# Analysis of the drivers of industry 4.0 technology deployment to achieve agri-food supply chain sustainability: A hybrid approach

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***Abstract*—Agri-food supply chains (AFSCs) are struggling to achieve sustainability in the face of increasing social, environmental, and economic challenges. Industry 4.0 technologies are widely deployed to monitor, assess, and analyze their operational process, and thereby drive sustainable value. This study adopts a hybrid approach to analyze the drivers of industry 4.0 technology deployment to achieve AFSC sustainability. Thematic analysis of 24 interviews was carried out to identify 13 drivers, and these were used as inputs into the fuzzy analytic hierarchy process (AHP), total interpretive structural modeling (TISM), and fuzzy cross-impact matrix multiplications applied to classification (MICMAC). The results show that enhancing efficiency of water and fertilizer use, reducing carbon emissions, and reducing work intensity contribute significantly to economic, environmental, and social aspects of sustainability. We also identify that government subsidies for agricultural facilities and strengthening of farmers' agri-tech skills are key drivers that should be given priority.**

***Keywords—industry 4.0 technologies, agri-food supply chain sustainability, fuzzy AHP, TISM, fuzzy MICMAC***

## I. Introduction

Agri-food supply chains (AFSCs) comprise "farm-to-fork" processes linked from initial production to final consumption, including agriculture-related activities such as pre-producing, farming, processing, wholesaling, distributing, retailing, consuming, and post-consuming activities. The various organizations and stakeholders involved in these activities include agrichemical producers, pesticide residue testing organizations, international standard agencies, agricultural machinery rental businesses, and local and national agricultural departments. AFSCs' increasing complexity makes them difficult to monitor, operate, and coordinate effectively, and thus achieve sustainability. Extreme weather events around the globe, increasingly volatile and uncertain business environments, and social issues such as gender inequality and health and safety are additional pressures for making AFSCs sustainable.

To tackle these sustainability issues, AFSC practitioners are starting to trial and deploy industry 4.0 technologies to monitor and drive AFSCs toward operating effectiveness, lower costs, and higher profits, further transforming them to achieve sustainable development. Industry 4.0 technologies are characterized by wireless connectivity and advanced sensors that collect data continuously and increase visibility, thereby empowering business systems [1]. They include widely discussed technologies such as robots, additive manufacturing, big data, artificial intelligence, blockchain, the internet of things (IoT), and 3D printing. Industry 4.0 technologies promise a range of benefits for AFSCs, including increased coordination, enhanced traceability and visibility, and high collaboration and trust among ASFC members. However, the benefits are as yet unproven, and empirical evidence relating to specific industries is lacking. For example, recent review of literature on the role of industry 4.0 technology in achieving supply chain sustainability recommends a thorough examination covering three pillars of sustainability performance with the application of industry 4.0 technologies in supply chains [2]. Another review of literature exploring the application of industry 4.0 technologies in AFSC management suggests the necessity for research on effective ways to enable AFSC sustainability [3].

To address these research gaps, this study employs decision support methods to evaluate and analyze the drivers of industry 4.0 technology deployment to achieve AFSC sustainability. This will enable AFSC stakeholders to understand how deploying these technologies may improve economic, social, and environmental aspects of sustainability, guide agri-food

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businesses' research allocations, and inform governments seeking to formulate effective policies to help agri-food businesses to be more sustainable.

The paper is set up as follows. In Section 2 of this paper, we explain the aim and objectives of this study, and in Section 3 we present and justify our data collection and analysis methods. In Section 4 we present and discuss the findings of our analysis, and in Section 5 we draw conclusions and make recommendations.

## II. OBJECTIVES

This study had four research objectives. The first was to identify drivers associated with deploying industry 4.0 technologies to achieve AFSC sustainability. To accomplish this objective, we interviewed 24 AFSC practitioners working in various roles, and thematically analyzed the transcripts to identify drivers. The second objective was to prioritize these drivers to understand the contributions of industry 4.0 technologies to AFSC sustainability. We employed fuzzy AHP, a method widely used to analyze multi-criteria decision-making problems [4]. The third objective was to understand how to deploy industry 4.0 technologies in AFSCs effectively, or in other words to identify key drivers by constructing interrelationships. It is critical for AFSC practitioners to understand the key drivers, as more than 80% of agri-businesses are small- and medium-sized enterprises (SMEs) that may lack resources for sustainability initiatives [5]. TISM was implemented to allocate drivers to different layers of a framework and elucidate interrelationships between them. The fourth objective was to identify each driver's role in the system. We employed fuzzy MICMAC analysis to categorize the drivers into independent, dependent, linkage, and autonomous categories.

