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Digital-Intelligent Barriers to Resource Re-extraction in China′s Agrifood Manufacturing

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Abstract

China′s agrifood manufacturing sector produces millions of tons of organic and packaging waste annually, creating an urgent need for circular production models. Resource re-extraction (RE), the digital-enabled recovery of nutrients and materials from waste streams, offers a pathway toward sustainable value creation. However, its adoption remains limited despite strong policy incentives. Understanding why this resistance persists is critical for advancing the digital-intelligent circular economy agenda. This study addresses that gap by examining how cognitive barriers shape Resource Re-extraction Resistance (RRER), with a focus on identifying which obstacles carry the most weight in an emerging economy context. Drawing on Innovation Resistance Theory (IRT), we surveyed 256 agrifood manufacturers across multiple Chinese provinces and applied partial least squares structural equation modelling (PLS-SEM) to test the hypothesised barrier – resistance relationships. The model was evaluated using reliability, convergent and discriminant validity, and collinearity diagnostics, ensuring robust measurement quality. Structural analysis revealed that risk barriers exert the strongest influence on RRER, followed by image barriers and usage barriers, while tradition and value barriers had no significant effect. These results imply that resistance is driven more by concerns over operational failure, brand reputation, and process complexity than by cultural attachment or perceived return on investment. In response, we propose targeted digital-intelligent solutions such as AI-driven process simulation to mitigate perceived risks, blockchain-enabled traceability to safeguard brand image, and AR/VR-based training to lower complexity in implementation. By linking barrier diagnosis with technology-enabled management strategies, this research advances theoretical applications of IRT in industrial sustainability and provides actionable guidance for accelerating the circular transition in emerging markets.

Keywords: Resource Re-extraction Resistance; Circular Economy; Digital Barriers; Agrifood Manufacturing; Industry 4.0

1. Introduction

China's agrifood manufacturing sector is a formidable economic engine that also exerts significant environmental pressure. In 2019, food-related production, processing, packaging, and waste disposal collectively accounted for approximately 13.5% of China's total greenhouse gas emissions, reflecting the scale of the industry's environmental impact (Sandalow et al., 2022). Although official national data on waste tonnage is limited, industry reports estimate that hundreds of millions of tonnes of agricultural residues, livestock by-products, and packaging waste are generated each year (China-Italy Chamber of Commerce, 2022). When mismanaged, these waste streams contribute significantly to environmental degradation by releasing greenhouse gases, reducing soil fertility, and accelerating nutrient-driven eutrophication in surface waters (Abate et al., 2024). Nevertheless, research in Zhejiang's Huangyan region highlights the latent resource potential embedded in these waste streams—showing that theoretical recovery of nitrogen and phosphorus from tangerine and water bamboo residues could replace up to 59% of nitrogen and 15% of phosphorus fertilizer inputs, reinforcing resource re-extraction's promise for supply chain resilience and circular economy development (Santolin et al., 2024).

Resource re-extraction (RE) describes the process of retrieving these secondary resources from waste through specialized technological interventions. The integration of digital-intelligent technologies such as IoT-enabled monitoring, AI-driven process optimization, and robotic automation has further expanded the feasibility and efficiency of RE. Beyond improving recovery rates, these technologies generate operational data that support better traceability, predictive maintenance, and real-time quality assurance (Ellen MacArthur Foundation, 2021). Recent advancements in AI and digital twin technologies have further enhanced the capacity of agrifood manufacturers to simulate operational changes, reduce perceived risks, and optimize resource recovery processes (Ali et al., 2025; Meng & Li, 2025; R. Zhang et al., 2025).

In recognition of these opportunities, China has institutionalized RE within its broader circular economy framework through pivotal legislation and planning initiatives. The Circular Economy Promotion Law, enacted in 2009, explicitly mandates the reuse and comprehensive utilization of agricultural and industrial by-products, and includes incentives such as fiscal and technological support for recycling and waste recovery (Ministry of Ecology and Environment of the People's Republic of China [MEE], 2009). More recently, the 14th Five-Year Plan for Circular Economy Development (2021–2025), issued by the National Development and Reform Commission, advances this agenda by emphasizing enhanced recycling of agricultural materials, the construction of rural recycling infrastructure, and the expansion of biomass energy systems, with financial incentives and infrastructure support for agrifood sustainability (China Briefing, 2021).

Despite these favorable policies, adoption of RE practices remains uneven across agrifood manufacturers. Many firms perceive RE systems as financially risky, operationally disruptive, or possibly detrimental to brand image, especially in settings where consumer trust in food safety is paramount. This misalignment between policy intent and ground-level adoption underscores the urgency of examining the cognitive and organizational barriers that obstruct RE uptake.

The majority of existing research on RE adoption originates from developed economies with mature regulatory environments and digital infrastructure (Geissdoerfer et al., 2017; Kirchherr et al., 2018). In the Chinese context, leading studies on RE have typically concentrated on technical performance indicators such as nutrient recovery efficiencies and economic feasibility through cost-benefit analyses while largely overlooking the underlying behavioral and cognitive factors that influence organizational adoption decisions (Li et al., 2021; Xia & Ruan, 2020). Furthermore, while the literature on innovation resistance in manufacturing is well established, few studies have explored how digital-intelligent technologies could strategically target and reduce these barriers in a circular economy setting.

