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Digitalisation and Intelligentisation of the Inspection and Testing Industry: Current Status, Problems and Strategy Path.

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Abstract

Against the backdrop of a new round of digital construction and intelligent development, the inspection and testing industry has shown steady growth and is progressing well. This paper takes a general look at the current situation of digital and intelligent transformation in the inspection and testing industry, analyses the technology landscape, identifies the key barriers and problems, and puts forward strategic development paths. The study examines the application of digital technologies-such as Laboratory Information Management Systems, Internet of Things technologies, big data analytics, and artificial intelligence-in various parts of the industry. The major challenges found include a lack of digital infrastructure, data security risks, a shortage of talent, the absence of industry-wide standards, and the difficulty of translating technology into practice. A multi-stakeholder framework is proposed to drive market development through strategic planning, institution building, talent development, standard setting and ecosystem construction. Attention is also drawn to how vertically oriented AI agents can help address the lack of specialisation of general-purpose AI tools in specific areas. Policy suggestions are put forward at the end to support related research and development for the purposes of high-quality industry development.

Keywords

Inspection and Testing; Digital Transformation; Artificial Intelligence; Intelligent Agent; Industry 4.0.

1. Introduction

The inspection and testing industry is a core support for the quality system, providing essential services to ensure product safety and regulatory compliance across all sectors of the economy[1]. Food safety testing protects public health, environmental monitoring safeguards natural resources, pharmaceutical quality control ensures drug efficacy, and industrial inspections help prevent equipment failures. The scope and importance of the industry continue to grow.

In recent years, with new policies and the strengthening demand from consumers for high-quality products and the expansion of China's manufacturing base, the inspection and testing market around the world has shown continuous growth. According to the statistics of the industry, there are about 54,000 inspection and testing institutions in China, and more than 1,600 of them are located in Guangxi Province. This large-scale and diverse industry includes government laboratories, third-party inspection institutions, self-inspection facilities of enterprises, and many other sections, such as food and beverages, pharmaceuticals, environmental pollution, building materials, electronics, industrial production, etc.

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There are now many problems in the old operating mode of the industry. A large number of new national and industry standards have emerged, and they are becoming more complicated each year. Regulations are constantly changing, requiring continuous adaptation. Customers are getting used to faster service speeds and lower prices. At the same time, as more and more data are produced by testing activities, manual management is no longer a viable option.

Digital and intelligent transformation has gradually begun to be implemented to address these challenges [2, 3, 4]. With the help of technologies such as Laboratory Information Management Systems, Internet of Things sensors, big data analysis, cloud computing, artificial intelligence, etc., inspection and testing institutions can improve operational efficiency, enhance the quality of decision-making, reduce compliance risks, and develop new value-added services. These technologies also make testing faster, more accurate, and less wasteful of resources.

This paper provides a systematic examination of the digital and intelligent transformation of the inspection and testing industry. It reviews the current state of technology adoption, identifies key challenges and barriers, and proposes strategic pathways for accelerating transformation. The analysis draws on industry data, case studies, and recent research to provide actionable insights for industry stakeholders including testing organizations, technology providers, regulators, and customers.