## III. METHODOLOGY

A hybrid approach was adopted to identify, prioritize, link, and categorize drivers of industry 4.0 technology deployment to achieve sustainable AFSCs. We conducted semi-structured interviews with experienced Chinese AFSC practitioners to collect empirical data, followed by employing thematic analysis to generate drivers. Three complementary data analysis methods – fuzzy AHP, TISM, and fuzzy MICMAC – were implemented. These methods are combined and implemented, allowing us to understand complex social phenomena through qualitative analysis, explain the phenomena using statistical analysis, and explore this world from different research angles.

### *A. Data Collection Method*

Semi-structured interviews were conducted to collect data from experienced Chinese AFSC practitioners. This method was employed for several reasons. First, it allowed deeper exploration of participants' experiences of, thoughts on, and attitudes to deploying industry 4.0 technologies to achieve AFSC sustainability. Second, it enabled the interviewers to ask participants to elaborate, explain, and clarify responses. Third, semi-structured interviews have a loose and flexible structure, while maintaining focus using core and follow-up questions [6].

Our interview guide was formulated in discussion with a professor in operations management and decision making. After seeking background information on interviewees and their companies, and the next questions asked about the main technologies used in the agriculture sector, including a specific section on the impact of industry 4.0 technologies on AFSC sustainability. Our final questions were barriers to deploying industry 4.0 technologies in AFSCs. We then conducted pilot interviews with two professionals in agri-food technology management and two agri-food industry practitioners from China. Based on their comments, we modified some questions, for example by adding more illustrative examples, preparing follow-up questions to elicit more information, and practicing probing skills.

Two PhD students fluent in Chinese were asked to conduct interviews in China between November 2021 and February 2022. We selected this specific period because most advanced agricultural technologies, such as intelligent greenhouses, IoT, mobile applications, and precision farming technologies, are used to supply off-season vegetables. We employed purposive sampling followed by snowball sampling to identify suitable participants, using three selection criteria. First, they should cover a wide range of AFSC practitioners, including farmers, processors, logistics service providers, wholesalers, distributors, and retailers, to ensure that we would gain insights from various perspectives. Second, the participants should have over five years' experience of working with agricultural technologies, to ensure high levels of expertise. Third, participants must be middle or senior management team members who would have a comprehensive understanding of the benefits of deploying industry 4.0 technologies. Based on these criteria, we identified 24 participants willing to participate in our research.

### *B. Data Analysis Methods*

We employed four data analysis methods to analyze the data collected from the semi-structured interviews: thematic analysis to identify drivers of industry 4.0 technology deployment in the agri-food industry, fuzzy AHP to prioritize the drivers, TISM to elucidate interrelationships, and fuzzy MICMAC analysis to distinguish the role of each driver in the system.

Thematic analysis is a qualitative data analysis method widely used to identify themes within a dataset [7]. We used this method to identify drivers for three reasons. First, it has been described as a translator to communicate qualitative and quantitative research methods [8], and was thus suited to our hybrid approach to investigate the topic. Second, thematic analysis has been used to explore AFSC issues, as it produces results that both academics and industry practitioners can easily understand, thereby widening their impact [9]. Third, thematic analysis provides high flexibility, which is lacking in other qualitative data analysis methods.

We then applied fuzzy AHP to prioritize the identified drivers and gain an effective understanding of industry 4.0 technology deployment to achieve AFSC sustainability. Fuzzy AHP was used for two reasons. First, this method is widely used to structure multi-criteria decision-making problems systematically. However, imprecision may emerge during pair-wise comparison because AHP require judgments by experts, who may have limited information or capacity to conduct their evaluation. To deal with imprecision in AHP, fuzzy rather than numbers exact numbers are used to present the linguistic expressions [10]. Second, fuzzy AHP follows a structured process to follow and is characterized by ease of use.

Fuzzy AHP provided an understanding of the contributions of industry 4.0 technology deployment to achieve AFSC sustainability. However, it is difficult for ASFC practitioners to understand which drivers should be prioritized for development, especially when facing with many choices. More than 80% of agri-food businesses are SMEs that may lack resources to develop sustainability. TISM is a qualitative modeling technique that can transform complicated systems into unambiguous and straightforward models, integrate expert explanations into the model to interpret links between drivers, and answer what, how and why questions. The latter two advantages are not offered by other methods, such as interpretive structural modeling and structural equation modeling. Thus, we applied TISM to identify the key drivers of the system by constructing interrelationships.