While China has made significant policy commitments to advancing a circular economy, the agrifood manufacturing sector still faces mounting sustainability and security pressures. A strategic 10-year initiative underscores the state's commitment to food resilience, yet rising waste volumes, nearly 27% lost across the supply chain, rivet this urgency (Dong et al., 2024; Reuters, Apr 7 2025) . The agrifood system transformation itself introduces new stressors, such as growing demand for feed and meat, greater reliance on imports, and the balancing act between food production and environmental goals (Zhao et al., 2023) . Compounding these dynamics, agriculture accounts for nearly 19% of China's greenhouse gas emissions, intensifying the challenge of safeguarding food security within climate-targeted transitions (China Daily, Jul 31 2025) . The persistence of adoption resistance amid these pressures not only slows progress toward a digital-intelligent circular economy but directly threatens the long-term sustainability and resilience of China's food systems. Against this backdrop, this study advances both theory and practice in three distinctive ways. Contextually speaking, It applies Innovation Resistance Theory (IRT) (Ram & Sheth, 1989) to an emerging economy agrifood sector, a context characterized by different institutional pressures, cultural norms, and digital maturity levels compared to developed economies. Theoretically speaking, it integrates digital-intelligent solution pathways such as AI-based risk modeling, blockchain-enabled traceability, and augmented reality (AR) operational guidance directly into the conceptualization of barrier mitigation, bridging the gap between resistance theory and Industry 4.0 applications. Empirically speaking, it employs partial least squares structural equation modelling (PLS-SEM) analysis on a cross-regional sample of 256 Chinese agrifood manufacturers, offering a robust empirical basis for ranking the influence of different cognitive barriers on RE adoption resistance. By doing so, the research not only clarifies the hierarchy of barriers in a real-world industrial context but also aligns these insights with digital-intelligent management strategies that can accelerate circular economy transitions.

Overall, this study contributes to digital economy scholarship by showing how cognitive resistance factors interact with digital-intelligent management interventions in shaping technology adoption. It also informs policy design by identifying which barriers require targeted support measures and which are less influential in the current Chinese agrifood manufacturing environment. The study addresses the following research question: What cognitive barriers significantly influence resource re-extraction resistance in China's agrifood manufacturing sector, and what digital-intelligent technologies can be leveraged to mitigate them?

This question serves as the foundation for this study and outlines the following sections. Section 2 discusses the theoretical framework and hypotheses, where we define each barrier, derive our hypotheses, and link them to potential digital-intelligent management solutions. Section 3 describes the methodology used in this study, followed by the results and analysis in Section 4. Section 5 discusses the major findings and answers the research question. Section 5 concludes this study by showing its implications, contributions, limitations, and future research suggestions.

2. Theoretical Framework and Hypotheses

Innovation adoption in industrial contexts rarely depends solely on technical feasibility or policy alignment; rather, it is mediated by a range of organizational, cognitive, and cultural factors that can significantly delay or derail implementation (Menichini et al., 2024; Sharma et al., 2025). For China's agrifood manufacturers, the decision to integrate resource re-extraction (RE) technologies must be evaluated not only in terms of cost-benefit outcomes but also through the lens of perceived risks, operational compatibility, and stakeholder perception. Understanding these resistance drivers is critical because they directly influence the pace and scale of circular economy adoption, regardless of regulatory incentives.

To systematically capture and analyze these drivers, this study employs Innovation Resistance Theory (IRT) as its conceptual foundation. IRT provides a structured way to categorize and measure the distinct psychological and functional barriers that can hinder technology uptake (Kaur et al., 2020). In adapting IRT to the context of digital-intelligent RE, we not only identify the barriers but also consider how emerging Industry 4.0 tools can actively counteract them. The following subsections outline how IRT is applied in this research, define each barrier construct, and develop hypotheses for empirical testing.

2.1. Innovation Resistance Theory in a Digital-Circular Economy Context

Innovation Resistance Theory (IRT), first articulated by Ram and Sheth (1989), posits that adoption of new technologies is not simply a function of perceived benefits but is often hindered by various functional and psychological barriers. These barriers arise when the innovation disrupts existing processes, challenges established norms, or introduces uncertainties that exceed an adopter's tolerance threshold.

In the context of digital-enabled resource re-extraction (RE), IRT offers a valuable analytical lens for understanding why Chinese agrifood manufacturers, despite technical feasibility and policy support, still resist adoption. The decision to adopt RE systems often requires altering established workflows, reconfiguring supply chains, and committing financial resources to unproven technology, all of which can trigger resistance (Aktaş et al., 2021; Zhao et al., 2024a).

This study adapts IRT to the digital-circular economy by integrating Industry 4.0 tools like digital twins, IoT, and blockchain as potential countermeasures to the barriers identified. In this way, it helps to test IRT's explanatory power in a novel agrifood manufacturing setting and demonstrate how specific technologies can address distinct resistance barriers (Zhao et al., 2024a; Zhao et al., 2024b).

2.2. Conceptualizing Resource Re-extraction Resistance (RRER)

For this study, Resource Re-extraction Resistance (RRER) refers to the degree to which agrifood manufacturers demonstrate reluctance, whether overt or implicit, toward adopting technological solutions for recovering secondary materials from waste streams. RRER encompasses unctional concerns, such as operational fit, cost-effectiveness, and supply chain integration, and psychological factors, including brand image, consumer perception, and cultural preferences (Heidenreich & Kraemer, 2016; Talwar et al., 2021).

In China's agrifood manufacturing sector, these resistance dynamics are shaped by historical risk aversion linked to food safety incidents, the complexity of production processes, and the dominance of low-margin operational models that prioritize short-term cost control over long-term sustainability investments (Bleischwitz et al., 2022; Farooque et al., 2019). Even when RE technologies are technically viable and supported by policy incentives, adoption may be hampered if perceived risks outweigh anticipated returns (Laukkanen, 2016).

2.3. Defining and Linking the Barriers

Having established the conceptual definitions and interrelationships of the five barriers, it is now essential to examine each in greater depth. This allows us to unpack the mechanisms through which they may influence resistance to RE adoption in the agrifood manufacturing context. We begin with the risk barrier, which, given the sector's operational sensitivities and the preliminary results of prior research, is expected to exert a particularly strong influence.

