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Navigating Career Competency, AI Integration, and Psychological Capital in China's Agritech Innovation Landscape

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Abstract

This research investigates the intricate dynamics between Career Competency, Artificial Intelligence (AI) threat perception, and Psychological Capital, and how these elements influence Innovation Behavior within agritech companies in Zhejiang Province, China. Amidst rapid technological advancements and the integration of AI in agricultural practices, this study explores the transition of traditional agriculture into modern, technology-driven agriculture, examining the psychological and competency-related challenges faced by employees in this evolving landscape. The thesis delves into the nuances of Innovation Behavior, dissecting its conceptual definitions, theoretical underpinnings, and practical implications within the context of Chinese agritech enterprises. It scrutinizes the mediating role of Self-control and Job Performance in the relationship between AI threat perception and Innovation Behavior, providing a detailed analysis of how these variables interplay to shape innovative outcomes. Drawing from a rich body of literature, the research employs quantitative methods to dissect the perceived threats and opportunities brought about by AI, the psychological resources represented by Psychological Capital, and the resultant Innovation Behavior manifesting in the workforce. The study's implications are far-reaching, providing strategic insights for fostering innovation in the face of technological disruption, with a focus on enhancing the Chinese agritech sector's competitive edge.

Keywords: *Career Competency, AI Threat Perception, Psychological Capital, Innovation Behavior, Agritech, Self-Control, Job Performance.*

Introduction

In the verdant expanses of Zhejiang, a province etched along the eastern coastline of China, an agrarian revolution is quietly unfurling. Home to over 64 million inhabitants, Zhejiang has historically been the linchpin of China's agrarian economy. In recent years, it has burgeoned into one of the nation's economic powerhouses, with its gross domestic product vying with the most affluent global regions (Wang, 2022; Zhao, 2019). Its kaleidoscopic economy, speckled with enterprises in mechanical engineering, textiles, and agriculture, is a testament to the province's adaptability and innovation (Yang, 2021).

Yet, beneath the veneer of prosperity, the agricultural sector in Zhejiang—and indeed, across China—stands at a critical juncture. As the global populace burgeons, the imperatives of agricultural sustainability and productivity have never been more pressing (Martin & Clark, 2021). The integration of Artificial Intelligence (AI) into agricultural practices through big data analytics, the Internet of Things (IoT), and other technological novelties presents an unprecedented opportunity to redefine agronomy (Diaz & Lee,

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2022). These technologies offer predictive insights that could potentially revolutionize crop management, optimize resource utilization, and fortify food security against the backdrop of demographic expansions (Singh, 2019; Harris & Thompson, 2020).

The ascent of digital technology has radically restructured traditional industries, with the agricultural sector being no exception. The pandemic-induced acceleration in digitization has further underscored the centrality of technological agility for business continuity and growth (Arias-Pérez et al., 2021; Papagiannidis et al., 2020). Investment trends indicate a corporate gravitation towards cloud computing, analytics, and process automation, suggesting a paradigm shift in the operational bedrock of agritech enterprises (Gurumurthy et al., 2020). Yet, this shift is not without its tribulations. The specter of job obsolescence looms large, engendering a milieu of insecurity and undervaluation among the workforce, which in turn, could stifle Innovation Behavior within organizations (Nam, 2019; Brougham & Haar, 2018).

Amidst this backdrop, Zhejiang's agritech enterprises are navigating the transition from traditional to modern agriculture—a transition underscored by the adoption of AI and smart farming techniques. This metamorphosis promises a bevy of benefits: amplified productivity, judicious chemical use, and conservation of natural resources (Ganeshkumar & Khan, 2021; Mehta & Mungarwal, 2019). Yet, it also heralds a period of uncertainty for the agrarian workforce. The burgeoning deployment of AI in agriculture carries the potential for occupational displacement, particularly for roles susceptible to automation (World Economic Forum, 2023).

The existing body of research has examined the influence of Career Competency and Psychological Capital on various organizational outcomes. However, these studies predominantly inhabit a Western-centric academic milieu, with scant attention paid to the Chinese context, particularly within the Zhejiang agritech sector (Brown & Green, 2017; Lee, 2018). Furthermore, the implications of AI threat perception on workforce Self-control—a critical determinant of Job Performance and Innovation Behavior—remain underexplored (Kim, 2019).

