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THE INFLUENCE OF CAREER COMPETENCE, AI THREATS PERCEPTION AND PSYCHOLOGICAL CAPITAL ON INNOVATION BEHAVIOR OF AGRITECH COMPANIES IN CHINA

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Abstract

Innovation can promote the development and progress of organizations; agricultural researchers, technology companies and agricultural management agencies are striving to innovate to achieve the goal of smart agriculture. This paper takes the top 20 agricultural technology companies in Zhejiang Province as the research object to explore the influence of career competence, AI threats perception and psychological capital on innovation behavior and takes self-control as a variable to explore the mediating effect of it. The conclusions are as follows: career competence, AI threats perception and psychological capital will promote innovation behavior, self-control mediates the relationship between career competence, AI threats perception and psychological capital will improve innovation behavior.

Keywords: Career competence; AI threats perception; Psychological Capital, Self-control; Innovation Behavior.

INTRODUCTION

Eastern Chinese coastal province Zhejiang. Zhejiang is China's fifth-largest province, with 64.6 million residents. China relies on it. Chinese economic reforms have made Zhejiang province wealthy. Fourth and fifth in national GDP rankings, its nominal GDP per capital was 5.62 trillion CN yuan, or 849 billion USD, in 2018. This eclipses Paris and London's riches. Mechanical, electrical, textile, chemical, culinary, agricultural and construction goods drive Zhejiang's economy.

Economic sustainability depends on agriculture (Porter & Heppelmann, 2020). It's necessary for economic growth and structural change, although its impacts differ by country. Agriculture has traditionally been centered on food and crops. It now processes, produces, markets, and distributes products and cattle after 20 years. Agricultural operations feed people, improve GDP, facilitate trade, reduce unemployment, offer raw materials for other sectors and support economic development. As the global population expands, it is crucial to reassess agricultural practices in order to discover innovative methods for protecting and enhancing agriculture. Big data analytics, the internet of things, cheap sensors and cameras, drones and widespread internet connectivity will enable AI in agriculture (Nelson et al., 2022).

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Artificial intelligence (AI) algorithms may anticipate the best crop to grow in a given year and the ideal time for sowing and harvesting in a location by assessing soil management data, including temperature, weather, soil analysis, moisture levels and previous crop innovation behavior (Roberts& Jackson, 2023).

Crop yields grow while water, fertilizer and pesticide consumption decrease (Simons et al.,2020). The value of business innovation Behavior has increased, notably in Zhejiang, a traditional agricultural region with contemporary technologies (Smith, 2018).

Agriculture production and management are easier with AI (Johnson, 2019), but employment instability is an issue. AI may replace monotonous positions like bank tellers and data entry clerks, according to the Future of Positions 2023. Demand for data analysts, scientists, big data specialists, AI and machine learning specialists, and cybersecurity workers will climb 30% by 2027Qu, G. (2021).

In 2023, the World Economic Forum found that 42% of enterprises will prioritize AI and big data training for employees within five years. A preliminary study examines how career competence and psychological capital affect self-control and inventiveness (Brown & Green, 2017).

This study examines Western culture (Lee, 2018). There is little research on similar ties in China, especially among Zhejiang agri-tech companies. AI threats perception and self-control research are rare (Kim, 2019). AI in China's agriculture economy: career challenges and uncertainty for creative people and experts? Will Zhejiang agri-tech workers' career competence, AI threats perception, psychological capital, and self-control affect corporate success and innovation? Understanding how these variables interact and providing strategic guidance based on Zhejiang agri-tech companies is crucial. This will increase the company's innovation and competitiveness. This research presents these questions based on context and the problem statement:

Question 1: How does career competence promote self-control and innovation behavior?

Question 2: Does self-control act as a mediator between AI threats perception and the innovation behavior?

Question 3: How does psychological capital promote self-control and innovation behavior?

Research Objectives

Based on the above research questions, this research raises the following research questions:

1) To explore the effects of career competence on the self-control of experts in Zhejiang Agricultural Company, China.

2) To study the internal influencing mechanism of AI threats perception, self-control and innovation behavior in Zhejiang Agricultural Company, China.

3) To create the effects of psychological capital on the self-control and innovation behavior of experts in Zhejiang Agricultural Company, China.