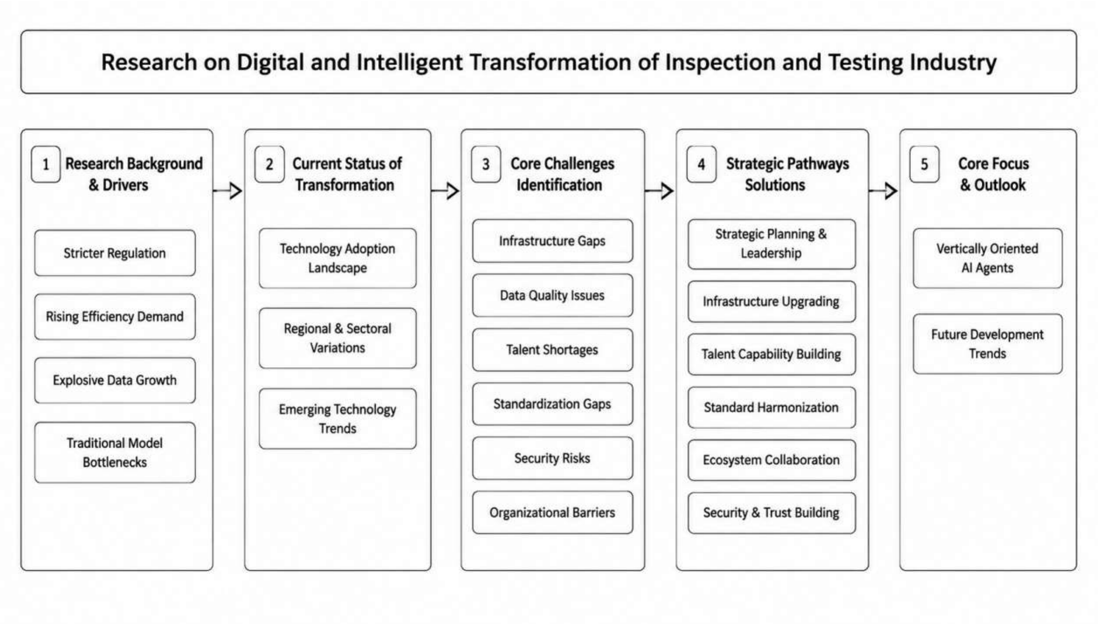

Figure 1. Full-text logical framework diagram

2. Current State of Digital and Intelligent Transformation

2.1. Technology Adoption Landscape

The application of digital technologies in inspection and testing enterprises differs greatly from one another and among different types of enterprises [5]. Generally speaking, the large, well-funded laboratories and national test centres have made further progress in the digitalisation process than the small, resource-poor organisations.

Most inspection laboratories have now adopted Laboratory Information Management Systems as the basic digital technology. Modern LIMS platforms can take care of all the links in the testing life cycle, such as sample registration and task assignment, data collection, quality control, report output, recordkeeping, etc. [6] Leading LIMS companies have developed platforms that are compatible with analytical instruments and enterprise systems. However,

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their adoption has been uneven, and many small laboratories have not yet begun to use automation or sophisticated software.

Connecting analytical instruments and testing equipment to a digital network can be used to automatically collect data, monitor in real time, operate remotely, etc. Many new instruments have started to support standard communication protocols, but older ones do not. The cost and difficulty of instrument connection are still problems for many organisations [7].

New data analysis can be performed on the accumulated testing results. These analytical tools can be used for the trend analysis of quality, root cause analysis of non-conformities, predictive modelling for equipment maintenance and performance benchmarking, etc. Due to problems with data quality, data integration and a lack of skills, the full expected benefits of testing data analysis have not yet been realised.

Artificial intelligence applications in inspection and testing are emerging but remain at relatively early stages of adoption[8]. Current applications include automated visual inspection using computer vision, natural language processing for document analysis, predictive analytics for quality forecasting, and intelligent assistants for knowledge retrieval[9]. Most AI implementations remain focused on specific, well-defined tasks rather than end-to-end workflow automation. The development of vertically oriented AI agents tailored to inspection and testing domains represents the next frontier[10].

