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EXPLORING THE FORMATION MECHANISM OF TECHNOLOGY STANDARD COMPETITIVENESS IN ARTIFICIAL INTELLIGENCE INDUSTRY: A FUZZY-SET QUALITATIVE COMPARATIVE ANALYSIS

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Abstract. This study aims to reveal the complex mechanism influencing technology standard competitiveness (TSC) in the artificial intelligence industry. Compared with research using traditional linear models, this research adopts the fuzzy-set qualitative comparative analysis (fsQCA) method to obtain the multiple equivalent paths for different factors that jointly produce TSC. The sample of this study involves 32 countries, and the research framework is constructed from the technological, organizational, and environmental aspects of the phenomenon. The fsQCA method was used to demonstrate the asymmetric relationship between cause and effect. The results indicate four configuration paths but no necessary conditions leading to TSC. Academic research intensity and market size play vital roles in developing TSC. Some logically complementary relationships exist between organizational participation, technological innovation ability, and international competitive pressure. These findings are helpful for policymakers in their formulation of artificial intelligence–related strategies.

Keywords: technology standardization, artificial intelligence industry, fsQCA, technology–organization–environment (TOE) framework, technology standard competitiveness, configurations.

JEL Classification: L15, O32, O57.

Introduction

Technology standards catalyze the development of cutting edge technology and the technology sector (Özsomer & Cavusgil, 2000; Jiang et al., 2018a; Blind & von Laer, 2022). The creation and development of intelligent technologies are inextricably linked to technology standards, especially in emerging industries. Absolute competitive advantages can be achieved through a mastery of the discursive power of technology standards (Lee & Oh, 2006; Gao et al., 2014; Narayanan & Chen, 2012; Jiang et al., 2020a). Technology standardization is crucial for preserving market stability, lowering market uncertainty, securing competitive

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advantage, and enhancing production effectiveness (Funk & Methe, 2001; Wakke et al., 2016; van de Kaa & Greeven, 2017; Blind & von Laer, 2022). It can promote industry-wide technological progress and technological dissemination and even affect a country or region's economic growth (Jiang et al., 2016; Paik et al., 2017; Jiang et al., 2018a).

Artificial intelligence (AI) has progressed from being computational to perceptual to cognitive (Liu et al., 2020; Margetis et al., 2021). AI has become a crucial driving force for industrial transformation in the fourth industrial revolution due to its wide applicability and the growing trend of data intelligence (Wu et al., 2020; af Malmborg & Trondal, 2021; Su et al., 2022). The direction of technical progress, the prospect of industrial development, and even the interests of countries are all significantly affected by ongoing developments in AI in which technology standards play a crucial role (Zielke, 2020).

The United States, Germany, Japan, and other developed countries have adopted AI technology standards as a strategic tool to outperform its competitors (Fatima et al., 2020). In "US Leadership In AI: A Plan for Federal Engagement in Developing Technology Standards and Related Tools," the National Institute of Standards and Technology [NIST] of the United States outlined nine areas of support (NIST, 2019). In addition, the Human Brain Project of the European Union and the AI/Big Data/Internet of Things/Network Security Integrated Project (AIP) of Japan prioritize standards and implementation specifications. After the conflict over information and communication technology (ICT) and 5G standards, the battle for AI technology standards, with all its discursive power, has taken center stage. It is a fundamental practical problem worth studying to explore the development path of national artificial intelligence technology standardization to clarify the formation mechanism of technology standard competitiveness (TSC).

Studies have suggested that technology standardization is affected by a diverse and complex set of factors, including technical background, system design, market environment, and the characteristics of the standard's participants (Doganoglu & Wright, 2006; Blind, 2006; Gao, 2007; Brunsson et al., 2012; Li et al., 2019; Moon & Lee, 2021; Blind & von Laer, 2022; Malik et al., 2021). Additionally, the formulation and implementation of technology standardization development strategies in various countries exhibit path dependence (Kim, 1997; Kano, 2000; Jho, 2007; Lee & Oh, 2006, 2008; Lee et al., 2009; Choung et al., 2011). This study introduces the TOE framework based on previous research on technology standardization and constructs a research framework affecting the formation of TSC from three aspects: technology, organization, and environment. Furthermore, the research methods were primarily based on traditional net effects research models such as multiple regression (Paik et al., 2017; Blind & von Laer, 2022), structural equation modeling (Li et al., 2019; Jiang et al., 2020b), or case studies (Kwak et al., 2011; Choung et al., 2011; Kim et al., 2018). However, the traditional symmetry causal approach may not be suitable in a specific scenario and could not adequately predict actuality (Arrow et al., 2008; Papatheodorou & Pappas, 2017; Woodside, 2018), which is why complexity theory and configuration theory have gradually become popular (De Toni & Pessot, 2021; Jancenelle, 2021). In view of the complexity of technology standardization and the dynamic development of the artificial intelligence industry, it is necessary to explore the influence mechanism and path of TSC based on the configuration perspective and multi-dimensionality.

