The Impact of Human-Machine Collaboration on Knowledge Workers' Innovative Behavior: The Mediating Role of Autonomous Learning Willingness

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Abstract. With the continuous development of informatization, the human-machine collaboration model has exerted a significant impact on employment in current society. Knowledge workers represent a crucial force across various industries, and the evolution of the human-machine collaboration model has also impacted their employment prospects. The autonomous learning motivation of knowledge workers has been further enhanced, leading them to actively improve their knowledge reservoir and engage in more innovative behaviors. This paper primarily conducts a questionnaire survey on knowledge workers using five dimensions: organizational innovation atmosphere, self-driven consciousness, innovation efficacy, planned learning arrangements, and self-crisis awareness. It employs the VAR regression model and utilizes SPSS software for questionnaire validity and regression data analysis. The research validates three hypotheses: that the human-machine collaboration model causes occupational replacement risks for knowledge workers, that the effect of the occupational replacement risks of the human-machine collaboration model positively influences knowledge workers' autonomous learning motivation, and that autonomous learning motivation significantly enhances knowledge workers' innovative behaviors. Autonomous learning motivation is taken as the mediating variable, ultimately demonstrating the significant positive effect of the human-machine collaboration model on knowledge workers' innovative behaviors.

Keywords: human-machine collaboration model; knowledge workers; innovative behaviors; autonomous learning motivation.

1 Introduction

With the continuous development of the internet and algorithms, the human-machine collaboration model has had a significant impact on employment, not only affecting labor-intensive employees but also impacting knowledge workers' employment. Under

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the human-machine collaboration model, Knowledge workers also bear the risk of employment obsolescence with current knowledge they master, which in turn fosters their autonomous learning motivation.

The autonomous learning motivation of knowledge workers has been growing, leading to an increase in their knowledge reservoir and promoting innovative behaviors. Our country has always attached great importance to innovation work, especially since the 18th National Congress of the Communist Party of China. Innovation has become a national strategy, igniting a wave of innovation. The 20th National Congress of the Communist Party of China explicitly stated that we must adhere to the principles that science and technology are primary productive forces, talents are the primary resource, and innovation is the primary driving force. We should deeply implement strategies for developing the country through science and education, building a strong nation through talents, and driving development through innovation. We need to open new areas and avenues for development, and continuously foster new driving forces and competitive advantages.

In the era of vigorously implementing the strategy for building a talented nation, the human-machine collaboration model has been widely adopted, especially in labor-intensive or repetitive tasks. This form of human-machine collaboration significantly reduces labor costs, frees up more working time, and provides space for contemplating work efficiency. This study investigates the relationship between occupational replacement risk effects and the autonomous learning intention of knowledge workers, using autonomous learning intention as a mediating variable. Interviews and questionnaires are conducted with personnel involved in human-machine collaboration projects to explore this relationship.

2 Theoretical Foundation and Research Method

2.1 Theoretical Foundation

The theoretical foundation is the prerequisite for conducting research. This paper primarily employs innovation theory and learning theory to analyze the innovative behavior of knowledge workers. The measurement of knowledge workers' autonomous learning willingness is conducted through five dimensions: organizational innovation atmosphere, self-driven consciousness, innovation efficacy, planned learning arrangements, and self-crisis awareness.

2.1.1 Innovation theory.

Innovation refers to create new things in the use of existing nature resources. The theory of Innovation can be traced back to the "Theory of Economic Development" proposed by Harvard University professor Joseph Schumpeter in 1912. Schumpeter defined innovation as the establishment of a new production function, wherein entrepreneurs implement new combinations of production factors. Innovation has continuously evolved with social development, particularly in the era of mass entrepreneurship and innovation. Its significance has become more prominent.

With technological progress and social development, the understanding of innovation is constantly evolving. Especially with the advent of the knowledge society, changes in innovation models have been further studied and recognized. Innovation has always been a crucial engine for economic development, continually promoting the advancement of human social productivity. Research on innovation theory will greatly contribute to human‘s understanding of the world and the development of social productivity, enabling continuous progress for humanity.

China has already regarded innovation as an essential national strategy, investing substantial labor and material resources each year to promote social development and innovation. The nation has sparked a wave of mass entrepreneurship and innovation, actively cultivating innovation consciousness and protecting intellectual property rights of innovative outcomes. China has now become a major innovator, with the number of innovative achievements ranking among the world's top. Innovation has also become a critical engine for China's economic development, and enhancing innovative capabilities has become a consensus throughout society.

