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# A Dual-Learning Pathway: How Digital Orientation and Financial Literacy Shape Digital Transformation in Chinese Agriculture Enterprises

Haoran Fu [1] and T. Ramayah [1, 2, 3, 4, *]

[1] School of Management, Universiti Sains Malaysia, Minden, 11800, Penang, Malaysia
[2] Department of Information Technology & Management, Daffodil International University, Birulia, Bangladesh
[3] University Center for Research & Development (UCRD), Chandigarh University, 140413, Punjab, India
[4] Faculty of Business, Sohar University, P.C 311, Sohar, Oman

* Corresponding Author Email: ramayah@usm.my

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## Abstract

This study mainly explores the direct effects of financial literacy, acquisitive learning, and experiential learning on digital transformation, while also analyzing the direct influence of digital orientation on both acquisitive and experiential learning. At the same time, this study also explores the mediating effects of acquisitive learning and experimental learning between digital orientation and digital transformation. This research is grounded in dynamic capability theory, focuses on Chinese agricultural firms. Data were collected through a structured questionnaire from 279 managers of Agricultural industrialization leading enterprises in China, and analyzed using PLS-SEM. The research findings indicate that financial literacy, acquisitive learning, and experiential learning all significantly enhance digital transformation, with acquisitive learning serving as a more crucial mediating factor in the relationship between digital orientation and digital transformation. Furthermore, the significance of digital orientation in promoting acquisition learning and experimental learning has also been confirmed. The research in this article provides theoretical basis and practical guidance for how agricultural enterprises can enhance their digital capabilities by improving financial literacy and learning mechanisms in the process of digital transformation.

**Keywords:** Digital transformation, digital orientation, financial literacy, acquisitive learning, experimental learning, agriculture enterprises.

## 1. Introduction

Agriculture remains one of the most essential sectors for national development, playing a pivotal role in GDP contribution, employment creation, and poverty alleviation across the globe (Abioye et al., 2020; Suarez et al., 2022). It is central to ensuring food security, improving rural livelihoods, and promoting environmental sustainability (Gumbi et al., 2023; Pawlak & Kolodziejczak, 2020). However, the global agri-food system is under mounting strain: over 800 million people are still undernourished, and global food production must increase by 70% by 2050 to meet projected demand (Ali & Dahlhaus, 2022; Duru et al., 2022).

Agriculture has been a key part of China's national development for a long time. It has helped the economy grow, reduced poverty, and made the country self-sufficient in food (Hua et al., 2022; Xu et al., 2019; Zhang et al., 2023). But the industry still has problems with its structure and is under more and more pressure from the environment. As the digital economy grows, Digital transformation (DT) is increasingly seen as a strategic need to modernize farming and solve its long-standing problems (Zhu & Wang, 2021). According to Pfeiffer et al. (2021), DT could make production more efficient, boost sustainable practices, and make agricultural supply chains more open and easier to trace.

Agriculture is slower to adopt new technology than other industries, although though DT has great potential. In 2022, China's digital economy accounted for 41.5% of GDP, although just 10.5% of farmers employed digital tools, compared to 44.7% in the tertiary sector (Liu et al., 2023). Research shows that farming is digitalizing slower than industry or services (Shi et al., 2021). Agricultural enterprises connect small farmers to markets. They help bring digital technologies to the entire agri-food value chain (Liu et al., 2023). But not wanting to, not being able to, and fearing change are their biggest impediments.

The first barrier, "unwillingness to transform," shows that there isn't enough strategic clarity or commitment. A strong digital orientation (DO) is the first step in solving this problem. It shows that a business is ready to use digital tools and leads to changes in the company. Despite increasing scholarly interest in digitalization, how firms internally organize and leverage digital strategies remains underexplored (Hess et al., 2016; Singh et al., 2020). DO can serve as a distinctive strategic capability, shaping organizational behavior, resource alignment, and ultimately, competitive advantage (Kindermann et al., 2021; Li & Shao, 2023).

The second barrier, "inability to transform," is a lack of digital skills and experience. Most companies must "cross the river by feeling the stones," borrowing, imitating, and making mistakes to learn (Tortorella et al., 2020). Organizational learning (OL) is crucial for strategic renewal and implementing digital transformation (DT), particularly when organizations learn from other digital pioneers (Lenart-Gansiniec & Sułkowski, 2020; Xiao et al., 2021). Few studies have examined how DO affects DT outcomes through OL. This study examines how OL helps agricultural enterprises access digital resources and adapt swiftly (Helfat and Raubitschek, 2018; Teece et al., 2016).

The third barrier, “afraid to transform,” is rooted in financial concerns—digital transformation is costly, complex, and irreversible. Ensuring adequate and sustainable funding is critical (Liu et al., 2023). Financial constraints have been cited as one of the top inhibitors of digital initiatives, especially for smaller firms (Arranz et al., 2023). While prior research has linked financial literacy (FL) to financial inclusion, satisfaction, and decision-making (Zaimovic et al., 2023), its role in supporting enterprise-level DT remains underexplored. With the rise of digital finance, FL is gaining renewed relevance, yet its strategic implications for organizational change—particularly in developing contexts—require deeper investigation.

In summary, the slow pace of agricultural digitalization in China can be attributed to the persistent triad of “unwillingness,” “inability,” and “fear” among agricultural enterprises. While DT is widely recognized as essential, there is a pressing need to unpack how digital orientation, organizational learning, and financial literacy interact to support it. Despite the growing body of literature, limited theoretical insight exists into the specific drivers that enable DT within agriculture.

To address the above challenges, this study adopts dynamic capabilities theory to explore how Chinese agricultural firms can facilitate DT. It focuses on three key enablers: DO as a strategic driver, OL as a capability-building process, and FL as a means to alleviate financial constraints and risk aversion. These insights contribute to a deeper understanding of how agricultural enterprises can advance DT and promote agricultural modernization in the digital era.

## 2. Theoretical Background and Hypothesis Development

### *2.1. Dynamic Capability Theory*

Dynamic capability theory emphasizes how organizations continuously adapt by sensing, seizing, and transforming resources to maintain competitive advantage in dynamic environments (Helfat et al., 2009; Teece, 2007). Within this framework, DO serves as a strategic capability that directs an organization’s digital transformation efforts (Kindermann et al., 2021). FL supports firms in recognizing financial constraints and making informed decisions, thereby facilitating effective resource deployment in dynamic conditions (Tian et al., 2022)). As key learning mechanisms, acquisitive learning (AL) enables organizations to absorb external knowledge and integrate digital technologies, while experimental learning (EL) enhances internal resource alignment through practice (Zhao et al., 2011). Together, these factors act as dynamic capabilities that collectively foster successful DT. The dynamic capacity theory offers robust theoretical support for the study framework of this paper and demonstrates that the chosen variables are essential components for advancing DT.