Simply understanding the key drivers is insufficient for several reasons. First, agri-food organizations may focus on various aspects to achieve sustainability, including social, environmental, and economic perspectives. Thus, concentrating on only a few drivers of industry 4.0 technology deployment may limit organizations' potential to achieve sustainability. Second, some drivers may produce synergies, while others may conflict with each other or be ineffective. Therefore, we conducted fuzzy MICMAC analysis to understand the role of each driver in the system. This method improves sensitivity analysis and complements TISM.

## IV. RESULTS AND DISCUSSION

### A. *Thematic Analysis to Identify Drivers*

We implemented thematic analysis in three steps. First, we transcribed each interview audio file word-for-word, and edited each transcript to remove irrelevant data. Second, we familiarized ourselves with the data by reading each transcript several times, coding data relevant to drivers of industry 4.0 technology deployment to achieve AFSC sustainability, refining codes by moving forth and back between relevant theory and literature, and categorizing codes by associating the findings with categories. Third, we organized our thematic analysis results using first-order codes, second-order themes, and aggregate dimensions [11]. We identified 13 drivers: five related to social sustainability (reducing work intensity, reducing labor headcount, reducing human exposure to pesticides, strengthening farmers' agri-tech skills training, improving working conditions), three to environmental sustainability (reducing carbon emissions, reducing groundwater pollution, reducing waste by controlling resource competition), and five to economic sustainability (enhancing efficiency of water and fertilizer use, government subsidies for agricultural facilities, increasing product safety and farms' productivity, reducing labor costs, accelerating circular agriculture).

### B. *Fuzzy AHP to Rank Drivers*

The outputs of thematic analysis were used as inputs into fuzzy AHP, which was implemented in five steps.

Step 1: Constructing hierarchical structure. A three-layer hierarchical structure was built to understand how to rank the identified drivers. This included the research objective of ranking drivers in the top layer of the hierarchical structure, followed by evaluation criteria in the medium layer, and drivers in the bottom layer.

Step 2: Establishing fuzzy judgment matrix $\tilde{E}$. Pair-wise comparisons were conducted of drivers and of evaluation criteria. Linguistic terms were assigned to the pair-wise comparisons by asking which of the two was more important:

$$\tilde{E} = \begin{bmatrix} \tilde{1} & \tilde{E}_{12} & \dots & \tilde{E}_{1n} \\ \tilde{E}_{21} & \tilde{1} & \dots & \tilde{E}_{2n} \\ \dots & \dots & \dots & \dots \\ \tilde{E}_{n1} & \tilde{E}_{n2} & \dots & \tilde{1} \end{bmatrix} = \begin{bmatrix} \tilde{1} & \tilde{E}_{12} & \dots & \tilde{E}_{1n} \\ \tilde{E}_{12}^{-1} & \tilde{1} & \dots & \tilde{E}_{2n} \\ \dots & \dots & \dots & \dots \\ \tilde{E}_{1n}^{-1} & \tilde{E}_{2n}^{-1} & \dots & \tilde{1} \end{bmatrix},$$

where

$$\begin{cases} \tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9}, \text{criterion i is more important than criterion j,} \\ \tilde{1}, i = j, \\ \tilde{1}^{-1}, \tilde{3}^{-1}, \tilde{5}^{-1}, \tilde{7}^{-1}, \tilde{9}^{-1}, \text{criterion i is less important than criterion j} \end{cases}$$

Step 3: Calculating fuzzy weights for each criterion. These were calculated based on the following equations:

$$\tilde{r}_i = [\tilde{E}_{i1} \otimes \tilde{E}_{i2} \otimes \tilde{E}_{13} \dots \otimes \tilde{E}_{in}]^{1/n}, \forall \text{i} = 1, 2, 3\dots, \text{n},$$

$$\widetilde{w}_i = \frac{\tilde{r}_i}{\tilde{r}_1 \oplus \tilde{r}_2 \oplus \tilde{r}_3 \dots \oplus \tilde{r}_n},$$

where $\tilde{E}_{ij}$ represents the fuzzy comparison value of criterion i to criterion j, $\tilde{r}_i$ represents the geometric mean of the fuzzy comparison value of criterion i to each criterion, and $\widetilde{w}_i$ represents the fuzzy weight of the ith criterion.

Step 4: Hierarchical layer sequencing. We used the following equation to calculate the fuzzy weight value of each alternative:

$$\widetilde{U}_i = \sum_{j=1}^{n} \widetilde{w}_j . \tilde{r}_{ij}$$

where $\tilde{r}_{ij}$ represents the fuzzy weight value of the jth criterion to the ith enablers. $\tilde{u}_i$ can be indicated by a triangular fuzzy number, $\widetilde{U}_i = (l, m, u)$.