The main contribution of this study lies is in its construction of a framework of how technology standardization develops, from the perspective of technology–organization–environment (TOE) theory. In addition, to account for asymmetry, this study adopts the fuzzy-set qualitative comparative analysis (fsQCA) to obtain a variety of equivalent paths leading to TSC. The research results reveal the complexity of the path to technology standardization, constituting a novel contribution to the literature.

The remaining parts of this study is structured as follows. The first section reviews the literature on the factors influencing technology standardization. The second section proposes a research framework based on TOE theory. The third section introduces the principles and advantages of the fsQCA method and each variable's measurement methods and data sources. The fourth section presents results on descriptive statistics, on necessary analysis, and sufficient analysis. The discussion section emphasizes the key variables and supplementary logic of the antecedent variables in the configuration path. The last section summarizes this study's research results and practical significance, discusses our study's limitations, and outlines future research directions.

1. Literature review

Technology standardization is a complex and dynamic process that includes licensing, standards development, and technological research and development, also can be regarded as the process of technology accumulation and development reaching a certain threshold, evolving into technical standards, and realizing comprehensive innovation (Paik et al., 2017; Jiang et al., 2018a). Uncertain factors are rife in the formation and industry-wide adoption of technology standards (Blind et al., 2017). First, the technical characteristics of the standard itself affects its scope of application and effectiveness (Doganoglu & Wright, 2006; Blind, 2006). Technical compatibility refers to the shared elements between various products and plays a vital role in restraining related subjects' "multi-ownership" behavior from improving the market competitiveness of standards (Doganoglu & Wright, 2006). Standards with a higher level of technical compatibility are less costly to adopt and more easily promoted throughout an industry. Likewise, technology standards differ in their characteristics depending on the sophistication of the technology in question (Jiang et al., 2016). A more technologically sophisticated organization is more likely to develop and implement new technology standards to explore new markets (Blind & Mangelsdorf, 2016; De Vries et al., 2009).

According to actor–network theory, technology standardization is a process featuring cooperation among various participants and involving technological and social factors that interweave to form a network (Gao, 2007). Many scholars have studied the behavioral motivations of participants in technology standardization (such as enterprises, suppliers, standard-setting organizations, users, and governments) in different industries and the interaction of these roles in technology standardization (Markard & Erlinghagen, 2017; Wiegmann et al., 2017; Kim et al., 2018). For example, to meet the needs of consumers, enterprises ensure product quality through compliance with technology standards (Moon et al., 2018; Fontagné et al., 2015; Moon & Lee, 2017). At times, these enterprises form or participate in standards alliances to expand the market and to ensure that technology standards are favorable to their interests (Wang et al., 2016). Users, namely consumers and technology producers, contribute to the technology standardization process by participating in standardization and providing an on-the-ground perspective (De Vries & Slob, 2006; Jakobs et al., 1998). In addition, from the external context of standardization activities, market success opportunities are determined by social, institutional, and economic factors and by soft factors, such as political, social, and cultural factors, that influence the selection of technology. These factors are essential for standardization strategies (Hobday, 1995; Amsden, 2001; Choung et al., 2011).

The formulation and development of technology standards is a complex process that involve a variety of factors and strategic trade-offs. By analyzing the implementation of Terrestrial Digital Technology in Latin America, Angulo et al. (2011) argued that technical characteristics, network externalities, and socioeconomic characteristics are key factors affecting the development of standardization. With regard to participation in international standardization, the models adopted in China and the United States are characterized by systematic participation in standardization and by decentralized standardization, respectively (Blind & von Laer, 2022). Countries differ in their location toward standardization activities. In South Korea, the development of technology standards is viewed as a strategic tool for catching up with technologically advanced countries (Lee et al., 2005). In Europe, regulatory governance plays the most prominent role in standardization activities (Egyedi, 2006).

Furthermore, countries differ considerably in their institutions and these institutions' effect on the market, level of technological development, and level of standardization (Whitley, 1999); in general, government policy is central to the ebb and flow of technology standardization in a country (Shin et al., 2015). Compared with those in developed countries, governments in developing countries tend to play a broader role in standardization, in relation to innovation, due to these countries' low level of economic, human, and technological resources (Gao, 2014; Zoo et al., 2017; Dubé et al., 2012). In other words, the government not only directly invests in standards development and offer incentives but also coordinates the actions of standards stakeholders and balances stakeholder interests (Gao et al., 2014; Kshetri et al., 2011). Taking light-emitting diode (LED) technology standards as an example, van de Kaa and Greeven (2017) found that compared with those in other countries, China's top-down economic institutions make greater use of standardization in the LED market. In particular, many studies focusing on the ICT industry have reported that countries greatly differ in their standardization development paths and strategies (Lee & Oh, 2006, 2008; Lee et al., 2009; Choung et al., 2011). For example, Kang et al. (2014) found that China prioritizes independent technological innovation to develop domestic standardization, whereas South Korea develops global standardization based on international standards established by local technology.