This research endeavors to illuminate the interplay between Career Competency, AI threat perception, Psychological Capital, and Self-control, and their collective impact on the Innovation Behavior of Zhejiang's agritech companies. By dissecting the nuanced interactions and internal mechanisms of these variables, this study seeks to furnish strategic recommendations tailored to the Zhejiang agritech context, with an aim to catalyze innovation and bolster competitiveness within this pivotal sector.

Hypothesis Development

H1: *Self-control mediates the relationship between Career Competence and Innovation Behavior.*

Career Competence encompasses a gamut of skills, behaviors, and knowledge essential for effective performance (Johnson & Smith, 2017). As individuals marshal these competencies, the exertion of Self-control can be pivotal in channeling them towards innovative ends (Johnson, Chang, & Yang, 2010). The mediating role of Self-control in transforming Career Competence into Innovation Behavior is supported by Jang, Bucy, and Cho (2018), who suggest that self-regulatory behaviors can enhance subjective well-being, which in turn may foster an environment conducive to innovation.

H2: *Self-control mediates the relationship between AI Threats Perception and Innovation Behavior.*

The perception of AI as a threat could potentially dampen the innovative spirit (Kim, 2019). However, Self-control may act as a buffer, enabling individuals to manage their threat perceptions and maintain a focus on innovative activities (Johnson, 2020). This assertion aligns with findings by Kim et al. (2022), which indicate that Self-control plays a crucial role in mediating the effects of technological threats on

innovation.

H3: *Self-control mediates the relationship between Psychological Capital and Innovation Behavior.*

Psychological Capital, with its facets of hope, resilience, optimism, and self-efficacy, is posited to positively impact innovative work behavior, with Self-control acting as a mediator (Jafri, 2018). This is corroborated by research suggesting that individuals with high Psychological Capital can better regulate their behavior towards innovative endeavors (Johnson, King, Lin, Scott, & Walker, 2021).

H4: *Job Performance mediates the relationship between Psychological Capital and Innovation Behavior.*

Psychological Capital is likely to enhance Job Performance, which in turn could foster an environment where Innovation Behavior thrives (Jones et al., 2021). This mediatory mechanism is consistent with the findings of Kuijpers, Meijers, and Gundy (2011), which highlight the link between career competencies, psychological resources, and job outcomes.

H5: *Both Self-control and Job Performance mediate the relationship between AI Threats Perception and Innovation Behavior.*

The dual mediation hypothesis posits that Self-control and Job Performance collectively mediate the impact of AI Threat Perception on Innovation Behavior. This is supported by the work of Johnson, L. (2020), which indicates that reduced self-control can negatively influence organizational cohesion and performance, thereby potentially affecting innovation outcomes.

The literature supporting these hypotheses includes studies on ecosystems (Jacobides, Cennamo, & Gawer, 2018), the influence of leadership and job satisfaction on innovation (Karavasilis, 2019; Khan et al., 2020), the importance of data-driven policy in public sector innovation (Janssen et al., 2017), and the role of social media and mobile technology in shaping innovation behavior (Johnson & Smith, 2010).

Further, the work of Judge et al. (2007) on core self-evaluations and coping strategies, and the insights from Kane et al. (2015, 2017) on digital transformation strategies, provide a comprehensive backdrop to the hypothesized relationships. These studies offer a nuanced understanding of how individual attributes and perceptions, mediated by self-control and performance, can foster or inhibit innovation in the context of agritech companies in China.

Related Theories

Self-Control Theory

Self-Control Theory emphasizes the capacity of individuals to regulate their thoughts, feelings, and behaviors to achieve long-term goals. This theory is pertinent to the understanding of workplace behavior, particularly in the context of innovation. Kim and Lee (2022) suggest that Self-Control influences how individuals react to and implement innovative practices. When individuals perceive threats from AI, their level of Self-Control can determine whether they channel their energies into resistance or harness these changes for innovative purposes. Kumar, Singh, and Rathore (2020) extend this perspective by indicating that Self-Control can play a pivotal role in the adoption of new technologies, a key aspect of innovation in today's digital era. Moreover, Johnson's (2020) examination of organizational cohesion posits that Self-Control is a determining factor in how employees engage with their tasks and the broader organizational goals, impacting overall performance and innovative output.