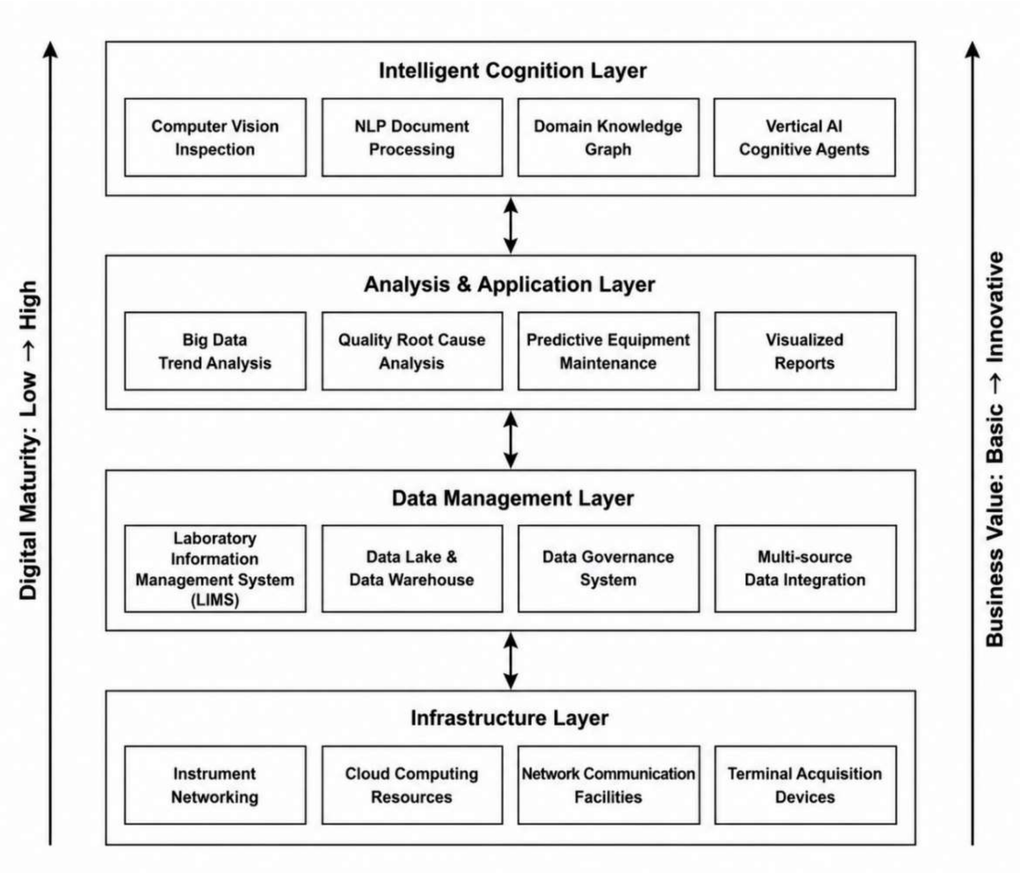

Figure 2. Digital Technology Hierarchical Architecture Diagram for Inspection and Testing

2.2. Regional and Sectoral Variations

The speed and extent of the digital economy development in different areas and industries are uneven.

Generally speaking, the eastern coastal area of China has been at the forefront of the digital economy and development, thanks to a large number of high-tech enterprises and research institutions [11]. Although there have been some improvements, the industrial structure, lack of talent and investment capacity in the Guangxi Zhuang Autonomous Region are still problems. Guangxi is an important link in the market of the Association of Southeast Asian Nations, and therefore, the development of inspection capabilities that support cross-border trade will be a new direction for Guangxi.

Pharmaceuticals, food safety, environmental monitoring, etc., are areas with a strong regulatory system and a large number of tests; thus, they have been making more investments in digitalisation. Due to stricter regulations in the field, many new technologies have been introduced, and a large amount of data has been collected for digital analysis. There are fewer regulations in this area and the test market is dispersed; therefore, the application of digital technology has been delayed.

2.3. Emerging Technology Trends

Several technologies are developing now that will drive the development of digital and intelligent transformation in inspection and testing.

With the development of various artificial intelligence capabilities, such as natural language processing, computer vision, speech recognition and knowledge reasoning, many of them have been combined to build unified cognitive agent systems [12]. These agents can handle text standards, interpret pictures and sounds, process questions, give advice and so on, thus enabling a more natural and efficient human-computer collaboration.

The edge computer will carry out some preliminary processing and then send the collected data to the cloud for detailed analysis. Urgent work can be done at the instrument or in the laboratory on-site, and computationally intensive training and analysis will be carried out in the cloud [13].

A knowledge graph can be constructed based on the domain to help intelligent systems learn about various relationships among standards, methods, equipment and test results. Semantic Technologies can help retrieve information and reason over it more easily [14].

Generative AI is now being used to automate the production of reports, test plans, training materials, regulatory documents and so on. These applications can reduce the need for manual labour and improve the uniformity and quality of the work [15].

3. Key Challenges and Barriers

Despite its considerable promise, the digitalisation and intelligentisation of the inspection and testing industry still face many problems [16].