Step 5: Ranking alternatives. The final fuzzy weight value of each alternative was obtained using the following equation:

$$x(\widetilde{U}_i) = \frac{(l + m + u)}{3}$$

where $l$ represents the minimum value of each triangular fuzzy number, $m$ represents the mean value, and $u$ represents the maximum value.

Table 1 Final ranking of drivers ranking of drivers of deploying industry 4.0

| Category of drivers | Relative weighting | Relative rank | Specific drivers | Relative weighting | Relative rank | Global weighting | Global rank |
|---|---|---|---|---|---|---|---|
| Social | 0.1292 | 3 | Reducing work intensity | 0.4331 | 1 | 0.1178 | 4 |
| | | | Reducing labor headcount | 0.2837 | 2 | 0.0966 | 5 |
| | | | Reducing human exposure to pesticides | 0.0576 | 5 | 0.0208 | 11 |
| | | | Strengthening farmers' agri-tech skills training | 0.0730 | 4 | 0.0287 | 10 |
| | | | Improving work conditions | 0.1526 | 3 | 0.0418 | 8 |
| Environmental | 0.2924 | 2 | Reducing carbon emissions | 0.6688 | 1 | 0.0933 | 6 |
| | | | Reducing groundwater pollution | 0.2276 | 2 | 0.0645 | 7 |
| | | | Reducing waste by controlling resource competition | 0.1036 | 3 | 0.0389 | 9 |
| Economical | 0.5784 | 1 | Enhancing efficiency of water and fertilizer use | 0.4607 | 1 | 0.1998 | 1 |
| | | | Government subsidies for agricultural facilities | 0.0534 | 5 | 0.0194 | 12 |
| | | | Increasing product safety and farms' productivity | 0.2321 | 2 | 0.1377 | 2 |
| | | | Reducing labor costs | 0.1773 | 3 | 0.1225 | 3 |
| | | | Accelerating circular agriculture | 0.0765 | 4 | 0.0183 | 13 |

The fuzzy AHP analysis results (see Table 1) provide some insights into the drivers' contributions to industry 4.0 technology deployment to achieve AFSC sustainability. For example, the economic, environmental, and social categories are ranked first, second, and third, respectively. The results indicate that AFSC practitioners attach the highest priority to achieving economic sustainability by deploying industry 4.0 technologies, whereas social sustainability receives the least attention. Some social phenomena in China indicate that the social dimension of sustainability should be strengthened. One issue is that the current 996 working system requires employees to work from 9am to 9pm, six days per week, and another is that AFSC practitioners do not have the necessary personal protective equipment when using agrichemical products. We also identify that enhancing the efficiency of water and fertilizer use is ranked top among the five drivers in the economic category, reducing carbon emissions has the highest priority among the three drivers in the environmental category, and reducing work intensity is ranked the first in the social category. Our results show that industry 4.0 technologies, such as automatic tractors, water and fertilizer integration systems, intelligent greenhouses,

IoT, remote control systems, and advanced sensors, are relatively effective in helping AFSC practitioners to enhance water and fertilizer use efficiency, reduce employees' work intensity, and reduce carbon emissions.

### C. *TISM to Build Interrelationships between Drivers*

A nine-step TISM process was applied in this study:

Step 1: Identification and definition of drivers. This step involved identifying and defining the drivers to be modeled. The 13 drivers identified through thematic analysis were used as inputs into the TISM process.

Step 2: Determination of contextual relationships between drivers. In building interrelationships, a contextual relationship between two drivers was defined as "driver A will achieve or enhance driver B."

Step 3: Interpretation of relationships between drivers. Two experts who had collaborated with the agri-food industry for more than 30 years were involved in determining whether "driver A will achieve or enhance driver B." If the experts confirmed that a relationship existed between drivers, a further question was asked: "In what way will driver A help to achieve or enhance driver B."

Step 4: Interpretive logic of pair-wise comparisons between drivers. We developed an interpretive logic-knowledge base comprising 156 rows based on pair-wise comparisons of the 13 identified drivers.

Step 5: Formulation of final reachability matrix and transitivity test. Based on the interpretive logic-knowledge base, we formulated an initial reachability matrix by entering 1 in the respective cell to represent a relationship between two drivers, and 0 to represent no relationship. We then ran a transitivity check to transform the initial reachability matrix into the final reachability matrix using the transitivity rule: if driver A relates to driver B, and driver B relates to driver C, driver A necessarily relates to driver C. The final reachability matrix of drivers is shown in Table 2.