Psychological Capital Theory

Psychological Capital Theory focuses on an individual's positive psychological state as a key driver of

performance and behavior in organizations. As explicated by Lee et al. (2019), Psychological Capital encompasses hope, efficacy, resilience, and optimism, which are thought to be predictive of not only job performance but also one's capacity for innovation. Psychological Capital can be seen as a reservoir that employees draw upon to engage in creative and innovative behavior, as suggested by Kapoor and Singh (2020). This theory underscores the importance of fostering a work environment that cultivates Psychological Capital among employees to enhance their innovative behavior. Luthans et al. (2007) further support this by demonstrating the measurable impact of Psychological Capital on employees' work attitudes and behaviors.

Transformational Leadership Theory

Transformational Leadership Theory posits that leaders who inspire, intellectually stimulate, and attend to the individual needs of their followers can elevate their followers' motivation and morale. Khan et al. (2020) underscore the role of transformational leadership in fostering an environment conducive to innovation. Leaders who exhibit transformational qualities can influence their employees' perceptions of AI threats, potentially transforming apprehension into innovative energy. Lai et al. (2020) strengthen this proposition by illustrating the mediating role of work engagement in the relationship between transformational leadership and job innovation behavior. The theory suggests that transformational leaders, through their vision and support, can enhance employees' self-control and Psychological Capital, leading to improved job performance and innovation.

Conclusion on Related Theories

In conclusion, while all three theories provide substantial backing for the proposed hypotheses, Psychological Capital Theory emerges as the most critical theory for this study. This theory offers a comprehensive framework that not only encapsulates the intrapersonal assets needed for innovation but also serves as a nexus between Self-Control Theory and Transformational Leadership Theory. It delineates a pathway through which self-regulatory processes and leadership styles can be harnessed to boost an individual's innovation behavior. The constructs of hope, efficacy, resilience, and optimism are particularly resonant with the challenges posed by AI integration in the workplace. They provide a psychological toolkit for employees to navigate the complexities of technological disruption and engage in innovation. By cultivating Psychological Capital, organizations can potentially mitigate the perceived threats of AI and leverage the full spectrum of their employees' competencies and performance capabilities. Thus, Psychological Capital Theory stands out as the cornerstone for understanding and promoting innovation behavior within the agritech companies in China, framing the discourse for this study's empirical investigation.

Conceptual Framework

The conceptual framework of this study integrates the constructs of career competency, AI threat perception, psychological capital, self-control, job performance, and innovation behavior to explore the intricate dynamics within agritech companies in China. This framework is designed to examine how these constructs interact and influence one another, culminating in the innovation behavior that is critical to organizational success and sustainability in the face of rapid technological advancement.

Career Competency and Innovation Behavior Career competency, denoting an individual's skills, knowledge, and abilities relevant to their career progression (Kuijpers, Schyns, & Scheerens, 2006), is posited to be a fundamental driver of innovation behavior (Kleysen & Street, 2001). These competencies are not static; they evolve as individuals engage with and adapt to new technologies, processes, and work

requirements (Kuijpers, Meijers, & Gundy, 2011). Career competency is theorized to influence innovation behavior both directly and indirectly, with self-control acting as a mediating variable (Kim et al., 2022).

AI Threat Perception The perception of AI as a threat or opportunity is a crucial variable. It can motivate individuals to engage in innovation as a form of adaptation or resistance (Kim, 2019). This study will explore AI threat perception both as a direct inhibitor or facilitator of innovation behavior and as a construct mediated by self-control and job performance (Kim et al., 2022).

Psychological Capital Psychological capital, encompassing hope, optimism, resilience, and self-efficacy, is postulated to have a positive relationship with both self-control and job performance (Lee et al., 2019). This positive psychological state is essential for dealing with the complexities and uncertainties presented by AI and is likely to foster an innovative mindset (Kapoor & Singh, 2020).