3.1. Digital Infrastructure Gaps

Many inspection laboratories, especially the smaller and older ones, have not yet been converted to the new form. The old information system, weak network coverage, insufficient computing power, lack of connection to the instrument, etc., are the basic reasons [17]. The investment in upgrading the infrastructure will be a large amount, and many organisations have small budgets.

There are still old systems. Many of the laboratories' LIMS implementations are many years old or more, and due to custom modifications, replacement or upgrading is difficult. Integrating new digital capabilities with the old systems creates a lot of technical difficulties.

3.2. Data Quality and Integration Challenges

The quality of the digitalisation will ultimately be determined by the quality of the basic data. Many inspection institutions have problems with their data quality, such as being incomplete, inconsistent, redundant and erroneous [18]. The reasons for these problems are manual data

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entry errors, inconsistent data formats, lack of a data management system, and fragmentation of data across many systems.

Another issue is the lack of data integration. The data from the several systems that contain inspection information are not linked, and these systems include LIMS, instrument software, ERP and CRM. Forming a joint view of the inspection process requires considerable effort. There are many different data formats, protocols and semantics.

3.3. Talent and Skills Shortages

The digitalisation and intelligentisation of inspection and testing face a shortage of talent. Key personnel needed include data scientists and analysts who can use testing data to extract information, build predictive models, and apply machine learning technologies; engineers who can construct and maintain AI systems in the production environment; domain experts who are proficient in both inspection and AI and can translate business needs into technical plans; and leaders with change management skills to steer organisational transformation.

There is high demand for these skills, and many technology companies and other industries are more willing to offer good salaries and job prospects than inspection agencies.

3.4. Standardization Gaps

There is no standard set of digital technologies for inspection and testing in the entire industry, resulting in fragmentation. The different laboratories have various data formats, different system architectures and other integration methods [19, 20]. This leads to high costs and inconvenience in cooperation for ecosystem services.

Shortcomings in standardisation include: norms for the data exchange of inspection data among different organisations, APIs to connect AI functions with old systems, knowledge representation norms for domain knowledge graphs, evaluation indicators for AI systems in inspection applications, etc.

3.5. Security and Privacy Concerns

Inspection data usually contain confidential information on products, production processes and suppliers. Digitalisation of the inspection will also bring about new security and privacy problems that need to be dealt with [21]. These include the risk of cyber security for the digital system and data, privacy problems in the collection and use of inspection data, intellectual property protection for proprietary testing methods and results, and compliance with data protection regulations.

The organisation needs to strengthen the construction of security facilities and plans, and raise the security consciousness of all staff. The cost and difficulty of security will slow the pace of change.

3.6. Organizational and Cultural Barriers

Digitalisation and intelligence transformation need to be carried out in terms of organisation and culture. Resistance to change, a lack of digital literacy, fear of losing one's job, and old ways of working can all be problems.

Leaders must be willing to transform the company. Without a clear digital plan, relevant staff and leadership support, many organisations have been unable to make good progress. The advantages of the reform will take some time to appear; this will require patience and continuous investment.

4. Strategic Pathways for Accelerated Transformation

To address these problems, many sides have begun to work together [22]. The following are the strategic paths put forward.