Table 2 Final reachability matrix of drivers

| Drivers | S1 | S2 | S3 | S4 | S5 | E1 | E2 | E3 | C1 | C2 | C3 | C4 | C5 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **S1** | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **S2** | 0 | 1 | 0 | 0 | 0 | 0 | 1* | 0 | 0 | 0 | 1 | 1 | 0 |
| **S3** | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **S4** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 |
| **S5** | 1 | 1 | 1* | 0 | 1 | 1 | 1 | 1* | 1 | 0 | 1 | 1 | 1* |
| **E1** | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **E2** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| **E3** | 1* | 1* | 1* | 0 | 1* | 1 | 1 | 1 | 1 | 0 | 1* | 1* | 1 |
| **C1** | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 0 |
| **C2** | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **C3** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 |
| **C4** | 0 | 1 | 0 | 0 | 0 | 0 | 1* | 0 | 0 | 0 | 1* | 1 | 0 |
| **C5** | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1* | 1 | 0 | 1 | 1 | 1 |

Step 6: Determining levels by partitioning the reachability matrix. The antecedent and reachability sets of the final reachability matrix were used as a basis to determine the level of each driver. The level partitioning process was performed until the levels of all drivers had been determined.

Step 7: Digraph development. We developed a digraph by arranging all the drivers into their respective levels, drawing direct links according to the relationships shown in the final reachability matrix and depicting significant transitive links with dotted lines.

Step 8: Interpretive matrix. We developed a binary interaction matrix by translating all interactions in the digraph into 1 in the respective cell. We then selected appropriate interpretations from the knowledge base to interpret the relationships between drivers.

Step 9: Total interpretive structural model. We built a TISM model to demonstrate interrelationships between the drivers (see Figure 1).