2.3.1. Risk Barrier (RB)

The risk barrier arises from the perception that an innovation could lead to financial losses, operational inefficiencies, or reputational harm (Heidenreich & Kraemer, 2016). In RE, these risks may be heightened by uncertainties surrounding equipment reliability, regulatory compliance, product quality, and market acceptance (Bleischwitz et al., 2022; Farooque et al., 2019). In China's agrifood sector where past food safety incidents have intensified managerial risk aversion (Despoudi et al., 2025; Reitano et al., 2024), perceived vulnerability to operational failure or public backlash can deter adoption. As a potential mitigation strategy, AI-driven digital twins can model RE processes under varying operational scenarios, enabling firms to forecast performance outcomes and identify possible points of failure before physical implementation (Ball & Badakhshan, 2022; Javaid et al., 2023). Hypothesis 1 is proposes as follows.

H1: The risk barrier has a positive and significant effect on RRER.

2.3.2. Image Barrier (IB)

The image barrier reflects the extent to which an innovation is seen as misaligned with a firm's desired brand image or public reputation (Rogers, 2003). For agrifood manufacturers, adopting RE might be misconstrued as an admission of excessive waste generation or potential contamination risks, especially if stakeholders misunderstand the technology's purpose

(Despoudi et al., 2025) . In China's consumer market where brand trust is fragile, these perceptions can significantly shape managerial decisions. Digital solutions such as blockchain-enabled traceability can counteract such concerns by providing verifiable proof of sustainable practices, reframing RE adoption as a brand-enhancing innovation rather than a reputational liability (Saberi et al., 2019). Hypothesis 2 is proposed as below.

H2: The image barrier has a positive and significant effect on RRER.

2.3.3. Usage Barrier (UB)

The usage barrier emerges when a new technology is perceived as complex, requiring significant changes in routines or extensive training (Ram & Sheth, 1989) . For RE, these challenges may involve integration with existing production lines, new waste segregation protocols, and advanced data management systems (Chauhan et al., 2022; Vahdanjoo et al., 2025) . Such perceptions can slow adoption, particularly in small and medium-sized enterprises with limited technical capacity. Immersive training tools such as augmented reality (AR) and virtual reality (VR) can reduce perceived complexity by enabling hands-on simulations that simplify the learning process (Masood & Egger, 2019). Hypothesis 3 is proposed as below.

H3: The usage barrier has a positive and significant effect on RRER.

2.3.4. Tradition Barrier (TB)

The tradition barrier reflects resistance rooted in cultural norms, habitual practices, and organizational inertia (Talwar et al., 2021). In the agrifood industry, some firms may prefer long-standing waste disposal methods even when these are environmentally suboptimal due to perceived reliability and familiarity (Okaibedi Eke et al., 2024). While China's efficiency-driven manufacturing culture may reduce the weight of tradition compared to other contexts, it can still limit openness to process innovations. Digital tools such as gamified training and knowledge-sharing platforms can gradually shift organizational norms, although the effect may be weaker where performance metrics dominate decision-making. Hypothesis 4 is proposed accordingly.

H4: The tradition barrier has a positive and significant effect on RRER.

2.3.5. Value Barrier (VB)

The value barrier arises when the perceived return on investment (ROI) of an innovation is insufficient to justify its adoption (Laukkanen, 2016) . For RE, this could involve doubts about the market value of recovered materials, payback periods, or overall cost savings (Masi et al., 2017) . In China's agrifood sector where profit margins are often thin, such concerns may be particularly influential. Predictive analytics can enhance perceived value by modeling long-term cost savings, identifying secondary revenue streams, and quantifying the strategic benefits of adopting RE technologies (Tseng et al., 2020). Hypothesis 5 is thereby proposed.

H5: The value barrier has a positive and significant effect on RRER.

2.4. Proposed Research Model

Figure 1 depicts the conceptual model tested in this study. Each barrier is hypothesized to positively influence RRER, with the relative strength of these relationships revealing a barrier hierarchy. By examining these links, the study identifies where digital-intelligent interventions can have the most impact, thereby operationalizing IRT within a digital-circular economy framework.

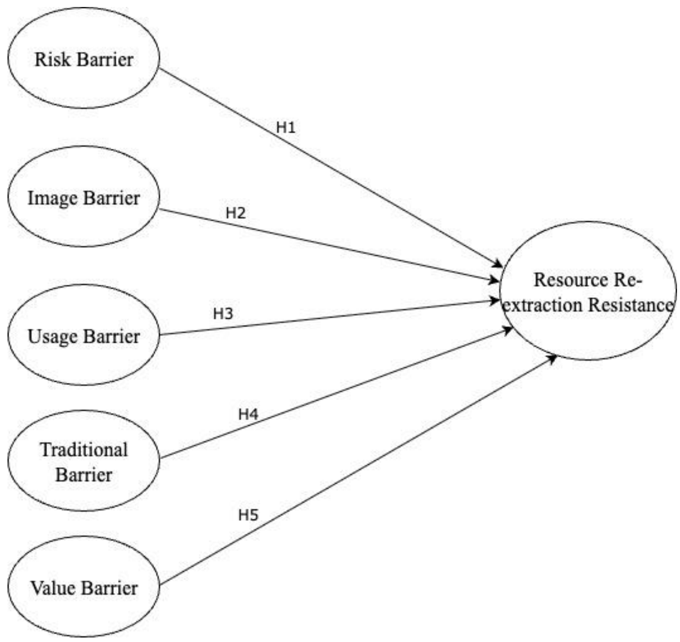

Figure 1. Conceptual Framework

3. Methodology

Having established the theoretical underpinnings and hypotheses in Section 2, the next step is to empirically test the proposed model using reliable contextually relevant data. The methodological design is informed by the dual need to capture nuanced perceptions of cognitive barriers among agrifood manufacturers and apply an analytical approach that can handle the predictive and explanatory aims of the study.

