A study of smart agriculture trends in new normal of economy: a perspective of academic genealogy

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Abstract: In the new normal of economy, smart agriculture iterations and deep integration of industry, overcomes the limitations of traditional agriculture. However, the study of intrinsic regularity in smart agriculture is still in its infancy, and the endogenous causes of high situational dependence are less studied. In this paper, we use co-citation context analysis (CCA) method based on the academic genealogy retrospective literature perspective, statistics the distribution and common features of the research fields to which the wisdom agriculture literature belongs. We made use of VOSviewer's co-occurrence statistics to reflect the industrial integration common thread linkage chain, cross research trends and research hotspots of wisdom agriculture, and discover the inspiration of the integration effectiveness of wisdom agriculture. We provide theories for the systematic process of traditional agricultural upgrading and industrial economic development, and also provide practical reference for farmers, entrepreneurs, and investors to choose economic activities and behaviour strategies.

Keywords: smart agriculture; SA; co-citation context analysis; CCA; technological convergence; industry integration; development trend.

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1 Introduction

In new normal of economy, the solution to any problem in the production practice scenario may often rely on the intermingling of cross-disciplinary ideas, and not necessarily on a single approach (iResearch INC., 2017). The intersection of the internet, big data, artificial intelligence, management, operations and game theory and other fields and disciplines allows smart agriculture (SA) to effectively drive or directly generate factors of production such as agricultural production tools to achieve innovation-driven agricultural economic development. However, in agricultural production practices, the understanding of production practices and the definition of the actual factors of production issues are as important as the mechanisms and models used. The former largely determines whether the latter can operate effectively or profitably, which is the key to the integration of SA and agricultural production being able to take place and the industry being upgraded; SA has already made it possible to achieve intelligence and automation of production and industrial operations in specific scenarios of the new economy, and the formal and executive aspects of the integration of SA and the agricultural industry determine the fundamental patterns of the production factors in their interaction with the external environment.

As new economic patterns emerge as emerging technology policies continue to intensify, the diffusion of technological innovation will induce a large volume of technological innovation associated with it, which in turn will induce a wider range of technological changes and diffusion effects, thus promoting the integration of technology with industry or factors of production. The discussion of SA technological convergence trends based on the new economic norm aims to provide a more accurate dissection and assessment of the extent of technological convergence in the SA research area. The research intent of this thesis is to reflect the SA performance of the academic field of innovative research or the technological diffusion integration of sustainability science, providing clues to the study of the inherent regularity of SA. Also to discover the linkage chains and commonalities between SA and cross-disciplinary and domain issues such as techno-economics, humanities and society, and to guide the dissemination of knowledge between different fields of study.

1.1 New economic formation

The New Economy refers to a new economic form. That is, a low-inflation, high-growth economic pattern that has emerged in the context of technological change and global integration. This matches the inflationary inverse effect depicted by the Phillips Curve. With the advancement of internet technology, emerging technologies or technology industries represented by big data and artificial intelligence are gradually recognised. A fundamental, dynamic change in the traditional economy (Karanasos et al., 2017). The current new economic form is one in which innovative knowledge dominates society and the economy, with the information economy and the smart economy taking precedence and core (Meng, 2017). The trends that have emerged in the new economy in recent years come from two sources. One is the globalisation of the economy and the other is the information technology revolution (Zheng, 2002; Chen, 2015; Shen et al., 2016; Morgan, 2018). Theoretical analysis suggests that industry integration is a developmental model and form of industrial organisation in the context of technological innovation and rapid iterative development in the context of the changing global economic integration, with industry increasing productivity and competitiveness (Delgado et al., 2014; Grodal et al., 2015).

1.2 SA scenario

The new economy exhibits sustained low inflation, high growth, and a globally integrated economy with high rates of technological change, economic efficiency and effectiveness. The benefits of its dependence and development are twofold, on the one hand, the global informatisation brought about by the technological revolution in the field of information technology. On the other hand, there is global economic integration that leads to the weakening of national economic boundaries (Wang, 2004). SA is fully demonstrating the technological change of dependence on and development of the new economy, the global informatisation brought about by innovation, and the integration of the global economy. The fit between these two aspects of the macro-environment and the agricultural scene may be the driving force behind the development of the agricultural industry and its micro-subjects. In the new economic normal, the solution to any problem in industrial practice is often likely to be multidisciplinary and cross-cutting rather than path-dependent on a single approach. The cross-integration of the internet, big data, artificial intelligence, management, operations and game theory and other fields and disciplines makes SA effectively drive or directly generate industrial micro-economy decisions and realise innovation-driven real economy transformation and development. But in industry and capacity practice, understanding and defining the actual problem scenario becomes even more important. The first step in launching the SA system is to understand its industry and capacity practice scenario. In other words, SA's industry and capacity practices are highly context-dependent, and the performance of SA system capabilities often varies from one macro, industry, sector and micro real economy individual. The proliferation of emerging technologies such as the internet, big data and artificial intelligence, and the innovative integration with a range of other application areas, driving the emergence of a new economy the reality of global economic integration

(Xing, 2016). The SA part of the integration of the internet, big data and artificial intelligence information technology features. Its technological convergence with the microreal economy is in turn an expression of its dynamic capacity for microeconomic entities. This is consistent with the findings of correlation between the characteristics of dynamic capabilities and environmental volatility as proposed by Eisenhardt and Martin (2000). This thesis emphasises that in the turbulent environment of new economic formations, SA exhibits the characteristic properties of dynamic capacity structures and models. That is, to emphasise the variability and selectivity of SA characterisation under the new economic norm.

2 Method of CCA

Based on the specific procedures and operation of the qualitative research method, this paper follows the Grounded Theory method proposed by Glaser and Strauss (1967), and based on the academic genealogy retrospective literature perspective, it is a holistic exploration of the development trend of SA after extensive and systematic collection and the process of three-level coding. Firstly, the co-citation context analysis (CCA) method was used to inductively analyze the literature and form research leads. Secondly, through the statistics of 'SA' as the keyword of the literature attributed to the research field and distribution, to refine the new economic scenario of SA trend linkage chain. Third, through the hierarchical clustering algorithm, the cited literature data are clustered and analyzed with VOSviewer's co-occurrence statistics to reflect the common attribute characteristics and hotspots of SA research. Finally, the utility revelations of the integration of SA and industry are found for interpretive understanding.