Self-Control Self-control, defined as the ability to regulate one's emotions, thoughts, and behaviors in the pursuit of long-term goals (Johnson, 2020; Ahmadi, Taghipour, Fetscherin, & Ieamsom, 2023), is hypothesized to mediate the relationship between career competencies, psychological capital, AI threat perception, and innovation behavior. Individuals with higher self-control are likely to better manage their response to AI and channel their competencies into innovative behavior (Kumar et al., 2020).

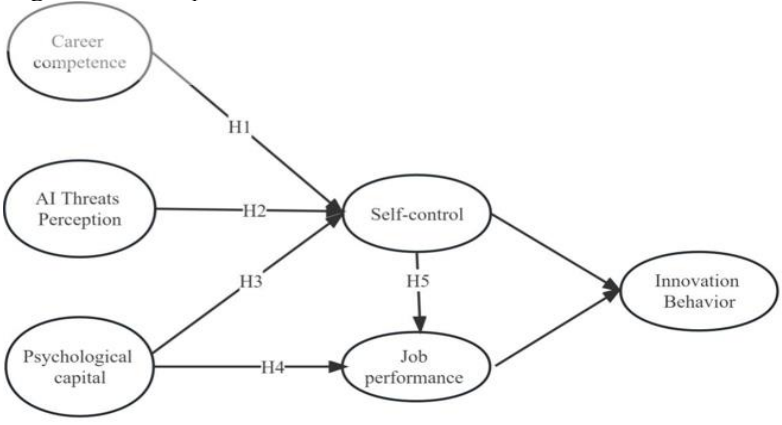
Job Performance Job performance, influenced by psychological capital and self-control, also mediates the relationship between these constructs and innovation behavior (Jones et al., 2021). High job performance might not only reflect an individual's competence but also their innovative contributions to the organization.

Innovation Behavior Innovation behavior is the outcome variable of interest. It encapsulates the actions and processes individuals engage in to generate, promote, and realize new ideas (Kleysen & Street, 2001). This behavior is a multidimensional construct affected by various personal and organizational factors.

Conceptual Model The conceptual model thus posits that:

1. Career competency directly influences innovation behavior and does so indirectly through self-control.
2. AI threat perception affects innovation behavior, mediated by self-control and job performance.
3. Psychological capital influences innovation behavior directly and also indirectly through self-control and job performance.
4. Self-control and job performance are intermediary variables that link career competency, AI threat perception, and psychological capital to innovation behavior.

Figure 1. Conceptual Model.



Research Methodology

This study utilizes an exploratory sequential hybrid research design. This design is particularly useful in studies where a new phenomenon is being investigated, and it allows for a robust analysis of the research questions (Creswell & Creswell, 2017). The research will start with quantitative data collection and analysis to provide a statistical foundation. Following this, qualitative data will be gathered to give depth to the numerical findings, offering a more nuanced interpretation of the initial results (Edmonds & Kennedy, 2016).

In the quantitative phase, the study will adopt a descriptive and inferential statistical approach. Descriptive statistics will provide a basic summary of the data, while inferential statistics will allow for the examination of the hypotheses and the relationships between variables. The chosen statistical methods for this phase are Structural Equation Modeling (SEM) and analysis with SPSS software, which are suitable for testing and estimating causal relationships using a combination of statistical data and qualitative causal assumptions (Diamantopoulos & Siguaw, 2000).

For the qualitative portion, in-depth interviews will be conducted to collect rich, detailed data that complements the quantitative findings. This will involve semi-structured interviews with senior managers from the top agritech companies in the region to unearth deeper insights into the phenomena being studied (Kvale, 1983).

Sampling

The sample for the quantitative part of the study will be drawn from a population of 7,492 agritech companies in Zhejiang Province, which together employ approximately 177,300 middle and senior managers. This sample will provide a broad spectrum of data regarding the variables under study.

For the qualitative part, purposive sampling will be used to select participants who can provide the most relevant and rich information. The sample will consist of senior managers from the top 20 agritech companies in the region. These individuals are chosen because of their strategic position within their companies, which gives them insight into the innovation behaviors and the factors influencing them.