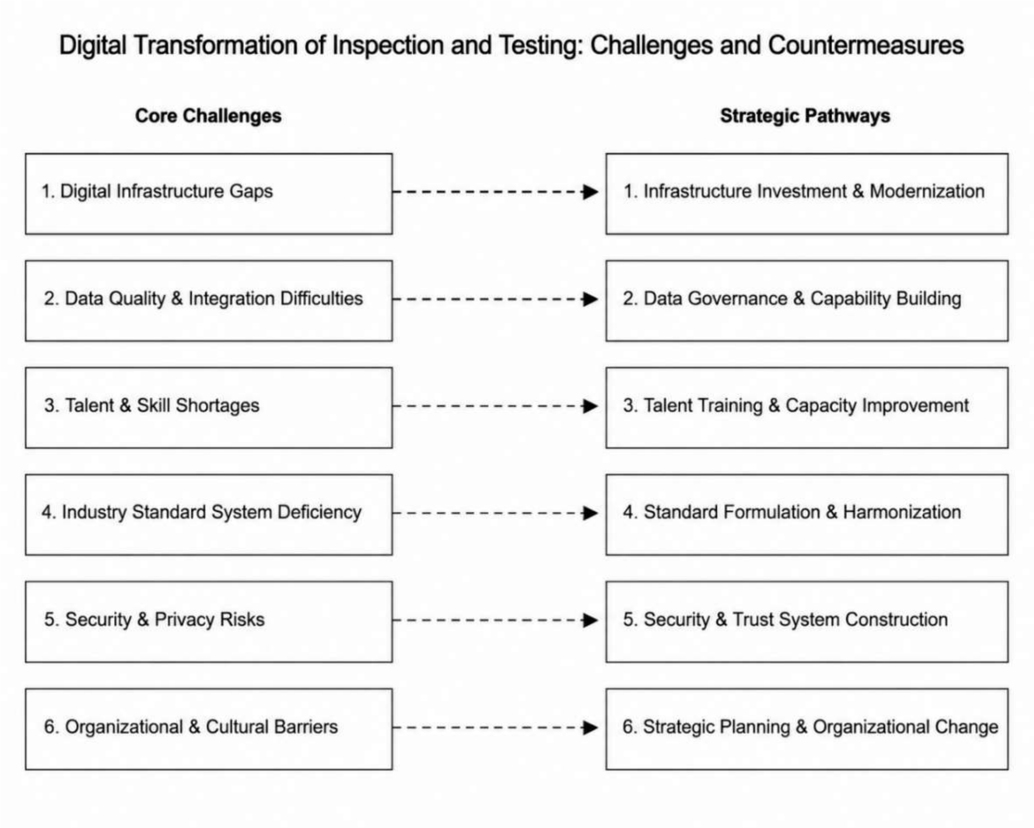

Figure 3. Challenge – Strategic Path Correspondence Framework Diagram

4.1. Strategic Planning and Leadership

The digital strategy of the inspection organisation needs to serve the purpose of its operations. The plan for the development of strategies should include applications of technology, strengthening of capacity building, reform of institutions and alteration of investment plans. They should be in line with the actual circumstances and future needs.

A special function or position should be created to lead the digital transformation of the company. This function needs to have the proper power, resources and expertise to lead the changes in the organisation.

Given the complexity and size of the transformation, it is proposed that a few steps should be taken first to obtain some results and then gradually expand. A fast-track project will be carried out to show some results and create some momentum in the case for additional investment.

4.2. Infrastructure Investment and Modernization

To advance the digitalisation, a new flexible information system needs to be constructed. The new kind of solution for the firm will have relatively low capital costs. A new LIMS platform has been released, and now there is also an API for other-system integration [23].

Instruments and equipment have been connected to the digital network for automatic data acquisition and do not need to be operated manually. Standard protocols and interfaces will be used to reduce the cost of integration.

To make better use of the data for analysis and artificial intelligence, an investment in building a data lake, a data warehouse and a data governance system can be made. Data quality management needs to be done urgently [24].

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4.3. Talent Development and Capability Building

Companies will train their current employees to be more digitally literate. Training programmes need to improve people's skills in data analysis, artificial intelligence, system management, etc., as well as soft skills such as change management and digital leadership.

Specialised professionals who are competent in the new technologies of the industry and AI should be hired. Organisations will need to compete with technology companies for this talent and will therefore have to offer competitive compensation and career development opportunities.

Cooperation with universities and technical colleges can foster an excellent talent pool. Internship programmes, joint research projects and curriculum development can all do this.

A culture that is open to digital technology and learning needs to be built. Leaders should set an example of digital behaviour, recognise digital achievements and convey the direction of digital transformation.

4.4. Standards Development and Harmonization

The inspection body, the technology enterprise and the regulatory department will jointly issue new regulations on the application of digital technology in inspections and testing.

To solve the problem of vendor lock-in and achieve interoperability, one can use open-source software [25].

Sharing experiences, learning from the mistakes of others, and disseminating good practices through industry associations and professional networks can accelerate learning and avoid repetition.