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Significance of the study

This study analyzed agricultural science and technology companies' innovation behavior. Career competence, AI threats perception and psychological capital gained fresh views. This study improves innovation management and OBT. A quantitative study analyzed Zhejiang agricultural science and technology firms. Empirical inquiry provides new ideas and references. Researchers utilize AI, psychology, management and agricultural science and technology to demonstrate an interdisciplinary research paradigm and present a roadmap for future investigations. This research can assist the government in creating policies that encourage agri-technology firm innovation. For the government to understand farm technology enterprises' needs, this study examines Zhejiang. Sustainable local economic growth is the goal. This study can increase agricultural science, technology, production efficiency and product quality, raising living standards and social welfare. This study suggests that agri-tech businesses improve innovation behavior by improving career competence, AI threats perception and psychological capital. Promote employee career advancement: This study shows organizations how to promote and engage people's inventiveness, boosting career advancement and organizational effectiveness. This study can help Zhejiang agricultural science and technology enterprises innovate and compete, boosting industry growth.

LITERATURE REVIEW

Career competence encompasses a person's knowledge, abilities, attitudes, and other relevant traits for a certain job (Boyatzis et al., 1982). These aspects impact a person's job performance and success. Intellectual, skill, attitude and value competencies, interpersonal skills, adaptability and innovation are common career competencies. An individual's ability to actively control and govern their thoughts, emotions, behaviors and wants is called self-control (Mischel et al., 1989). Psychological capital improves teamwork, creativity and organizational performance (Lopez et al., 2002). Hope, efficacy, resilience and optimism (known as "hero") make up psychological capital. AI threats perception may encompass career safety, privacy, social ethics, interpersonal connections, etc. (Davenport & Kirby, 2016; Lingmont & Alexiou, 2020). As an industry or firm undergoes AI transformation, employees tend to regard emerging digital technologies as a danger to their jobs or careers, especially intelligent process automation (Luthans et al., 2007). Self-control includes desire control, emotional regulation, attention and cognitive control, behavioral regulation, moral and value guidance and more. Academic accomplishment, career success, physical health and relationship satisfaction are all linked to personality and self-control. An individual or organization's cognitive and emotional response to AI risks, adverse impacts and threats is called AI threats perception.

Relationship between Career competence and Self-control

Self-control involves proactive planning, organization and time management, which these people do more of (Bandura, 1986). Career competence typically includes adaptability and resilience (Dweck, 2006). This ability to handle setbacks may also include impulse control and self-regulation (Baumeister et al., 1996). Chin et al. (2019) examined career competence and

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self-control in careers. Career competence and self-control were positively correlated, suggesting that people with higher career competence ratings had better self-control (Chin et al., 2019). Career competence, which emphasizes abilities, behaviors and attitudes that improve work success, can help build self-control in numerous circumstances. The evidence reveals that career competence and self-control are positively correlated (Chin et al., 2019). Career competences improve self-regulation, goal-setting and adaptation, which may increase self-control (Bandura, 1986; Baumeister et al., 1996; Dweck, 2006). This hypothesis suggests that career-related qualities may affect self-control, career performance and well-being.

H1: Career competence has a positive effect on Self-control.

Relationship between Psychological Capital and Self-control

Self-efficacy, hope, optimism and resilience are psychological capital (Luthans et al., 2007). These factors greatly affect an individual's life, especially their self-control. Schneider (2001) defines self-control as the ability to manage ideas, emotions and behaviors to attain goals. Psychological capital seems to improve self-control. Self-efficacy links psychological capital with self-control, according to Garaika, G. et al. (2019). Self-efficacy is a person's confidence in their capacity to complete activities or reach goals. Strong self-efficacy leads to ambitious objectives and hard work, which improves self-control. They value long-term goals over short-term gains. Hope and optimism, crucial psychological capital components, boost self-control (Yilma& Karaoglan, 2023). According to Garaika, G. et al. (2019), hope is the conviction that one can plan and overcome difficulties to reach their goals. On the other side, optimism entails looking forward. Positive mental resources motivate and inspire self-control, helping people overcome temptations and obstacles (Bertelsen, & Ozer,2021). Psychological capital is essential for self-control. Self-efficacy, hope and optimism help people resist temptation and focus on long-term goals. Psychological capital's intrinsic strength can help people live a harmonious and joyful existence, opening up new conjectures in the subject.

H2: Psychological Capital has a positive effect on Self-control.