This paper mainly analyzes the innovative behavior of knowledge workers through innovation theory, measuring their autonomous learning willingness from five dimensions: organizational innovation atmosphere, self-driven consciousness, innovation efficacy, planned learning arrangements, and self-crisis awareness. This paper studies the relationship between the human-machine collaboration model and innovative behaviors of knowledge workers by using autonomous learning willingness as an intermediary variable,

2.1.2 Learning Theory.

Learning theory refers to various doctrines that explain the nature, process, and factors influencing learning for both humans and animals. Autonomous learning is a modern learning method contrasting with traditional receptive learning. Autonomous learning for knowledge workers refers to their voluntary and conscious learning, characterized by independence, self-regulation, and self-discipline. Autonomous learning willingness is a prerequisite for engaging in autonomous learning, as it determines the autonomous learning behavior of knowledge workers. Through autonomous learning, knowledge workers can acquire more knowledge and update their knowledge structure, thereby providing a foundation for innovation.

2.2 Research Method

Selecting appropriate research methods significantly influences the research outcomes. This paper mainly utilizes literature research, questionnaire surveys, and data analysis.

2.2.1 Literature Research Method.

By reviewing and summarizing domestic and international literature, this paper aims to understand the current research status of relevant concepts and the main research fields both at home and abroad, such as "human-machine collaboration model" and "knowledge workers". Based on these studies, it delves into the current situation and challenges of knowledge workers' innovative behavior. Combining innovation theory, this paper proposes research hypotheses and an innovation regression model for the innovative behavior of knowledge workers.

According to Gong et al. [1], in the context of an aging population, the application of artificial intelligence (AI) technology can mitigate the potential problems arising from the decline in the labor force. However, human workers need to further explore their innovative decision-making abilities to adapt better to the new changes brought about by the intelligent society. In the sample data of teachers, it is also observed that the content of AI technology is shifting from procedural physical labor to procedural cognitive labor. Some job processes and tasks involve repetitive labor with low skill requirements, which seems incongruent with the strategies of talent empowerment and innovation-driven development in building a strong nation.

Xia [2] and his colleagues categorize the collaboration modes of artificial intelligence into participatory collaboration, division-of-labor collaboration, and disruptive collaboration. To implement these models correctly, the correct mindset should be fostered, and the gradual promotion of human-machine collaborative services is essential. Additionally, Xia pointed out that true implementation of AI requires deep integration with application scenarios. To enter the era of strong AI, breakthroughs in systemic cognition and scientific decision-making abilities are necessary to address future challenges.

Wu [3] pointed out that each stage of knowledge innovation is an accumulative evolution. The emergence of new innovative methods does not necessarily replace old models; rather, it adds new possibilities. For instance, the innovation model of human-machine collaboration still requires individual creative thinking. Even with highly evolved AI, individual knowledge innovation remains the most fundamental form of knowledge creation. Furthermore, there have been numerous studies on motivating knowledge-intensive employees both domestically and internationally. Main issues include formalized employee training, unfair remuneration, lack of fair promotion opportunities, and a lack of differentiated reward mechanisms. Based on research, Chen [4] believes that establishing adaptive management approaches and providing robust organizational support are effective incentive measures. Cao [5] emphasized that managing the developmental needs of knowledge workers in the direction of innovation and addressing their desire for work autonomy are crucial. Building a sustainable training system and empowering knowledge workers with autonomy are vital aspects. Creating an enabling environment for their innovative activities and encouraging learning and innovation is essential. This fosters a sense of strong support from the organization for their innovative endeavors, inspiring their enthusiasm for innovation and continuously driving the company's vitality and development.

According to Manish Gupta [6], knowledge workers at the lower levels of organizational hierarchy often face challenges from external employees, and motivational driving factors play a significant role in their influence. Workers experience turbulence, challenges, and intrinsic motivational factors. The relationship between work-related factors and motivation is influenced by both employees and employers. Therefore, enhancing autonomous motivation requires the inclusion of work-related factors.

2.2.2 Questionnaire Survey Method.

Through the questionnaire survey method, this paper collects data from knowledge workers to investigate the factors influencing knowledge workers' innovative behavior under the human-machine collaboration model and the data for their autonomous learning willingness. Efforts are made to cover a broad range of participants to ensure data accuracy and comprehensiveness. In the data selection process, the primary focus lies in including personnel already engaged in AI-assisted modes. Diversity is sought to be maximized in the selection of industries, thereby mitigating the potential influence of data bias on empirical circumstances.