4.5. Ecosystem Collaboration and Partnerships

Working with technology companies can help organisations acquire some good new tools quickly. Organisations need to check the qualifications and long-term plans of the service companies.

Several organisations have been leading industry cooperation to solve problems that affect all participants and explore joint-venture solutions. Usually, the categories are shared data platforms, joint research projects and common standard initiatives.

Together with customers and suppliers, organisations can work together to build value through shared data, integrated processes, etc. Digital technology has enabled the new type of collaboration now seen in the industry.

4.6. Security and Trust Building

The three pillars of a company's security should be people, processes and technology. Organisations should regularly conduct safety inspections, arrange staff training, and develop accident prevention plans.

The purpose of using customer data and what safety measures have been taken should be explained to the public, and the reasons for AI's decisions should also be made transparent.

Organisations need to comply with all laws and regulations in the digitalisation process. They should take the initiative to work with the authorities for better policies.

5. The Role of Vertically Oriented AI Agents

Among the technologies for intelligent transformation, vertically oriented AI agents are very popular as they can meet the specific demands of inspection and test areas [26].

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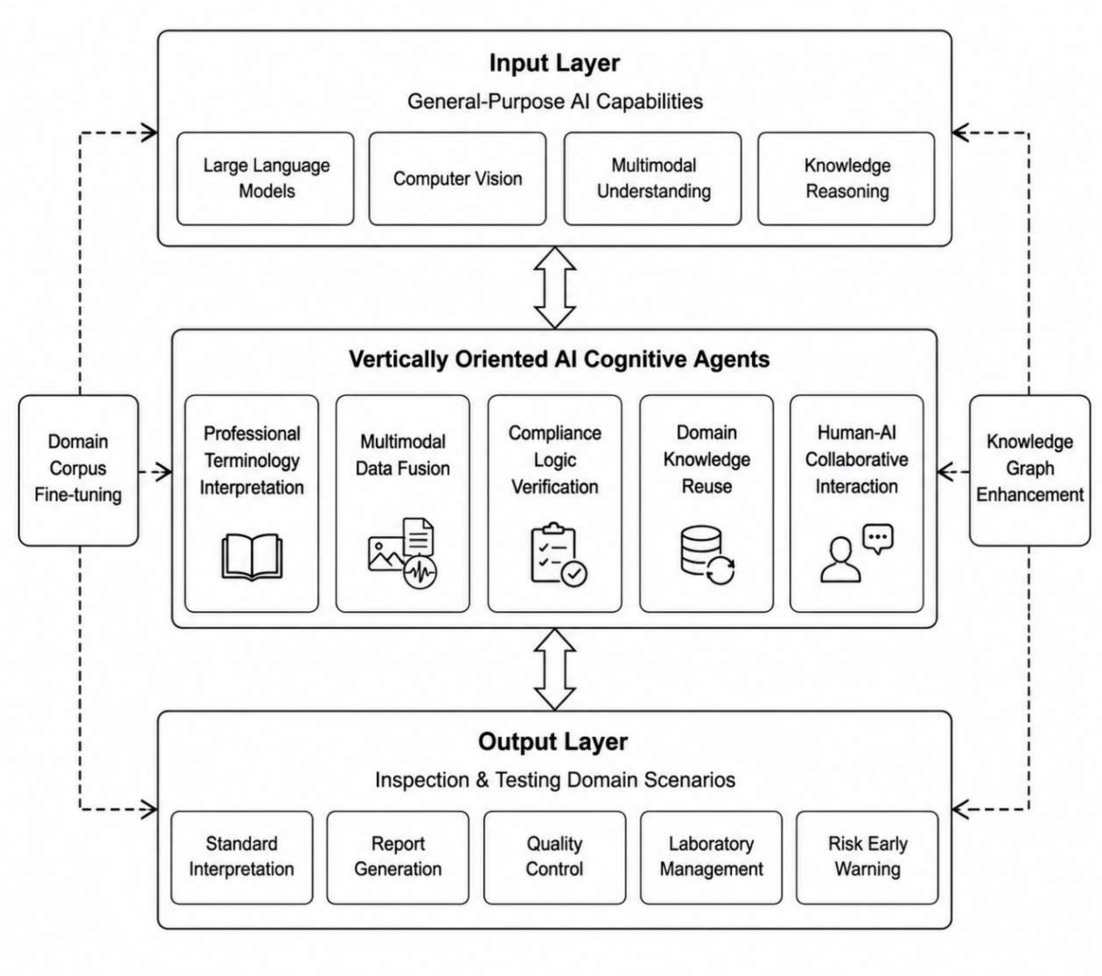