Relationship between AI Threats Perception and Self-control

The AI Threats Perception describes how humans view the possible issues of integrating AI into many aspects of work and life. It may indicate self-control, according to Wright & Schultz (2018). This theory suggests that those who think AI would harm the environment will have better self-control (Wright & Schultz, 2018). Psychologically, anticipating AI-related issues can inspire people to actively control themselves to adapt (Baumeister & Heatherton, 1996; Carver & Scheier, 1998). Wright and Schultz (2018) suggest that AI worries may help people prioritize long-term goals, control impulsivity and adopt solutions that reduce future risks. Bandura introduced Social Cognitive Theory in 1986, which can be applied to this notion. People who feel AI will pose severe environmental threats in the future are likely to assume they can handle them (Bandura, 1986). People who worry about AI harming the environment might use strategic planning and time management to address their concerns, developing self-control (Wright & Schultz, 2018). The literature suggests that AI threats perception improves

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self-control. Those who think AI will have a big impact are more likely to use self-regulation approaches to solve these problems, which may increase their self-control. This theory suggests that AI-related fears may affect self-control and has implications for understanding how external factors affect self-regulation. Therefore, we propose the following theory.

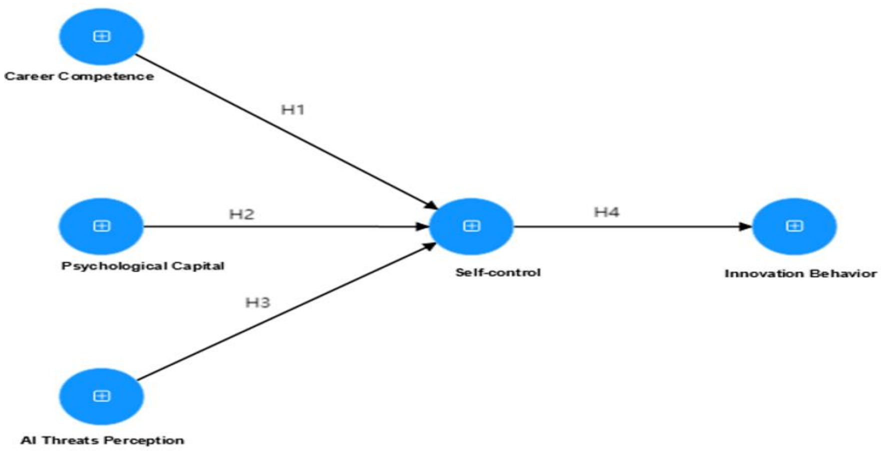
H3: AI Threats Perception has a positive effect on Self-control.

Relationship between Self-control and Innovation Behavior

Organizations and individuals value innovation. Innovation Behavior promotion and maintenance are complicated. Researchers study how psychological self-control affects innovation. Self-control is the ability to manage impulses and actions for long-term goals (Werner et al., 2023). Despite its complex consequences for creativity, self-control is good. Most research has examined how self-control fosters creativity. Self-control encourages creativity, according to Johnson et al. (2010). Over self-control limits creativity, according to Shaw et al. (2012). Self-control improves creative behavior in innovative organizations, according to Miller et al. (2015). Cross-cultural studies link self-control and inventiveness. In 2018, Chen et al. examined Asian and Western self-control and innovation. Cultural context moderates this link, they discovered. Self-regulation is linked to team innovation. Wu et al. (2010) found that self-control boosts team innovation, especially when members have autonomy and variety. Kumar et al. (2020) study how self-control promotes technological adoption and creativity. The study implies that self-control aids technology adoption and innovation. Sanders et al. (2021) examine how culture and self-control effect innovation. This study proposes the next research hypothesis.

H4: Self-control has a positive effect on Innovation Behavior

This chapter focuses on career competence, AI threats perception, psychological capital and self-control, the concepts of innovation Behavior is defined, the influencing factors of latent variables are discussed and the division of dimensions is summarized. Through the discussion of the relationship between variables and the review of the development of research hypotheses, four research hypotheses are proposed to construct the research model. It provides a theoretical basis for the follow-up study.