3.1. Research Design

This research adopts a cross-sectional survey design, which is well suited to examining perceptions and attitudes across a broad geographically dispersed sample (Creswell & Creswell, 2018) . While longitudinal designs can track changes over time, a cross-sectional approach provides a robust snapshot of current resistance patterns, particularly valuable in a sector undergoing active policy and technological change.

3.2. Sampling and Data Collection

The study targeted 256 agrifood manufacturing firms across seven major regions in China, selected through stratified random sampling to ensure diversity in sub-sectors and firm sizes. Provinces were chosen to capture regional variations in industrialization levels and policy enforcement intensity. From June to October 2024, data were collected via structured questionnaires distributed both electronically and in person, with follow-up calls to increase response rates. Respondents were typically senior operations managers or sustainability officers, as these roles hold decision-making authority over technology adoption. To minimize social desirability bias, the survey assured anonymity and emphasized that there were no “right” or “wrong” answers.

3.3. Measurement Development

The constructs were operationalized using 5-point Likert scales (1 = strongly disagree, 5 = strongly agree), adapted from established innovation resistance measures (Heidenreich & Kraemer, 2016; Ram & Sheth, 1989) and tailored to the RE context. Each barrier construct, risk, image, usage, tradition, and value, was measured using four to five items, while RRER was measured using four items assessing reluctance to adopt RE technologies. Pilot test was conducted with 19 industry practitioners and three academic experts in industrial management to refine wording and ensure cultural and sectoral relevance. Minor adjustments were made to clarify technical terms and align with Chinese manufacturing practices.

3.4. Data Analysis Method

Partial Least Squares Structural Equation Modeling (PLS-SEM) was selected for three reasons:

Prediction-oriented focus: The study aims to identify which barriers have the greatest predictive power for RRER (Hair, 2019).

Model complexity: The framework includes multiple latent variables, each with reflective measurement models, requiring an approach that can handle multicollinearity and smaller sample sizes.

Adaptation of theory: As this is among the first applications of IRT in the digital-circular economy context of China’s agrifood sector, PLS-SEM’s flexibility makes it suitable for theory extension and model refinement.

Analysis was conducted using SmartPLS 4, which offers advanced bootstrapping and predictive relevance testing capabilities.

3.5. Analytical Procedure

The analysis proceeded in three stages. The first stage is for the measurement model assessment through testing for reliability (Cronbach’s α, composite reliability), convergent validity (average variance extracted, AVE), and discriminant validity (Fornell–Larcker criterion). The second stage is for the structural model assessment by estimating path coefficients, significance levels (t-values, p-values), and effect sizes (f^2). The third stage is for the predictive relevance testing by using Q^2 statistics from blindfolding procedures to determine the model’s predictive validity. The methodological rigor outlined here ensures that the empirical findings are statistically robust and contextually grounded. With the data collection and analytical procedures firmly established, the next section presents the results accordingly.

4. Results

Following the procedures outlined in Section 3, the results are presented in three major parts: (1) demographic and descriptive analyses; (2) measurement model validation, ensuring that the constructs meet the reliability and validity requirements; and (3) structural model assessment, testing the hypothesized relationships and evaluating the predictive strength of the model.

4.1. Demographic Analysis

The demographic profile of surveyed firms provides further context to the resistance patterns (see Figure 2). The largest proportion of respondents came from fruit and vegetable processing companies (18.8%), followed by jam, jelly, and preserve manufacturers (14.1%) and frozen food manufacturers (13.3%). This distribution reflects the strong representation of firms engaged in the processing and preservation of perishable commodities, a sub-sector where waste generation is a notable challenge due to product shelf-life constraints. In addition, a considerable share of participants were organic and natural food brands (11.7%) and juice and beverage manufacturers (10.9%), both of which operate in high-volume production environments where process innovation could substantially impact waste management and RE adoption.

Category	Sub-Category	Frequency (R = 256)	Percentage (%)
Main Industry	Fruit and Vegetable Processing Companies	48	18.8
	Jam, Jelly, and Preserve Manufacturers	36	14.1
	Frozen Food Manufacturers	34	13.3
	Organic and Natural Food Brands	30	11.7
	Juice and Beverage Manufacturers	28	10.9
	Sauce and Condiment Producers	15	5.9
	Specialty Food Producers	14	5.5
	Culinary and Artisanal Food Producers	12	4.7
	Private Label and Contract Manufacturers	12	4.7
	Distribution and Retailers	12	4.7
	Dried Fruit and Nut Companies	6	2.3
	Others	5	2.0
	Pickling and Fermentation Companies	4	1.6
Years Established	6 – 10 years	113	44.1
	Less than 5 years	107	41.8
	11 – 20 years	28	10.9
	21 – 30 years	6	2.3
	More than 30 years	2	0.8
Total Employee Size	51 - 100 employees	94	36.7
	101 - 500 employees	64	25.0
	Less than 50 employees	58	22.7
	501 - 1000 employees	32	12.5
	More than 1000 employees	8	3.1
Annual Revenue (CNY)	Less than RMB30 million	103	40.2
	RMB30 million – RMB50 million	83	32.4
	RMB50 million – RMB100 million	52	20.3
	More than RMB100 million	18	7.0
Ownership Status	Private	180	70.3
	State-owned	26	10.2
	Shareholding	25	9.8
	Foreign invested	24	9.4
	Others	1	0.3
Firm Location	East China	88	34.4
	South China	46	18.0
	Central China	44	17.2
	North China	36	14.1
	Northeast China	18	7.0
	Southwest China	17	6.6
	Northwest China	7	2.7
Monthly food waste generated	6-10 tons	109	42.6
	Less than 5 tons	80	31.3
	11-20 tons	44	17.2
	21-30 tons	18	7.0
	31-40 tons	5	2.0

Figure 2. Distribution of Firm Profile

In terms of business maturity, nearly half of the firms had been established for 6 to10 years (44.1%), and a further 41.8% had been operating for less than 5 years. Only 10.9% had been in business for 11 to 20 years, and less than 3% had operated for more than two decades. This relatively young age profile suggests that the sample is dominated by firms still in their growth or consolidation phases, where investment priorities may be shaped by rapid market adaptation rather than long-term tradition.