*2.2. Development of Hypothesis and Research Frame Work*

Learning behaviors are shaped by contextual factors such as managerial direction, organizational support, and developmental priorities (Strobl et al., 2022). DO influences how enterprises engage with digital technologies by fostering a strategic mindset that prioritizes rapid, top-down investment in digital initiatives (Khin and Ho, 2018). When facing resource constraints, digitally oriented firms adopt proactive strategies—regularly assessing internal gaps and leveraging external solutions through mechanisms like benchmarking and knowledge transfer. This shows that people are trying to learn on purpose to speed up digital transition. DO also helps companies connect with each other and learn more by making it easier for them to share information and access a wide range of knowledge sources (Ardito et al., 2021). In short, DO does more than only encourage the use of technology; it also helps people learn by getting them to acquire new knowledge and build new skills. It makes the conditions right for the development of learning processes that are necessary for success in the digital world. Based on this synthesis, we can make the following hypothesis:

- H1: Digital orientation has a positive effect on acquisitive learning.

DO shows that a business is serious about using new digital technologies and is an important part of building EL. Companies with strong DO are more willing to try new things, which makes it easier for people in the company to use digital tools to solve old problems (Solberg et al., 2020). More critically, DO encourages a risk-tolerant, innovation-friendly culture where employees, supported by management, are motivated to explore and share digital practices (Maravilhas and Martins, 2019). This internal engagement forms the basis for sustained EL. Moreover, DO promotes cross-functional and inter-organizational collaboration, encouraging iterative experimentation among employees, customers, and partners to refine digital practices and enhance adaptability (Vial, 2021). Thus, DO is not only a technological orientation but also a cultural and behavioral enabler that strengthens EL through resource alignment and organizational learning mechanisms. Based on this integrative perspective, the following hypothesis is proposed:

- H2: Digital orientation has a positive effect on experimental learning.

DT often requires significant financial investment, making capital constraints a major barrier for many firms. FL equips managers with the skills to plan budgets, manage cash flow, and make strategic investment decisions, thereby improving the quality and efficiency of capital utilization (Agyapong & Attram, 2019; García-Pérez-de-Lema et al., 2021). FL also makes it easier to get outside funding by making information more equal and making finances more trustworthy. More importantly, FL helps companies better plan for, allocate, and manage their resources, which lowers the cost and risk of implementing DT. In this way, financial literacy is a strategic skill that helps ease financial stress and keeps transformation initiatives going in the long run (Antoni, 2023). FL can help make effective DT happen by giving decision-makers the power to go around budget limits. The following hypothesis is based on this line of thought:

- H3: Financial literacy has a positive effect on digital transformation.

DT is not a one-time event; it demands companies to change how they compete and work with larger digital ecosystems (Blackburn et al., 2020). To achieve DT, stakeholders need to work together and share resources, which requires both external integration and internal capability development. AL is quite important in this process since it helps companies quickly get and use digital information from other sources. AL lowers the costs of change and speeds up the use of digital technology by using benchmarking, digital platforms, and tried-and-true digital solutions. It also helps reduce the problems that come with using new technology by keeping the company's knowledge base up to date (Do and Mai, 2021) and lowering the risk that comes with using new technology (Zhou and Wu, 2019). Instead of just sitting back and doing nothing, AL encourages strategic learning that connects outside inquiry with inside application. This makes it an important part of DT. Because of this logic, the following hypothesis is put forward:

- H4: Acquisitive learning has a positive effect on digital transformation.

Proksch et al. (2021) say that it's important to be able to handle some failure in the early phases of DT. This is especially true in the farming industry, where long-standing habits are hard to break. In these kinds of situations, DT usually needs to adapt slowly and steadily instead of making sudden changes (Ferreira et al., 2019). Also, Smith and Beretta (2021) say that failures are typically unavoidable when changing old workflows and management systems. Importantly, DT is more than just using digital tools; it also means adding these technologies to current business processes and value chains in a way that makes sense and is planned (Matarazzo et al., 2021). In this way, EL lets companies try things out, make changes, and slowly change their behavior models to better meet the needs of development. EL helps companies become more independent in the digital world and facilitates the creation of new digital products without losing their basic strengths by encouraging a logic of adaptive trial-and-error. Thus, EL is not simply a support mechanism but a critical driver of transformation. It helps organizations manage the risks of failure, reshape routines, and move toward sustained digital maturity. Based on this reasoning, the following hypothesis is proposed:

- H5: Experimental learning has a positive effect on digital transformation.

DO reflects an organization's strategic intent and commitment to adopting digital technologies to enhance competitiveness (Khin and Ho, 2018; Saunila et al., 2021). However, the realization of this intent often depends on the availability of digital resources. In this regard, AL plays a critical role in expanding an organization's digital resource base, enabling DO to translate into effective DT. In the digital economy, where modular, mobile, and replicable digital assets replace traditional VRIN-based advantages, firms lacking digital resources face substantial barriers to transformation (Cuthbertson and Furseth, 2022). AL helps address this deficit by facilitating the acquisition of ready-to-use digital solutions that can be applied across various functions—ranging from product development to operations management—thus reducing the risk of costly missteps (Li et al., 2018). AL is not just about getting resources; it also helps organizations learn by combining advanced technologies and management methods. This way of learning helps DT's strategy renewal, which means not only using new technology but also getting rid of old habits and changing key processes (Ghezzi and Cavallo, 2020; Volberda et al., 2021). AL also helps conventional companies get back on track with digital demands by taking in new information from outside sources and changing old behaviors from the industrial period. Organizations that can adapt better to changes in the environment are more likely to be able to follow new strategic orientations and speed up change (Liu et al., 2021). This synthesis leads to the following hypothesis:

- H6: Acquisitive learning positively mediates the relationship between digital orientation and digital transformation.