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RESEARCH METHODOLOGY

This study investigates the use of quantitative methods. We selected 20 important agricultural science and technology enterprises in Zhejiang Province, China for the quantitative section of this study, based on sampling criteria. A total of 500 managers, 25 from each firm, were randomly selected. We measured career competence, AI threats perception, psychological capital, self-control and Innovation behavior. SEM and SPSS statistical analyses were performed on the data (Diamantopoulos & Siguaw, 2000).

Questionnaire Design

Measurement scales help researchers understand the constructs they're evaluating. This improves questionnaire accuracy and consistency verification, resulting in dependable results. The scientists studied the importance and benefits of each variable, including their hypotheses, their characteristics and their evaluation criteria. Each variable then had a tabular representation.

Collect data

This study collects data via a questionnaire. Initially, 500 managers receive emails explaining the study's purpose. After receiving the response, experts receive questionnaire star links or two-dimensional codes. If no response is received, the community will be randomly sampled until 500 samples are collected. We instructed participants to carefully complete the questionnaire and write their responses. We achieved an effective rate of 99% with 495 questionnaires.

Process the data

Check the number and validity of the questionnaires. Validating received surveys prevents the use of inaccurate data that could compromise results. Dismiss a survey with more than 20% unresolved questions. Lack of interest or confusing questions might skew the survey results. Eliminating such questionnaires enhances data integrity and precision. The method must include managing information gaps. Insufficient data can skew and reduce analytical efficacy, affecting survey results. To ensure sample representativeness and reduce bias, it is imperative to address these inconsistencies. Missing data can be managed using strong statistical criteria.

RESULTS

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

Reliability Analysis

To test the structural model, that is, to test the reliability and validity of latent variables and all corresponding explicit variables, including five tests: variable reliability, uniqueness, internal consistency, convergent validity and discriminant validity.

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Cronbach's coefficient is used for testing. If its value reaches above 0.70, then this set of latent variables is considered to be uniquely dimensional. The combined reliability coefficient of the latent variable is used for testing internal consistency. If its value reaches above 0.70, the latent variable is considered to have good internal consistency. Import the questionnaire data collected from the formal survey into SMARTPLS 4.0 software, perform reliability analysis on the 5 latent variables and 15 dimensions one by one, sort out the Cronbach's Alpha and combined reliability coefficient values of each latent variable, and make analysis and judgment based on the results. The specific reliability test results are as follows.

Table 4-1: Reliability analysis in each dimension

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)
AI Threats Perception	0.921	0.922	0.935
Attention _Control	0.889	0.889	0.931
Career Adaptation	0.909	0.910	0.943
Career Competence	0.909	0.912	0.926
Career Control	0.895	0.897	0.935
Double Perception	0.859	0.861	0.914
Efficacy	0.879	0.879	0.925
Emotional _Regulation	0.875	0.875	0.923
Hope	0.856	0.856	0.912
Idea Generation	0.921	0.921	0.950
Idea Implementation	0.913	0.913	0.945
Idea Promotion	0.912	0.912	0.944
Impulse _Control	0.884	0.885	0.928
Innovation Behavior	0.922	0.933	0.936
Negative Perception	0.860	0.860	0.914
Personal Qualities	0.924	0.924	0.952
Positive Perception	0.856	0.856	0.912
Psychological Capital	0.922	0.922	0.935
Resilience	0.873	0.874	0.922
Self-control	0.929	0.930	0.941

In the reliability analysis results table, each dimension was evaluated using two indicators, Cronbach Alpha and composite reliability. Cronbach Alpha, as an indicator of internal consistency, shows that the measurement tools of each dimension have high consistency on different underlying concepts, with values ranging from 0.844 to 0.929. This means that the questions in each dimension are consistent with each other as a whole and can reliably reflect the corresponding concepts. On the other hand, composite reliability, as another measure of internal consistency, was consistent with Cronbach's alpha results. The composite reliability value of each dimension is very close to the corresponding Cronbach's alpha value, both ranging from 0.856 to 0.929. Each item in the scale consistently measures the intended construct and contributes to the overall validity of the measurement.

Construct validity

Construct validity: Construct validity is used in measurement situations with multiple indicators.

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There are also two sub types of this type of validity:

1) **Convergent validity**: This type of validity exists when multiple indicators measuring the same construct converge or are related to each other. Convergent validity refers to the degree to which multiple indicators converge or correlate with each other when measuring the same construct. In a measurement tool with high convergent validity, different observed items of the same latent variable should show a high degree of consistency, that is, they have similar information in measuring the same construct. Key metrics include loading factors and average variance extracted (AVE). A high loading coefficient indicates that the observed term reflects the latent variable well, while a high AVE value indicates that the observed term explains most of the variance of the latent variable.