In summary, the influencing factors of technological standardization of emerging industries include the technical characteristics of standards, standardization participants, and the external environment. Countries differ in their paths toward technology standardization due to differences in their economic climate, economic system, and standardization activity orientation. Based on the TOE theoretical framework, this study's framework contains technological, organizational, and environmental factors influencing technology standardization. This study adopted configuration analysis to explore the path leading to technology standardization in the AI industry in various countries.

2. Research model construction

TOE theory describes how technological innovation adoption and application at the organizational level are affected by technological, organizational, and environmental factors (Tornatzky & Fleischer, 1990). This theory mainly explains organizational technology integration and adoption behavior (Cruz-Jesus et al., 2019). TOE is used to evaluate the adoption of technological innovation, such as cloud computing adoption (Borgman et al., 2013), blockchain technology (Malik et al., 2021), and hospital information systems (Ahmadi et al., 2017).

In TOE theory, technological factors pertain to the relationship between technology and organizations, such as technological innovation capability (Jiang et al., 2018a; Cruz-Jesus et al., 2019), characteristics of the technology itself (Cruz-Jesus et al., 2019; Malik et al., 2021) and technological advancement (Jiang et al., 2016; Blind & Mangelsdorf, 2016; De Vries et al., 2009). Organizational factors pertain to the organization's characteristics, such as its size (Cho et al., 2022; Walker, 2014), resources, and structure (Chen et al., 2019; Pateli et al., 2020). Environmental factors pertain to the level of development and the organization's industry (Borgman et al., 2013; Chen et al., 2019), market demand (Malik et al., 2021; Pateli et al., 2020), external pressure, and other factors (Pateli et al., 2020; Cruz-Jesus et al., 2019). Based on TOE theory and the characteristics of research objects, this study constructs a multivariate model describing the many factors driving TSC (see Figure 1).

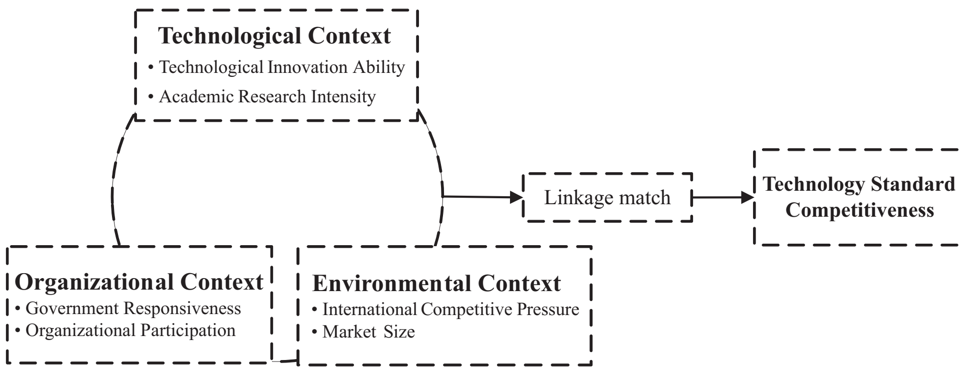

Figure 1. Technology-Organization-Environment (TOE) framework

2.1. Technological context

The previous technology standardization studies (Jakobs et al., 1998; Paik et al., 2017; Wiegmann et al., 2017; Blind & von Laer, 2022) indicated that standardization is part of the R&D process (Jiang et al., 2018b). Technical background in the development of standards is a crucial factor influencing technology standardization (Wiegmann et al., 2017), including technical compatibility (Doganoglu & Wright, 2006), technological innovation capability (Blind, 2006; Wen et al., 2020), technological advancement (Jiang et al., 2016; Blind & Mangelsdorf, 2016), technological uncertainty (Blind et al., 2017), academic research intensity (Choung et al., 2011) and other technological characteristics. This research considers two innovation characteristics within the technological context as the effect factors of TSC, namely, technological innovation ability and academic research intensity.

Technology standardization is closely related to technological innovation (Blind, 2006). The upgrading of technology standards depends on the development of technological innovation, and standardization promotes technological innovation by influencing innovation performance and process innovation (Farrell & Saloner, 1985; Utterback, 1994; Blind, 2002; Wen et al., 2020).

In other words, the standardization process is a continuation of R&D within an organization, and participation in standardization activities enables the organization to deliver products that consumers want and to obtain technologies that are suited to market conditions (Blind, 2006; Farrell & Saloner, 1985). Patent intensity and R&D intensity determine the technological standardization ability of enterprises (Blind & Thumm, 2004; Blind, 2006; Blind & Mangelsdorf, 2016). In addition, technology standardization requires both technical and nontechnical competence (Choung et al., 2011). For countries as a whole, the volume of scholarly publications can reflect its focus on a given set of emerging technologies.