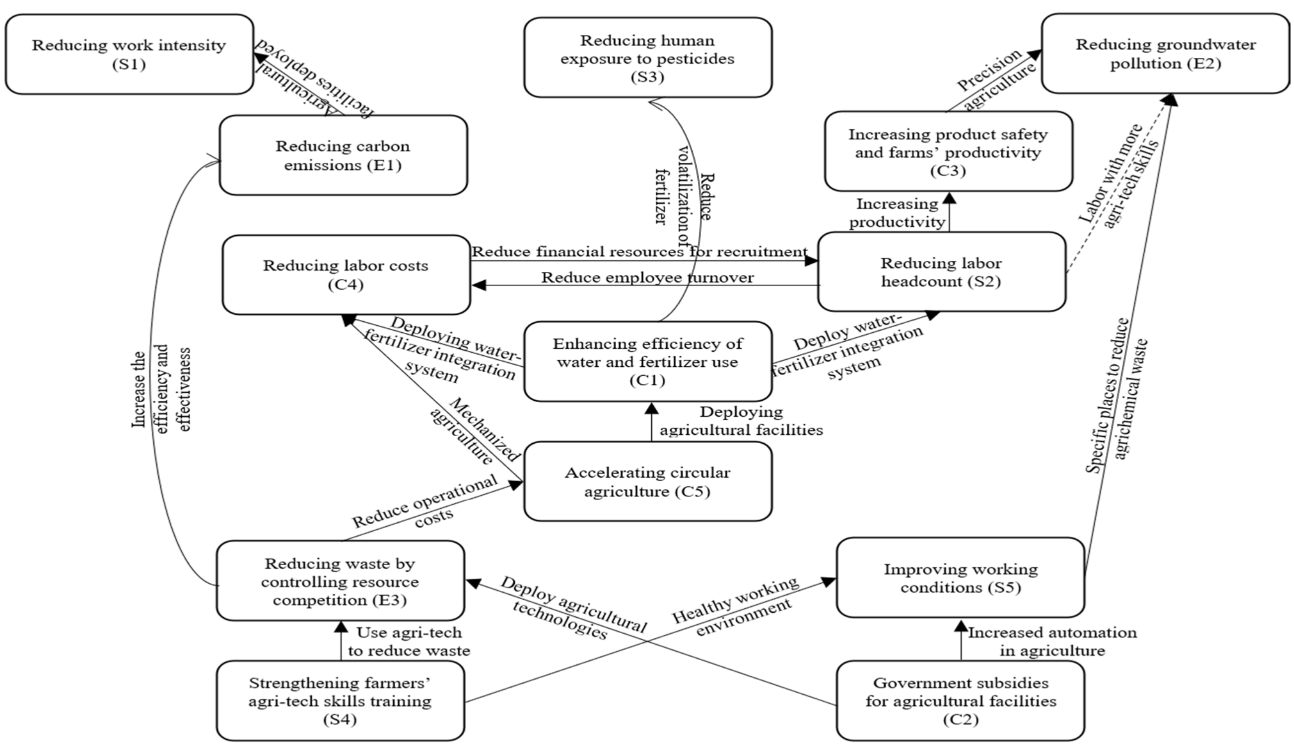


Figure 1 TISM model of drivers

The analysis resulted in a seven-level TISM model. Drivers located at lower levels of the model have greater ability to elicit other drivers, while drivers at higher levels have less ability to do so. Strengthening farmers' agri-tech skill training (S4) and government subsidies for agricultural facilities (C2) occupy level VII of the model, reducing work intensity (S1), reducing human exposure to pesticides (S3), and reducing groundwater pollution are located in level I, and the remaining eight drivers are distributed from levels II to VI. Government subsidies for agricultural facilities (C2) play an important role in enabling agricultural practitioners to increase productivity. For example, subsidy levels can reach 35% if agricultural practitioners promote and apply intelligent, high-end agricultural machinery. Relevant agri-tech skills training is also critical for successful adoption of advanced intelligent agricultural technologies, particularly for big farmers with more than 200 or 300 acres of land for production. Agricultural subsidy policies and relevant agri-tech skills training facilitate the application of agricultural machinery, thereby improving working conditions (S5) and reducing waste by controlling resource competition (E3). In its Thirteenth Five-Year Plan, the Chinese government proposed resource controls, carbon dioxide emissions reduction, and more efficient agricultural production. Accordingly, agrarian practitioners have deployed intelligent agricultural machinery and facilities to accelerate circular agriculture processes (C5), such as deploying water-fertilizer integration systems, drip irrigation systems, advanced sensors (e.g., light, humidity, carbon dioxide, and irrigation monitoring), and intelligent greenhouses to enhance efficiency of water and fertilizer use (C1). This has reduced labor costs (C4) and labor headcount (S2). With the application of industry 4.0 agriculture-related technologies, product safety and farms' productivity have been improved. For example, using advanced sensors and water-fertilizer integration systems enable more precise fertilization. As one of our interviewees stated, "*more than 70% of water saving and a certain level of sustainability can be achieved. Additionally, fertilizing plants precisely can avoid underground seepage pollution.*" Thus, groundwater pollution can be avoided or alleviated (E2). Other benefits, such as reducing human exposure to pesticides (S3), reducing carbon emissions (E1), and reducing work intensity, can also be achieved by deploying industry 4.0 agricultural related technologies.

### *D. Fuzzy MICMAC to Identify the Role of Each Driver*

Three steps were undertaken in the fuzzy MICMAC analysis.

Step 1: Obtaining a binary direct relationship matrix (BDRM). A BDRM was obtained by ignoring transitivity and converting the diagonal entries into zeros from the final reachability matrix.

Step 2: Building a fuzzy direct relationship matrix (FDRM). The two experts involved in interpreting relationships between pairs of drivers were asked to re-rate these relationships by assigning numerical values: 0 – no relationship, 0.1 – very low, 0.3 – low, 0.5 – medium, 0.7 – high, 0.9 – very high, and 1 – absolute relationship. These values were then superimposed on the BDRM to obtain the FDRM.

Step 3: Building a fuzzy MICMAC stabilized matrix (FMSM). The driving power and dependence power of each driver were obtained by building an FMSM. According to fuzzy set theory, when two fuzzy matrices are multiplied, the outcome is still a fuzzy matrix. Thus, we repeated the matrix multiplication process until the driving power and dependence power of each driver were constant. The following equation was used to calculate the FMSM:

$$C = A,B = [\max k(\min(a_{ik}, b_{kj}))], \text{ where } A = [a_{ik}] \text{ and } b = [b_{kj}]$$

Based on the fuzzy MICMAC analysis, we clustered the drivers into four categories based on their role in the system, as shown in Figure 2.