2.2.3 Data Analysis Method.

This paper employs SPSS software for statistical analysis, examining the reliability and validity of the questionnaire and conducting regression analysis to identify the factors affecting knowledge workers' innovative behavior under the human-machine collaboration model. By utilizing the VAR regression model, statistical analysis reveals the impact of the human-machine collaboration mode on knowledge workers' innovative behavior.

3 Hypotheses and Methodology

3.1 Research Participants

The survey targeted employees from various industries within the Sichuan Province, including internet, education, banking, and legal sectors. A probability sampling method was employed to distribute questionnaires among different levels of employees (managers/staff). Interviews were conducted simultaneously. A total of 200 questionnaires were distributed, and 186 valid responses were collected. The distribution of responses is as Figure 1.

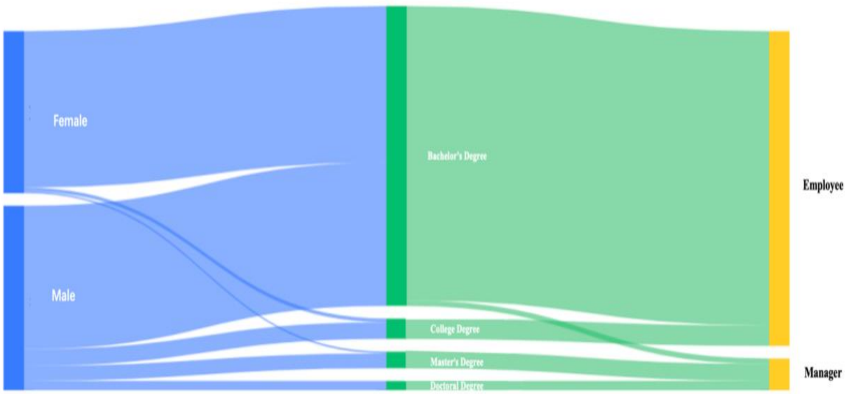

Fig. 1. Sankey diagram of participants characteristics

3.2 Research Hypotheses

As model shown in Figure 2, the following hypotheses are proposed:

Hypothesis 1: The human-machine collaboration model induces the risk of occupational replacement for knowledge workers.

Hypothesis 2: The effect of occupational replacement risk on knowledge workers under the human-machine collaboration model positively influences their autonomous learning willingness.

Hypothesis 3: The autonomous learning willingness of knowledge workers positively influences their innovative behaviors.

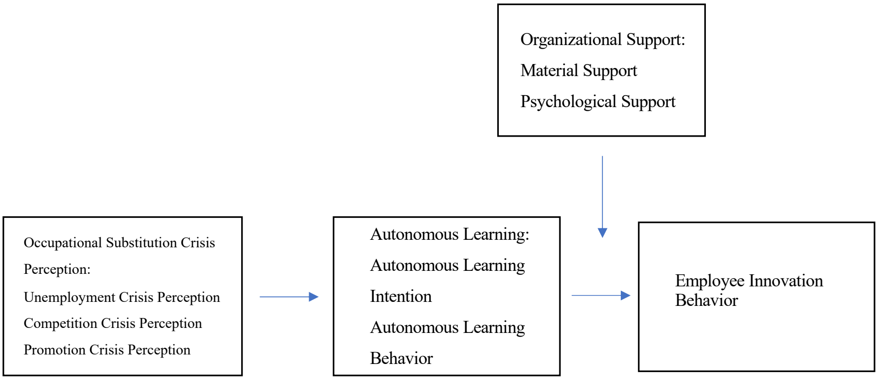

Fig. 2. Generation mechanism of knowledge workers' innovative behaviors underlying the human-machine collaboration model

3.3 Research Contents

3.3.1 Individual Characteristics.

Participants were categorized based on gender, age, job level, and education. The sample statistics are as Table 1.

Table 1. Participants Characteristics

Age	Mean	Maximum	Minimum	
	27	45	20	
Gender	Male	Female		
	99	87		
Education	Bachelor's degree	College degree	Master's degree	Doctorate degree
	161	11	9	5
Job Level	Manager	Employee		
	17	169		

3.3.2 Work Situation.
The Table 2 below shows company size, company nature, and industry type.

Table 2. Participants Work Characteristics

Company Size	0-100 employees	100-300 employees	300-1000 employees	1000 or more employees
	18	45	72	51
Company Nature	Private Listed	Private Non-listed	State-Owned Enterprise	Public Institutions/Government
	81	24	43	38
Industry Type	Energy	IT/Internet/Intelligent Manufacturing	Fast-moving Consumer Goods /Durable Goods	Telecom Operators/Equipment Suppliers
	23	93	46	24