2.2. Organizational context

This study is based on the TOE theoretical framework to identify the organizational factors affecting the TSC, including technology standard alliance collaboration (Li et al., 2019; Jiang et al., 2020b), standardization "culture" (Wiegmann et al., 2017), standard participants (Ho & O'Sullivan, 2017; Markard & Erlinghagen, 2017), institutional and strategy context (Lee & Oh, 2006, 2008; Moon & Lee, 2021), government support (Gao, 2007; Kwak et al., 2011; Moon & Lee, 2021), organization participation (Blind, 2002; Blind & von Laer, 2022) and other organizational characteristics. This research examines two innovation characteristics within the organizational context to explain the influencing factors of TSC: government responsiveness and organizational participation.

The process leading to the achievement of standards-based competitiveness and the diffusion of standards also involves government behavior, which is essential to standardization (Gao, 2007; Li et al., 2019). In addition to formulating policy, governments also deploy national resources (e.g., by investing in science parks) and set the country's strategy (Blind & Thumm, 2004; Moon & Lee, 2021; Funk & Methe, 2001). Governments can also mandate standardization or intervene in the standards formulation process (Khemani, 1993), shape the market environment through regulatory mechanisms, and influence the behavior of technology standardization–related actors (Blind, 2012).

However, the effect of such intervention on innovation depends on the uncertainty present in the market and the technological landscape (Blind et al., 2017). Blind noted that export ratio, market concentration, and the degree of participation in international competition are critical factors driving technology standardization (Blind, 2002; Blind & Thumm, 2004). Early participation in international standardization is crucial for a country's commercial success in various industries (Blind & von Laer, 2022). In 2018, the International Organization for Standardization and the first joint technical committee of the International Electrotechnical Commission (ISO/IEC JTC 1) began focusing on information technology. The AI subtechnical committee (SC 42) of the organization is tasked with AI-related standardization, with a focus on basic commonalities, key general technologies, credibility, and the ethics of AI. The ISO/IEC JTC 1 has also focused on AI security and AI applications in key industries.

2.3. Environmental context

The institutional theory holds that organizations must consider not only the influence of technological characteristics but also face the constraints of institutional factors such as market environment, beliefs, and social values (DiMaggio & Powell, 1983). Based on previous technology standardization studies and the definition of the environmental dimension of the TOE framework, it can include the installation base, namely the scale of users (De Vries & Slob, 2006; Zhang & He, 2015), market environment (Delcamp & Leiponen, 2014), public demand (Malik et al., 2021), institutional pressure (DiMaggio & Powell, 1983; Brunsson et al., 2012) and other environmental characteristics. This research examines two innovation characteristics within the environmental context to explain the influencing factors of TSC: international competitive pressure and market size.

Institutional theorists emphasize the role of coercive, normative, and isomorphic pressures in the adoption and diffusion of standards (DiMaggio & Powell, 1983). Among these pressures, coercive pressure may emerge from international organizations' assignment of tasks to member states and NGOs' pressure on enterprises to comply with environmental standards (Brunsson et al., 2012). Normative pressures are more prevalent in professions with a joint knowledge base, emphasizing the positive effects of adopting standards. Isomorphic pressure refers to the pressure faced by an actor when another actor copies its strategy (e.g., the government of one city imitating the government of another city), giving rise to competition. Pressure from the external environment also drives the organization to reevaluate its allocation of and deficiencies in the resources at its disposal (García-Sánchez et al., 2018).

A more turbulent competitive environment allows an organization to better self-renewal, reconfigure its resources to adapt to the environment, and leverage opportunities that may arise from an everchanging situation (Eisingerich et al., 2010). Ultimately, technology standardization is essential to organizing the market (Brunsson et al., 2012) and can reduce the inherent information asymmetry between producers and consumers (Akerlof, 1970). With the increase in turnover and the expansion of the emerging technology market, a lack of technology standards dampens the willingness of organizations to adopt new technologies (Malik et al., 2021). The formulation and implementation of technology standards are to meet the market demand, and the broader the market prospect of standards is more valuable (Delcamp & Leiponen, 2014).

3. Method

3.1. Fuzzy-set qualitative comparative analysis

Ragin first proposed qualitative comparative analysis (QCA) in the 1980s (Ragin, 1987). This method combines case-oriented QCA with a variable-oriented quantitative comparative analysis to uncover the organic combination of qualitative and quantitative characteristics constituting a given phenomenon (Acquah et al., 2021). QCA has three main variations: crisp-set QCA (csQCA), multi-value QCA (mvQCA), and fuzzy-set QCA (fsQCA) (Pappas & Woodside, 2021). CsQCA is used to process complex binary data sets. The most significant limitation of this method is that binary variables cannot fully capture the complexity of cases that vary with level or degree (Ragin, 2008a). MvQCA is an extension of csQCA, preserving the idea of data set synthesis in csQCA. Unlike csQCA, mvQCA also allows the processing of multi-valued variables. Because the antecedent variables and outcome variables in this study were continuous, not dichotomous variables or multi-valued variables, it was more appropriate to adopt a fuzzy set for QCA, that is, to transform each variable into a fuzzy membership relationship between 0 and 1 (Abbott, 2001).