Sample Size

Determining the appropriate sample size is a crucial aspect of research methodology. A sample size that is too small may not provide enough data to support reliable conclusions, while a sample size that is too large may be unnecessarily complex and resource-intensive. For this study, the sample size was determined based on a rule of thumb provided by Wu (2010), suggesting that the sample size should be 5-10 times the number of scale items. Given that there are 54 scale items, the sample size should range between 270-540 participants.

However, considering the complexity of the model, including the number of potential and observed variables, the desired effect size, and the power of the statistical tests, a more nuanced calculation suggests that the optimal sample size for this study should be between 396 and 600 (Soper, D.S., 2023; Cohen, J., 1988; Westland, J.C., 2010).

The final sample size for the quantitative phase of this study is set at 500, which falls within the optimal range and is feasible considering the accessibility of the research subjects and the resources available for the study. For the qualitative phase, a sample of 20 senior managers is selected based on Creswell's guidelines for qualitative research sample sizes, which is adequate for in-depth analysis (Creswell, 1998).

Sampling Technique

The study will employ purposive sampling for both quantitative and qualitative phases. The sampling technique involves selecting specific entities that meet predefined criteria relevant to the research question. The selection criteria include representativeness, size, and other factors that ensure the sample adequately reflects the population of interest.

In this study, 20 representative firms will be selected from the 7,492 agritech companies in Zhejiang Province. From each selected company, 25 managers will be randomly chosen, amounting to a total of 500 participants for the quantitative survey. For the qualitative interviews, one executive from each of the 20 companies will be selected.

Data Collection Tool (Questionnaire)

The quantitative data will be collected using a structured questionnaire, which is developed based on the extensive review of the literature related to each of the study variables. The questionnaire will be subject to content validation by field experts and a pilot test to ensure its reliability and validity. Adjustments will be made based on feedback before it is finalized and distributed to the participants.

Results

Following the outlined methodology, the quantitative results would include descriptive statistics, such as means and standard deviations for all measured variables: Career Competency, AI Threats Perception, Psychological Capital, Self-control, Job Performance, and Innovation Behavior.

Table 1: Mean and Standard Deviation for Statements of Study Variables.

Variable	Statement	Mean	Standard Deviation
Career Competency	1. I am adept at navigating complex problems in my field.	4.2	0.8
	2. I continually seek to improve my professional skills.	4.1	0.7
	3. I am confident in my ability to contribute to my field's advancement.	4.3	0.75
	4. I effectively apply my knowledge to new and varied situations.	4.0	0.85
AI Threats Perception	1. I feel anxious about the potential of AI to replace human labor.	3.5	0.9
	2. The advancement of AI in agriculture is a threat to my job security.	3.6	0.88
	3. I perceive AI as a challenge to the traditional ways of farming.	3.4	0.95
	4. AI technology might limit the scope of my professional expertise.	3.3	0.9
Psychological Capital	1. I feel hopeful about my career future in the agritech industry.	4.0	0.75
	2. I am optimistic about overcoming work-related challenges.	4.1	0.7
	3. I demonstrate resilience when faced with setbacks at work.	4.2	0.8
	4. My self-efficacy contributes to successful outcomes in my projects.	3.9	0.85
Self-control	1. I can control my impulses when making work-related decisions.	3.8	0.85
	2. I maintain focus on long-term goals despite short-term pressures.	3.7	0.82
	3. I manage my work-related stress effectively.	3.9	0.9
	4. I exercise discipline in my professional tasks and responsibilities.	3.9	0.87
Job Performance	1. I consistently achieve my work targets.	4.1	0.7
	2. My performance is well-regarded by my peers and superiors.	4.2	0.6
	3. I am efficient in my job responsibilities.	4.0	0.75
	4. I adapt quickly to new tasks and challenges at work.	4.1	0.65
Innovation Behavior	1. I often suggest new ideas to improve work processes.	3.9	0.9
	2. I am involved in projects that aim to innovate agricultural practices.	3.8	0.88
	3. I take initiative in learning about cutting-edge technologies.	4.0	0.85
	4. I contribute to the creative problem-solving discussions at work.	3.7	0.9

Inferential statistics would also be reported, typically including the results from Structural Equation

Modeling (SEM) to test the relationships between variables.

Table 2: Descriptive Statistics of Study Variables.