2.1 Statistical description

CCA (Small, 1980; Chen and Lin, 2020), using In order to evaluate the common attributes and relevance of the research field of SA, summarise the categories of their research fields, and characterise the convergence trend of SA. The specific operation is as follows: Cited literature, clustering, and co-occurrence analysis are measured using 'SA' as a keyword to explore three aspects: RQ1, SA covered area. RQ2, Status of research topics. RQ3, discovering theoretical associations and common attributes of SA (RQ3).

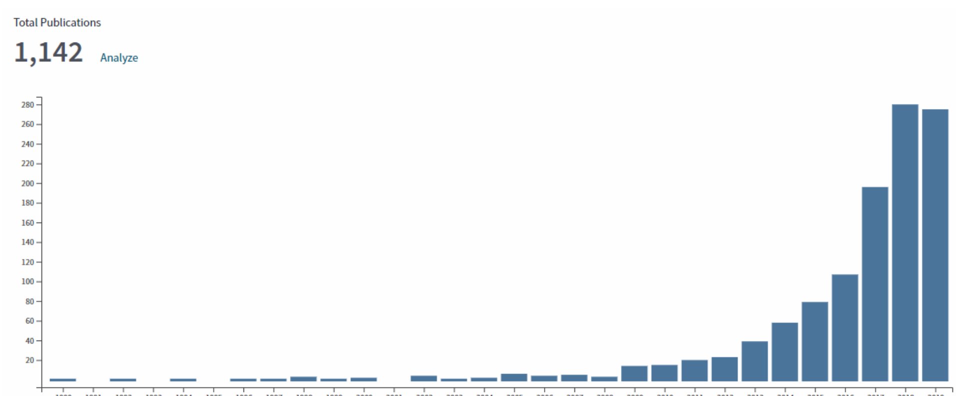
2.1.1 Data collation

This thesis selects SCI-EXPANDED, SSCI, A & HCI, CPCI-S, CPCI-SSH, ESCI as the data retrieval source in the core collection of Web of Science (WoS), using keywords (including the researcher keyword 'DE', and research content Add the keyword 'ID'), and perform accurate search with 'SA' as the subject key. The literature search fields include the title, abstract, author and affiliation, journal name, and publication year, according to the citation information publication year (PY), the researcher's address (AD) and research direction (SC) were classified by category. The literature accumulation time span was 1975–2019. The data was last updated on 27 March 2020. 1,142 citations and literature information were retrieved from the subject. A total of 8,232 citations, 13 highly cited papers, 1 hot papers in field, and h-index (high citation frequency) of 38, far exceeding the average citation frequency of 7.21.

2.1.2 Subject inventory literature statistics and descriptions

According to the statistical distribution of the number of literatures (shown in Figure 1), related themes for SA have been documented since 1990, from 38 in 2008 to after 2013, it showed a steep increase year by year. In 2018, it reached 280 documents with a maximum number of citations of 1,877 times. In 2019, there were a slight decline in 275 articles, but its maximum number of citations was 2,927 times. The number of research areas covered by the stock literature of the SA theme is also increasing, from less than four subject areas in the early 1980s to more than 40 research areas and directions in 2019, showing that SA is a booming The articles discipline also highlight the characteristics of SA's interdisciplinary development. Among them, engineering (N = 279), agriculture (N = 258), computer science (N = 242), and environmental sciences ecology (N = 216) are the top 4 subject areas and directions, and the cumulative number of research literatures is the largest, reaching 1,142. Copies accounted for 87.182% of the total literature inventory, showing the high dependence and common attributes of the existing literature on the subject area, but this only reflects the subject area affiliation of the existing literature, and its interdisciplinary and cross-research should be reflected in the distribution of citations.

Figure 1 Time series distribution statistics of SA literature (see online version for colours)



2.1.3 Citation statistics and descriptions

The number of citations for the SA theme research increased from 38 in 2008 to 2014 and increased rapidly year after year. The highest peak in 2019 was 119 citations and 1,198 citations. The total number is 4,284 (shown in Figure 2). The literature covers 64 research areas, and the citation covers 124 research areas. From the perspective of citation structure, the citing documents and highly cited documents reflect the discreteness of the research space of the subject area and the interdisciplinary and cross-cutting nature of the SA theme research. From the analysis of the citations of the subject areas, it can be found that the research of the subject areas of SA Top10 (as shown in Table 1) includes all elements of discipline integration, technological convergence , application convergence and industry integration. SA technological convergence multiple technical theories and methods [multispectral imaging, artificial intelligence, unmanned aerial vehicles (UAVs), machine learning (ML), graphics processing unit (GPU), nanotechnology, wireless sensor network, deep learning, the climate-smart village (CSV), climate-smart agriculture (CSA)] (Chen and Lee, 2019; Ampatzidis and Partel, 2019; Partel et al., 2019; Kumaret al., 2019; Shakhatreh et al., 2018; Muangprathub et al., 2019), development ideas (De Witet al., 2019; Raliya et al., 2017; Kamilaris and Prenafeta-Boldú, 2018; Lipper et al., 2014), policy guidance (Raza et al., 2019; Ort et al., 2015; Wolfert et al., 2017), technology prediction and socio-cultural change (Tittonell, 2014; Aggarwal et al., 2018; Shamshiri et al., 2018) and so on.