This study chose fsQCA because it offered several advantages over its conventional counterparts. First, traditional symmetric empirical methods such as linear regression analysis and structural equation modeling can only identify one independent variable, and the prediction results are often unrealistic due to uncertainty in the market environment (Woodside, 2018; Papatheodorou & Pappas, 2017). Results in fsQCA are reflective of a combination of multiple conditions rather than a single factor. In fsQCA, Boolean algebra is used to compare and analyze each feature of multiple cases and to explore the combination of various configuration paths leading to the presence or absence of an outcome from a holistic perspective, allowing the method to capture asymmetry between antecedent variables and outcomes (Ragin & Fiss, 2008). Furthermore, fsQCA can be used to examine and combine multiple antecedent conditions to generate a result, and fsQCA can be used to determine numerous effective alternatives that produce the same equifinal outcome (Dahms, 2019; Russo et al., 2019; Witt et al., 2021; Fiss, 2011; Schneider & Wagemann, 2012). Finally, because fsQCA didn't involve underlying hypothesis, correlation analysis, or single explanatory variable, thus this method was not subject to the endogenous influence caused by outliers or variable deviations (Witt et al., 2021; Fiss, 2011; Schneider & Wagemann, 2012).

Therefore, fsQCA was used to examine how the degree of membership of cases (i.e., countries) in antecedent conditions (i.e., influence factors based on the TOE framework) is related to their degree of membership in the outcome (i.e., technology standard competitiveness).

3.2. Data collection and variables

(1) Dependent variable

Variable 1: Technology standard competitiveness

This study measured the TSC from two aspects: the number of AI-related standards issued by the country and the number of associations participating in the formulation of standards. Data on this variable were obtained from the National Library of Standards, which has collected more than 1 million volumes of standards from 60 countries, over 70 international and regional standardization organizations, and more than 450 professional associations. The National Library of Standards collects data from standards databases, such as the Information Handling Services (IHS) database, the Perinorm database, the Korean standards database, the Taiwan standards database, and the Verein Deutscher Ingenieure (VDI) standards database. Using 24 keywords such as "artificial intelligence," "wisdom city," "intelligent manufacturing," and "fingerprint identification" to determine the number of AI-related technology standards published in each country and the number of associations that participated in standards setting no later than March 30, 2022, 2253 standards and 33 associations were identified.

(2) Technological context

Variable 2: Technological Innovation Ability

The technological innovation ability of a given country was indicated using the number of AI patents from that country. The patent retrieval type TI = ("artificial intelligence" OR "AI" OR "Depth learning" OR "Natural language processing" OR "Speech Recognition" OR "Computer vision" OR "Gesture control "OR "smart robot*" OR "Video recognition*" OR "Voice translation" OR "Image Recognition" OR "Machine learning") was used to collect the AI-related patents of each country from the Derwent database (Lyu et al., 2019) submitted between January 1, 1950, to March 19, 2022; 69141 patents were collected.

Variable 3: Academic Research Intensity

Academic research intensity at the national level was indicated by the number of AI-related papers published by scholars from each country. Specifically, this study employed "TI = artificial Intelligence" to retrieve literature from the core set in Web of Science, and "Computer Science artificial Intelligence" was then selected to classify the papers (Gao et al., 2021). Finally, this study sets the period to between January 1, 1950, and March 17, 2022, and collected 12,413 pieces of literature.

(3) Organizational context

Variable 4: Government Responsiveness

This study measured government responsiveness on two dimensions: the speed at which countries publish their AI strategies and the breadth of their strategies. The data on government responsiveness was drawn from Fatima's data set (2020), which covered 34 nations' strategic AI plans as of January 31, 2022. He classified 34 nations' strategic content into six themes and 37 codes using NVivo data analysis software. The speed of the AI strategy's release means the number of days between the release date and March 15, 2016, when Alpha Go defeat the human Go player Li Shishi, signaling the arrival of a new generation of Artificial Intelligence. The breadth of AI strategies were measured using Fatima's (2020) statistics on the fields involved in AI strategies in various countries.

Variable 5: Organizational Participation

In international standards organizations such as the International Organization for Standardization (ISO), International Electrotechnical Commission (IEC), and International Telecommunication Union (ITU), members can be participating members (P-membership) or observing members (O-membership). The number of countries that were participating and observing members was determined in committees for the standardization on Artificial Intelligence, such as the ISO/IEC JTC1/SC42, ISO/TC199, IEC/TC65, and ITU-T, from the websites of the ISO, IEC, and ITU.

(4) Environmental context

Variable 6: International Competitive Pressure

This study adopts the AI Innovation Index from the 2020 Global Artificial Intelligence Innovation Index Reprot (Institute of Scientific and Technical Information of China [ISTIC],

2021) to measure international competitive pressure. This report measures the AI Innovation Index of each country from four aspects: essential support, innovation resources and environment, science and technology research and development, and industry and application. The report divides 46 countries into four echelons based on the AI Innovation Index's overall score. In the study sample, all countries were in the second and third echelon, except the United States, which was in the first echelon.