3.4 Scale Selection

In this study, five questionnaire items were selected as determining factors: organizational innovation atmosphere, self-driven consciousness, innovation efficacy, self-crisis awareness, and planned learning arrangements. The respondents were asked to rate their agreement with each item using the following scale: "Strongly Agree," "Agree," "Uncertain," "Disagree," and "Strongly Disagree." In the reliability analysis, the following steps were adopted:

Cronbach's α Coefficient (or Split-Half Coefficient) Analysis: There is no unified standard for Cronbach's α coefficient, but according to the majority of scholars' viewpoints, a Cronbach's α coefficient (or Split-Half Coefficient) above 0.9 indicates excellent reliability for the test or scale, while a value between 0.8 and 0.9 indicates good reliability. A range of 0.7 to 0.8 suggests acceptable reliability, 0.6 to 0.7 indicates moderate reliability, and 0.5 to 0.6 suggests relatively less ideal reliability. If the value is below 0.5, reconsideration and reordering of the questionnaire items may be necessary.

Further Analysis of the Item-Total Correlation Table: This step involves examining which items might contribute to the overall decrease in reliability. If the "Corrected Item-Total Correlation" value is below 0.3 or if the "Cronbach's α after Deletion" value is significantly higher than the original α coefficient, it may be appropriate to consider removing that item from the scale.

Table 3. Cronbach's α Coefficient Results

Cronbach's α coefficient	Standardized Cronbach's α coefficient	Number of items	Sample size
0.822	0.829	5	186

The Table 3 above presents the results of the Cronbach's α coefficient for the model, including the Cronbach's α coefficient value, standardized Cronbach's α coefficient value, the number of items, and the sample size. These values are used to assess the reliability of collected data. Cronbach's α coefficient value is value that evaluates whether the collected data is reliable and consistent, helping identify poorly constructed items or careless responses. Standardized Cronbach's α coefficient value is when standardization is applied to transform scales with different scoring systems into a unified measurement. For example, when 5-point and 10-point scales analyzed together, standardization can be used to solve the inconsistent measurement scales. Number of items is the number of variables involved in the reliability analysis. The Cronbach's α coefficient value is 0.822, indicating good reliability for the questionnaire.

Furthermore, the analysis considered the deletion of certain items. As can be seen from Table 4, the results from the item-total correlation analysis show that the overall correlation (CITC) and Cronbach's α coefficient after the deletion of the above-mentioned five items perform well. Therefore, it is deemed unnecessary to make modifications to the items in the scale.

Table 4. Total Correlation Analysis Results

	Mean after deletion	Variance after deletion	Correlation between the deleted item(s) and the overall data after deletion	Cronbach's α coefficient after deletion
Organizational innovation atmosphere	13.102	5.671	0.683	0.769
Self-driven consciousness	13.022	5.405	0.563	0.809
Planned learning arrangements	12.968	5.685	0.592	0.795
Self-crisis awareness	13.048	6.035	0.639	0.784
Innovation efficacy	12.978	5.664	0.636	0.781

In addition, a Kaiser-Meyer-Olkin (KMO) test was also performed. The KMO test assesses the sampling adequacy for factor analysis. The KMO value ranges from 0 to 1, with the following interpretations: 0.9 and above, very suitable for factor analysis; 0.8 to 0.9, quite suitable for factor analysis; 0.7 to 0.8, Suitable for factor analysis; 0.6 to 0.7, moderately suitable for factor analysis; 0.5 to 0.6, Marginally suitable for factor analysis; below 0.5, Inadequate for factor analysis, and it is recommended to abandon it. A high KMO value indicates that there is sufficient correlation among the item variables, which meets the requirements for factor analysis. On the other hand, Bartlett's test was also conducted. If the significance level is less than 0.05, the null hypothesis is rejected, suggesting that factor analysis can be performed. If the null hypothesis is not rejected, it implies that the variables may provide independent information and are not suitable for factor analysis.

As shown in Table 5, the analysis results indicate a KMO value of 0.81, which is considered suitable for factor analysis.

Table 5. KMO test and Bartlett's Test

KMO Test and Bartlett's Test		
KMO Value		0.81
Bartlett's Sphericity Test	Approx. Chi-Square	323.478
	df	10
	P	0.000***

Note: ***、**、* represent significance levels of 1%, 5%, and 10%, respectively.

The table above presents the results of the Kaiser-Meyer-Olkin (KMO) test and the Bartlett's sphericity test, which are used to assess the suitability of conducting factor analysis.