Figure 2 Time series statistics distribution of SA citations (see online version for colours)

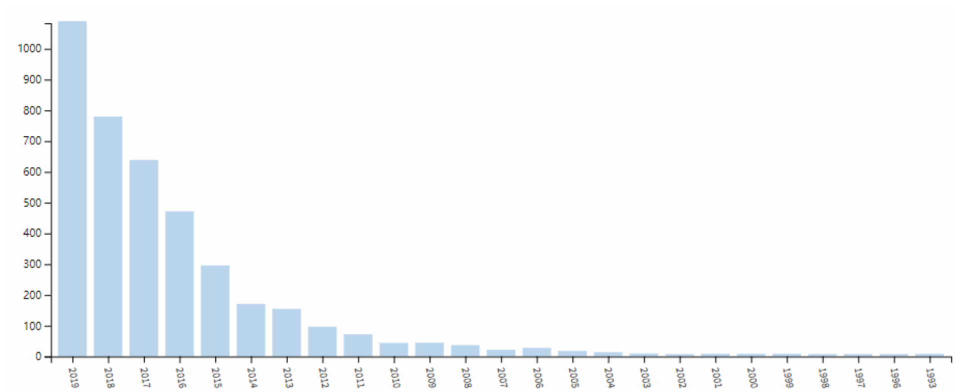


Table 1 Statistics of citation TOP10 subject areas

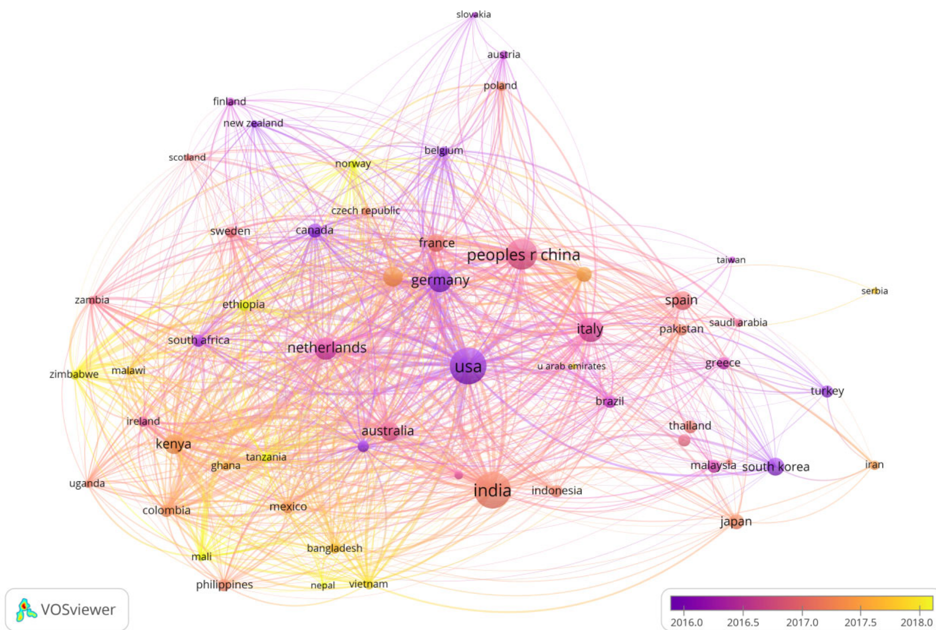
Research areas		*Records*	*% of 7,124*
1	Environmental sciences ecology	1,755	24.635
2	Agriculture	1,669	23.428
3	Engineering	1,041	14.613
4	Science technology other topics	917	12.872
5	Computer science	682	9.573
6	Plant sciences	483	6.780
7	Chemistry	469	6.583
8	Energy fuels	317	4.450
9	Materials science	272	3.818
10	Business economics	265	3.720

2.1.4 Co-occurrence and centrality statistics of stock literature

This thesis uses SA as the key word for the search (the literature inventory spans 1975–2019, and the data was last updated on 27 March 2020. A total of 7,124 citations and literature information were obtained from the WoS topic search, excluding self-citation rates). From the statistics of the co-occurrence and centrality of the existing literature (as shown in Figure 3), the maximum centrality of the USA node degree is 29,835, the number of documents is 170, and the number of citations is 2,751. The second is Kenya, with a maximum degree of 22,599, compared with 53 stocks of literature and 949 citations. The third is India, with a maximum degree centrality of

18,419. In contrast, the stock of literature is 175 and the number of citations is 915. From the research hotspots, it shows the dynamic changes of the research fields and directions of SA. The legend ruler in the figure represents the gradient colour (purple-red-yellow-green) between 2012 and 2015. It is not difficult to find that the SA stock literature began to accumulate around 2016. The USA and Germany, Canada, Africa, South Korea, Belgium, and Australia are in the same period of time, and it is regarded as a research hotspot of mainstream technology. Countries such as Netherlands, France, Italy, and Japan began to follow up in 2016 and have performed well; Kenya has increased rapidly after the above countries, showing a rapid development trend. It is worth mentioning that Vietnam has shown significant co-occurrenceity and centrality of citations since 2018, highlighting the trend of courage to catch up.

Figure 3 Statistic chart of co-occurrence and centrality of stock literature by country category (see online version for colours)



2.2 Cluster analysis

SA originates from the technological convergence of the internet, big data, and artificial intelligence. As technological convergence is considered to be one of the innovation drivers in recent decades, researchers in academia and industry are increasingly conducting interdisciplinary research, and the industry combines or merges different technologies into emerging technologies or new applications development of new products and services (Curran et al., 2010; Lee et al., 2015; Kose and Sakata, 2018). In the field of technology management, due to the different definitions of technological convergence, some researchers have tried to provide a comprehensive definition (Curran et al., 2010; Karvonen and Kassi, 2013; Kim et al., 2015), Curran et al. (2010) proposes to subdivide the integration into four categories: discipline integration, technological convergence , application convergence and industry integration. In most situations, the definition and paradigm of technological convergence have been used interchangeably. Choi et al. (2015) divides fusion into three categories according to technology level and measurement methods: discipline convergence, technological convergence, and industry integration. They used cluster analysis to classify that related indicators into 24 items, and classified them according to five main methods, namely co-word analysis, co-citation context analysis, co-author analysis, categorical analysis and input-output analysis.