Variable 7: Market Size

Market size was conceptualized as having two dimensions: enterprise scale and economic scale. The enterprise scale was measured by the number of enterprises involved in the research and development of AI patents and employ their revenue to measure economic scale. The data on market size were from Bureau van Dijk's Orbis database. This study adopts Chang's (2021) AI patent classification and screening method to select companies applying for AI patents. He integrated the USPTO classification method of Tseng and Ting (2013) and the JPO classification method of Hidemichi and Shunsuke (2017). Finally, the data on 33,434 companies and their revenues for the most recent available year was collected. Table 1 displays the operational definitions and sources of the study variables.

Table 1. Definitions and abbreviations of variables

Abbreviation	Variable	Description	Source
Dependent variable			
TSC	Technology Standard Competitiveness	The number of AI-related standards issued by country and the number of associations participating in standard-setting	National Library of Standards
Technological context			
TIA	Technology Innovation Ability	The number of patents for AI-related inventions held by the country	Derwent database
ARI	Academic Research Intensity	The number of AI-related academic papers published by the country	Web of Science
Organizational context			
GR	Government Responsiveness	The speed and breadth of AI strategy released by countries	Fatima et al. (2020)'s data set
OP	Organizational Participation	The frequency of countries as P-membership and O-membership in the international standards organization of artificial intelligence	The websites of the ISO, IEC, and ITU
Environmental context			
ICP	International Competitive Pressure	The AI Innovation Index score of countries	2020 Global Artificial Intelligence Innovation Index Reprot
MS	Market Size	The scale of AI enterprises and their economic scale in each country	Bureau van Dijk's Orbis database

4. Results

4.1. Descriptive analysis and data calibration

The study had a sample of 32 countries. In fsQCA, each variable is represented as an independent set. The calibration of research data is foundational to the QCA method where each research case is assigned a set-membership degree (Ragin, 2006). A given case with a calibrated score of 1.0 means "full in," a value of .5 indicates the crossover point that somewhere in between, "full out" can be assigned a value of 0. To calibrate the data, the research utilized the 75th percentile for full membership, the 50th percentile in case of ambiguity, and the 25th percentile for absence (Ragin, 2008a). Finally, the "calibrate" function was used to transform variable data into a fuzzy set using the fsQCA 3.0 software. Table 2 presents these variables' descriptive statistics and calibration anchor.

Table 2. Descriptive statistics and calibration

Variable	Mean	SD	Minimum	Maximum	Calibration
TSC	49.594	119.513	0	648.2	(49;7;1.575)
TIA	723.056	2150.717	0	10352.9	(65.575;4.8;1.4)
ARI	216.33	312.738	8.7	1429.5	(229.975;100.5;41.525)
GR	0.357	0.255	0	0.962	(0.516;0.408;0.167)
OP	6.347	2.179	0.6	8.4	(8;7.4;4.675)
ICP	30.808	12.193	15.27	66.31	(37.325;28.845;20.285)
MS	0.097	0.220	0	0.902	(0.047;0.019;0.004)

4.2. Necessary analysis

The consistency index, representing the consistency of cases with the same combination of antecedent variables explaining a given outcome variable, is used to indicate necessary conditions in fsQCA (Ragin, 2008b). A condition that is always present when the outcome occurs is a necessary condition (Ragin, 2008a).

According to Table 3, the consistency score ranged from .330 to .800. For high-TSC, the condition "market size" had the highest consistency value (.800). Generally, a conditional variable with a value greater than .9 can be necessary for forming a specific result (Fiss, 2011; Schneider et al., 2010). Therefore, the results provide no necessary conditions for the presence or absence of TSC. The results demonstrate that the factors affecting TSC are complex. That is, high-TSC needs the linkage and matching of technological, organizational, and environmental conditions.

Table 3. Results of the necessary conditions

Condition	High-TSC		Low-TSC	
	Consistency	Coverage	Consistency	Coverage
fs_TIA	0.747	0.751	0.330	0.373

End of Table 3

Condition	High-TSC		Low-TSC	
	Consistency	Coverage	Consistency	Coverage
~fs_TIA	0.376	0.333	0.779	0.776
fs_ARI	0.785	0.736	0.350	0.369
~fs_ARI	0.327	0.309	0.750	0.797
fs_GR	0.800	0.730	0.388	0.398
~fs_GR	0.341	0.331	0.737	0.806
fs_OP	0.747	0.680	0.416	0.426
~fs_OP	0.370	0.360	0.688	0.754
fs_ICP	0.738	0.680	0.445	0.461
~fs_ICP	0.414	0.399	0.691	0.748
fs_MS	0.784	0.727	0.411	0.429
~fs_MS	0.384	0.367	0.738	0.793

Note: *fs_* indicates presence of the condition and *~fs_* indicates absence of the condition.