- KMO Test: If the KMO value is greater than 0.6, it indicates that there is sufficient correlation among the item variables, which meets the requirements for factor analysis.
- Bartlett's Test: If the significance level (P-value) is less than 0.05, it indicates that the result is statistically significant, and factor analysis can be performed.

The KMO test result shows a KMO value of 0.81, indicating that the item variables have significant correlation, which is suitable for factor analysis. Additionally, Table 6 below shows the result of Bartlett's sphericity test exhibiting a highly significant P-value of 0.000***, which rejects the null hypothesis. This further confirms that the variables are correlated, making factor analysis an effective and suitable approach for this study.

Table 6. Total Variance Explanation

Total Variance Explained						
	Eigenvalue			Rotated Variance Explained		
Component	Eigen-value	Variance Explained (%)	Cumulative Percentage (%)	Eigen-value	Variance Explained (%)	Cumulative Percentage (%)
1	2.973	59.5	59.5	2.973	59.5	59.5
2	0.689	13.8	73.2			
3	0.548	11	84.2			
4	0.465	9.3	93.5			
5	0.326	6.5	100			

The table above is a variance explained table, which primarily shows the contribution rate of each factor to the explanation of the variables (i.e., how many factors are needed to express the variables as 100%). In general, it is considered appropriate for the factors to explain more than 80% of the variables' variance, which corresponds to the number of principal components when the eigenvalues are less than 1. If the explained variance falls below 80%, it may be necessary to adjust the factor data. However, this decision should be based on the specific circumstances and requires a case-by-case analysis. Generally, a higher variance explained rate indicates that the principal component is more important, and its corresponding weight should be higher as well. Weight calculation is the variance explained rate / cumulative variance explained rate.

In the variance explained table, when selecting one principal component (i.e., using only one factor), the eigenvalue for the explanation of the variables is higher than 1, and the variance explained rate reaches 59.5%.

4 Data Analysis and Hypothesis Testing

4.1 CRITIC Weighting Analysis

The analysis is used to analyze the core points of human-machine collaboration on knowledge workers. The procedure includes the following steps:

Step 1: Calculate the weights of each indicator based on the weight calculation results.

Step 2: Generate the weight analysis matrix using the weight calculation results.

Step 3: Summarize the analysis.

Table 7. Weight Calculation Result

Indicator	Variability	Conflict	Information	Weight (%)
Organizational innovation atmosphere	0.717	1.869	1.34	17.282
Self-driven consciousness	0.887	2.206	1.957	25.238
Self-crisis awareness	0.654	1.976	1.292	16.654
Planned learning arrangements	0.785	2.105	1.652	21.297
Innovation efficacy	0.754	2.009	1.515	19.529

According to the CRITIC weight calculation results shown in the Table 7, the weights of each indicator are as follows: Organizational Innovation Climate (17.282%), Self-Driven Consciousness (25.238%), Self-Crisis Awareness (16.654%), Planned Learning Arrangement (21.297%), and Innovation Efficacy (19.529%). The highest weight is assigned to Self-Driven Consciousness (25.238%), while the lowest weight is assigned to Self-Crisis Awareness (16.654%).

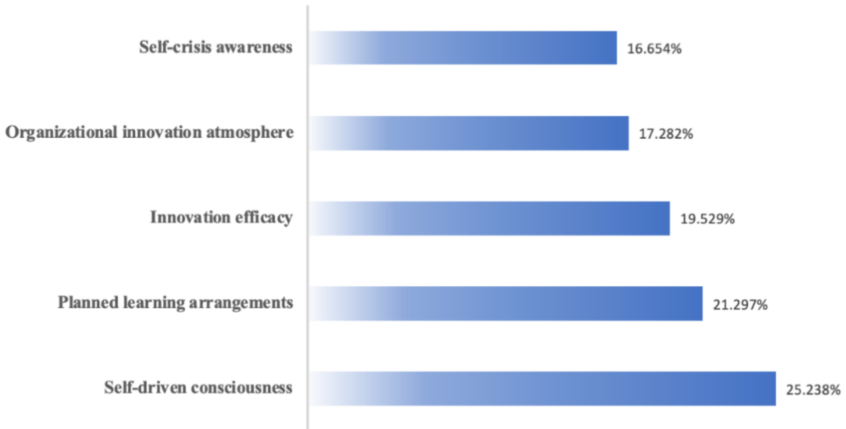

Fig. 3. CRITIC Weight Calculation Results

Based on the importance ranking in the above Figure 3, it is evident that Self-Driven Consciousness has the most significant impact on the influence of human-machine collaboration on knowledge workers' innovative behavior.