A total of 256 research topic keywords (including the researcher keyword 'DE' and the research content supplement keyword 'ID') were extracted from the cited literature records, and the export correlation chain (weight <links>) was 10,108, weight < total link strength > is 17,242, weight <occurrences> is 3,605 [as shown in Appendix (research topic keywords and cluster analysis statistics)]. According to the practice of Chen (2019) hierarchical aggregation analysis, the research area with total link strength > = 1% is selected as the co-occurrence, the total link strength of the topic keyword is used as the degree centrality degree, and the co-occurrence matrix of the hierarchical clustering analysis. In this paper, VOSviewer hierarchical cluster is used to group 256 research topic keywords into seven separate categories (as shown in Figure 4). Then, based on the distance between groups as the association relationship, the hierarchical clustering performed by SPSS 22.0 is used to merge the clusters, and the new clusters are merged with another similarity category, and so on, until all clusters For a generic. Finally, the tree-like diagram is used to show the common attribute generic relationship between the groups in the research domain. The co-occurrence value is used to aggregate the association chain. The higher the degree of association, the closer the attributes are, and vice versa. From the obtained hierarchical clustering, the common attribute generic relationships among the research domain groups can be summarised into four generic categories:

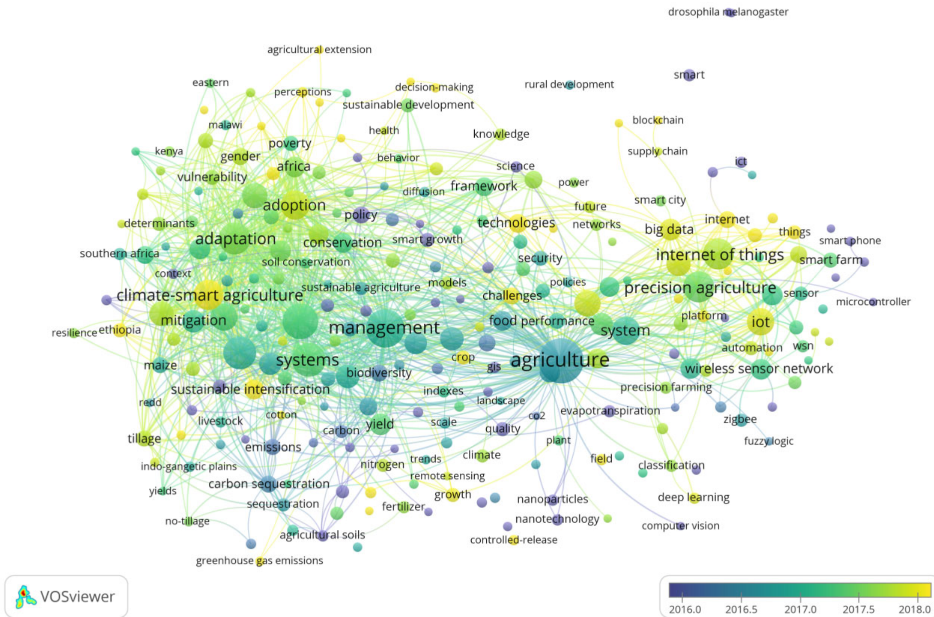
1 Disciplinary integration categories, including three research areas of agriculture, information systems, and management, show the common attributes and relevance of the three sets of the co-occurrence citations, highlighting the characteristic of disciplinary convergence.

2 Technological convergence category, including four research fields such as agriculture, artificial intelligence, engineering electrical and electronics, chemical engineering, etc., show the common attributes and relatedness of four sets of the co-occurrence citations, highlighting the characteristic attributes of technology fusion.

3 Application convergence categories, including policy orientation, operations research and management, and marketing, show the common attributes and relevance of the three sets of the co-occurrence citations, highlighting the characteristics of application convergence characteristics.

4 Industry integration category, including computer software engineering, industrial engineering, telecommunications, economics, engineering manufacturing, automatic control systems, engineering interdisciplinary, computer hardware, environmental science, nine research areas, showing nine sets of the co-occurrence citations and correlation degree highlight the characteristic of industrial integration.

Figure 4 Co-occurrence citations and centrality of the research topic keywords (see online version for colours)



3 Research induction

3.1 Definition of SA

The use of the term SA can be traced back to the idea of IBM's Smarter Planet. Smart Planet is divided into three elements, namely '3I': Instrumentation, Interconnectedness, Intelligence, which refers to the full application of the new generation of IT and internet technologies to various industries, and the sensors z equipped to hospitals, power grids, railways, bridges, tunnels, roads, buildings, water supply systems, dams, oil and gas pipelines around the world, through the internet to form the 'internet of things'. Then, through supercomputers and cloud computing, human beings can work and live in a more refined and dynamic way, so that the 'level of intelligence' is raised, and eventually 'internet + internet of things = smart planet'. Chen (2016) uses the concept of wisdom economy to describe wisdom agriculture, arguing that wisdom economy promotes resource integration and resource regeneration through knowledge innovation, institutional innovation, technological innovation, and model innovation, improves product added value, and realises the economic operation mode of industrial structure upgrading and sustainable economic development. SA is the specific manifestation of smart economy in agriculture, or smart economic form in agriculture.

Scholars and practitioners have successively defined the connotations of SA in approximate, similar, or different forms, but have interpreted them differently (Whelan and McBratney, 2003; McBratney et al., 2005; Tongke, 2013; Walter et al., 2017; Reina et al., 2018). There is no accepted and complete definition of the term 'SA'. The existing definitions were modified and perfected by drawing on the concept of technological innovation (Song et al., 2018). This thesis considers SA as a model for the economic operation of the smart economy in the agricultural industry. It is based on Instrumentation, Interconnectedness, Intelligence observations, measurements and responses to intercrop, field and climate change. Agricultural management concepts to save resources, reduce environmental risks, optimise inputs, improve the intrinsic quality of agricultural products and market them accurately. From the development deduction and key definitions of SA, it can be seen that has a high degree of technological dependence. SA relies on technological convergence and evolution, and iterative development. The above definition of SA can be summarised from three levels of data, practice and system:

1 At the data level, SA includes content attributes such as data integration, data quality, data management, and data processing. Data preparation and data utilisation are two separate and closely related core components of SA, which is defined as a technical support process based on data analysis. It expresses the conceptual agricultural management characteristics of SA-sensibility through data on intercrop, field and climate change, and market fragmentation dynamics.