4.3. Sufficient analysis

Sufficient analysis were determined using a truth table algorithm that computed all configurations that could cause the outcome. The truth tables were then sorted by frequency and consistency. This study sets the frequency cut-off value to 1, the raw consistency value to .80, and the PRI consistency values to .70. The consistency indicator represents the degree to which cases with the same combination of antecedent variables are consistent in explaining a result variable (Ragin, 2006). The core or peripheral conditions were determined by examining parsimonious and intermediate solutions, as is common in studies employing QCA (Fiss, 2011; Misangyi & Acharya, 2014). There are three solutions: complex, parsimonious, and intermediate solutions. The complex solutions included all possible combinations of conditions, which are unrealistic in most cases and make interpreting the results difficult (Pappas & Woodside, 2021). Subsequently, a parsimonious solution was obtained, which included the "core conditions that will exist in all solutions" (Fiss, 2011). Finally, through a counterfactual analysis of complex solutions and parsimonious solutions, intermediate solutions containing only theoretical counter-facts were obtained (Ragin, 2008b).

The interpretation of configurations depended on core and peripheral conditions because the core had a strong causal relationship with the outcome. However, peripheral conditions have a weaker causal relationship with the outcome but are still key because peripheral conditions can strengthen the casual features of core conditions (Fiss, 2011; Misangyi & Acharya, 2014). Presenting the intermediate solutions of the software output, Table 4 reports eight configurations that were consistently sufficient for giving rise to either high-TSC (H1a–H3) or low-TSC (L1–L3). Among them, H1a, H1b constituted the second-order equivalent configuration. That is, their core conditions were the same.

Table 4. Results of intermediate solutions

Variables		High-TSC				Low-TSC		
		H1a	H1b	H2	H3	L1	L2	L3
T	TIA	•	•	⊗	●	⊗		
	ARI	●	●	•	•	⊗	•	⊗
O	GR		•	•	⊗	⊗	⊗	•
	OP	⊗		●	•	⊗	⊗	●
E	ICP	●	●	⊗	⊗		⊗	●
	MS	•	•	●	●		⊗	⊗
Consistency		0.901	0.991	0.942	0.876	0.890	0.962	0.970
Raw coverage		0.169	0.587	0.119	0.108	0.487	0.148	0.132
Unique coverage		0.006	0.390	0.039	0.044	0.394	0.066	0.078
Overall solution consistency		0.949				0.908		
Overall solution coverage		0.683				0.634		

Note: • (bold circle) represents the presence of a causal conditions, and ⊗ (crossed circle) represents the absence of a casual condition. Blank spaces indicate "doesn't contribute to the configuration". Larger circles indicate core condition.

For the configurations producing high levels of the TSC, the overall solution consistency of .945 and coverage of .680 suggested that the connection between configurations and outcome was highly consistent, with these configurations explaining most of the set-relationship in the outcome. The coverage rate of the H1b configuration was the highest, including 58.7% of cases, which means that it is the most significant contribution to the solution of the model. As is shown in pathway H1b, with high academic research intensity and a favorable AI development environment as the core conditions, complementary high technology innovation ability, high government responsiveness, and high market size, regardless of organizational participation, could produce strong TSC. This configuration featured up to eight countries: the United States, China, Germany, the United Kingdom, Japan, France, South Korea, and Canada. Configuration H1a as an equivalent configuration of H1b also took academic research intensity and international competitive pressure as the core conditions. Unlike H1b, organizational participation did not exist in the path of H1a, and government responsiveness did not must exist, exemplified by Australia and Germany. The coverage of configurations H2 and H3 was relatively rare, only including Italy and Russia, respectively. More specifically, H2 indicated that with the core conditions of high organizational participation, high market size, complementary good academic research ability, and good government responsiveness, countries with insufficient innovation ability and international competitive advantage could also produce high-TSC. H3 showed that countries with strong AI technology innovation capability and large market size matched good academic research capability and active organizational participation. Even if the government's responsiveness and international competitive advantage were insufficient, it could also generate high-TSC.

As can be seen from Table 4, three configurations could generate the low-TSC. Among them, L1 and L2 shared the absence of government responsiveness and organizational participation; L1 additionally required the lack of technological innovation ability and academic research intensity. By contrast, L2 required academic research intensity and the absence of international competitive pressure and market size. In configuration L3, despite organizational dimension conditions (government response, organizational participation) and international competitive pressure exist, countries with low academic research intensity and insufficient market scale could not generate high-TSC. Finally, The robustness of QCA results was verified by increasing the consistency thresholds for inclusion. This study sets a higher raw consistency threshold of .85 and a PRI consistency threshold of .75 for high-TSC or low-TSC. The results were identical to those from the analysis, indicating the study's robustness.

