy may be at risk, which is why security evaluation is of particular importance .

By reviewing papers and standards, Tables 4 and 5 of standards and checklists [14], methods [19], [20], [21], [22] [23], [24], [25] have been reviewed in detail in Figures 5, 6 and 7 [245], [246], [247], [248], [249], [250], [251], [252].

As seen in Figure 5, various security evaluation methods are described. Security evaluation methods are techniques used to assess the security of a system or application. These methods involve systematically analyzing the security controls, vulnerabilities, and potential risks associated with the target system.

Privacy Evaluation Methods in Figure 6 are described. Privacy evaluation methods are techniques used to assess the level of privacy protection and compliance within an organization or system. These methods can include conducting privacy impact assessments, auditing privacy practices, or using privacy control frameworks to evaluate the effectiveness of privacy protections in place.

In Figure 7, we discussed penetration check methods, which include two groups: fault tolerance and failure tests. Fault tolerance methods are designed to prevent system failures by providing redundancy or backup mechanisms, such as duplication or mirroring of critical components. Failure tests, on the other hand, are used to actively test

Table 4. Transparency& Explainability

Transparency& Explainability
ISO/IEC 24027 [180]; ISO/IEC 24028 [181]; ISO/IEC 5338 [182];ISO/IEC 24368 [183]; ISO/IEC 4213 [184];IEEE P7000- 14 [185]; IEEE P2863 [186];IEEE P3652-1 [187];ISO/IEC 23894.2 [188];ISO/IEC 42001 [189];Transparency of Autonomous Systems (defining levels of transparency for measurement) (IEEE P7001) [190]; Certification for Products and Services In Transparency, Accountability, And Algorithmic Bias In Systems (IEEEECPAIS) [191].

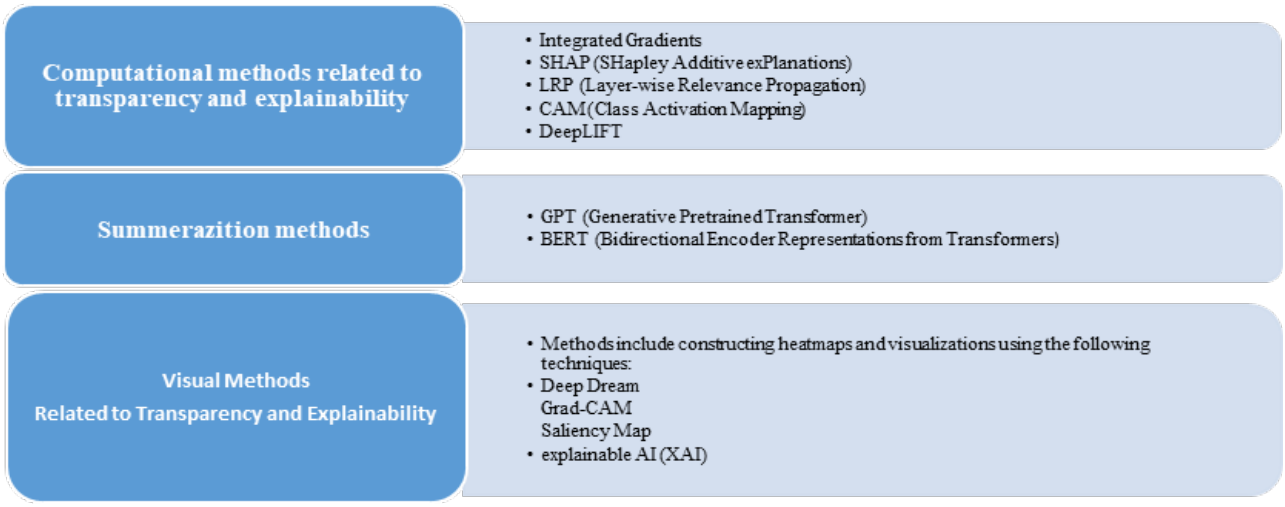

Fig 3. Methods related to transparency and explainability

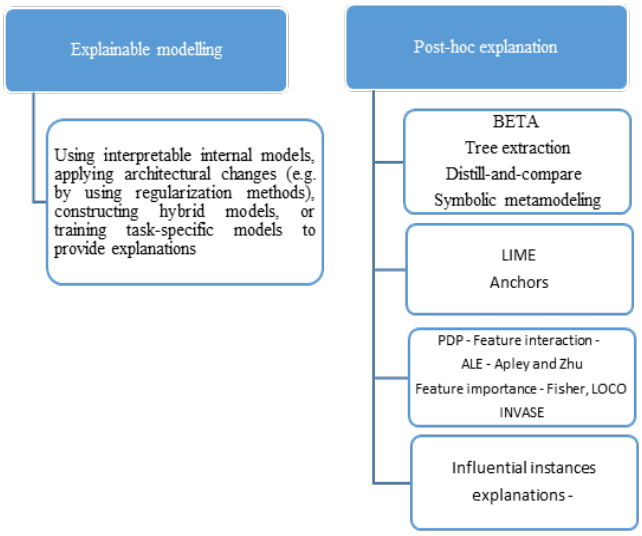

Fig 4. Evaluation Methods Related to Explainability

system vulnerabilities and identify weak points that may lead to system failures. These tests involve intentionally causing faults or failures in the system to assess its resilience and ability to recover from such events. Both fault tolerance and failure tests are important components of penetration testing, as they help to ensure the overall security and reliability of a system.

3.1.3. Bias

Bias is an important factor in AI evaluation, which refers to the concept of distortion in the collection, processing and/or interpretation of data by AI systems. Bias can lead to discrimination, as well as unfair decisions and results obtained by AI.[201][202][203].

Different approaches can be utilized to evaluate AI-based systems in terms of bias. The first step in bias evaluation is to identify and analyze the training data of the system. For example, if the training data contains only samples with certain characteristics, the system may make wrong decisions for data with different characteristics. By reviewing the papers and standards, in Figure 8, methods of this field have been examined in detail [204][205][206][207][208][209][210][211][212].