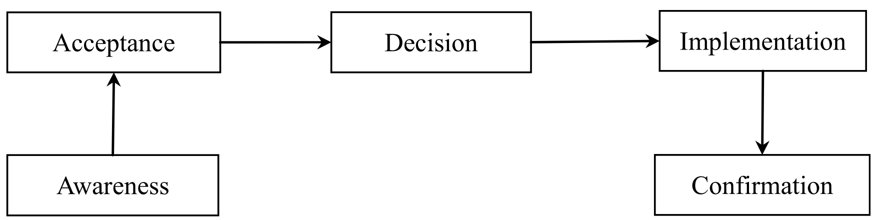
2 At the practical level, SA is about understanding and solving problems in practical agricultural activities. It is the process of searching, analyzing and processing information using information technology, presenting the interrelationship of facts and thus guiding actions to implement the desired goals and achieve the purpose of agricultural farming. SA is the basic ability of agricultural industrial organisation or micro-individualised information analysis and prediction, supporting decision-making, etc., to optimise inputs and improve the inherent quality of agricultural products. Conceptual characteristics of agricultural management that exhibit SMART's agriculture -transformation capability.

3 At the system level, SA is an information system that converts initial data into information to predict future trends or to reduce uncertainty in decision making. SA integrates data sources, cleans and filters data, extracts information, and then transforms and reconstructs it, presenting it as knowledge through data acquisition and OLAP tools. Information systems that drive decisions and ultimately save resources, reduce environmental risks and create value through precise sales. The conceptual characteristics of agricultural management that highlight SA-driven capabilities.

3.2 Technological integration in SA

The concept of technological integration in SA is derived from the theory of technological integration. Technology convergence (TC) refers to the process of diffusion, adoption of technological innovations among potential users through certain channels (Andergassen et al., 2017). TC refers to the process of radiation and diffusion of technological innovation, which manifests itself in two main forms, one is the practical process of transfer and diffusion of innovative technologies, and the other is the process of application, improvement, transformation, expansion and reinvention of emerging technologies by technology adopters (Papazoglou and Spanos, 2018). The factors that drive TC are multifaceted, such as pressure to change (motivation and capacity), innovative technology fit (compatibility), and dominant effects (observability) (Cannson and Villarlopez, 2014). Garcia and Calantone (2002) study argues that technology diffusion boundaries influence technology adoption; specifically, core and large-scale technologies are more likely to be adopted; technologies with lower losses or less risk, and technologies with perceived ease of use and perceived usefulness are more likely to be adopted; similarly, habitual adopters increase the chances of technology adoption because of higher learning perceptions. Conversely, because of the increased instability of technology, technology is not easily adopted even without disrupting conventional practices. Vonk (1979) argues that TC occurs through a five-step decision-making process (see Figure 5): awareness, acceptance, decision, implementation, and confirmation.

Figure 5 The process of technological convergence and decision making



Economic growth theory and practice have shown that technological convergence has become a necessary and sufficient condition for new economic growth. For business organisations, technological convergence is the lifeblood of their survival and innovative development. It has become an effective means for business organisations to improve their competitive advantage. Research on the diffusion and integration of technological innovations has undergone a shift from a 'linear paradigm' to a 'network paradigm' (Chen, 2007). Since then, the scope of integration studies has gradually shifted from within a single corporate organisation to the structural adjustment and interaction of corporate organisations with external organisations, leading to the emergence of the 'network paradigm'. The theory of technological convergence has the characteristic properties of a techno-economic theory and is not a purely technical theory. Its own impact on economic development is also not significant. And the real significant driver of economic development is the proliferation of technological innovation. The proliferation of technological innovation will induce the large volume of technological innovation associated with it, which in turn will induce the formation of larger technological change and diffusion effects. Facilitating the development of the integration of technology with industry or the real economy will, in turn, enable the innovators or stakeholders to profit, thereby driving a new round of technological innovation and diffusion, which in turn leads to the formation of a new economic cycle pattern of innovation-diffusion-reinnovation (Chen, 2007; Dziallas and Blind, 2018).

3.3 Effectiveness of SA

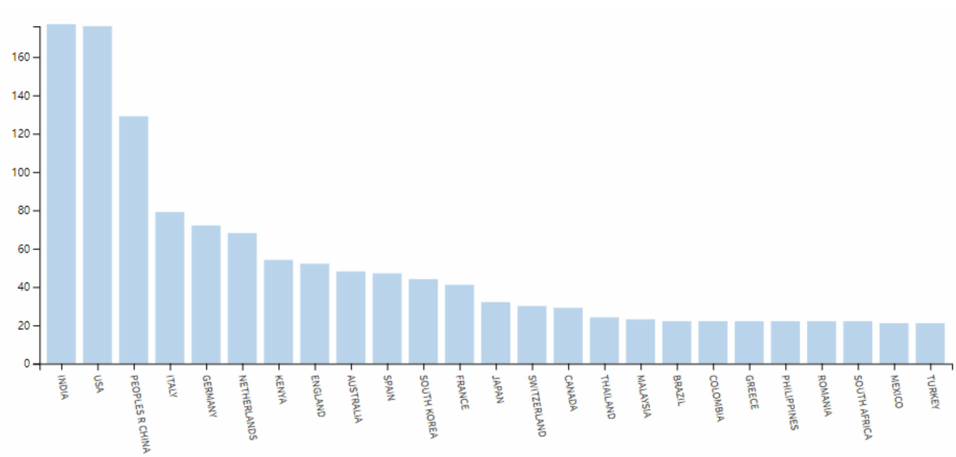
SA dominates decision-making in agricultural organisations and implements instrumentation, interconnectedness, intelligence (IoI) in agricultural practices, which will be effective when integrated with technology as follows.

Firstly, SA benefits from sensor embedding, allowing agricultural management to be optimally solved through mathematical models, and agricultural practices to achieve intelligent decision-making and automatic execution through IoT. Secondly, the development of the internet, which tends to data silos towards real-time system integration of structured and unstructured data, makes real-time classification management possible (HenningBaars and Hans-GeorgeKemper, 2008), and smart agricultural systems with real-time dynamic data, circumventing the problems of model performance decay and accuracy degradation caused by modelling of stock historical data (Ali, 2018). Third, artificial intelligence makes the powerful processing and storage capacity of intelligent agricultural systems a reality, it breaks through the upper limit of data quality to determine the possible model, breaks through the constraints of structural models and calculation rates, big data creates opportunities for new knowledge discovery, and the way of agricultural management and operation becomes more precise and dynamic.