4.2 Logistic Regression

In this study, logistic regression was used to analyze qualitative variables such as education and age and the result of sample variable analysis is shown in the Table 8.

Following the procedure outlined below:

Step 1: Describing the distribution of the categorical dependent variable.

Step 2: Conducting the likelihood ratio chi-square test to analyze the significance of the likelihood ratio chi-square. If the null hypothesis is rejected ($P < 0.05$), it indicates that the model is effective; otherwise, the model is not supported. If multiple models are designed, a comprehensive analysis can be performed by considering other evaluation criteria or information criteria (lower BIC value is preferred).

Step 3: Analyzing the impact of each predictor variable (X) on the outcome variable (Y) compared to the reference category. If the P-value of X is less than 0.05, it indicates that X has a significant effect on Y compared to the reference category.

Step 4: Analyzing the regression coefficients (B) and odds ratio (OR) values to compare and understand the impact of each predictor variable (X) on the outcome variable (Y) compared to the reference category.

Step 5: Combining the predictive classification confusion matrix and classification metrics from the model evaluation to analyze the model's predictions.

Table 8. Sample Variable Analysis

Dependent Variable	Option	Frequency	Percentage (%)
Education	Bachelor's Degree	161	86.559
	College Degree	11	5.914
	Master's Degree	9	4.839
	Doctoral Degree	5	2.688
	Total	186	100

Table 9. Model Evaluation

Likelihood ratio chi-square value	P	AIC	BIC
127.195	0.000***	163.195	221.259
Note: *** , ** , * represent significance levels of 1%, 5%, and 10% respectively.			

The Table 9 above displays model evaluation metrics, which can be used to assess the performance or validate the effectiveness of the model. It includes likelihood ratio test, P-value, AIC value, and BIC value. Analyzing the P-value, if it is less than 0.05, the model is considered effective; otherwise, the model is deemed ineffective. AIC and BIC values are used to compare the superiority of two models, where smaller values indicate better fit. In conclusion, the result of the likelihood ratio chi-square test shows a significant P-value of 0.000***, indicating a significant level of effectiveness, leading to the rejection of the null hypothesis. Thus, the model is considered valid.

Table 10. Multinomial Logistic Regression Results

Bachelor's Degree	Coefficient	standard errors	Wald	df	P	OR	OR value 95% confidence interval	
							Upper limit	Lower limit
Constant	-11.166	2.772	16.228	15	0.000***	0	0	0.003
Organizational innovation atmosphere	1.835	0.797	5.309	15	0.021**	6.266	1.315	29.855
Self-driven consciousness	1.92	1.007	3.639	15	0.056*	6.821	0.949	49.054
Self-crisis awareness	-0.004	0.592	0	15	0.994	0.996	0.312	3.175
Planned learning arrangements	0.741	0.734	1.019	15	0.313	2.099	0.498	8.852
Innovation efficacy	0.531	0.606	0.768	15	0.381	1.701	0.519	5.578
Master's Degree	**Coefficient**	**standard errors**	**Wald**	**df**	**P**	**OR**	**OR value 95% confidence interval**	
							Upper limit	**Lower limit**
Constant	-22.211	4.396	25.527	15	0.000***	0	0	0
Organizational innovation atmosphere	2.663	1.075	6.14	15	0.013**	14.34	1.745	117.855
Self-driven consciousness	0.603	1.273	0.224	15	0.636	1.828	0.151	22.164
Self-crisis awareness	2.058	0.98	4.413	15	0.036**	7.832	1.148	53.45
Planned learning arrangements	1.008	0.949	1.127	15	0.288	2.739	0.426	17.59
Innovation efficacy	0.809	0.97	0.696	15	0.404	2.246	0.336	15.03
Doctoral Degree	**Coefficient**	**standard errors**	**Wald**	**df**	**P**	**OR**	**OR value 95% confidence interval**	
							Upper limit	**Lower limit**
Constant	-27.923	5	31.185	15	0.000***	0	0	0
Organizational innovation atmosphere	2.933	2.633	1.241	15	0.265	18.784	0.108	3272.93
Self-driven consciousness	2.989	2.35	1.618	15	0.203	19.862	0.199	1986.514
Self-crisis awareness	0.484	1.645	0.086	15	0.769	1.622	0.065	40.784
Planned learning arrangements	1.106	2.072	0.285	15	0.594	3.021	0.052	175.22
Innovation efficacy	1.028	1.98	0.27	15	0.604	2.796	0.058	135.588
Note: ***, **, * represent significance levels of 1%, 5%, and 10%, respectively.								