Firm size also varied considerably. The most common category was 51–100 employees (36.7%), followed by 101–500 employees (25.0%) and less than 50 employees (22.7%). Larger firms employing over 500 workers accounted for 15.6% of the sample, indicating a mixture of small-to-medium-sized enterprises (SMEs) and larger industrial players. This diversity is important because firm size often influences the resources available for technological adoption and risk mitigation strategies.

In terms of financial capacity, 40.2% reported annual revenues below RMB 30 million, while 32.4% fell into the RMB 30–50 million range. Approximately one-fifth (20.3%) generated between RMB 50–100 million, and only 7% exceeded RMB 100 million in revenue. The predominance of lower-revenue firms suggests that capital constraints could shape perceptions of financial risk associated with RE investments, particularly in digital-intelligent solutions.

Ownership structures were dominated by private enterprises (70.3%), with smaller proportions of state-owned enterprises (10.2%), shareholding companies (9.8%), and foreign-invested firms (9.4%). The dominance of privately-owned companies may indicate a higher sensitivity to cost-benefit considerations and market image.

Geographically, the majority of firms were located in East China (34.4%), reflecting the region's industrial concentration and export-oriented agrifood processing capacity. Other notable clusters were in South China (18.0%) and Central China (17.2%), while the remaining regions had smaller shares, with Northwest China representing just 2.7% of respondents. This regional distribution highlights that the study's results are most representative of industrially developed areas, though inputs from less developed regions add diversity to the dataset.

Finally, the analysis of monthly food waste generation revealed that most firms produced 6–10 tons per month (42.6%), followed by those generating less than 5 tons (31.3%). A smaller share reported waste levels of 11–20 tons (17.2%) or more than 20 tons (less than 10% combined). This waste volume distribution aligns with the industrial scale of respondents and underscores the sector's potential for resource recovery if technological and cognitive barriers can be addressed.

Taken together, this demographic profile indicates a sample characterized by sectoral diversity, relatively young firms, predominance of SMEs, and a strong private ownership base. These characteristics have direct implications for understanding the cognitive barriers to RE adoption: younger, smaller, and privately-owned firms may exhibit higher sensitivity to risk and operational complexity, whereas larger or more established entities may have greater absorptive capacity for innovative digital-intelligent solutions.

4.2. Descriptive Analysis

Table 1 presents the descriptive statistics for the five barrier constructs. Mean scores indicate moderately high perceptions across all barriers, with usage (M = 3.77) ranked highest, followed by value (M = 3.66), image (M = 3.53), risk (M = 3.48), and tradition (M = 3.41). While these descriptive results highlight which barriers are perceived as most salient, their true influence on RRER requires testing through structural modelling, which is presented in the subsequent sections.

Table 1. Descriptive Analysis of Barrier Constructs

Construct	Mean	SD	Interpretation
Risk Barrier (RB)	3.48	1.101	High perceived uncertainty in financial/operational outcomes
Image Barrier (IB)	3.53	1.023	High concern over brand and market perception
Usage Barrier (UB)	3.77	0.887	Operational complexity and training burden highly significant
Value Barrier (VB)	3.66	0.935	High skepticism on ROI
Tradition Barrier (TB)	3.41	1.08	High attachment to legacy production habits

4.3. Measurement Model Validation

Table 2 reports the reliability and validity statistics for all constructs. Internal consistency was confirmed, with Cronbach's α values exceeding the 0.70 benchmark (Hair et al., 2010; Nunnally & Bernstein, 1995) for all constructs. Composite reliability (CR) scores were also above the 0.70 threshold, indicating that each construct's items consistently reflect their underlying latent variable. Convergent validity was supported, as the Average Variance Extracted (AVE) for all constructs exceeded 0.50 (Fornell & Larcker, 1981), confirming that the majority of variance in the indicators was explained by the respective constructs. Collinearity diagnostics revealed Variance Inflation Factor (VIF) values well below the critical value of 5 (Hair et al., 2019), with the exception of two items in the Usage Barrier construct (UB3 and UB5), which approached cautionary levels (4.237 and 4.136, respectively). Although these values remain within acceptable limits, they suggest a degree of redundancy between items. Retaining them is justified on theoretical grounds to preserve construct validity; however, this issue is acknowledged as a limitation. Future studies may refine these measures, consider formative approaches, or test item reduction strategies to minimize multicollinearity risk while maintaining robust construct representation.

Table 2. Measurement model evaluation

Construct	Items	Loadings	Cronbach's α	CR	AVE	VIF range
RRER	4	0.709–0.799	0.746	0.84	0.567	1.237–1.621
Risk Barrier (RB)	4	0.723–0.779	0.746	0.839	0.566	1.428–1.627
Image Barrier (IB)	5	0.789–0.874	0.897	0.924	0.709	2.059–3.794
Usage Barrier (UB)	4	0.692–0.840	0.794	0.866	0.62	1.413–4.237
Value Barrier (VB)	4	0.775–0.819	0.818	0.878	0.643	1.510–3.643
Tradition Barrier (TB)	4	0.818–0.897	0.865	0.908	0.712	1.745–2.837

The Fornell–Larcker criterion confirmed discriminant validity: the square root of each construct's AVE was greater than its correlations with other constructs. This suggests that the measures are empirically distinct and that multicollinearity is not a critical issue in the model.

4.4. Structural Model Results

Table 3 presents the structural path coefficients, t-values, p-values, effect sizes (f^2), and predictive relevance (Q^2). Hypotheses H1, H2, and H3 were supported, while H4 and H5 were not.