DO shows that a company wants to use new digital technologies not just by adopting them, but also by committing to ongoing innovation and value realization (Arias-Pérez and Vélez-Jaramillo, 2022; Khin and Ho, 2018). In this case, EL helps companies change how they do things by trying new things over and over again, making mistakes, and getting better at what they do (Zhao et al., 2011). This kind of learning helps organizations develop processes that turn data into useful information and helps digital resources become more productive. EL encourages active use of digital tools, which is different from passive use of technology. This makes sure that technical solutions meet genuine operational needs (Tortorella et al., 2020). It also helps the business renew its own capabilities by storing digital knowledge in its memory. Wu et al. (2021) also warn that digital technologies could make inefficiencies worse if they aren't used in a way that adapts to them. Therefore, firms cultivating EL are better positioned to navigate digital failures, encourage employee participation, and foster a culture tolerant of experimentation (Schiuma et al., 2022). In sum, EL plays a critical role in converting digital intent into effective transformation. Accordingly, the following hypothesis is proposed:

- H7: Experimental learning positively mediates the relationship between digital orientation and digital transformation.

The research framework of this study is shown in Figure 1, and the definitions of all constructs are shown in Table 1.

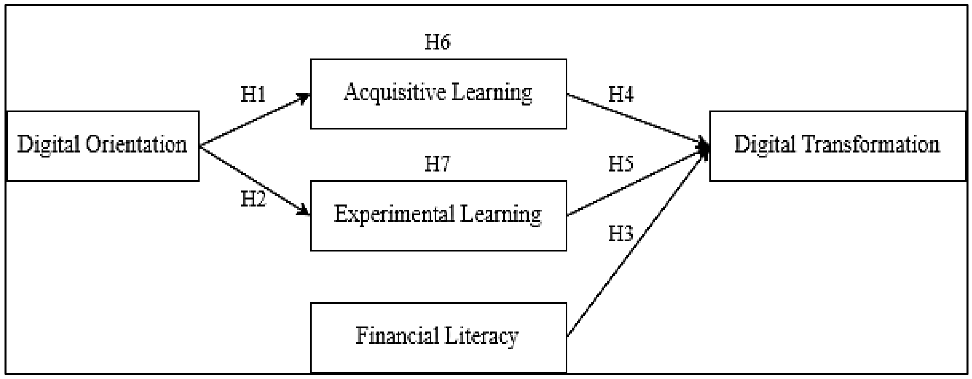


**Figure 1 Proposed Research Model**

Table 1 summarizes the constructs used in this study with their corresponding definitions.

**Table 1: Construct Definition**

| Construct | Definition |
|---|---|
| Digital Transformation (DT) | Digital transformation refers to the use of digital technologies to change a business model and provide new revenue and value-producing opportunities (Singh et al., 2021). |
| Digital Orientation (DO) | DO is conceptualized as technology orientation in a digital technology context and is defined as "an enterprise's commitment toward the application of digital technology to deliver innovative products, services, and solutions" (Khin and Ho, 2018). |
| Organizational Learning (OL) | OL is a process by which a enterprise acquires information, understanding, know-how, techniques, and practices to improve task performance (Zhao et al., 2011). |
| Experimental Learning (EL) | Experimental learning, also called incremental learning, adaptive learning, or single-loop learning, occurs inside the enterprise and generates knowledge distinctive to the enterprise (Dess et al., 2003; Zhao et al., 2011). |
| Acquisitive Learning (AL) | Acquisitive learning is defined as the acquisition and internalization of knowledge from the enterprise's external environment so the enterprise can learn new competencies beyond its boundaries to achieve radical innovations for new product categories (Morgan and Berthon, 2008; Zhao et al., 2011). |
| Financial Literacy (FL) | Financial literacy is the attainment of knowledge and skills to manage finances, utilize financial services and plan the consumer market effectively to achieve the financial objectives of an enterprise (Adomako et al., 2016). |

## 3. Methodology

*3.1 Study Context*

This study looks at Chinese farms and businesses that deal with agriculture. The agriculture sector in China, which is an important part of the national economy, has had a big impact on its growth and is a sign of economic trends (Hua et al., 2022; Xu et al., 2019; Zhang et al., 2023). China, one of the world's top agricultural countries, has been able to meet the nutritional needs of its 1.4 billion people and has made a big difference in world agriculture (Zuo et al., 2023). The progression of the digital economy requires the digital transformation of agriculture, in accordance with the emerging development paradigm (Zhu and Wang, 2021). Studies reveal that industrial and service companies constitute a greater share of entities involved in digital transformation, whereas agricultural businesses are relatively lesser (Shi et al., 2021). Moreover, the requirement for an extensive digital industrial chain and innovation network has led to a constrained size of agricultural digitization in China, which is significantly lagging behind the secondary and tertiary industries (Liu et al., 2023). Agricultural enterprises demonstrate an aversion to transformation due to a lack of clear strategic direction, insufficient transformation capabilities, apprehension regarding significant costs and extended transitional difficulties, ultimately facing a paradox of stagnation or adverse change. This study examines the antecedents of digital transformation via the perspective of dynamic capabilities to provide insights into this field.

*3.2. Measurement*

This study employed PLS-SEM for data analysis, utilizing SmartPLS 4.0 software. PLS-SEM is particularly suitable for the research with complex models, small-to-moderate sample sizes, and latent variables that are measured with multiple indicators (Hair et al., 2023).

This study did not require the development of new measurement scales, as existing validated measures from previous research are appropriate (See Appendix). The evaluation of Digital Transformation will utilize three items from Singh et al., (2021), which measure firms' ability to implement digital technology in their operations. The DO measurement adopted from Khin and Ho (2018), assesses an enterprise's commitment to utilizing digital technology in new product development and its preparedness and initiative to leverage digital opportunities.

This article references Zhao et al. (2011), who characterized "EL" as a second-order concept comprising three dimensions: internal communication (IC), exploitation of knowledge resources (EKR), and experience learning through practice (EAL). Eleven items measuring the three dimensions of EL and six items assessing AL were adapted from Zhao et al. (2011).

The original financial literacy questionnaire (FL1-FL4) focuses on the organization's preparation, examination, and analysis of financial statements, highlighting the internal application of financial data (Adomako et al., 2016). A data-driven culture is essential for company management and decision-making (Yu et al., 2021). When firms prioritize data and utilize it for decision-making, they can enhance their comprehension of financial indicators and increase the rigor and precision of financial judgments. This study integrates data-driven culture (FL5-FL8) (Yu et al., 2021) related items into the measurement of financial literacy, thereby providing a more comprehensive representation of firms' financial management competencies.