That can be divided into three categories: Bias mitigation algorithms aim to reduce the impact of biases in data and decision-making processes, while bias reduction techniques focus on eliminating biases entirely from a dataset or model, Data Bias refers to systematic errors introduced during the data collection process or data analysis that result in a misrepresentation of the true information .

3.1.4. Robustness Evaluation Methods

Recognizing the strengths and weaknesses of AI systems against new data is one of the most important challeng-

Table 4. Security and privacy standards

Standardization of security and privacy for AI-based products
ISO/IEC TS 4213 [184]; ISO/IEC 5338 [182]; ISO/IEC 4669 [192]; ISO/IEC 5469 [193]; ISO/IEC 23894.2 [188]; ISO/IEC 24029-1 [194]; ISO/IEC 24668 [195]; ETSI SAI 006 [196]; ISA/IEC 62443 [197], [198], [199], [200].

Table 5. Checklists Based on Security and Privacy from the Perspective of AI Governance

Continuous monitoring	Privacy Impact Evaluation	Third-party security	Risk Evaluation	Compliance	Incident Response Plan	Data retention	Encryption	Access control	Data protection measures
on-site evaluation of continuous monitoring processes	Risks and data protection impact Evaluations (DPIAs).	Evaluation of existing security measures for vendors and third-party partners.	Examination of risk Evaluation and current management processes.	Evaluation of system compliance with relevant regulations and standards such as GDPR and ISO 27001	Evaluation of system incident response plans and procedures.	Evaluation of data retention policies and procedures.	Examination of encryption methods used.	Evaluation of system access control mechanisms	**Evaluation of existing measures for protecting sensitive data and ensuring privacy**

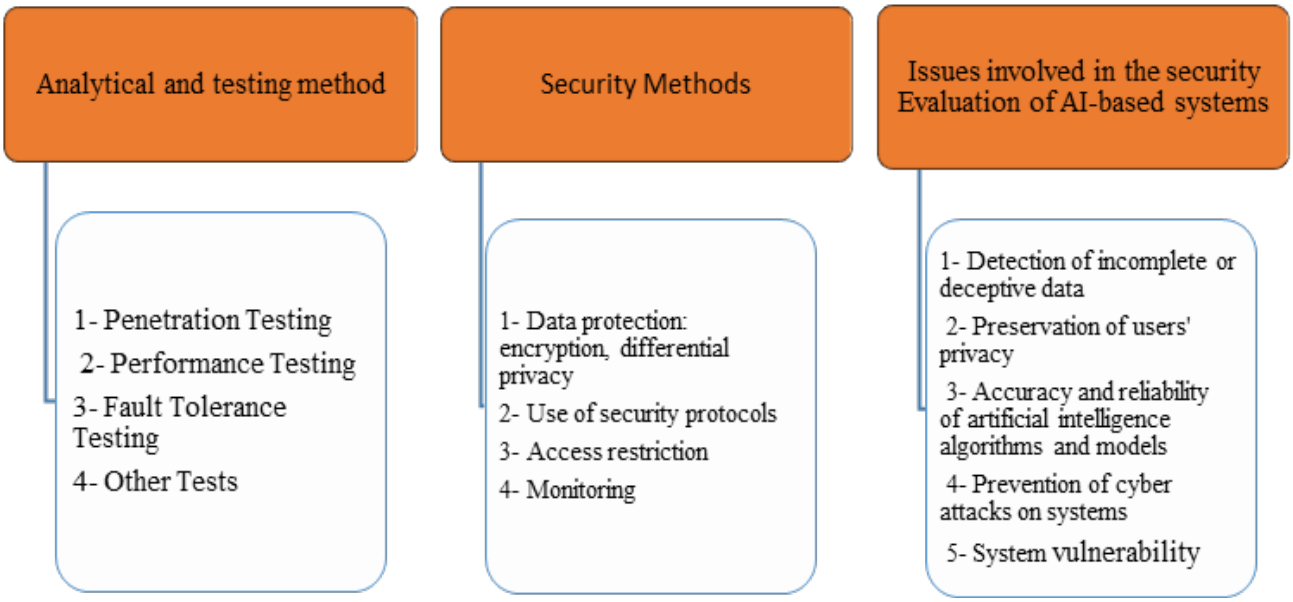

Fig 5. Security Evaluation Methods

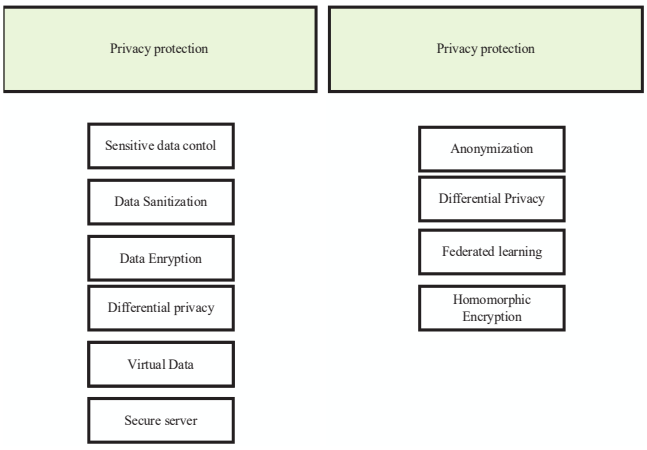

Fig 6. Privacy Evaluation Methods

es for this industry. Therefore, most AI systems have adopted the approach of being highly sensitive to environmental changes and noises and being prone to easy failure, which is why robustness evaluation methods have become of high importance. By reviewing the papers and standards, in Table 9 and Figure 9, the methods and standards of this field have been presented in detail in [257], [258], and [259].

In Figure 9, we have categorized the methods of robustness evaluation into four categories: removing outliers, dealing with data noise, evaluating the performance of several neurons, and adding new data.