3.4 Status and trends in SA

For the global technology development and iterative innovation of stock technology, the past few decades, the impression that the USA has been leading the world has been solidified; but as for today's SA technology research literature stock data, the perspective of the literature, India has overtaken the USA, and China is not far behind. For the cited literature, China has entered one of the fastest growing countries in the field of SA, and has become the first square of the global science and technology stock and technology development (as shown in Figure 6).

Figure 6 TOP10 the stock of literature by country category (see online version for colours)



The economic and environmental benefits of SA have also been confirmed in China, but China is lagging behind countries such as Europe and the USA because the Chinese agricultural system is characterised by small-scale family-run farms, which makes the adoption rate of SA lower than other countries. Therefore, China is trying to better introduce SA technology into its own country and reduce some risks, paving the way for China's technology to develop SA in the future (Kendall et al., 2017).

From manufacturing in China to intelligent manufacturing in China, China will give full play to the diffusion effect of emerging technology innovation. The acceleration of technology landing will be faster and the emerging business model will be more powerful, but the business development will still lack comprehensiveness and standardisation (iResearch INC., 2017). At present, China has achieved iterative development through breakthroughs in single-point technology, and has begun to focus on intensive cultivation of operations, gradually expanding from local optimum to global optimum. In addition, since the proliferation of emerging technology innovation represented by artificial intelligence in China in 2015 has entered an explosive period, high-level government officials have successively proposed a number of planning measures and policies to include emerging technologies represented by the internet, big data and artificial intelligence in development plans. It has become the focus of China's politics, economy, and academic fields, and China's SA has ushered in the best era.

4 Discussion

We argue that SA is the techno-economic integration of disciplines, technologies, applications and industries, not just technology integration. Since SA is the main body of research in this paper, the empowerment of industry by integrating SA and technology is viewed from the intersection of the academic genealogy and is not discussed from a single technological domain. In accordance with theoretical research guidelines, and following the common nature and linkage chain of technology, discipline, application and industrial integration, the integration of intelligent agriculture and technology is understood as the combination of intelligent agriculture and agricultural economy technology innovation diffusion, technology integration conductive power is manifested in the diffusion of innovation diffusion by computer information system technology and other emerging technologies; and cross-disciplinary integration is the process of micro-individuals perceive the usefulness and ease of use of emerging technologies, resulting in the conductive effect and role. Based on the research content of the topic, this paper selects the theory of technology integration and industrial integration, explains and extrapolates the practical guidance and theoretical revelation of intelligent agriculture and technology integration.

4.1 Practical implications

Technological convergence is a tool to promote innovation (Kose and Sakata, 2018). Based on the theory of technological convergence , this thesis focuses on the technologies represented by technological convergence feature attributes, including agriculture, artificial intelligence, engineering, electronics, and chemical engineering. The SA is defined as the diffusion of technological innovation, the promotion of the convergence of SA and economic entities, and the macro-industrial integration effect is used to explain the smart agricultural integration effect from a microscopic perspective.

Industry integration refers to the interaction, penetration and integration of different industries or industries in the same industry due to the diffusion of technological innovation and other reasons, and gradually forms a dynamic development process of new industries (Chen, 2007). SA and industry integration category, including computer software engineering, industrial engineering, telecommunications, economics, engineering manufacturing, automatic control systems, engineering interdisciplinary, computer hardware, environmental science nine research areas, showing nine groups of co-occurrence with the common attributes and degree of correlation, while highlighting the effects of technological convergence, reflect the industrial integration development mode of technological innovation diffusion and industrial penetration, which is the embodiment of the current deep integration of the internet, big data, artificial intelligence and the real economy, which is in line with the performance of industrial integration form is a realistic choice for industrial development.

Table 2 Comparison of industrial characteristics after integration

Characteristics	*Industry characterisation after technological convergence*	*Characterisation of traditional industries*
Technical characteristics	• Emphasis on global economic integration • Strategic change and dynamic allocation • Customisation or differentiation • People-oriented technical support • Plasticity or diversity brings extra profit	• Emphasis on economies of scale • Conventional dependence • Standardisation • Non-humanistic way of working • High cost of unified planning
Operating system characteristics	• Decentralised • Combined ability in discrete form • Plasticisable production system • Rolling or turning operation • Mass Custom Product Model • Innovation and strong response • Production on demand • Functional-centric concepts to facilitate reorganisation • Responsibility linked to expanded functions • Production of liquidity systems	• Centralised • Large interval operation • Supply-demand balance and production lines • Smooth running • Standard product design pattern • Low ratio change and high stability • Inventory management • Strengthen the concept of organisation as the core • Job refinement and related rewards • Mass production

4.2 Theoretical implications

Based on the citation synthesis analysis, according to the theory of industrial integration and the theory of technology integration, the integration of technology and industry shows the organisational structure effect, competitive structure effect, competitive ability effect, etc. We have deeply integrated the internet, big data and artificial intelligence with the real economy within the agricultural industry, and expanded the extension for the proliferation of technological innovation to promote the integration of intelligent agriculture and enterprises within the industry, intelligent agriculture shows the effect of both internal and external, but there is a difference with technology and industry integration. Following the guidance of the grounded theory approach, we discuss theoretical revelations by explaining the convergent efficacy of SA.

4.2.1 Structural effects

From the perspective of industrial integration theory, SA has spurred structural adjustments of enterprises outside the industry, and has also induced changes or variations in organisational practices of enterprises within the industry (Chen, 2007).

1. Structural adjustment of external industry organisations. The enterprise organisation began to make structural adjustments to its interaction with the outside organisation by weighing the transaction costs. From a vertically integrated organisational structure, it gradually evolved to a horizontally integrated organisational structure, allowing the enterprise to organise its own resources and external resources of the industry. Being fully utilised to form a dynamic ability to respond quickly to market demands. SA makes horizontal integration the normal state of the new economy and is the main form of the organisational structure of the real economy.