All items pertaining to DO, FL, AL and EL will utilize a five-point Likert scale (1="Strongly Disagree," 5="Strongly Agree"). Prior study has suggested that a five-point scale yields sufficiently adequate assessments (Bougie and Sekaran, 2019). Meanwhile, a 7-point Likert scale (1=" Strongly Disagree," 7=" Strongly Agree") will be used for all items of marker variable (cognitive rigidity). It best captures respondents' emotions and provides more accurate results (Ziólkowska, 2021). A six-point scale (1="Strongly Disagree," 6="Strongly Agree") was employed for the dependent variable (DT) to mitigate central tendency bias (Cooper and Schindler, 2014; Wong and Aspinwall, 2005). This transpires when respondents assign neutral rankings to their priorities.

The questionnaire underwent pre-testing by three PhD holders in management and two experts from the agricultural industry in China; the questions were slightly modified depending on their comments. The lead investigator, a native Chinese speaker fluent in English, translated the original questionnaire into Chinese. Subsequently, two translators were invited to execute the back-translation process to guarantee precision.

### *3.3. Sample and Data Collection*

The respondents in this study consist solely of individuals engaged in the management of Chinese Agricultural Industrialization Leading Enterprises, including directors, general managers, managers, and senior executives. The surveys were disseminated via the Wenjuxing platform to designated mid-level and senior managers within the agricultural sector. Respondents were requested to respond to a screening question to see if their agricultural enterprise was a leading agricultural enterprise. Participation was restricted to individuals who selected "yes." In total, 279 completed questionnaires were collected from September to November 2024, surpassing G*Power's recommended sample size threshold of 119. The respondents' demographic statistics are encapsulated in Table 2.

**Table 2: Demographic Profile**

| **Characteristic** | | **Freq.** | **%** |
|---|---|---|---|
| Leading Level | | | |
| | National-level | 41 | 14.7 |
| | Provincial-level | 64 | 22.9 |
| | City-level | 174 | 62.4 |
| Position | | | |
| | Top manager (e.g. presidents, CEO, director and deputy of these positions) | 86 | 30.8 |
| | Middle manager (e.g. manager of purchasing, marketing, production and other operations-related positions) | 193 | 69.2 |
| Current Department | | | |
| | Production Department / R&D Department | 18 | 6.5 |
| | Marketing Department | 48 | 17.2 |
| | Finance Department | 41 | 14.7 |
| | Human Resources Department | 34 | 12.2 |
| | Information Technology Department | 24 | 8.6 |
| | Supply Chain Management / Purchasing Department | 33 | 11.8 |
| | Customer Service Department | 40 | 14.3 |
| | Administrative Management Department | 41 | 14.7 |
| Agricultural Sector | | | |
| | Farming | 133 | 47.7 |
| | Animal husbandry | 65 | 23.3 |
| | Forest | 42 | 15.1 |
| | Fishery | 39 | 14.0 |
| Work Tenure | | | |
| | Less than 6 years | 19 | 6.8 |
| | 6-10 years | 58 | 20.8 |
| | 11-15 years | 157 | 56.3 |
| | More than 15 years | 45 | 16.1 |
| | | | |

| | | | |
|---|---|---|---|
| Education Level | | | |
| | College diploma | 58 | 20.8 |
| | Bachelor | 127 | 45.5 |
| | Master | 70 | 25.1 |
| | PhD | 24 | 8.6 |
| Annual Sales Turnover | | | |
| | Less than 5 billion | 168 | 60.2 |
| | 5–10 billion | 46 | 16.5 |
| | 11–50 billion | 38 | 13.6 |
| | More than 50 billion | 27 | 9.7 |
| Ownership Type | | | |
| | State owned | 74 | 26.5 |
| | Privately owned | 125 | 44.8 |
| | Foreign owned | 46 | 16.5 |
| | Joint venture | 34 | 12.2 |
| No. of Employees | | | |
| | Less than 1000 employees | 138 | 49.5 |
| | 1000–4999 employees | 66 | 23.7 |
| | 5000–9999 employees | 33 | 11.8 |
| | More than 10000 employees | 42 | 15.1 |
| Enterprise Tenure | | | |
| | Less than 10 years | 14 | 5.0 |
| | 10-15 years | 69 | 24.7 |
| | 16-20 years | 105 | 37.6 |
| | More than 20 years | 91 | 32.6 |

*3.4. Common Method Variance*

The marker-based technique (Podsakoff et al., 2003) was used to address CMV in self-report surveys before performing PLS-SEM. Table 3 demonstrates that the alterations in Beta (β) values and $R^2$ were not statistically significant after adding the marker variables. Therefore, the results indicate that the impact of CMV is minimal, and it can be concluded that CMV is not a major issue in this investigation.

**Table 3 Common Method Variance Comparison**

| Relationship | Baseline Model (Without Marker Variable) | | | Method factor Model (With Marker Variable) | | |
|---|---|---|---|---|---|---|
| | Beta | p-values | Remarks | Beta | p-values | Remarks |
| DO -> AL | 0.514 | $p < .001$ | Supported | 0.513 | $p < .001$ | Supported |
| DO -> EL | 0.469 | $p < .001$ | Supported | 0.470 | $p < .001$ | Supported |
| FL -> DT | 0.298 | $p < .001$ | Supported | 0.296 | $p < .001$ | Supported |
| AL -> DT | 0.346 | $p < .001$ | Supported | 0.341 | $p < .001$ | Supported |
| EL -> DT | 0.211 | $p < .001$ | Supported | 0.213 | $p < .001$ | Supported |
| DO -> AL -> DT | 0.178 | $p < .001$ | Supported | 0.175 | $p < .001$ | Supported |
| DO -> EL -> DT | 0.099 | $p < .001$ | Supported | 0.100 | $p < .001$ | Supported |
| | $R^2$ | | | $R^2$ | | |
| AL | 0.264 | | | 0.266 | | |
| DT | 0.411 | | | 0.416 | | |
| EL | 0.220 | | | 0.220 | | |

## 4. Results

### *4.1. Measurement Model*

The creation of the measurement model in PLS–SEM necessitates the evaluation of convergent validity, construct reliability, and discriminant validity. A hierarchical components model (reflective–reflective) was then utilized using a disjoint two-stage methodology (Sarstedt et al., 2019, 2021). EL was regarded as an endogenous variable. During the initial phase of the evaluation, the disjoint two-stage methodology exclusively utilized the lower-order constructs (LOCs) (i.e., internal communication, experience accumulated through learning-by-doing and exploitation of knowledge resources), with all other constructs in the model linked to these LOCs. In the second stage, the LOC scores (latent variable scores) served as markers for the higher-order construct (HOC), namely EL.