The Risk Barrier (H1) emerged as the strongest predictor of RRER ($\beta = 0.546$, $p < 0.001$), with a large effect size ($f^2 = 0.280$). This finding reflects the central role of operational uncertainty in agrifood manufacturing, a sector characterized by perishable raw materials, thin margins, and tight regulatory oversight. Even small disruptions in processing can lead to significant financial losses, product recalls, or export rejections. RE technologies, while promising, are still perceived as untested at scale, which amplifies managerial caution. This aligns with prior research suggesting that firms in food-related industries are disproportionately risk-averse when innovation introduces potential quality or safety variability (Shakuri & Barzinpour, 2024).

The Image Barrier (H2) also showed a significant positive effect ($\beta = 0.217$, $p = 0.009$), underscoring the reputational sensitivity of agrifood firms. Brand trust in China is fragile due to recurring food safety scandals, and consumers often equate product safety with purity and minimal interference (Tao & Chao, 2024). In this environment, reusing or reprocessing materials can easily be misconstrued as compromising quality. With digital media amplifying reputational risks, firms perceive RE as a potential liability unless supported by strong traceability and certification mechanisms. This helps explain why image considerations, even more than operational cost concerns, act as a major deterrent to adoption.

The Usage Barrier (H3) exerted a smaller but still significant influence ($\beta = 0.140$, $p = 0.027$). While not as dominant as risk or image, this barrier remains relevant due to the inherent complexity of perishable food operations. The review from Osman et al. (2023) of perishable food supply chain challenges illustrates how logistical and process barriers persist in this sector, supporting the significance of perceived usage complexity in RE adoption. It reflects the technical complexity of integrating RE systems into existing production lines, especially for small and medium-sized enterprises (SMEs) that dominate China's agrifood sector. Many SMEs lack advanced digital infrastructure or sufficient skilled labor to manage RE operations, making adoption appear resource-intensive and disruptive. Although digital literacy is increasing, the perceived effort of retraining workers and reconfiguring production processes continues to generate hesitation.

By contrast, the Tradition Barrier (H4) and Value Barrier (H5) did not significantly predict RRER. This divergence from findings in other cultural settings suggests that industrial modernization and strong state-led incentives in China reduce the influence of cultural inertia and short-term ROI skepticism. Firms increasingly prioritize efficiency and regulatory compliance over preserving traditional waste management practices. Moreover, subsidies and circular economy programs already improve the financial attractiveness of RE, diminishing value-related concerns. This resonates with arguments from institutional theory that coercive pressures from state policy can override traditional practices, while supportive incentives mitigate cost-related hesitation (Castro-Lopez et al., 2023; Juráček et al., 2025).

Table 3. Structural model evaluation

Hypothesis	Path	β (O)	t-value	p-value	f^2	Status
H1	RB → RRER	0.546	6.507	0	0.28	Supported
H2	IB → RRER	0.217	2.632	0.009	0.041	Supported
H3	UB → RRER	0.14	2.215	0.027	0.027	Supported
H4	TB → RRER	-0.069	0.916	0.359	0.004	Rejected
H5	VB → RRER	0.073	1.108	0.268	0.006	Rejected
Model fit	$R^2 = 0.640$	$Q^2 = 0.615$				

The model explains 64.0% of the variance in RRER, indicating substantial predictive power (Chin, 1998). The dominance of the risk barrier reflects firms' concerns over operational stability in perishable food production, where system failures can cause disproportionate losses. Image barriers highlight the sector's reputational sensitivity, particularly in consumer-facing subsectors such as organic, beverage, and specialty foods. Usage barriers, though weaker, remain significant due to the technical integration and training demands of RE adoption, especially for SMEs with limited digital infrastructure. By contrast, tradition and value barriers did not significantly influence resistance, suggesting that regulatory incentives and modernization pressures may already be mitigating cultural inertia and ROI skepticism. The Q^2 value of 0.615 confirms that the model has predictive relevance, indicating that it can forecast resistance patterns beyond the sample data. These findings provide the empirical foundation for the discussion that follows, where digital-intelligent strategies are mapped onto the most pressing barriers.

5. Discussion

This study examined the cognitive barriers influencing RRER in China's agrifood manufacturing sector. While the empirical results in Section 4.4 establish the hierarchy of barriers, this section explicitly links these findings to digital-intelligent solutions, demonstrating how tools such as AI-driven simulations, blockchain-enabled traceability, and AR/VR training can directly address the most influential resistance factors. The hierarchy of barriers reflects the sector's operational realities. Unlike many studies in developed contexts where tradition and value perceptions are prominent drivers of resistance (Ram & Sheth, 1989; Talwar et al., 2021), the Chinese agrifood industry appears to be pragmatically oriented. Here, firms are not bound by entrenched customs or skeptical about the intrinsic value of innovation; rather, they are constrained by the perceived dangers, reputational vulnerabilities, and practical difficulties of implementing RE technologies.

The findings of this study demonstrate that operational risk, image, and usage barriers significantly contribute to RRER in China's agrifood manufacturing sector, whereas tradition and value barriers do not exert a measurable influence. This ordering contrasts with studies in Western contexts, where tradition and value often feature prominently in explaining resistance to circular innovations (Talwar et al., 2021). The divergence highlights the context-specific nature of innovation resistance theory, underscoring the need to account for industrial priorities, regulatory pressures, and market structures.