Removing outliers: This category includes methods that focus on identifying and removing outlier data points from the dataset. Outliers can significantly affect the per-

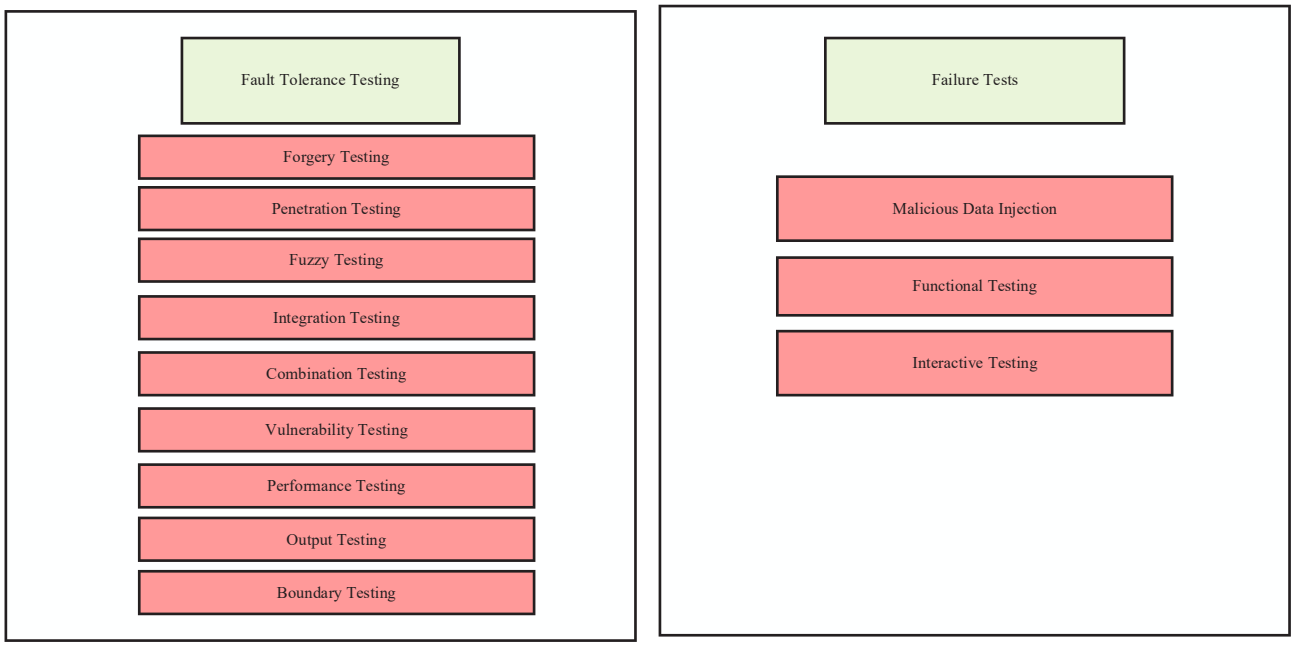

Fig 7. Penetration Check Methods

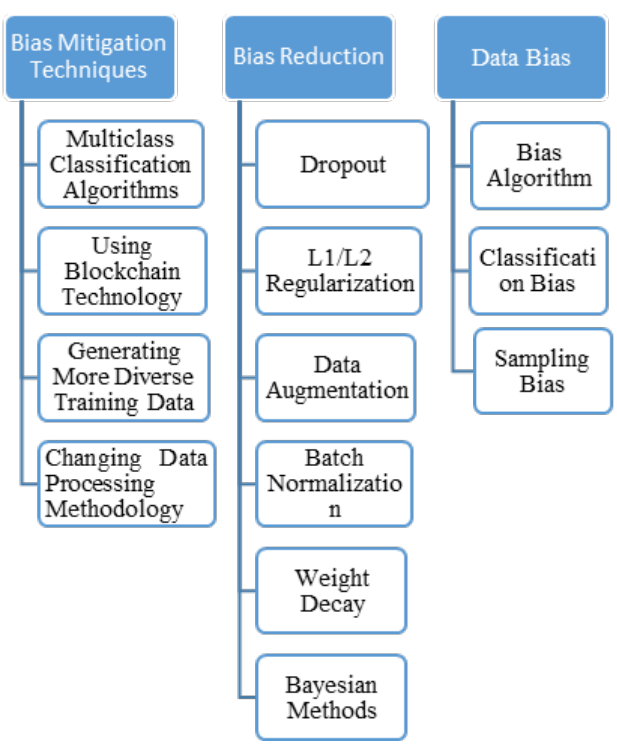

Fig 8. Bias Evaluation methods

Table 9. Robustness Standards

Robustness Standards and Methods
ISO/IEC TR 24029-1

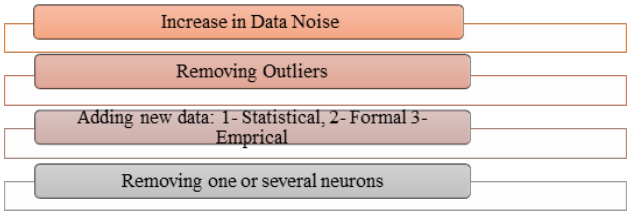

Fig 9. Robustness Evaluation Methods

formance of a model and by removing them, we can improve the robustness of the model.

Dealing with data noise: This category includes methods that aim to address the presence of noise in the dataset. Noisy data can lead to inaccurate predictions and can make the model less robust. Techniques such as smoothing or filtering can be used to reduce the impact of noise on the model. Robustness in the context of removing one or several neurons refers to the ability of a neural network to maintain its performance and functionality even when certain neurons are removed. This is an important aspect of evaluating the effectiveness and reliability of neural networks, as it can provide insights into how well the network can adapt to changes and disruptions.