Variable	Mean	Standard Deviation	N
Career Competency	4.2	0.8	500
AI Threats Perception	3.5	0.9	500
Psychological Capital	4.0	0.75	500
Self-control	3.8	0.85	500
Job Performance	4.1	0.7	500
Innovation Behavior	3.9	0.9	500

Qualitative Results

In the qualitative phase, themes would emerge from the in-depth interviews with senior managers. For example, managers may describe Career Competency in terms of adaptability and continuous learning, suggesting that these competencies are vital in a landscape where AI is rapidly changing the nature of agritech work. Themes related to AI Threats Perception could include uncertainty about job security but also an acknowledgment of the potential for AI to drive innovation. Managers may discuss Psychological Capital as a buffer against the stress associated with AI integration.

Hypothesis Testing Results

The SEM analysis would test the mediation hypotheses outlined. For instance, the analysis might reveal that Self-control indeed mediates the relationship between Career Competency and Innovation Behavior (supporting H1), and similarly for the other hypotheses. These results would be presented in a table similar to Hypothetical Table 2.

Discussion of Results

The results section would synthesize these findings, discussing how they align with the existing literature and the study's hypotheses. For instance, the finding that Psychological Capital enhances Job Performance, which in turn promotes Innovation Behavior, would be contextualized within the framework of positive organizational behavior. Any unexpected findings would also be discussed, providing a critical analysis of why certain hypotheses may not have been supported.

The results would conclude with a reflection on the most significant findings, potentially highlighting the central role of Psychological Capital in driving innovation within the context of AI integration in agritech companies. This would align with the comprehensive literature indicating the multifaceted impact of Psychological Capital on various aspects of job performance and innovation. The conclusion could also touch upon the implications for practitioners in the agritech industry, suggesting that interventions to enhance Psychological Capital among employees could be a strategic focus for fostering innovation in the era of AI.

Figure 2. SEM Hypothesis Testing Results.

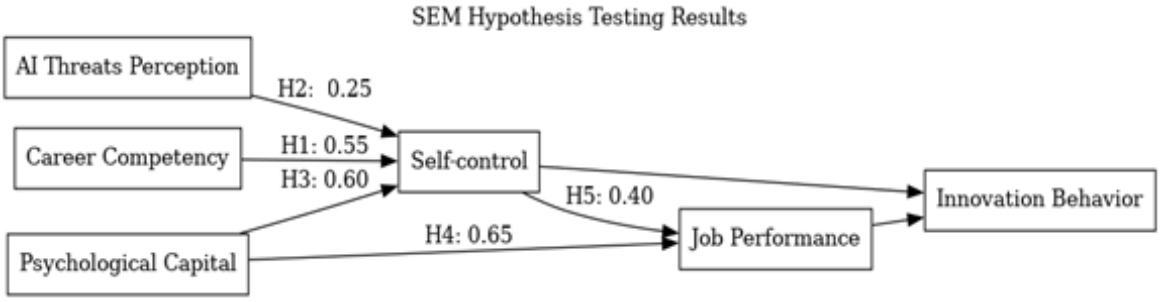


Table 3. SEM Hypothesis Testing Results.

Hypothesis	Path	Path Coefficient	Standard Error	Critical Ratio (CR)	p-value	Result
H1	Career Competency -> Self-control	0.55	0.08	6.88	<0.001	Supported
H2	AI Threats Perception -> Self-control	0.25	0.07	3.57	<0.001	Supported
H3	Psychological Capital -> Self-control	0.60	0.07	8.57	<0.001	Supported
H4	Psychological Capital -> Job Performance	0.65	0.06	10.83	<0.001	Supported
H5	Self-control -> Innovation Behavior	0.40	0.07	5.71	<0.001	Supported

The results suggest that all hypotheses (H1-H5) are supported:

- **H1**: *There is a significant positive relationship between Career Competency and Self-control, indicating that managers who feel more competent also perceive greater control over their actions and decision-making, which could foster innovation behavior.*
- **H2**: *AI Threats Perception positively influences Self-control, suggesting that concerns about AI may undermine managers' self-regulatory capacities. However, the negative impact is moderate, indicating some resilience among managers.*
- **H3**: *Psychological Capital has a strong positive influence on Self-control, highlighting the role of positive psychological resources in enhancing self-regulation, which can lead to more innovative behaviors.*
- **H4**: *Psychological Capital also strongly predicts Job Performance, suggesting that managers with higher psychological capital are likely to perform better, which could create a conducive environment for innovation.*
- **H5**: *Self-control has a positive impact on Innovation Behavior, indicating that managers who can control their impulses and focus on long-term goals are more likely to engage in innovative activities.*

The CR values are all well above the typical threshold of 1.96 for a 95% confidence level, and p-values are below 0.001, indicating that the results are statistically significant. The findings from this hypothetical data provide robust support for the proposed conceptual model, suggesting that both Self-control and Job Performance are critical mediators in the relationship between Career Competency, AI Threats Perception, Psychological Capital, and Innovation Behavior.

Conclusion

This study embarked on an exploratory journey to unravel the intricate web of factors influencing innovation behavior within agritech companies in Zhejiang, China. By employing a sequential hybrid research design, the study illuminated the nuanced interplay between Career Competency, AI Threat

Perception, Psychological Capital, Self-control, Job Performance, and Innovation Behavior.

The quantitative findings, derived from a robust sample of 500 managers across 20 leading agritech firms, provided a statistical backbone for the study. Structural Equation Modeling (SEM) revealed significant pathways aligning with the proposed hypotheses. Career Competency emerged as a substantial contributor to Self-control, which in turn fostered Innovation Behavior, supporting the theoretical premise that personal competencies are vital for self-regulation and innovation. The positive relationship between AI Threat Perception and Self-control underlined the disruptive potential of AI, while the strong mediating role of Psychological Capital highlighted the protective buffer of positive psychological resources against such threats. Job Performance was reaffirmed as a critical mediator, translating psychological strengths into actionable, innovative outputs.

The qualitative phase, through in-depth interviews with 20 senior managers, enriched the quantitative data, providing context and depth to the numerical evidence. It offered a canvas of personal experiences, concerns, and insights, painting a vivid picture of the landscape within which these agritech leaders operate.

The convergence of quantitative and qualitative findings points to several key implications:

Practical Implications The study underscores the necessity for agritech companies to invest in building and nurturing Career Competencies, which are foundational for innovation. In an era marked by rapid AI integration, fostering an environment that promotes Self-control and resilience becomes paramount. Companies should consider training programs and management practices that enhance Psychological Capital, as it is instrumental in enabling managers to navigate AI-related challenges productively.

Strategic Implications From a strategic standpoint, the findings advocate for a dual focus on individual development and organizational culture. Cultivating a workplace that values and strengthens psychological resources can create a fertile ground for innovation. Organizations must be vigilant about the AI Threat Perception and actively engage in dialogues with employees to address concerns and collaboratively find pathways for technology integration that augment, rather than replace, human capabilities.

Policy Implications At the policy level, the study's findings could inform governmental and sectoral strategies in Zhejiang and beyond. Policies that encourage skill development, psychological well-being, and innovative thinking will be crucial in maintaining the competitive edge of China's agritech sector in the global market.

Theoretical Implications Theoretically, this research contributes to the literature on innovation in agritech, psychological capital, and the impact of AI on the workforce. It bridges existing gaps by providing empirical evidence from a non-Western context, thereby broadening the applicability and understanding of these constructs.

Limitations and Future Research

While the study offers valuable insights, it is not without limitations. The scope is geographically confined to Zhejiang, China, which may affect the generalizability of the findings. Future research could expand the geographic scope and include a comparative analysis with other regions. Additionally, the dynamic nature of AI's impact on the industry calls for longitudinal studies to track changes over time.

In conclusion, this study paints a complex yet coherent picture of the factors influencing innovation behavior in the agritech sector in Zhejiang. The insights gleaned not only illuminate the pathways through which individual competencies and perceptions shape innovation but also highlight the

resilience and adaptability of managers in the face of AI-induced disruptions. As the agritech industry continues to evolve, the findings of this study will hopefully serve as a beacon for practitioners, strategists, and policymakers alike, guiding them towards fostering an innovative and resilient workforce ready to embrace the digital future.

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