The preliminary evaluation analyzed the convergent validity of the model's first- and second-order reflective constructs, as illustrated in Table 4. Convergent validity was assessed by factor loadings and AVE. The loading threshold was established at 0.5, signifying that the AVE must exceed 0.5 (Hair, Black, et al., 2019. The loading values varied from 0.762 to 0.908, thereby affirming that the indicators align with their intended measures. Concurrently, the AVE values varied from 0.660 to 0.769, signifying that each latent variable in the model accounts for a minimum of 50% of the variance in the respective indicator (Fornell & Larcker, 1981). Table 4 indicates that the measurement model satisfies all established criteria.

Construct reliability encompasses CR, with a threshold value established at 0.7 (Hair et al., 2019). Table 4 presents the CR values for the LOC and HOC that meet this condition.

**Table 4: Results for Measurement Models**

| **Construct** | | **Items** | **Loadings** | **AVE** | **CR** |
|---|---|---|---|---|---|
| **1st -order** | **2nd -order** | | | | |
| Acquisitive learning | | AL1 | 0.770 | 0.660 | 0.897 |
| | | AL2 | 0.823 | | |
| | | AL3 | 0.803 | | |
| | | AL4 | 0.809 | | |
| | | AL5 | 0.839 | | |
| | | AL6 | 0.826 | | |
| Digital orientation | | DO1 | 0.839 | 0.666 | 0.832 |
| | | DO2 | 0.762 | | |
| | | DO3 | 0.867 | | |
| | | DO4 | 0.791 | | |
| Digital transformation | | DT1 | 0.870 | 0.769 | 0.849 |
| | | DT2 | 0.900 | | |
| | | DT3 | 0.860 | | |
| Financial literacy | | FL1 | 0.791 | 0.702 | 0.788 |
| | | FL2 | 0.869 | | |
| | | FL3 | 0.798 | | |
| | | FL4 | 0.883 | | |
| | | FL5 | 0.827 | | |
| | | FL6 | 0.803 | | |
| | | FL7 | 0.785 | | |
| | | FL8 | 0.849 | | |
| Experience accumulated through learning-by-doing | | EAL1 | 0.908 | 0.767 | 0.848 |
| | | EAL2 | 0.856 | | |
| | | EAL3 | 0.862 | | |
| Exploitation of knowledge resources | | EKR1 | 0.808 | 0.663 | 0.832 |
| | | EKR2 | 0.816 | | |
| | | EKR3 | 0.826 | | |
| | | EKR4 | 0.807 | | |
| Internal communication | | IC1 | 0.821 | 0.717 | 0.868 |
| | | IC2 | 0.874 | | |
| | | IC3 | 0.858 | | |
| | | IC4 | 0.832 | | |
| | Experimental learning | EAL | 0.827 | 0.683 | 0.933 |
| | | EKR | 0.840 | | |
| | | IC | 0.846 | | |

Subsequently, we evaluated the discriminant validity with the HTMT criterion proposed by Henseler et al. (2015). The stringent criterion for HTMT values is < 0.85, while the more moderate criterion is ≤ 0.90 (Ramayah et al., 2018, p. 86). Table 5 indicates that all HTMT values were below the lenient threshold of < 0.90. Furthermore, bootstrapping demonstrated that the HTMT value significantly deviates from 1.00; hence, we conclude that the respondents recognized the four notions as separate. The tests have demonstrated that the measuring items are valid and reliable.

**Table 5: Discriminant Validity (HTMT)**

| Variable | AL | DO | DT | EL | FL |
|---|---|---|---|---|---|
| Acquisitive Learning (AL) | - | | | | |
| Digital Orientation (DO) | 0.592 | - | | | |
| Digital Transformation (DT) | 0.565 | 0.438 | - | | |
| Experimental Learning (EL) | 0.387 | 0.575 | 0.552 | - | |
| Financial Literacy (FL) | 0.293 | 0.391 | 0.537 | 0.495 | - |

*4.2. Structural Model*

The importance of the path coefficients was then evaluated. A bootstrapping approach with 10,000 subsamples was implemented to evaluate the proposed hypothesis (Becker et al., 2023; Hair et al., 2023). The structural model was evaluated by assessing inner VIF values, $R^2$, path coefficients (β), and their significance levels (t-values and p-values), along with predictive relevance ($Q^2$). Furthermore, the model's out-of-sample predictive power was examined using PLS-Predict with 10-fold cross-validation (Hair Jr et al., 2023).

Diamantopoulos and Siguaw (2006) assert that an appropriate VIF value must be below 3.3. Table 6 indicates that the VIF values for all endogenous items are below the threshold, so affirming that collinearity among these constructs is not a significant concern in this investigation. The $R^2$ for DT was 0.411, indicating that 41.1% of the variance in DT was accounted for by AL, EL, and FL. The $R^2$ for AL was 0.264, indicating that 26.4% of the variance in AL was elucidated by DO. The $R^2$ for EL was 0.22, indicating that 22% of the variance in EL was elucidated by DO (Table 3).

The importance of the path coefficients was then evaluated. A bootstrapping process with 10,000 subsamples and a significance level of 0.05 was utilized to examine the proposed associations, employing a percentile bootstrap for the confidence interval method (Becker et al., 2023; Hair Jr et al., 2023). Given that all t-values exceeded the threshold of 1.645

(one-tailed), p-values were below 0.05, and the confidence intervals excluded zero, the results provide strong statistical support for hypotheses H1, H2, H3, H4, and H5.

DO (DO → AL) had the largest effect size ($f^2$) of 0.359, classified as a big effect size according to Cohen's criteria (Cohen, 2013), followed by DO (DO → EL) with an impact size of $f^2$ = 0.282, categorized as a medium effect size. AL (AL → DT) is also regarded as a medium effect size. The other variables exhibited a small effect size.

The mediating effect (Table 6) indicates that AL mediated the association between DO and DT (β = 0.178, p< 0.001), while EL also mediated the relationship between DO and DT (β = 0.099, p< 0.001), thereby substantiating H6 and H7.