3.1.5. Safety and Reliability

In computer science, safety means ensuring that a system, software or device poses no risk to the user or the surrounding environment under any circumstances. In

Table 6. Safety Evaluation standards

Safety - Application
Railway- EN 20126 20128- EN20129; Elevator EN 811/PrA2; Autonomus/ ISO 26262; Machinary/ISOM13849 Process/IEC 61511; ISO/PAS 21448; UL/4600; ISO/IEC AW TR 5469; VDE-AR-E-2842-61-1; IEC 61508; ISO/IEC 24027: ISO/IEC 24028; IEEEP2846; ISO/DIS Road Vehicle -Functional Safety; IEC, "Functional safety of electrical/electronic/programmable electronic safety-related systems," IEC 61508:2010; ISO, "Road Vehicles – Functional Safety"; ISO, "Road Vehicles – Functional Safety" ISO 26262:2018; ISO, "Road Vehicles – Safety of the Intended Function"; ISO/PAS 21448:2019; Koopman, P. & Wagner, M., "Toward a framework for highly automated vehicle safety validation," SAE 2018-01-1071, 2018; Koopman, P. & Fratrik, F. "How many operational design domains, objects, and events?" SafeAI 2019; Ministry of Defence, "Safety Management Requirements for Defence Systems," Defence Standard 00-56, 2017; SAE, Guidelines and Methods for Conducting the Safety Evaluation Process on Civil Airborne Systems and Equipment, ARP4761, 2012; US Dept. of Commerce, https://www.commerce.gov/issues/regulatory-reform, 7 June 2019. US DoD, "Standard Practice: System Safety", MIL-STD-882E, 11-May-2012; AC 23.1309-1, System Safety Analysis and Evaluation for Part 23 Airplanes.

Table 7. General safety of artificial intelligence software [240], [241]

Software development phase	Software Safety Tasks
Conceptual Design	• Initial Hazard Analysis • Software Safety Program
Software Requirements Analysis	• Safety requirements analysis • Hazard testing • Review of safety requirements • FTA/FMEA based on user specifications
Software Architecture Design	**Software Architecture Design:** FTA/FMEA of software systems
Coding and Detailed Designing	• **Partial software safety analysis:** FMEA/FTA • Code-level safety analysis Defense Programming
Testing, Integration, and Verification	• **Software safety testing, analysis of software safety tests, and software safety case studies:** • Defense Programming

general, safety indicates preventing accidents and reducing risks associated with the use of complex systems and technologies [261], [262], [263], [264], [265], [266], [267], [268], [269], [270], [271], [272], [273], and [279]. In various industries, including automotive, aerospace, medical, and military industries, safety is one of the most important factors for designing and manufacturing products. In addition, safety is considered an important topic in the field of computer security as well as protection of data and computer systems .

To check the safety of AI systems, we assess these methods from two perspectives :

•Software safety in the production cycle of AI products

•Safety of algorithms of machine learning models in the production cycle of AI products

By reviewing the articles and standards, Tables 6, 7 and 8 [280], [281], [282], [283], [284], [285], [286], [284], [288], [286], [290], [291], [292], [293], [294], [295], [296], [297], [298], [299], [300], [301], [301], [302], [303], [304], [305], [306], [307], [308], [309], [310], [311], [312], [313], [313], [314], [315], [316], [317], [318], [319], [320], [321], [322], [323] present the checklists, methods and standards of this area in detail.

3.2. Hardware Development

We use the RAMI model as one of the most common and famous models in the development of AI products. RAMI 4.0 is the real reference architecture for Industry 4.0 with relevant standards. Accordingly, standardization during the development of AI systems is carried out according to Figure 10.

By reviewing the papers and standards, the standards of this field have been presented in detail in Table 9.

3.3. Software Testing

Most AI-based systems are composed of one or more AI components (e.g., an ML model) surrounded by a substantial array of traditional software that provides a supporting infrastructure, typically consisting of common components such as a user interface and a database. Even "pure" AI components are implemented in software and therefore can be flawed like any other software. There-

Table 8. Safety of Algorithms Of Machine Learning Models

Examples	Method categories	Method categories
scenario coverage [337] - input space ontology [338]	Data representatively requirements	**Requirements Engineering** Use available domain knowledge to formulate use-case and safety requirements
- adversarial robustness metric [339]	Robustness requirements	
- runtime monitoring - model diversity measure for redundancy [342,343,366]	System fault tolerance requirements	
- occlusion sensitivity [352]	Safety performance measures	
- AD behavior rules - sensible intermediate steps [358] - domain specific rules (physical, legal)	Plausibility requirements	
	Experience collection	
experience on model type, training method, initialization values [342]	Design based on experience	**Development Apply** Reasonable Design Choices at All Decision Points
[345,346]	Incorporation of uncertainty	
via loss function NNs [348, 36] – via topology NNs [349] - model repair RL [350] - safe learning [351, 352]	Inclusion of expert knowledge	
- regularization [353] - robustification of training data [353] - counterexample -guided data augmentation [354]	Robustness enhancements	
- solvers NNs [355,356] - boundary approximation NNs [357, 358] - search algorithms [359]	Formal verification of rules, model, KPIs	**Verification** Check Against Test Data and Model Requirements
		Validation **Find Missing.**
	Input space coverage checks	**. . . Test Cases**
	Experience coverage checks	
- concolic testing NNs [360] - counterexample generation [360, 361, 362]	Model coverage checks	
- back-propagation based, e.g. NNs [363] - model agnostic, e.g. [364,365,366]	Attention analysis through heatmapping	**. . . Requirements Via Qualitative Model Analysis**
- method collection [367]	Feature visualization	
- textual explanations NNs [368] - hierarchical information [369]	Explanatory output	
- locally via ILP [370] - global model agnostic, e.g. VIA [371] - global NN specific methods [372]	Rule extraction	**. . . Requirements Via Quantitative Model Analysis**
- Neural Stethoscopes NNs [373] - concept embedding and attribution analysis NNs [375, 374] - ReNN modularized topology [374]	Sub-task/concept analysis	

fore, when testing an AI-based system, conventional software testing methods are still required. However, AI-based systems have a number of special features that necessitate additional testing relative to conventional software systems. Figure 11 shows the types of tests in products based on AI .