The Table 10 above shows the results of the model's parameters, which can be used to generate the model formula. It includes the coefficients, standard errors, odds ratios (OR), and confidence intervals. Odds Ratio (OR): It represents the odds of an event occurring in the experimental group compared to the control group. For continuous predictor variables, the OR indicates that for each unit increase in the variable, the odds of the event occurring in the experimental group change by (OR value - 1) % compared to the control group. For dummy-coded categorical predictor variables (0-1), the OR indicates that for each unit increase in the variable (i.e., moving from 0 to 1 in the category level), the odds of the event occurring in the experimental group change by (OR value - 1) % compared to the control group.

Based on the reference category " College Degree " -> "Bachelor's Degree":

- The constant's significance level (P-value) is 0.000***, indicating its significant influence on the education level. The constant's odds of having a Bachelor's Degree is 99.999% lower than having an Associate Degree.

- The variable "Organizational Innovation Atmosphere" has a significance level (P-value) of 0.021**, indicating its significant influence on the education level. The odds of having a Bachelor's Degree increase by 526.635% with each unit increase in the organizational innovation atmosphere.
- The variable "Self-Crisis Sense" has a significance level (P-value) of 0.056*, indicating no significant influence on the education level.
- The variable "Self-Driven Consciousness" has a significance level (P-value) of 0.994, indicating no significant influence on the education level.
- The variable "Planned Learning Arrangement" has a significance level (P-value) of 0.313, indicating no significant influence on the education level.
- The variable "Innovation Efficacy Perception" has a significance level (P-value) of 0.381, indicating no significant influence on the education level.

Based on the comparison " College Degree" -> "Master's Degree":

- The constant's significance level (P-value) is 0.000***, indicating its significant influence on the education level. The constant's odds of having a Master's Degree are 100.0% lower than having an College Degree.
- The variable "Organizational Innovation Atmosphere" has a significance level (P-value) of 0.013**, indicating its significant influence on the education level. The odds of having a Master's Degree increase by 1333.997% with each unit increase in the organizational innovation atmosphere.
- The variable "Self-Crisis Sense" has a significance level (P-value) of 0.636, indicating no significant influence on the education level.
- The variable "Self-Driven Consciousness" has a significance level (P-value) of 0.036**, indicating its significant influence on the education level. The odds of having a Master's Degree increase by 683.238% with each unit increase in self-driven consciousness.
- The variable "Planned Learning Arrangement" has a significance level (P-value) of 0.288, indicating no significant influence on the education level.
- The variable "Innovation Efficacy Perception" has a significance level (P-value) of 0.404, indicating no significant influence on the education level.

Based on the comparison " College Degree " -> "Doctoral Degree":

- The constant's significance level (P-value) is 0.000***, indicating its significant influence on the education level. The constant's odds of having a Doctoral Degree are 100.0% lower than having an College Degree.
- The variable "Organizational Innovation Atmosphere" has a significance level (P-value) of 0.265, indicating no significant influence on the education level.
- The variable "Self-Crisis Sense" has a significance level (P-value) of 0.203, indicating no significant influence on the education level.
- The variable "Self-Driven Consciousness" has a significance level (P-value) of 0.769, indicating no significant influence on the education level.
- The variable "Planned Learning Arrangement" has a significance level (P-value) of 0.594, indicating no significant influence on the education level.

- The variable "Innovation Efficacy Perception" has a significance level (P-value) of 0.604, indicating no significant influence on the education level.

4.3 Correlation Analysis

First, a statistical test was conducted to determine whether there is a significant relationship ($P < 0.05$) between variables X and Y, and then analyze the direction (positive or negative) and strength of the correlation coefficient. Finally, summarizing the analysis results.

Table 11. Correlation Analysis Results

	Organizational innovation atmosphere	Self-driven consciousness	Planned learning arrangements	Self-crisis awareness	Innovation efficacy
Organizational innovation atmosphere	1(0.000***)	0.497(0.000***)	0.458(0.000***)	0.615(0.000***)	0.561(0.000***)
Self-driven consciousness	0.497(0.000***)	1(0.000***)	0.42(0.000***)	0.372(0.000***)	0.506(0.000***)
Planned learning arrangements	0.458(0.000***)	0.42(0.000***)	1(0.000***)	0.565(0.000***)	0.453(0.000***)
Self-crisis awareness	0.615(0.000***)	0.372(0.000***)	0.565(0.000***)	1(0.000***)	0.472(0.000***)
Innovation efficacy	0.561(0.000***)	0.506(0.000***)	0.453(0.000***)	0.472(0.000***)	1(0.000***)

Note: ***, **, * represent significance levels of 1%, 5%, and 10%, respectively.