**Table 6: Result of Structural Model Assessment**

| Hypo. | Relationship | Std. Beta | Std. Dev. | t-value | p-value | PCI LL | PCI UL | VIF | $f^2$ |
|---|---|---|---|---|---|---|---|---|---|
| H1 | DO → AL | 0.514 | 0.051 | 10.131 | p<.001 | 0.422 | 0.591 | 1.000 | 0.359 |
| H2 | DO → EL | 0.469 | 0.051 | 9.280 | p<.001 | 0.376 | 0.544 | 1.000 | 0.282 |
| H3 | FL → DT | 0.298 | 0.051 | 5.829 | p<.001 | 0.211 | 0.38 | 1.252 | 0.120 |
| H4 | AL → DT | 0.346 | 0.054 | 6.383 | p<.001 | 0.256 | 0.433 | 1.149 | 0.177 |
| H5 | EL → DT | 0.211 | 0.051 | 4.133 | p<.001 | 0.129 | 0.296 | 1.300 | 0.058 |
| H6 | DO → AL → DT | 0.178 | 0.032 | 5.598 | p<.001 | 0.128 | 0.233 | - | - |
| H7 | DO → EL → DT | 0.099 | 0.027 | 3.670 | p<.001 | 0.058 | 0.146 | - | - |

Hair et al. (2023) proposed employing PLS-Predict as a more dependable method for assessing the model's prediction capability in contrast to $Q^2$. Shmueli et al. (2019) presented PLSpredict, a technique employing 10-fold cross-validation to evaluate predictive relevance at the item level. PLS-Predict evaluates both the data utilized in model estimate and additional datasets excluded from the estimation process. Shmueli et al. (2019) posited that a model exhibits strong predictive power when all item differences in PLS-LM are positive and PLS-IA are negative; conversely, if all item differences in PLS-LM are negative and PLS-IA are positive, predictive relevance is not supported. Furthermore, if the majority of item differences in PLS-LM are positive and PLS-IA are negative, predictive power is deemed medium; whereas, if only a minority of item differences in PLS-LM are positive and PLS-IA are negative, predictive power is classified as low. Table 7 indicates that the majority of item differences for PLS-LM are positive, while those for PLS-IA are negative, suggesting that our model demonstrates medium predictive power.

**Table 7: PLS-Predict**

| MV | **Q² Predict** | **PLS-SEM** | **LM** | **IA** | **PLS - LM** | **PLS - IA** |
|---|---|---|---|---|---|---|
| | | MAE | | | MAE | |
| DT1 | 0.195 | 0.965 | 0.959 | 1.091 | 0.006 | -0.126 |
| DT2 | 0.176 | 1.169 | 1.187 | 1.345 | -0.018 | -0.176 |
| DT3 | 0.227 | 0.940 | 0.934 | 1.082 | 0.006 | -0.142 |

The medium level of predictive relevance indicates that the structural model has acceptable predictive power beyond the training sample. As noted by Hair et al. (2023), such performance exceeds that of basic benchmarks (e.g., linear regression), confirming the model's robustness in out-of-sample forecasting. This suggests the model is practically useful in anticipating digital transformation behaviors in agricultural enterprises. The demographic profile of respondents—predominantly bachelor's degree holders (45.5%) with 11–15 years of work experience (56.3%)—indicates a relatively experienced and educated managerial group, which may have enhanced response consistency and contributed to the model's predictive validity. Overall, the medium predictive capability implies that the model can offer practical insights for firms with similar profiles, helping guide strategies that emphasize financial literacy and organizational learning. Although not high, this level of prediction remains valuable for managerial and policy planning, and future work may improve it through more diverse sampling or cross-industry comparisons.

*4.3 Importance Performance Matrix Analysis*

Importance performance matrix analysis (IPMA) is a retrospective analysis performed for managerial implications (Figure 2). The IPMA utilized DT as a target construct to signify results that facilitate the identification of crucial areas for attention and action by researchers and management (Ringle & Sarstedt, 2016). According to the IPMA model, AL is identified as a critical factor influencing DT, with a significance score of 0.346, surpassing other variables such as FL (0.298), DO (0.277), and EL (0.211). Organizations ought to prioritize acquisitive learning. Simultaneously, initiatives should be undertaken to enhance financial literacy and digital orientation, since they exhibit intermediate significance. Nonetheless, EL, despite its comparatively minor significance, should not be entirely disregarded. Additional research is necessary to explore why EL does not assume a more significant role in enhancing DT.

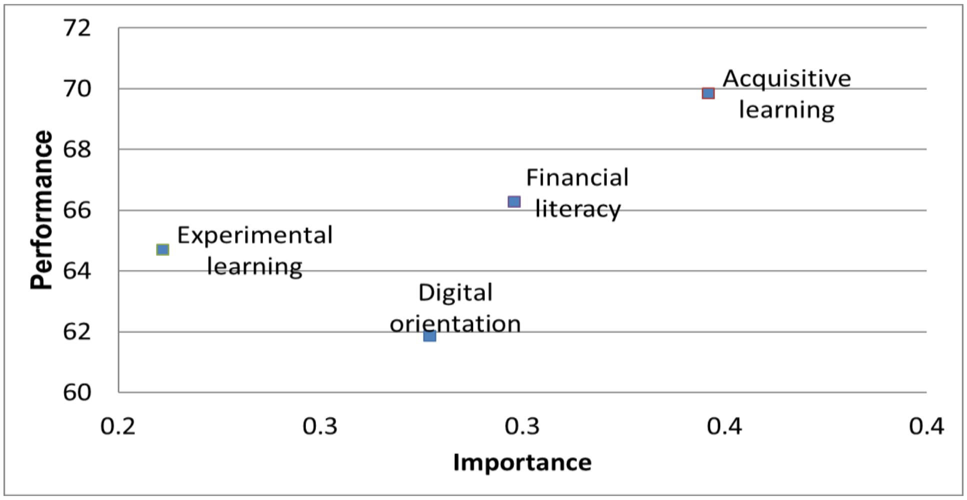


**Figure 3: Importance Performance Matrix Analysis**

## 5. Discussion

This study primarily investigates the direct impacts of FL, AL, and EL on DT, and further examines the influence of DO on both AL and EL. Mediating roles of AL and EL in the DO–DT relationship are also assessed, guided by dynamic capability theory, using data from managers in Chinese agricultural enterprises(Figure 1).