The risk barrier demonstrated the strongest influence on RRER, confirming previous research that firms in resource-intensive sectors often perceive technological change as financially hazardous when future payoffs are uncertain (Ram & Sheth, 1989; Talwar et al., 2021). The demographic analysis offers important explanatory insight. More than 85% of participating firms were established within the last decade, and over 62% reported annual revenues below RMB 50 million. Such firms typically have tighter cash flows, less financial buffering capacity, and shorter investment horizons, making them more risk-averse in allocating resources to untested processes like resource re-extraction. The concentration of small and medium-sized enterprises (SMEs) further compounds this effect, as SMEs in China often rely heavily on short-term profitability to maintain competitiveness (An & Zhang, 2021). These operational uncertainties are further magnified in contexts where digital infrastructure adoption is still maturing, as shown by recent findings on the digital–green coupling transition in Chinese agriculture, which highlight persistent gaps in technological integration and risk management (Hu et al., 2025). Thus, the dominance of the risk barrier in our model is not only statistically significant but also logically consistent with the financial and structural realities of the sampled firms.

The image barrier ranked second, aligning with prior studies that highlight reputational concerns as a core impediment to adopting green innovations in consumer-facing industries (Kumar & Nayak, 2022). This finding is reinforced by our demographic data. A large share of respondents operate in sectors such as fruit and vegetable processing, beverage manufacturing, and organic/natural products, where brand identity and consumer trust are critical assets. In such markets, perceived risks of product contamination, inconsistency in quality, or misalignment with brand values can outweigh the potential sustainability gains from RE. Moreover, for firms exporting to global markets, where sustainability narratives are often closely scrutinized, the fear of unintended reputational harm may act as a powerful deterrent to early adoption. Integrating blockchain-enabled traceability (Apeh & Nwulu, 2025) within RE systems has been shown to alleviate such concerns by offering verifiable proof of product integrity, a finding supported by recent reviews on sustainable circular agri-food supply chains (Zhao et al., 2025).

The usage barrier also emerged as a significant, though less dominant, factor. While technological solutions for RE are increasingly available, their integration into existing workflows remains challenging for firms with limited digital infrastructure or operational expertise (Muller et al., 2024; Raj et al., 2020). The demographic results show that over 70% of surveyed firms are located in East, South, and Central China, regions with stronger industrial infrastructure, but these advantages may be offset by the fact that more than one-third of firms employ fewer than 50 staff, limiting in-house capacity for technological onboarding. Additionally, high reported monthly food waste volumes among many respondents indicate that while potential input material for RE exists, process redesign and workforce training requirements may appear daunting, further reinforcing the perception of complexity.

The non-significant influence of tradition and value barriers offers an intriguing contrast to some innovation adoption studies in other cultural contexts (e.g., Talke & Heidenreich, 2014). This divergence can be interpreted through complementary theoretical lenses. From the perspective of Institutional Theory, firms in China's agrifood sector face strong coercive and mimetic pressures from government regulations and industry benchmarks that prioritize modernization and sustainability (Juráček et al., 2025). Such institutional forces can weaken the relevance of tradition, as firms adapt not primarily out of cultural preference but in response to regulatory compliance and competitive imitation. Similarly, insights from the Resource-Based View (RBV) help explain why value barriers did not significantly influence resistance. Policy instruments such as subsidies, tax incentives, and national standards effectively reduce the financial burden of adoption, allowing firms to perceive RE technologies less as risky investments and more as strategic resources that enhance competitiveness (Awad et al., 2025). Together, these complementary lenses highlight that institutional and resource configurations in China's agrifood industry mediate the salience of traditional and value-related concerns.

When viewed through the lens of Innovation Resistance Theory, these results extend the understanding of how barrier salience may shift in emerging market contexts. Whereas much of the IRT literature highlights tradition and value barriers as prominent obstacles, our findings suggest that in dynamic, policy-supported sectors like China's agrifood manufacturing, these barriers are overshadowed by risk, image, and usage considerations. This aligns with emerging evidence from sustainability adoption studies in Asia, where operational uncertainty and market perception increasingly determine the pace of technological uptake (Rizos et al., 2016).

By incorporating demographic evidence, this study adds nuance to existing frameworks, showing that barrier intensity is not uniform but shaped by firm age, size, market positioning, and product category. For instance, younger SMEs in consumer-oriented industries are disproportionately sensitive to financial and reputational uncertainties, which explains why technological complexity and brand image concerns remain highly salient even in regions with strong digital infrastructure.

Collectively, these findings suggest that strategies to promote RE adoption in China should not rely solely on financial incentives or appeals to cultural change. Instead, interventions must directly reduce perceived risk, safeguard brand image, and streamline operational integration, priorities that are consistent with the technological potential of Industry 4.0 solutions. However, it is important to recognize that the sample in this study is skewed toward firms in more industrialized regions, particularly East China, which accounted for over one-third of respondents. This regional concentration means that the findings are most representative of areas with advanced infrastructure and stronger policy enforcement, and they may not fully capture the barriers faced by firms in less developed regions such as Northwest China. Future research should therefore adopt a more balanced regional sampling strategy to improve generalizability and to reveal whether the observed barrier hierarchy is consistent across different institutional and economic settings.

Overall, these findings reaffirm the relevance of the innovation resistance framework while signalling the need for sector-specific recalibration. In China's agrifood manufacturing sector, the weight of operational and reputational considerations surpasses both cultural and short-term economic concerns, providing clear strategic priorities for policymakers, technology providers, and industry leaders seeking to advance the circular economy agenda.

6. Implications

The findings of this study carry several actionable implications for theory, practice, and policy.

6.1. Theoretical Implications

By extending Innovation Resistance Theory to the context of digital-enabled circular food systems, this study highlights the context-dependent salience of barriers, showing that operational risk, image, and usage outweigh tradition and value in China's agrifood sector. Future research should further integrate complementary theories such as Institutional Theory and the Resource-Based View.

6.2. Managerial Implications

For agrifood manufacturing managers, these findings signal the need to prioritize risk mitigation over tradition-challenging initiatives. Operational risk emerged as the strongest deterrent, suggesting that investments in predictive digital tools such as AI-powered process simulations should precede large-scale RE rollout. By providing empirical evidence of system reliability under various scenarios, these tools can address managers' loss-aversion tendencies and operational hesitations (Vecchio et al., 2021).