5. Discussion

This study clarified the causal complexity behind the mechanism underlying the TSC within the AI industry. Previous studies have been unable to identify combinations of multiple factors due to their use of linear correlation analyses. The fsQCA approach adopted in our study can establish the relationships between different antecedent combinations and outcome variables, which is the main contribution of this study.

This study identifies four configurations that lead to high-TSC. First, academic research intensity and market size exist as core or marginal conditions in all paths towards high-TSC. Market size is a key determinant of continued innovation (Malik et al., 2021; North, 1990). For example, the United States gives relatively free rein to market forces. More than 600 decentralized and diversified standardization development organizations are driven by market demand (O'Sullivan & Brévignon-Dodin, 2012). Countries have been paying greater attention to AI research intensity. According to Stanford University's Artificial Intelligence Index Report 2022, from 2010 to 2021, the total number of AI publications doubled, increasing 2.5 times since 2015.

Second, as indicated by a comparison of the conditions in paths H1a and H1b with those in paths H2 and H3, countries must improve organizational participation to realize high-TSC when the international competitive pressure of AI is lacking. Early participation in international standardization organizations, such as ISO, not only allows for the development of standards according to one's needs and for the sharing of information but is also critical to the success of a country's businesses (Büthe & Mattli, 2011).

Additionally, by observing configuration H2 and configuration H3, high participation of international standards organizations can supplement the lack of AI technological innovation ability, and high technological innovation ability can supplement the lack of government responsiveness to AI. Blind and von Laer (2022) argued that path dependence: a country's R&D initiative in a specific field is directly proportional to a country's participation in international standardization in that field. The close relationship between R&D intensity and standardization participation has also been verified at a government-department and enterprise level (Blind & Mangelsdorf, 2016; Blind, 2002).

In all cases, Russia is the only country with a path where government responsiveness is missing as a core condition but still produces high-TSC. Studies have shown that due to the relatively weak strength of government departments in developing countries, a "small government" approach can mitigate the problem of improper coordination caused by decentralized institutions and provide more space for participants to act, thus facilitating standardization and innovation (Bekker et al., 2008; Zoo et al., 2017).

Conclusions

The results of this study can provide theoretical support and practical guidance for national governments in formulating and implementing AI technology standards strategy. Based on insights from the TOE theory, this study uses fsQCA to determine the configuration path that achieves high-TSC. The results suggest that different combinations of technology, organizational, and environmental factors can yield different pathways toward the same outcome.

Our study provides several extensions and contributions to theory and practice. First, in view of the complexity and dynamics of technology standardization, this study combines the influencing factors of national artificial intelligence industry technology standardization based on the TOE theoretical framework, starting from multiple dimensions: technical background, organizational participation, government responsiveness, market demand, and development environment of the artificial intelligence industry, a comprehensive model of influencing factors of the whole process of technology standardization from the stage of technology patenting, patent standardization and standard industrialization is constructed. This study takes a novel perspective, expands the application range of the TOE theoretical model, and deepens the relevant research on the TSC.

Second, this study breaks the traditional symmetry causal thinking and analyzes the causal complexity of multiple factors from the perspective of configuration theory. This study uses the fuzzy-set qualitative comparative analysis method to explore the different matching combinations of multiple variable conditions in producing high-TSC and analyzes the heterogeneity, causal asymmetric relationship between cases, and the equivalent path of producing the same result. The results of this study reveal the multi-driving path of the TSC of the artificial intelligence industry and open the black box of the complex interaction between the standard innovation endowment and the standard competitiveness of each country.

Third, the results indicate no necessary conditions for high-TSC, which indicates that independent conditions cannot constitute the bottleneck of high-TSC. Governments should pay attention to the linkage and matching of multiple factors to improve the competitiveness of AI technology standards. The results also indicate four configuration paths serving sufficient conditions for high-TSC. Among them, high academic research intensity and high market size are the decisive factors forming the national high-TSC. In addition, two sets of potentially complementary logic in the path emerge when these two decisive factors exist. High participation of international standards organizations can supplement the lack of AI technological innovation ability, and high technological innovation ability can supplement the lack of government responsiveness to AI. These findings suggest that the government should first pursue high quality in the academic field and the large-scale development of the AI market when resources are insufficient. At the same time, governments should combine their existing foundations and conditions to optimize gradually.

This research has some limitations, which future studies can address. Because data for some variables were unavailable, only 32 countries were included in the selected research samples. However, this small sample size made it difficult to uncover a more diverse set of paths. The AI industry was developing rapidly with the evolution and creation of organizations and continued technological and environmental innovation changing specific path dependence. Therefore, the future research framework can be improved according to the abundance of relevant data. The research method can combine dynamic QCA to analyze the path dependence during conditional or configuration evolution.

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Author contributions

Conceptualization and methodology, S. L., L. ZH and J.Y.; Collected data, data analysis and writing, S. L.; Revised advice, L. ZH and J.Y.; All authors have read and agreed to the published version of the manuscript.

Disclosure statement

The authors declare no conflict of interest.

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