The analysis confirms that DO significantly enhances both AL and EL. This aligns with prior research suggesting that digital orientation fosters openness to innovation and capability building (Bendig et al., 2023; Wang et al., 2024). Firms with strong DO can better identify external knowledge and opportunities, thus promoting dual learning processes.

Moreover, the direct effects of AL, EL, and FL on DT are statistically significant. Financial literacy helps you make better decisions and manage your resources better, which is important for digital projects that cost a lot of money (Li et al., 2024). Getting more knowledge helps with strategic adaption and being ready for digital (Sagala & Hori,2024). Most of the people who answered this study are middle-level managers (69.2%), have more than 11 years of work experience (56.3%), and have a bachelor's degree or higher (78.5%). These traits point to a workforce with enough experience and expertise to help with learning and making financial decisions at the enterprise level, which strengthens the effects of AL, EL, and FL on DT.

The results also show that DT is a gradual, path-dependent process, especially in farming, where processes are set in stone and budgets are tight. Vial (2021) and Ferreira et al. (2019)

say that DT needs to integrate digital tools with real operational needs, and structured learning mechanisms can help with this.

Finally, mediation analysis shows that AL and EL mediate the connection between DO and DT, with AL being the more important of the two. This difference is based on theory: AL helps people learn new things quickly from the outside world, which improves their ability to sense and seize opportunities. EL, on the other hand, focuses on long-term adaptation. These results are in line with what Barba-Sánchez et al. (2024) say, which is that higher-order skills like strategic reconfiguration and organizational learning become more important as DT goes on. The fact that the answers came from different departments and sectors adds to the evidence for this multimodal learning process.

When it comes to farming businesses, the effects of DT go beyond making things run more smoothly to include important issues like food security. Digital tools can help with real-time monitoring of crop yields, make supply chains more efficient, and better allocate resources. These are all important for long-term agricultural productivity. As food systems around the world come under more and more pressure, especially in developing areas, it is important that DT is successfully used in agriculture to make sure that food is always available and that the systems can handle environmental shocks (Sargani et al., 2025). The fact that most of our respondents were experienced middle managers from fields like farming (47.7%) and animal husbandry (23.3%) shows how useful these findings are in real life. Their ideas show how financial literacy and learning can help break down old boundaries. This makes DT a strategic tool for modernizing agriculture and making sure there is enough food.

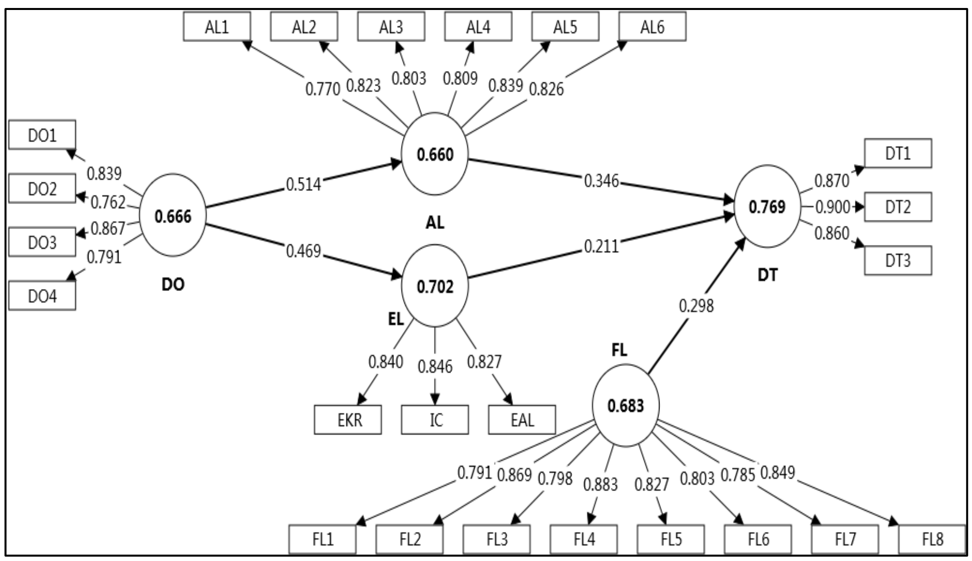


**Figure 3: Structural Model ($R^2$ and t-value)**

*5.1. Theoretical Implications*

First, this study extends the application of dynamic capability theory by contextualizing it within the DT of Chinese agricultural enterprises—a sector previously underexplored in the DCT literature. While DCT posits that firms need to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments(Teece, 2007), our findings demonstrate that DO acts as a strategic sensing mechanism. It enables agricultural firms to perceive opportunities for transformation and develop requisite learning routines, thereby validating the DCT assumption that strategy-driven sensing and learning are precursors to dynamic transformation.

Second, this study introduces FL as an important extension to DCT. Traditional applications of the theory have focused on technological and operational capabilities, but our results suggest that FL functions as a critical dynamic capability—particularly in resource-constrained agricultural contexts. It facilitates effective resource orchestration and risk assessment, aligning with the “seizing” component of DCT. By showing that FL significantly enhances DT outcomes, we expand the DCT framework to include financial competencies as enablers of sustainable transformation.

Third, the mediating roles of AL and EL between DO and DT further refine the internal mechanisms of dynamic capabilities. These findings are congruent with the DCT proposition that learning is central to capability evolution. Specifically, AL supports rapid knowledge acquisition from external sources (sensing and seizing), while EL enables iterative adaptation (reconfiguring), collectively reinforcing the theory's emphasis on learning as a foundation for strategic renewal.

Overall, the findings do not contradict but rather enrich DCT by introducing novel constructs such as FL, clarifying learning dynamics in agricultural DT, and offering empirical insights into how different capabilities are activated at various stages of transformation. This study thus strengthens the theoretical applicability and explanatory power of DCT in a non-traditional yet increasingly critical industry sector.

*5.2. Practical Implications*

First, agricultural firms must first define explicit digital strategy objectives and methodically devise a plan to acquire the latest theoretical knowledge, encompassing new technologies, expertise, and market demand dynamics, using digital channels. Furthermore, agricultural firms want to employ digital tools to save expenses associated with redundant trials. Agricultural firms must develop CEOs with advanced financial literacy and improve their financial decision-making and resource allocation skills during digital transformation. Consequently, organizations can enhance the financial expertise of managers and employees via targeted financial training and support from external professional entities, enabling them to more effectively comprehend and address the challenges of digital transformation, such as resource allocation, risk management, and financial planning.