2. Changes in corporate organisational practices in internal industries. The internal organisation structure of the traditional agricultural industry's real economy is mostly a pyramidal vertical management model. In new normal of economy, it is difficult to match the development of emerging industries. SA's business organisation economic form will evolve into an information-based virtual economy and a dual economic structure that interacts with the global integrated real economy. The virtual economy will become the mainstream model of future business organisation operations, which requires business organisations to make Organisational conventions change to form a dynamic capability to adapt to the development trend of the new economic environment and industrial adjustment. The internal structure of the enterprise organisation will undergo a fundamental change, which will cause changes in the overall organisational practices of the agricultural industry.

4.2.2 Competitive structural effect

From the perspective of technology integration, SA drives the change of organisational practices within the industry, and promotes strategic adjustment of the organisation. The position of agricultural economies of scale in the strategy is replaced by economies of scope, which are superimposed on organisational structure effects. Together, they have promoted horizontal mergers and acquisitions of enterprise organisations in the industry, leading to changes in competition and cooperation relations. From monopolistic competitive markets to fully competitive markets, economic efficiency has been improved.

4.2.3 Competitive ability effect

SA has an effect on the improvement of the competitiveness of the enterprise organisation within the agricultural industry, which is reflected in the dynamic ability of the enterprise organisation. According to the theory of dynamic capability, the competition between enterprise organisations is actually the competition in all links of the agricultural industry value chain. SA is an endogenous motivation for the improvement of corporate organisational competitiveness, which is consistent with the evolution of dynamic capabilities. SA has realised the dynamic capabilities of enterprise organisations, and its integration process has been introduced to the operational level of various business units within the enterprise organisation, thereby achieving the system capabilities of SA. In addition, the external horizontal integration of the organisational structure has accelerated the evolution of technological convergence, which has intensified the competition among industrial organisations, and the competitive capability effect has triggered a new round of technological innovation diffusion, forming a circular evolution of competitive capability effects.

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Appendix

Table A1 Research topic keywords and cluster analysis statistics

Label	*Cluster*	*Weight <links>*	*Weight <total link strength>*	*Weight <occurrences>*
Agriculture	1	190	543	130
Algorithm	1	12	14	7
Android	1	17	19	6
Applications	1	19	23	5
Architecture	1	26	35	5
Arduino	1	15	20	11
Artificial intelligence	1	23	28	7
Automation	1	32	50	13
Big data	1	55	106	31
Challenges	1	76	106	18
Classification	1	16	24	10
Cloud	1	19	26	7
Cloud computing	1	33	71	19
Communication technologies	1	18	27	5
Component	1	13	15	6
Computer vision	1	6	11	5
Cyber-physical systems	1	8	8	5
Deep learning	1	13	19	8
Design	1	63	93	25
Environmental monitoring	1	16	20	5
Evapotranspiration	1	24	30	10
Field	1	19	22	8
Future	1	40	49	10
Fuzzy logic	1	8	10	5
GPS	1	12	12	5

Table A1 Research topic keywords and cluster analysis statistics (continued)

Label	*Cluster*	*Weight <links>*	*Weight <total link strength>*	*Weight <occurrences>*
Greenhouse	1	32	45	13
GSM	1	6	6	6
ICT	1	16	16	9
Identification	1	23	27	5
Image processing	1	19	23	10
Internet	1	49	101	19
Internet of things	1	74	179	63
Internet of things (IoT)	1	24	36	13
IoT	1	65	161	48
Irrigation	1	94	149	33
Lora	1	14	16	5
Machine learning	1	27	43	13
Micro controller	1	8	9	5
Mobile application	1	14	16	5
Mobile computing	1	13	14	5
Network	1	33	36	7
Of-the-art	1	31	36	6
Performance	1	55	73	17
Phenology	1	20	24	5
Plant	1	33	34	7
Platform	1	35	57	10
Policies	1	39	45	7
Power	1	22	22	7
Precision agriculture	1	90	231	63
Precision farming	1	25	35	10
Prediction	1	25	28	9
Raspberry pi	1	15	16	5
Renewable energy	1	7	8	6
RFID	1	15	17	6
Sensor	1	29	42	13
Sensor networks	1	8	9	5
Sensors	1	53	97	27
Smart agriculture	1	103	170	44
Smart city	1	20	22	8
Smart farm	1	15	25	15
Smart farming	1	67	151	40
Smart irrigation	1	15	26	9
Smart phone	1	5	7	6

Table A1 Research topic keywords and cluster analysis statistics (continued)

Label	*Cluster*	*Weight <links>*	*Weight <total link strength>*	*Weight <occurrences>*
Soil moisture	1	22	22	6
Soil moisture sensor	1	7	7	5
System	1	97	177	50
Technologies	1	78	130	23
Temperature	1	86	129	26
Things	1	28	56	14
Wireless sensor network	1	51	98	29
Wireless sensor network (WSN)	1	14	14	6
Wireless sensor networks	1	43	90	28
WSN	1	24	32	10
Zigbee	1	18	23	11
Agricultural soils	2	27	41	9
Agroecology	2	29	30	8
Arbuscular mycorrhizal fungi	2	17	18	5
Carbon	2	52	61	12
Carbon sequestration	2	61	97	18
CO_2	2	25	26	5
Conservation tillage	2	26	33	7
Controlled-release	2	8	10	7
Crop yield	2	32	44	6
Dynamics	2	31	36	9
Electrical-conductivity	2	17	17	6
Environment	2	27	28	7
Farming systems	2	54	79	11
Fertiliser	2	35	45	10
Food	2	74	108	25
Food security	2	131	390	71
Global warming	2	20	24	6
Greenhouse gas emissions	2	24	33	6
Greenhouse-gas emissions	2	37	48	9
Growth	2	43	60	14
Life-cycle assessment	2	24	27	6
Livelihoods	2	39	49	6
Livestock	2	30	37	9
microbial biomass	2	21	24	5
N_2O emissions	2	31	42	11
Nanoparticles	2	14	18	9
Nanotechnology	2	10	15	9