3.4. Data governance

In AI(AI), governance is often presented in two parts: data and AI. The former refers to the policies, procedures and practices that organizations have in place to manage the data they collect, store and use. It is critical for ensuring the quality, integrity, and security of data, which are in turn essential to the development and deployment of AI systems.

Data governance also involves privacy, ethics and data transparency. On the other hand, AI governance refers to the policies, regulations, and guidelines established to control the development, deployment, and use of AI systems [26][27]. In data governance, the quality and integrity of data, communication with other areas, compliance with access protocols and data processing capabilities are covered.

In the field of data governance, there are three key roles

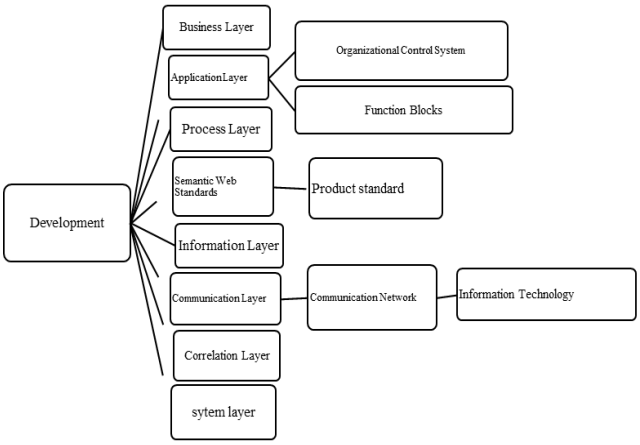

Fig 10. AI-based product development layers

of data management, data supervisor and data technician. All three roles are responsible for overseeing the three areas of data operations, data quality monitoring, and data quality improvement. Figure 12 shows the tasks of each role in each area.

By reviewing the papers and standards, Tables 10, 11, 12, 13 and 14 present the checklists, methods and standards of this field in detail [28]; [16]; [29]; [30]

Data governance frameworks provide a systematic approach to managing and regulating data management in an organization. The most famous frameworks are as follows: Strategic Information Management Model (SAM), Asset Information Model (AIM), DAMA-DMBOK Framework, DMBOK Framework, DAMA Advanced Data Management Framework, Data Governance Institute (DGI)