Secondly, agricultural firms can integrate cutting-edge technology and management expertise by establishing external collaboration networks, enhancing partnerships with universities, research institutions, and technology suppliers, and routinely engaging in collaborative research and development and technical exchange initiatives. Moreover, firms must to enhance the knowledge acquisition system and swiftly assimilate external sophisticated digital technologies and concepts through engagement in industry forums and technology fairs. Simultaneously, create a knowledge-sharing platform and an online learning system to promote the acquisition of external knowledge by employees and its practical application. Agricultural firms must to assess the viability of novel technologies and processes by implementing small-scale pilot projects and progressively broadening their application. Simultaneously, organizations ought to offer incentives for experimentation to motivate employees to suggest and evaluate digital innovation ideas, mitigate consequences for failure, and cultivate a corporate culture that embraces risk-taking.

Finally, the IPMA results give us further information on how to improve our strategic emphasis. AL is the most important and best-performing of the main elements, which means that companies should keep making external knowledge acquisition a top priority. FL is also quite important, which means that spending money on programs that teach people about money and how to use it can lead to real increases in digital transformation outcomes. EL is helpful, but it's not as important as other things, therefore it might be more important for long-term innovation than short-term change. DO stands out as the least important and least effective, which could be a sign of a strategy gap. To get the most out of digital, companies should enhance their digital leadership, make sure that top management is aware of it, and make sure that digital plans are more closely aligned with operational goals. These insights give agricultural businesses that are going through digital transformation a realistic way to decide which resources to focus on and how to improve their skills.

### *5.3 Limitations and Future Studies*

This study gives us useful information about how digital orientation, financial literacy, acquisitive learning, and experiential learning can help Chinese agricultural businesses go digital. However, it also has some problems that need to be pointed out, which could be the basis for more research in the future.

First, this study focused on Chinese agricultural enterprises, perhaps making the findings context-specific and limiting their relevance to other industries or countries. Future research may examine the significance of these connections across diverse sectors or cultural contexts, such as manufacturing or healthcare, to assess the contextual robustness of the proposed framework.

Secondly, this research primarily emphasizes organizational-level analysis. While it offers a significant viewpoint on the influence of financial literacy and organizational learning on digital transformation, subsequent research should broaden the study's scope to include external elements such as governmental policies, industry rules, and market dynamics. External influences may profoundly affect the interplay among digital orientation, learning behavior, and digital transformation, especially within agribusiness. Individual-level research can enhance the understanding of the dynamic process of digital transformation, particularly in fostering successful implementation through the development of individual talents, innovative behaviors, and adaptable capabilities. Future study must focus more on the pivotal role of persons in digital transformation, augment existing organizational-level studies, and advance both theory and practice.

Finally, although this study examined the mediating role of AL and EL but did not investigate potential moderating factors. Future work could introduce moderators such as organizational culture, leadership style, or resource slack to better understand the boundary conditions under which learning behaviors enhance DT. This would deepen the theoretical contribution and offer more nuanced managerial guidance.

Lastly, from a methodological perspective, this study employed PLS-SEM; future research could adopt alternative analytical approaches, such as longitudinal designs or fsQCA, to further validate the causal and configurational complexity of the proposed relationships. Moreover, expanding the theoretical lens by incorporating frameworks such as Institutional Theory or UTAUT / UTAUT2 may offer deeper insights into the mechanisms of digital transformation in agriculture and other sectors.

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## Appendix

| Constructs and Measurement Items | |
|---|---|
| Digital transformation | |
| DT1 | The new business processes of our firm are built on technologies such as big data, analytic, cloud, mobile and social media platform |
| DT2 | The digital technologies of our firm such as social media, big data, analytic, cloud and mobile technologies are integrated to drive change |
| DT3 | The business operations of our firm are shifting toward making use of digital technologies such as big data, analytic, cloud, mobile and social media platform. |
| Digital Orientation | |
| DO1 | Our firm is committed to using digital technologies to develop our new solutions. |
| DO2 | Our firm's solutions have superior digital technology. |
| DO3 | New digital technology is readily accepted in our firm. |
| DO4 | Our firm always looks for opportunities to use digital technology in innovation. |
| Acquisitive Learning | |
| AL1 | Our firm has actively acquired new technologies from business partners |
| AL2 | Our firm has actively acquired market development skills from business partners |
| AL3 | Our firm has actively collected information on technological developments |
| AL4 | Our firm has actively collected information on consumer needs and preferences |
| AL5 | Our firm has actively obtained new and important information from business partners |
| AL6 | Our firm has actively collected government-related information |
| Experimental Learning | |
| Internal Communication | |
| IC1 | Work experiences from one strategic business unit or department of our firm has quickly diffused to other units. |
| IC2 | Experience of serving customers of our firm has shared among internal departments |
| IC3 | Departments of our firm have strongly motivated to learn from each other |
| IC4 | Employees of our firm have taken part in decision making based on team discussions |
| Exploitation of Knowledge Resources | |
| EKR1 | Our firm has exploited process technology |
| EKR2 | Our firm has exploited technology transferred from outside |
| EKR3 | Our firm has exploited know-how and patents |
| EKR4 | Our firm has exploited technological equipment |

| | |
|---|---|
| Experience Accumulated through Learning-By-Doing | |
| EAL1 | Cooperation of our firm among departments and job functions has been encouraged |
| EAL2 | Employees of our firm have been encouraged to try new work methods |
| EAL3 | Employees of our firm have taken part in decision making based on their experience |
| Financial Literacy | |
| FL1 | Our firm prepares monthly company financial statement (income statement and balance sheet) |
| FL2 | Our firm reviews monthly financial statements |
| FL3 | Our firm performs financial analysis on monthly financial statements |
| FL4 | Our firm understands the company's gross profit ratio and its contribution to the overall profit |
| FL5 | Our firm considers data a tangible asset |
| FL6 | Our firm bases our decisions on data rather than on instinct |
| FL7 | Our firm is willing to override our own intuition when data contradict our viewpoints |
| FL8 | Our firm continuously coaches our employees to make decisions based on data |
| Cognitive Rigidity (Marker Variable) | |
| CR1 | Once our firm has come to a conclusion, we are not likely to change our mind |
| CR2 | Our firm does not change our minds easily |
| CR3 | Our firm views are very consistent over time |