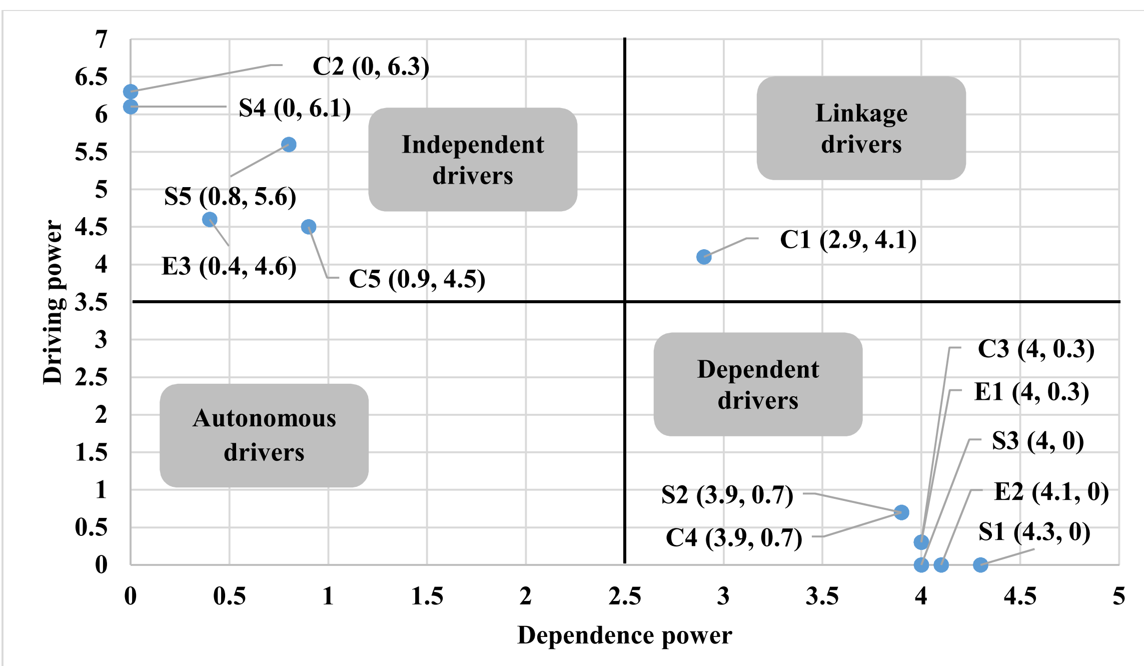


Figure 2 Fuzzy MICMAC analysis of drivers

Independent drivers, which act as drivers of the system, are characterized by high driving power and low dependence power. We identified five independent drivers of industry 4.0 technology deployment to achieve AFSC sustainability: government subsidies for agricultural facilities (C2), strengthening farmers' agri-tech skills training (S4), improving working conditions (S5), reducing waste by controlling resource competition (E3), and accelerating circular agriculture (C5). Amongst these, government subsidies for agricultural facilities (C2) and strengthening farmers' agri-tech skills training (S4) are critical drivers, as they have relatively high driving power and are located at the lowest level of the TISM hierarchy.

Linkage drivers, which act as links in the system, are characterized by relatively high driving and dependence power. For example, enhancing efficiency of water and fertilizer use (C1), located in the middle level of the TISM model and acts as a linkage between independent and dependent drivers. Developed countries such as the USA and the Netherlands have 70% agrichemical use efficiency, China's is only 50%. Therefore, most industry 4.0 agriculture-related technologies are deployed to increase the efficiency of water and fertilizer use, such as water-fertilizer integration systems, drip irrigation systems, advanced sensors, and IoT.

Autonomous drivers, characterized by low driving and dependence power, are considered to have few connections with the system. No autonomous drivers were identified in this study because all 13 drivers contribute to AFSC sustainability. For example, the fuzzy AHP results show that enhancing efficiency of water and fertilizer use makes the greatest contribution, and accelerating circular agriculture the least.

Dependence drivers, characterized by low driving power and high dependence power, depend on other drivers to achieve them. In this study, seven dependence drivers were identified: reducing work intensity (S1), reducing labor headcount (S2), reducing human exposure to pesticides (S3), reducing carbon emissions (E1), reducing groundwater pollution (E2), increasing product safety and farms' productivity (C3), and reducing labor costs (C4). Clearly, it is impossible to achieve these dependence drivers without government subsidies and agri-tech training.