Second, the prominence of image concerns calls for proactive brand management strategies. Blockchain-enabled traceability platforms can provide transparent proof of quality and safety, ensuring that sustainability claims are credible and verifiable. This transparency is particularly crucial for export-oriented firms that face stricter international scrutiny on food safety standards (FAO, 2021).

Third, the complexity barrier underscores the necessity of human capital development alongside technological adoption. AR/VR-based training programs can accelerate skill acquisition while minimizing production disruptions. By embedding these training tools into daily workflows, firms can reduce the perceived operational burden of RE adoption.

6.3. Policy Implications

From a policy perspective, these results suggest that generic sustainability subsidies may not be sufficient to overcome the most influential barriers. Instead, targeted policy instruments that build on China's existing frameworks are needed. For instance, government-backed demonstration projects using AI-driven simulations, such as the MARA-sponsored "Fuxi Farms" under the 2024–2028 Smart Agriculture Action Plan (Ministry of Agriculture and Rural Affairs of the People's Republic of China, 2024) could be aligned with the *Digital China* initiative. These farms exemplify how AI-enabled "digital brain" systems, sensor networks, and real-time data platforms foster transparency and operational confidence (People's Daily Online, 2025) , supporting the broader digital and circular transition. Similarly, a national digital traceability standard for reextracted resources could be developed under the *"Zero-Waste City"* pilot programs (Chai et al., 2025) , ensuring consistent quality assurance and transparency across regions while aligning with China's export competitiveness goals (OECD, 2023) . Moreover, skills development policies could be explicitly tied to the *"Double Carbon"* objectives by supporting digital upskilling programs for agrifood workers (Zhang et al., 2023) , co-funded through public–private partnerships. Linking these targeted measures with existing national strategies ensures coherence, accelerates implementation, and embeds RE adoption within China's broader sustainability agenda (Ghisellini et al., 2016).

6.4. Research Limitations and Future Research Suggestions

While this study makes both theoretical and practical contributions, several limitations warrant consideration. First, the empirical analysis relies on cross-sectional survey data, which captures perceptions and behaviours at a single point in time. This limits our ability to observe how resistance to RRER evolves as firms gain more exposure to digital-intelligent solutions or as regulatory environments shift. Future research should adopt longitudinal designs to track barrier dynamics over time, enabling more robust causal inferences.

Second, the sample is geographically confined to Chinese agrifood manufacturers, a sector characterised by distinct operational, cultural, and regulatory contexts. While this focus enhances internal validity, it constrains the generalisability of findings to other industries or economies. Comparative studies across emerging and developed markets, particularly in the ASEAN and EU contexts, could reveal whether the barrier hierarchy observed here is universal or context-specific.

Third, the study's operationalisation of barriers follows IRT constructs adapted from prior literature. Although these constructs demonstrated strong measurement validity, they may not fully capture sector-specific nuances such as supply chain traceability requirements or the perishability of input materials. Incorporating qualitative approaches such as in-depth interviews or ethnographic fieldwork could enrich our understanding of the micro-level mechanisms underlying resistance.

Finally, the digital-intelligent solutions proposed in this study remain conceptual. While grounded in technological feasibility and aligned with Industry 4.0 developments, their effectiveness in practice has not yet been empirically tested. Future studies should examine the scalability of integrated AI–digital twin frameworks, as they have shown promising results in improving both operational efficiency and environmental outcomes in China's agrifood manufacturing (Ali et al., 2025; Andika et al., 2025; Hu et al., 2025; Meng & Li, 2025; R. Zhang et al., 2025).

By addressing these limitations, future scholarship can build a more comprehensive, context-sensitive, and empirically validated framework for overcoming resistance in circular economy transitions.

6.5. Conclusion

This study set out to investigate the cognitive barriers that significantly influence RRER in China's agrifood manufacturing sector and to propose digital-intelligent strategies capable of overcoming these barriers. Drawing on IRT and employing PLS-SEM, we provided empirical evidence that risk, image, and usage barriers are the primary determinants of RRER, whereas tradition and value barriers have little to no significant impact in this context. The dominance of risk concerns underscores the sector's sensitivity to operational uncertainty, while the significance of image and usage barriers reflects the reputational and procedural challenges manufacturers perceive in adopting RE practices.

By integrating these findings with the technological capabilities of Industry 4.0, we have outlined targeted solutions, AI-driven risk simulations, blockchain-enabled traceability, and AR/VR-based training, that directly address the most influential barriers. This linkage between barrier diagnosis and tailored technological intervention advances the application of IRT in the digital-circular economy domain, offering a model that is both theoretically grounded and practically actionable.

The implications extend beyond the Chinese context, suggesting that in other emerging economies, effective RE adoption strategies should prioritise the mitigation of uncertainty and complexity rather than solely focusing on altering cultural traditions or demonstrating economic returns. Policymakers, industry leaders, and researchers can draw from this framework to design integrated management strategies that align digital transformation with circular economy objectives.

In closing, the study not only answers its initial research question but also contributes to a broader understanding of how cognitive barriers interact with technological enablers in shaping industrial sustainability transitions. By doing so, it lays a foundation for academic inquiry and policy innovation aimed at accelerating the adoption of resource re-extraction in global manufacturing systems.

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Conceptualization, X.Y. and L.C.; methodology, X.Y.; software, X.Y.; validation, X.Y., L.C. and X.W.; formal analysis, X.Y.; investigation, X.Y.; resources, X.Y.; data curation, X.Y.; writing—original draft preparation, X.Y.; writing—review and editing, X.Y., L.C. and X.W.; visualization, X.Y.; supervision, X.Y.; project administration, X.Y., L.C. and X.W. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement:

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement:

The raw data supporting the conclusions of this article will be made available by the authors on request.

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Conflict of Interest:

The authors declare no conflict of interest.

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