Figure 4. Mechanism Diagram of the Role of AI Agents in Vertical Industries

Unlike general-purpose AI systems, vertically oriented agents are specifically designed for particular domains, incorporating domain knowledge, specialized vocabularies, and domain-specific reasoning patterns. In inspection and testing, such agents can perform several critical functions.

Train on the domain-specific corpus and add a knowledge graph to help the vertically oriented agent learn the special terms and regulations better [27].

Inspection workflows involve many kinds of data, such as text standards, pictures, numerical measurements and audio annotations. Vertically oriented agents can process each of these types according to the requirements of the domain.

These agents can utilise their regulatory knowledge and reasoning abilities to help ensure that inspections are in line with the relevant regulations [28].

By capturing and organising domain knowledge, vertically oriented agents can be reused in different organisations and over time to solve the problem of knowledge fragmentation.

By observing workflows across different levels of the organisation, connections have been established to link ground-level agents with human experts or artificial intelligence systems for the purpose of achieving specific goals [29].

The construction of vertically oriented AI agents for inspection and testing needs the cooperation of AI researchers, domain experts and practitioners. It should also be constructed according to the particular data, knowledge and assessment system in that area.

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6. Future Outlook and Recommendations

The digitalisation and intelligentisation of the inspection and testing industry will be unavoidable in the future. Several new developments are expected to emerge.

The capabilities of artificial intelligence will keep improving; strong models, superior multimodality and advanced reasoning are all hoped for in the future. Edge computing, 5G and quantum computing will be used in new ways in the future [30].

The amount of inspection data will continue to rise, and thus, more advanced analysis and artificial intelligence can be employed. Various organisations have already provided useful ideas and reference models.

With the development of digital technology, regulatory policies will also change accordingly. It is advisable to take the initiative and maintain contact with the authorities.

More and more customers are seeking paperless, convenient services for their daily transactions, including online ordering, real-time status tracking, and digital report delivery.

The Talent Market for Digital Skills will continue to change, and new jobs will be added and old ones will change.

Based on the preceding analysis, the following recommendations are put forward.

Inspection organisations need to build a sound digital strategy internally, strengthen the necessary infrastructure and talent pool, draw up a timetable for phased changes, form alliances, and join the development of industry norms [31].

Technology companies should develop all kinds of applications according to the needs of various industries, support open-source programmes, multiple ways of construction, and so on.

The regulatory authorities should build a favourable policy environment, strengthen their own digital power, cooperate with the industry to formulate joint regulations, explore the application of new technologies for good governance, etc[32].

For the industry association, it can spread knowledge, build industry standards, support the training of workers and advocate for favourable policies[33, 34].

7. Conclusion

The digital and intelligent transformation of the inspection and testing industry presents both challenges and opportunities . Although there are many problems in the industry, such as lack of infrastructure, poor data quality, a shortage of talent and standardisation issues, it has the potential to bring economic benefits, increase production efficiency and enhance quality levels.

To achieve this, coordinated efforts will need to be made in various areas: strategic planning and leadership, infrastructure investment, talent cultivation, standardisation, ecosystem cooperation, security construction, etc. Vertically oriented AI agents are for inspection and testing; thus, they can be applied to expand the functions of general-purpose AI and meet the needs of a particular industry.

It is not only a matter of introducing new technologies but also of altering the fundamental mode of operation, competition and value creation by inspection and testing institutions. Organizations that are in the process of changing will be better equipped to meet the new demands of their customers and the change in regulations. Those who are slow to respond will be left behind in the development of digital and intelligent industries.

The road to digitalisation and intelligentisation is long and difficult, but the destination is a more efficient, reliable and valuable inspection and testing industry.

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