### E. Discussion

We identify 13 drivers of industry 4.0 technology deployment to achieve AFSC sustainability. Compared with empirical findings in the literature, the majority of the drivers identified in this study are new, and thus contribute to knowledge of the impact of industry 4.0 technologies on AFSC sustainability. For example, an extant systematic review of the literature [2] identifies that industry 4.0 can contribute to various sustainability values, such as efficient energy use, waste reduction, food safety, circular economy performance, resource allocation, and a good working environment. Our empirical findings partially support the literature. For example, we identify that industry 4.0 technology deployment may contribute to achieving AFSC sustainability by accelerating circular agriculture, increasing product safety and farms' productivity, improving work conditions, and enhancing water and fertilizer use efficiency. A previous study [12] proposes that industry 4.0 technologies may contribute to enhanced production efficiency and productivity, operational efficiency, and improved responsiveness and revenue growth. Our empirical research produces different results. We presume that our findings differ from those of most studies focusing on the impact of industry 4.0 technologies on AFSC sustainability for two reasons. First, frequently discussed industry 4.0 technologies, such as artificial intelligence, blockchain, additive manufacturing, and big data analytics technologies, are seldom deployed in AFSCs in China because applying these technologies significantly increases the costs of terminal logistics. As one of our interviewees stated, "*when the internet of things or blockchain is deployed in rural areas, the logistics cost at the end is too high.*" The industry 4.0 technologies frequently used in AFSCs in China are water-fertilizer integration systems, intelligent greenhouses, mobile applications, advanced sensors, and global positioning systems. Second, the Chinese government has imported some digital agricultural technologies from the Netherlands and Israel, but regional differences in light, heat, soil, and humidity mean that these technologies cannot be fully applied. Thus, the environmental context means that our results differ from others.

This study prioritizes drivers of industry 4.0 technology deployment to achieve AFSC sustainability. A previous study [12] indicates that cross-functional collaboration and continuous monitoring of cost and performance are two key drivers of transiting to a sustainable supply chain using industry 4.0 technologies. However, our findings show that enhancing efficiency of water and fertilizer use and increasing product safety and farms' productivity are key drivers in our context. Another study [13] highlights three drivers of industry 4.0 deployment for sustainability in manufacturing supply chains in India: reducing emissions (environmental category), increasing productivity (economic category), and non-invasive interactions (social category). Our study partially supports those results by confirming the top rankings of reducing work intensity (social category), reducing carbon emissions (environmental category), and enhancing efficiency of water and fertilizer use (economic category).

Finally, our study reveals that government subsidies for agricultural facilities and strengthening farmers' agri-tech skills training are critical in enabling AFSC practitioners to achieve sustainability using industry 4.0 technologies. A previous study [14] identifies 13 drivers that are important for achieving supply chain sustainability, but does not identify key drivers. Another study [15] highlights supportive government policies and collaboration and transparency among supply chain members as two key drivers of industry 4.0 technology application that differ from our findings; and another study [3] identifies the four most influential drivers as overcoming operational challenges, speeding up operations, saving costs and improving profits, but does not provide insights into the agri-food industry. Applying industry 4.0 technologies to achieve AFSC sustainability requires not only government subsidies, but also appropriate agri-tech skills training for farmers, since most farmers in China are elderly, with less willingness to learn new knowledge or skills.

## V. CONCLUSIONS AND RECOMMENDATIONS

In this study, we deployed a hybrid approach to investigate drivers of industry 4.0 technology deployment to achieve AFSC sustainability. First, we employed semi-structured interviews and thematic analysis to identify 13 drivers. These drivers were then used as inputs into fuzzy AHP, TISM, and fuzzy MICMAC analysis. Our results show that deploying industry 4.0 technologies in AFSCs can contribute to sustainability in various ways, including reducing water and fertilizer use (economic perspective), reducing carbon emissions (environmental), and reducing work intensity (social). We also identify a potential pathway for AFSC practitioners to deploy industry 4.0 technologies more effectively to achieve AFSC sustainability. Governments should offer subsidies for agricultural facilities, and agri-businesses should strengthen farmers' agri-tech skills training.

### A. *Limitations and Future Research Directions*

This study has some limitations. First, it analyzes the drivers of industry 4.0 technology deployment to achieve AFSC sustainability, but does not analyze barriers preventing AFSC practitioners from doing so. A comprehensive understanding of drivers and barriers might help AFSC practitioners to deploy industry 4.0 technologies more effectively. Thus, we propose using our methodology to analyze barriers.

Second, we collected empirical data from China, and mainly from two provinces, Henan and Shandong. Other provinces may have different soil and climate conditions, and so may use different industry 4.0 technologies to achieve ASFC sustainability, potentially limiting the generalizability of our findings [16]. Future research might examine more provinces in other geographical locations with different climate and soil conditions.

Third, we conducted interviews with 24 AFSC practitioners. However, the sample size may not be enough to have an in-depth understanding of the phenomenon investigated. According to [17], 30 interviews are adequate to understand a social phenomenon. Thus, more interviews should be integrated into future research.


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