The Table 11 above shows the results of model testing, including correlation coefficients and significance P-values. First, a test is conducted to determine whether there is a statistically significant relationship between X and Y by examining the significance level ($P<0.05$). If the significance level is met, it indicates that there is a correlation between the two variables; otherwise, there is no correlation between the variables. The analysis involves studying the direction and strength of the correlation coefficient. Correlation coefficient heatmap is shown in Figure 4 below.

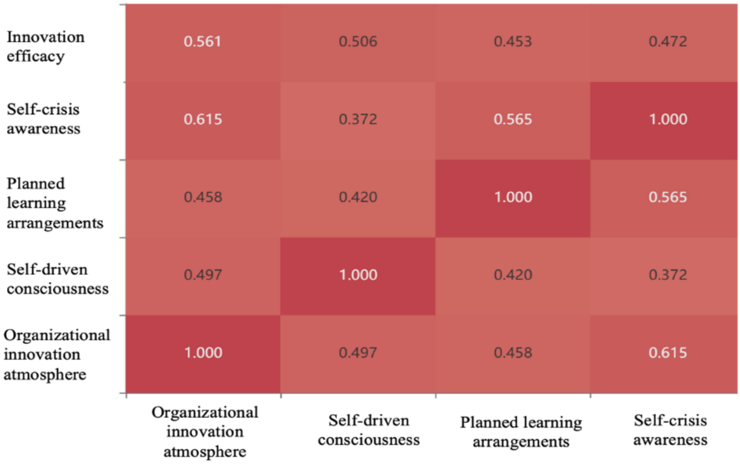

Fig. 4. Correlation Coefficient Heatmap

5 Conclusion and Recommendations

Focus on fostering self-drive consciousness and creating a supportive environment: The data shows that self-drive consciousness has the highest weightage of 25.238% in influencing the innovative behavior of knowledge workers. Through interviews and communication, it has been understood that in the context of artificial intelligence-driven collaboration, employees' subjective initiative requires conscious guidance in the face of new work scenarios and models. Therefore, it is essential to guide employees' self-drive consciousness in the context of AI-driven collaboration. To achieve this, it is essential to deepen the positive impact and influence of human collaboration and advocate its effectiveness. Additionally, employing psychological cues and techniques in cultivating self-drive awareness can be beneficial. Guiding employees to embrace a competitive mindset while simultaneously reducing their anticipation of being replaced by AI in their job roles is crucial. Scholars such as Liu Qiong et al. [7] point out that positive expectations from teachers are conducive to forming positive psychological cues in students, especially during times of difficulty or self-doubt. Trust and positive feedback from teachers can empower students to believe in their ability to overcome challenges and enhance their self-efficacy. Successful experiences lead to a sense of achievement, enabling students to generate positive emotions like happiness and relaxation. These positive emotions facilitate flexible planning, monitoring, and self-assessment of their learning, thus increasing their engagement in the learning process. Therefore, in the cultivation of self-drive awareness and self-efficacy, drawing inspiration from the role of "teachers" or "mentors" in learning organizations can facilitate two-way encouragement and support in the work environment.

Promote educational advancement: Based on the results of logistic regression, individuals with higher degrees (e.g., Master's and Ph.D. holders) exhibit higher values in various dimensions. To foster innovation, organizations should establish knowledge reservoirs that align with both company strategic development and individual career paths. Emphasizing continuous learning and encouraging employees to pursue higher education can boost their innovation capabilities. As Gong Yao [1] pointed out, higher education levels are negatively correlated with the potential risk of job replacement, making education crucial for maintaining competitiveness in the job market.

Provide positive guidance for self-crisis awareness: Literature on the occupational substitution effect of artificial intelligence indicates that AI's occupational substitution effect poses potential risks, leading to increased self-crisis awareness among employees [8]. Providing positive guidance and support can help alleviate these concerns. Acknowledging the changing job landscape due to AI while emphasizing the acquisition of new skills and adaptability can foster a more positive attitude towards AI adoption and avoid potentially impact their acceptance of work changes and overall work efficiency.

Conscious motivation for learning: It is essential to consciously guide employees' learning motivation by instilling positive professional cognitive awareness. Rewarding and encouraging proactive participation can strengthen their motivation to learn. Recognizing learning as a vital non-intellectual factor in education can be a breakthrough point [9]. Considering the positive effects of AI on knowledge workers' autonomous learning willingness proving by data and interview results, organizations should actively cultivate learning motivation through conscious efforts.

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