2) **Discriminant validity**: This type of validity is also called divergence validity, which is the opposite of convergent validity. Refers to the absence of correlation It refers to the lack of correlation between different constructs in a measurement instrument. In the case of high discriminant validity, observed items of different latent variables should show lower correlations with each other. Assessment of discriminant validity usually involves cross-loading and correlation analyses. By checking the loading of observed items of different constructs on other latent variables and conducting correlation analysis, we can ensure that they are relatively independent in measurement.

Convergence validity

The convergent validity test is to determine whether the latent variable effectively uses the variance information of the manifest variable, thereby testing whether the latent variable has convergence and judging the reliability of the latent variable.

The average variance extraction rate (AVE) is used to measure and its value needs to be above 0.5, then the latent variable is considered to have convergence and is reliable.

Table 4-2: Result table of AVE values for each dimension

	Average variance extracted (AVE)
AI Threats Perception	0.613
Attention _Control	0.818
Career Adaptation	0.847
Career Competence	0.584
Career Control	0.827
Double Perception	0.781
Efficacy	0.805
Emotional _Regulation	0.800
Hope	0.776
Idea Generation	0.864
Idea Implementation	0.851
Idea Promotion	0.850
Impulse _Control	0.812
Innovation Behavior	0.623
Negative Perception	0.781

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Personal Qualities	0.868
Positive Perception	0.776
Psychological Capital	0.615
Resilience	0.798
Self-control	0.639

The results in the table above reveal the average variance extracted (AVE) value for each dimension.

Generally speaking, the higher the AVE value, the more effectively the measurement tool captures the latent variable, because the high AVE value reflects the observation item explaining the variance of the latent variable.

The ability is relatively strong. In this study, all first-order and second-order dimensions showed satisfactory AVE values, ranging from 0.584 to 0.868, indicating that the measurement tools of these dimensions have good consistency and validity in measuring the corresponding latent variables, passed the convergent validity test.

Descriptive statistical analysis

This article conducts a descriptive statistical analysis of the problem by calculating the mean, standard deviation, skewness and kurtosis of each dimension of the problem. The results are as follows:

Table 4-3: Descriptive statistical analysis results

	Mean	Median	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness	Number of observations used	Cramér-von Mises test statistic	Cramér-von Mises p value
Attention Control	0	-0.051	-1.592	1.585	0.464	1.717	0.274	495	0.801	0
Career Adaptation	0	0.039	-2.185	1.761	0.539	2.248	-0.243	495	1.053	0
Career Control	0	-0.09	-1.715	2.298	0.672	1.062	0.866	495	1.52	0
Double Perception	0	0.066	-1.699	1.47	0.492	1.579	-0.709	495	1.493	0
Efficacy	0	0.068	-2.227	1.231	0.48	4.825	-1.567	495	1.731	0
Emotional _Regulation	0	0.058	-2.108	1.36	0.47	3.025	-0.909	495	1.31	0
Hope	0	0.024	-2.091	1.423	0.494	1.463	-0.479	495	0.473	0
Idea Generation	0	-0.085	-1.016	1.75	0.415	1.198	0.998	495	2.004	0
Idea Implementation	0	0.191	-2.525	1.838	0.733	1.763	-1.338	495	3.977	0
Idea Promotion	0	-0.009	-2.226	0.944	0.326	4.848	-0.315	495	0.815	0
Impulse _Control	0	0.015	-2.649	1.317	0.442	6.129	-1.11	495	1.184	0
Innovation Behavior	0	-0.001	-2.595	2.658	0.622	2.658	-0.467	495	0.548	0
Negative Perception	0	-0.004	-1.805	2.047	0.464	2.641	0.122	495	0.531	0
Personal Qualities	0	0.054	-1.339	0.925	0.442	0.867	-0.833	495	1.325	0
Positive Perception	0	-0.035	-1.462	1.731	0.424	1.282	0.179	495	0.423	0
Resilience	0	-0.069	-1.521	1.959	0.444	3.373	0.909	495	1.256	0
Self-control	0	0.056	-3.4	2.363	0.591	4.684	-0.681	495	2	0

Direct path analysis

This article solves the model based on the path that has been set, and performs 1000 random samplings based on bootstrap to calculate each path coefficient, its standard deviation and the corresponding P - value and analyze it based on the path coefficient.