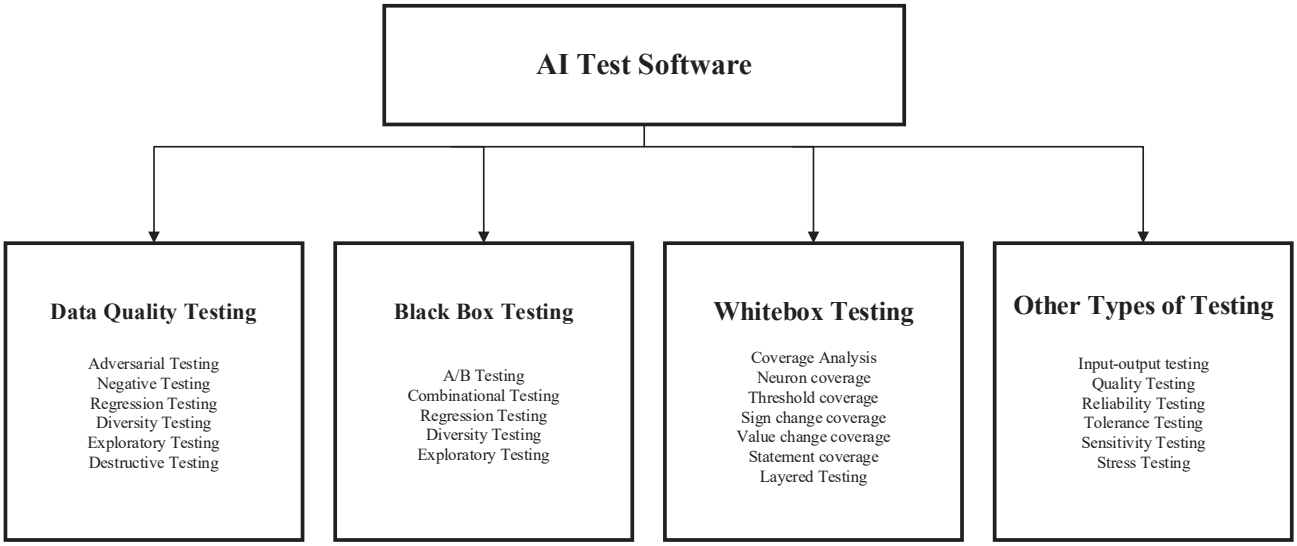

Fig 11. Types of Testing in Products Based on Artificial Intelligence

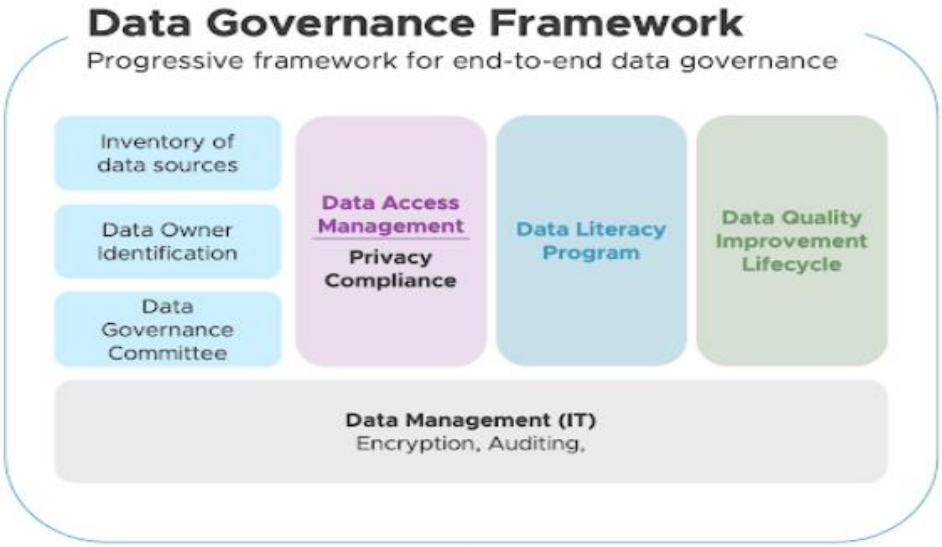

Fig 12. Data Quality

Table 9. Development phase standards

ISO/IEC JTC1 AG08 Standard	Development Layer
IEC/ISO 62264 - Enterprise Control System [35], [36], [37], [38], [39], [40]; ISO/IEC 30141 [41]; IEC 61499 – Function blocks [42], [43], [44]; IEC 61512 – Batch control [45], [46], [47], [48]; ISO/IEC 42010 – Systems and software engineering – Architecture description [49]	**Business Layer**
ISO/IEC JTC 1 SC41 [50]	**Application Layer**
RFC8259 – The JavaScript Object Notation (JSON) Data Interchange Format [51]; IEC 63339 ED1 [52]; ISO 13584-4/IEC 61360 – Classification and product description [53], [54]; IEC 61987 – Industrial-process measurement and control – Data structures and elements in process equipment catalogues [55]; ISO 29002-5 [56]; AML IEC 62714 – Engineering data exchange format for use in industrial automation systems engineering – Automation Markup Language [57], [58], [59], [60], [61]; ISO 13584-4/IEC 61360 – Classification and product description [62], [63]; IEC 61987 – Industrial-process measurement and control – Data structures and elements in process equipment catalogues [64];IEC 62714 – Engineering data exchange format for use in industrial automation systems engineering – Automation Markup Language [65], [66], [67], [68], [69]; ISO/IEC 19788-7:2019 – Information technology – Learning, education and training – Metadata for learning resources [70]; ISO 16684-1:2019 – Graphic technology – Extensible metadata platform (XMP) [71]; ISO/IEC 15944-10:2013 – Information technology – Business operational view – Part 10: IT-enabled coded domains as semantic components in business transactions [72] ISO 1087:2019 – Terminology work and terminology science – Vocabulary [73]; ISO/IEC 1179 – Metadata Registry (MDR) [74, 75]; ISO 21597-1:2020 – Information container for linked document delivery – Exchange specification [76]	**Process Layer**
IEC 61158-1 [77]; IEC 61784-2 [78]; ISO/TC 184 – IEC/TC 65/JWG 21 [79], [80]; IEC 62591:2016 [81]; IEC 62601 (WIAPA), IEC 62734 (ISA100a) [82], [83]; IEC 62948 (WIA-FA) [84]; IEC 62657-2 [85]; IEC 62541-1 presents the concepts and overview of the OPC Unified Architecture and serves as the basis for further specification [86].; IEC 62541-2 – security model [87], IEC 62541-3 Address Space Model [88]; IEC 62541-4 services [89], IEC 62541-5 Information Mode [90]l; IEC 62541-6 Mappings [91]; IEC 62541- 7 Profiles [92]; IEC 62541-8 Data access [93], IEC 62541-9 Alarms and Conditions [94]; IEC 62541-10 Programs [95]; IEC 62541-11 Historical access [96]; IEC 62541-12 Discovery and global [97]; IEC 62541-13 Aggregates [98]; IEC 62541-14 PubSub [99]; IEC 62541-100 Device interface [100]; IEC 61784 – Industrial communication networks [101]; IEC 61158 series, to be used in the design of devices involved in communication in factory manufacturing and process control [102], [103], [104], [105], [106], [107], [108], [109], [110], [111], [112], [113], [114], [115], [116], [117], [118], [119], [120], [121], [122], [123], [124], [125], [126], [127], [128], [129], [130], [131], [132], [133], [134], [135], [136], [137], [138], [139]; IEC 61784 2 [140]; IEC 61784 3 series [141]; IEC 61784-5 series [142]; IEC 61918. [143]; IEC 61850:2020 – Communication networks and systems for power utility automation [144]; ANSI/MTC1.4 – 2018 – MT Connect [145]; ISO/IEC 19464:2014 – Information Technology – Advanced Message Queuing Protocol (AMQP) v1.0 specification [146] ; The IEEE FIPA (Foundation for Intelligent Physical Agents) specifications represent a collection of standards which are intended to promote the interoperati of heterogeneous agents and the services that they can represent [147];.IEC 61850:2020 – Communication networks and systems for power utility automation [148];ISO/IEC 19464:2014 – Information Technology – Advanced Message Queuing Protocol (AMQP) v1.0 specification [149]; ISO 18000-7 – Information technology – Radio frequency identification for item management – Part 7: Parameters for active air interface communications at 433 MHz [150]; IEEE 802.15.1 – Bluetooth LE [151]; IEEE 802.15.4 – ZigBee [152]; IEEE 802.11 – Wireless Local Networks [153];	**Information Layer**
ISO 11354 - Advanced automation technologies and their applications — Requirements for establishing manufacturing enterprise process interoperability [154]; IEC 63339 [155]; ISO 15745 Industrial automation systems and integration — Open systems application integration framework [156]; IEC 62264 Enterprise-control system integration [157], [158], [159], [160], [161], [162], [163]; IEEE 2660.1-2020 - IEEE Recommended Practice for Industrial Agents: Integration of Software Agents and Low-Level Automation Functions [164]; VDI/VDE 2653 - Multi-agent systems in industrial automation [165].	**Integration Layer**
IEC 62832 CD 2 Part 1 [166]; IEC 61360 [167], [168], [169]; ISO 29002-5 [56]; ISO/IEC 11179-5 [56]; IEC 61131 – Programmable controllers [170]; IEC 62832 [171], [172], [173]; IEC 61508 - functional safety requirements [174]; IEC 62443 - Industrial communication networks - IT security for networks and systems [175], [176], [177], [178]; IEC 61131 – Programmable controllers [179].	**System Layer**