Table A1 Research topic keywords and cluster analysis statistics (continued)

Label	*Cluster*	*Weight <links>*	*Weight <total link strength>*	*Weight <occurrences>*
Nitrogen	2	42	53	11
Nitrous-oxide emissions	2	39	44	11
No-tillage	2	24	35	6
Organic-matter	2	12	15	5
Plant-growth	2	11	12	6
Politics	2	27	32	5
Remote Sensing	2	11	11	5
Scale	2	28	29	8
Sequestration	2	41	68	12
Soil	2	92	172	35
Soil Carbon Sequestration	2	25	28	5
South-Asia	2	24	41	6
Sustainable Agriculture	2	38	48	12
Sustainable Intensification	2	79	165	25
Tanzania	2	23	27	6
Tillage	2	61	121	16
Use Efficiency	2	25	31	5
Water	2	68	99	27
Water Productivity	2	24	34	6
Water-Use Efficiency	2	22	24	7
Wheat	2	44	55	9
Yield	2	89	151	31
Yields	2	31	45	5
Benefits	3	30	38	7
Biodiversity	3	63	88	18
Biodiversity Conservation	3	23	31	6
China	3	27	31	9
Climate-Change	3	101	202	32
Connectivity	3	19	24	6
Conservation	3	88	150	25
Conversion	3	11	14	5
Crop	3	53	71	13
Deforestation	3	45	67	9
Diversity	3	54	78	15
Ecosystem Services	3	70	111	21
Energy	3	42	50	14
Forest	3	32	40	7
GIS	3	27	28	8

Table A1 Research topic keywords and cluster analysis statistics (continued)

Label	*Cluster*	*Weight <links>*	*Weight <total link strength>*	*Weight <occurrences>*
Governance	3	28	32	6
India	3	24	25	8
Information	3	55	73	14
Institutions	3	24	32	5
Land	3	54	74	13
Land Preservation	3	7	13	5
Land-Use	3	53	67	13
Land-Use Change	3	27	31	7
Landscape	3	25	31	5
Landscapes	3	22	27	5
Management	3	174	509	96
Models	3	40	46	10
Policy	3	54	90	19
Programs	3	19	21	6
Quality	3	35	43	14
Redd	3	18	24	5
Region	3	28	28	6
Risk	3	35	44	9
Smart Cities	3	13	14	5
Smart Growth	3	23	34	13
Soil Conservation	3	36	53	8
Soil Fertility	3	35	45	9
Support	3	26	31	6
Sustainability	3	100	143	34
Urbanisation	3	20	21	8
Adaptation	4	135	464	67
Adoption	4	121	364	55
Africa	4	84	172	27
Agricultural Extension	4	18	20	5
Attitudes	4	19	23	5
Climate Smart Agriculture	4	104	234	43
Conservation Agriculture	4	94	268	39
Decision-Making	4	22	22	6
Diffusion	4	25	30	7
Eastern	4	29	43	6
Efficiency	4	32	34	12
Farmers	4	85	179	27
Gender	4	57	90	18
Impacts	4	117	309	47
Innovations	4	30	36	5

Table A1 Research topic keywords and cluster analysis statistics (continued)

Label	*Cluster*	*Weight <links>*	*Weight <total link strength>*	*Weight <occurrences>*
Kenya	4	25	30	7
Knowledge	4	38	48	10
Malawi	4	26	29	7
Nigeria	4	7	7	5
Perceptions	4	40	56	7
Poverty	4	52	84	15
Principal component analysis	4	28	30	6
Productivity	4	85	166	28
Resources	4	15	21	5
Smallholder Farmers	4	61	114	15
Southern Africa	4	46	76	10
Sub-Saharan Africa	4	64	124	21
Technology	4	74	121	22
Technology Adoption	4	55	91	12
Zambia	4	29	36	5
Zimbabwe	4	32	49	6
Agroforestry	5	46	70	11
Climate	5	30	34	11
Climate Change	5	136	438	81
Climate-smart agriculture	5	128	365	58
Constraints	5	33	36	7
Context	5	27	35	7
Cotton	5	27	29	5
Crop production	5	24	32	6
Determinants	5	56	94	13
Ecological intensification	5	20	21	5
Emissions	5	56	93	16
Ghana	5	17	21	5
Impact	5	74	129	25
Indexes	5	32	40	8
Indo-gangetic plains	5	34	49	7
Innovation	5	31	44	12
Mitigation	5	89	216	34
Model	5	76	137	37
Opportunities	5	39	47	8
Participation	5	29	39	6
Precipitation	5	37	41	7
Prioritisation	5	27	39	7

Table A1 Research topic keywords and cluster analysis statistics (continued)

Label	*Cluster*	*Weight <links>*	*Weight <total link strength>*	*Weight <occurrences>*
Resilience	5	27	38	7
Rice	5	40	56	13
Science	5	29	38	8
Simulation	5	52	73	18
Smallholder	5	35	42	5
Systems	5	139	449	73
Trends	5	18	19	6
Water management	5	24	25	6
Adaptive capacity	6	30	41	5
Bangladesh	6	36	45	7
Behavior	6	20	21	6
Biomass	6	20	21	8
Burkina-faso	6	30	39	5
Change adaptation	6	41	63	9
Climate change adaptation	6	37	49	11
Drought	6	42	59	13
Ethiopia	6	47	85	13
Households	6	35	43	5
Intensification	6	49	66	8
Maize	6	63	105	16
Responses	6	41	55	9
Security	6	68	87	15
Strategies	6	48	74	11
Variability	6	57	93	15
Vulnerability	6	50	96	15
Blockchain	7	12	13	5
Crops	7	35	43	9
Diversification	7	31	36	5
Drosophila melanogaster	7	2	5	5
Framework	7	71	122	24
Health	7	29	35	5
Networks	7	32	38	10
Nutrition	7	33	40	5
Optimisation	7	37	48	13
Rural development	7	9	9	6
Smart	7	14	15	10
Somatic mutation	7	2	5	5
Supply chain	7	10	11	5
Sustainable development	7	38	56	13