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The direct path calculation results are as follows Table 4-4:

Table 4-4: Direct path analysis results table

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI Threats Perception -> Double Perception	0.871	0.869	0.015	59.103	0.000
AI Threats Perception -> Negative Perception	0.886	0.885	0.015	59.051	0.000
AI Threats Perception -> Positive Perception	0.906	0.905	0.011	82.869	0.000
AI Threats Perception -> Self-control	0.435	0.435	0.080	5.473	0.000
Career Competence -> Career Adaptation	0.842	0.843	0.016	52.332	0.000
Career Competence -> Career Control	0.741	0.737	0.030	24.502	0.000
Career Competence -> Personal Qualities	0.897	0.897	0.009	100.722	0.000
Career Competence -> Self-control	0.161	0.161	0.049	3.254	0.001
Innovation Behavior -> Idea Generation	0.910	0.910	0.008	121.080	0.000
Innovation Behavior -> Idea Implementation	0.680	0.679	0.040	17.112	0.000
Innovation Behavior -> Idea Promotion	0.945	0.946	0.007	142.958	0.000
Psychological Capital -> Self-Efficacy	0.877	0.877	0.015	57.193	0.000
Psychological Capital -> Hope	0.870	0.869	0.016	54.964	0.000
Psychological Capital -> Resilience	0.896	0.896	0.013	66.837	0.000
Psychological Capital -> Self-control	0.270	0.270	0.084	3.199	0.001
Self-control -> Attention _Control	0.886	0.885	0.013	68.088	0.000
Self-control -> Emotional _Regulation	0.883	0.882	0.015	60.351	0.000
Self-control -> Impulse _Control	0.897	0.897	0.016	57.027	0.000
Self-control -> Innovation Behavior	0.897	0.784	0.027	28.516	0.000

This direct path analysis results table provides detailed information on the relationship between the variables in the research model, through indicators such as path coefficients, standard deviations, t-statistics and p-values, as can be seen in this article.

AI threats Perception, as one of the key variables of the research model, shows a significant positive impact on multiple other concepts. Specifically, the path coefficients of AI threats Perception to Double perception, Negative perception, Positive perception and Self-control are 0.871,0.886, 0.878, 0.906 and 0.435 respectively.

This shows that an individual's perception of the threats of artificial intelligence has a significant positive impact on his or her attitude toward work, negative perceptions, and positive perceptions ($p<0.05$).

The path coefficient of Career Competence shows its significant positive impact on career adaptation, career control, job performance and personal qualities. The path coefficients of Career Competence to Career Adaptation, Career Control and Personal Qualities and Self-control are 0.842, 0.741, 0.897 and 0.161 respectively.

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This means that the sense of professional competence has a significant positive impact on individuals' adaptation, control and performance in their careers ($p<0.05$).

Third, Innovation Behavior shows its significant positive impact on Idea Implementation, Idea Promotion and Idea Generation in the model, with path coefficients of 0.680, 0.945 and 0.910 respectively. This shows that innovation behavior has a significant positive impact on the implementation, promotion and generation of new ideas ($p<0.05$).

In addition, Psychological Capital also shows its positive impact on multiple concepts in the model. Specifically, the path coefficients of Psychological Capital on Self-efficacy, Hope, and Resilience are 0.877,0.870 and 0.896 respectively. This highlights the positive role of psychological capital in individual beliefs, expectations, work performance, stress resistance and self-control ($p<0.05$).

Finally, the path coefficients of Self-control for Attention control, Emotional regulation, Impulse control and Innovation Behavior are 0.886, 0.883, 0.897, 0.897 respectively. This highlights that Self-control has a positive effect on Attention control, Emotional regulation, Impulse control, Innovation Behavior ($p<0.05$) as shown in Figure1