Table 10. Data governance standards

Data Governance Standards
ISO/IEC 5259-6 [213], PWI 8183 [227]; 8183 AI Data life; 5259-X Data quality [228];22989 AI Functional Overview [223];ISO/IEC 38507 Information Technology- Governance of IT- Governance implications of the use of artificial intelligence by organization [229]; ISO/IEC 5259-(1-4) [230]; ISO/IEC 24372 [225]; ISO/IEC 24668 Process management framework for big data analytics [195]; ISO/ IEC 5259-x (1-7) Data quality for analytics and ML [231], [232], [233], [234], [235]; ISO/IEC 20547-1: 2020 Information technology- Bigdata inference architecture – part1: framework and application process [236]; ISO/IEC 20547-2: 2020 Information technology- Bigdata inference architecture – part2: use cases and derived requirements [237]; ISO/IEC 20547-3:2018 Information Technology- Bigdata reference architecture- part 5: Standards Roadmap [238].

Table 11. General and specific evaluation criteria of data sources of AI-based systems

Data Evaluation Criteria	
General data protection regulations (GDPR) Sensitive data quality	**Cloud computing**
Security	**Hidden data**
Integration of various resources	**Internet of Things (IoT)**
Security in distributed processing	**Blockchain**

Table 12. Data governance Evaluation checklist

1.Features of content management systems 2. Organizational content management systems 3. Document management systems 4. Content and Document management standards 5. KPIs for content and document management (KPI stands for Key Performance Indicators)	**Document management**
1. Extract, Transform, Load (ETL) process 2. Data latency or data lag 3. Interaction models 4. Data interoperability and integration architecture 5. Interoperability standards 6.KPIs for data interoperability and integration (KPI stands for Key Performance Indicators)	**Data integration**
1.Secondary data 2. Primary data 3. Difference between primary and secondary data 4. Standards for primary and secondary data 5.KPIs for primary and secondary data (KPI stands for Key Performance Indicators(	**Master data management**
1.. Data encryption 2. Types of data security 3. Classification of data security 4.Data security risks 5.Data security standards 6.Data security KPIs (KPI stands for Key Performance Indicators(	**Data security**
1.Data warehouse structure 2. Data warehouse standards 3. Data warehousing KPIs (KPI stands for Key Performance Indicators)	**Data warehousing and business intelligence**
1.Data characteristics in a database 2. Database components 3. Database architectures 4. Approaches to organizational data storage 5. Data storage standards 6. Data storage KPIs (KPI stands for Key Performance Indicators(	**Cloud data management**
1.Data model components 2. Data model granularity levels" 3. Factors influencing data model improvement 4. Data modeling standards 5. Data model KPIs (KPI stands for Key Performance Indicators)	**Data modeling**
1.Enterprise architecture framework 2. Organizational data architecture 3. Data architecture standards 4. Data architecture KPIs (KPI stands for Key Performance Indicators)	**Data architecture**

Table 13. Data quality Evaluation checklist

Data cascade					**Data management**		
Data quality	Data fitting	Trustworthy performance	Scalability solution	Performance testing	Data cleansing for structured data	Fairness	Data cleaning
					Consistency constraints	Understanding potential data interactions Artificial data analysis	Cleaning poisoned data/Cybersecurity /Self-control/Filtering spam

Table 14. Evaluation criteria

Artificial Intelligence Performance Evaluation Metrics			
Supervised learning		Unsupervised learning	Reinforcement Learning
Regression	Classification	Clustering	-
MAPE RMSE MAE RSquard (R^2)	Accuracy Precision ROC Curve Confusion Matrix	Jaccard Index Silhouette Coefficient Rand Index (RI) Davies-Bouldin Index	-

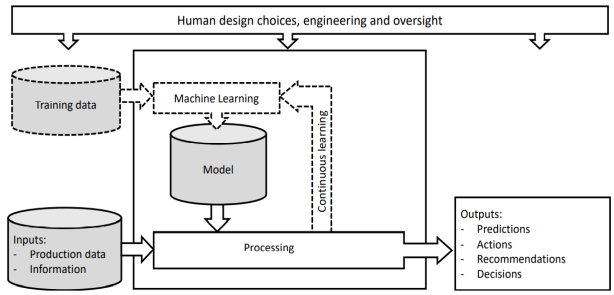

Fig 13. Examining the stages of AI software development

Table 15. AI reliability Evaluation in the life cycle

Trustworthy AI										
Establishment and monitoring	Modeling			Collect and understand data						
Trustworthy deployment Choose Trustworthy monitoring tools Evaluation the Trustworthy of the model	Trustworthy post-processing	Trustworthy training	trustworthy preprocessing	data privacy	crowdsourcing	augmenting data	unbiased data	quality control	Administrative and organizational data	Social network data
Border erosion	Unfair post-processing Adversarial attacks	Domain robustness Fairness-enhancing processing Adversaries Attack Explainability	Domain adaptation Unfair pre-processing Data cleansing Explainability		Unbiased Quality control Impartiality	collapse	Social unbias Representation unbias Data preparation unbias data non-poisoning Temporal unbias	Targeted data collection Obvious cheatin	Historical prejudices Label correction	Quality precision Reliability Folk accents, non-standard dialects, misspellings

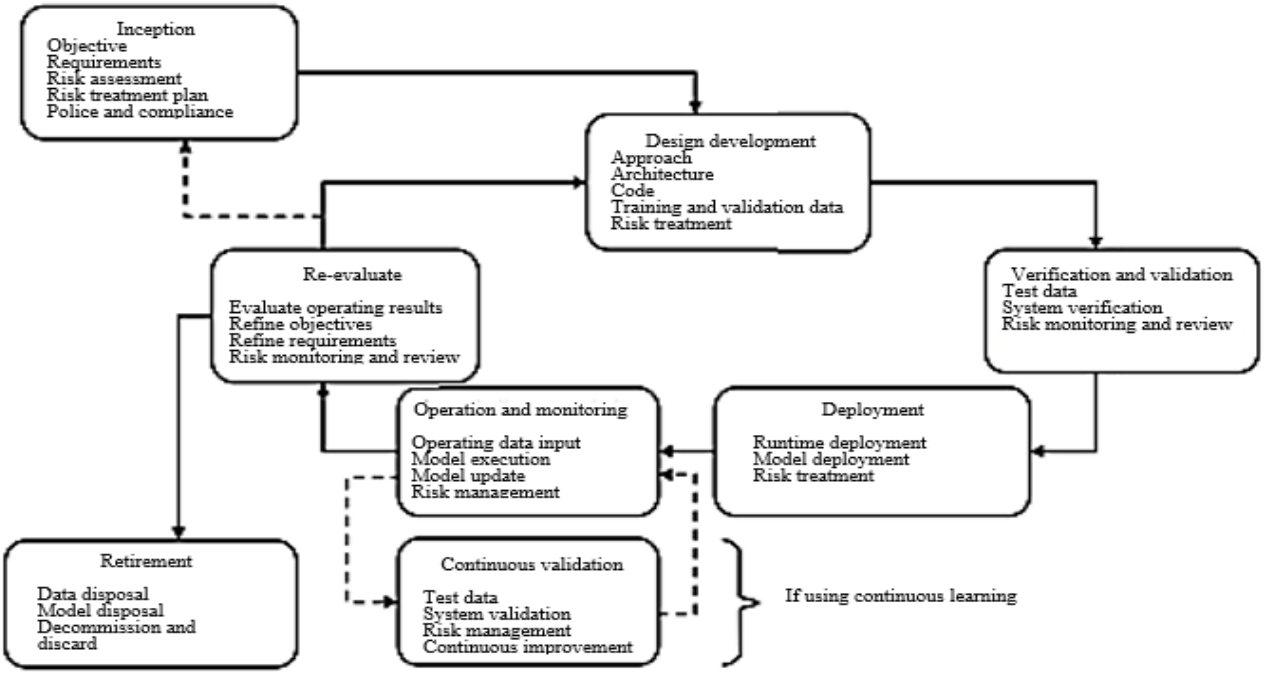

Fig 14. Details of Construction Stages of AI-Based Systems

Table 16. Life cycle-based system Evaluation

Trustworthy AI										
Establishment and monitoring	Modeling			Collect and understand data						
Trustworthy deployment Choose Trustworthy monitoring tools Evaluation the Trustworthy of the model	Trustworthy post-processing	Trustworthy training	trustworthy preprocessing	data privacy	crowdsourcing	augmenting data	unbiased data	quality control	Administrative and organizational data	Social network data
Border erosion	Unfair post-processing Adversarial attacks	Domain robustness Fairness-enhancing processing Adversaries Attack Explainability	Domain adaptation Unfair pre-processing Data cleansing Explainability		Unbiased Quality control Impartiality	collapse	Social unbias Representation unbias Data preparation unbias data non-poisoning Temporal unbias	Targeted data collection Obvious cheatin	Historical prejudices Label correction	Quality precision Reliability Folk accents, non-standard dialects, misspellings

Framework, IBM Data Governance Council Framework, SAS Data Governance Framework. These frameworks provide a comprehensive approach to managing data from creation to provision (throughout the data lifecycle), including data quality, data architecture, data modeling, cloud data management, data warehousing and business intelligence, data storage and operations, data security, master data management, data integration, content and documentation management. Based on this framework, the following checklist should be checked. Based on [13] and [31], the data governance Evaluation checklist and data quality Evaluation are compiled in Tables 12 and 13.

3.5. Evaluation Criteria in Machine Learning Algorithms

The evaluation of AI products involves functional [32]; [33] and non-functional [34] evaluation; in this section, the focus is on performance criteria of AI systems. The criteria that are obtained based on mathematical formulas are meant for measuring the quantitative behavior of a system. Table 14 shows the evaluation criteria in different AI issues.

4. Discussion section & Results

In this section, we present the final conclusion of this paper. Figure 13 shows that a majority of these evaluations is effective in the data section; the designed architecture model of machine learning and the results of these tests and evaluations can be seen in the outputs section.

Based on [16] and [324], Table 15 shows the checklist of reliability evaluation of AI-based system during its life cycle.

Considering the lack of a comprehensive standard covering all aspects of AI product production, we decided to present a roadmap for standardization by studying, collecting and categorizing standards in the field of AI product production. In Figure 16, all stages of life cycle, the steps of evaluation, validation and elimination of risks are presented. These steps are achieved by evaluating the quantitative and qualitative criteria mentioned in this paper.

5.Conclusion

The proliferation of AI products and the rapid adoption of algorithms in business and global society have created the need for regulatory frameworks and evaluation criteria to ensure that the public interest is maintained. Standards, checklists, and Evaluation criteria provide a structured approach to the development, evaluation, and monitoring of AI-based products. The use of standards, tests and checklists has become necessary to create public trust, accountability and operationalization of AI systems. This paper has been presented to guide researchers and practitioners in the field of evaluation and testing of AI systems. For the first time, this survey presented a comprehensive and complete review (by examining more than 200 papers and standards) on how to evaluate AI systems according to the categories of standards, checklists and methods. These categories have been offered according to the review of papers in terms of quantitative and qualitative evaluations during the development of AI products. As a future research direction, we may present specific and clear examples of how to use checklists, test and evaluations in critical industries and use cases.

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Consent for publication
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