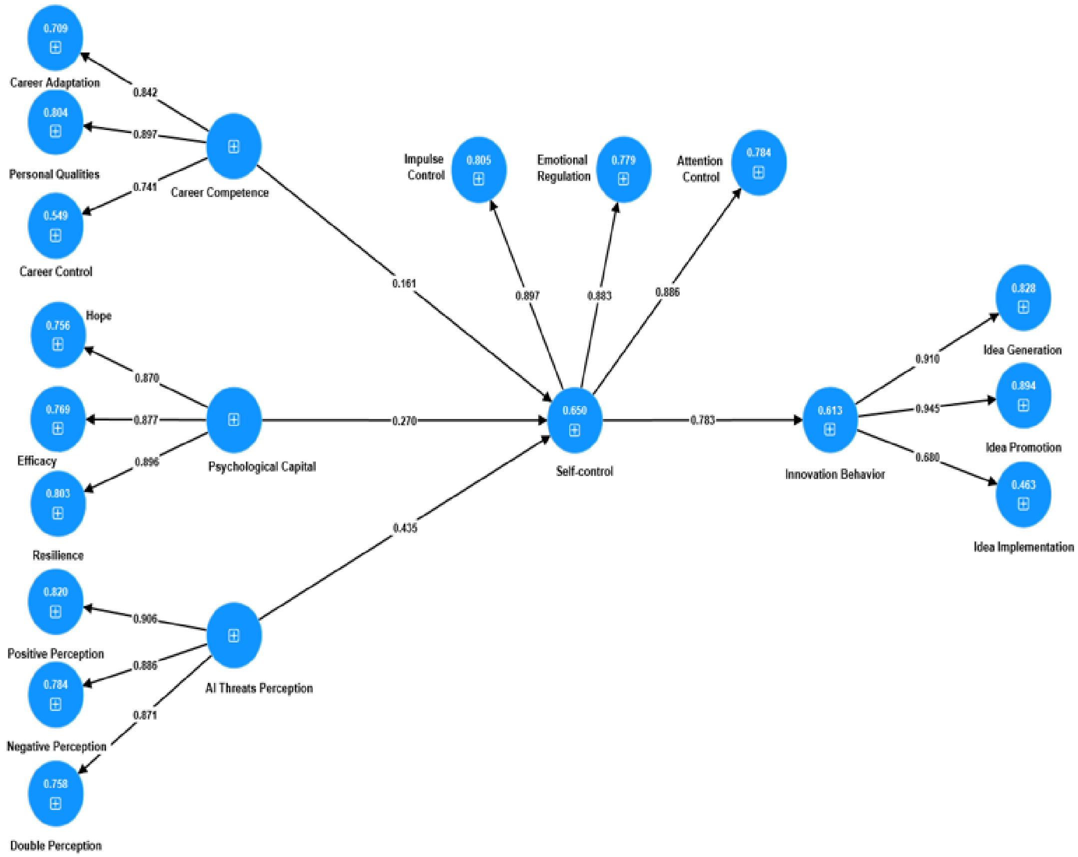

Figure 1: SEM Hypothesis Testing Results

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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 is critical mediators in the relationship between Career competence, 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 quantitative research design, the study illuminated the nuanced interplay between Career competence, AI threats Perception, Psychological Capital, Self-control and Innovation Behavior.

Quantitative findings obtained from a substantial sample of 500 managers from 20 prominent agritech companies supported the study. These findings served as a statistical foundation for the study. The application of structural equation modeling (SEM) identified meaningful paths that are consistent with the proposed hypotheses.

The study found that career competence plays a significant role in promoting self-control, which in turn enhances innovation behavior. This supports the idea that personal competence is crucial for self-regulation and innovation.

The study emphasized the inverse correlation between the perception of AI risks and self-control, illustrating the disruptive capacity of AI. Additionally, it highlighted the significant mediating influence of psychological capital, which serves as a protective barrier of positive psychological resources against these threats.

The convergence of quantitative findings points to several key implications:

In a time characterized by the swift incorporation of AI, it becomes crucial to cultivate an atmosphere that prioritizes self-discipline and the ability to recover quickly from difficulties.

Companies should prioritize implementing training programs and management practices that boost psychological capital, since it plays a crucial role in enabling managers to effectively traverse problems associated with AI.

Organizations must remain watchful over the perception of AI dangers and actively participate in dialogues with employees to address concerns and collaborate to find solutions to integrate technologies that enhance, rather than replace, human talents.

This study enhances the existing body of knowledge on innovation in agritech, psychological capital, and the effects of AI on the labor force. By presenting empirical evidence from the Chinese context, this study fills in existing gaps and enhances the applicability and comprehension of these categories.

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