Research on Technological Innovation Efficiency of Chinese Large and Medium-Sized Civil Unmanned Aircraft Enterprises from The Perspective of Life Cycle

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Abstract. Based on the enterprise life cycle theory, this study constructs an analytical framework of "stage classification-efficiency measurement-driving mechanism" to investigate the dynamic patterns of innovation efficiency. Using a sample of 74 Chinese civilian UAV enterprises, we apply K-means clustering, DEA models, and stage-specific Tobit regression for empirical analysis. The results show that: (1) Enterprises in the growth stage exhibit the highest efficiency (CCR mean = 0.854), while those in decline perform the worst (0.403); (2) Policy tools require dynamic adaptation (the marginal effect of subsidies in the growth stage is 3.2 times that in the decline stage); (3) There exists a "hardware investment trap" in R&D resource allocation; and (4) The transition of management efficiency plays a critical role. Accordingly, we propose stage-specific policy support, modular resource allocation, and agile management enhancement strategies.

Keywords: Civilian UAV enterprises; Enterprise life cycle; Technological innovation efficiency; Dynamic management efficiency.

1 Introduction

The civilian UAV industry is experiencing rapid development, where technological innovation capability serves as the core competitive advantage. Enterprise life cycle theory reveals significant variations across different development stages, which directly influence firms' technological innovation behaviors, necessitating tailored optimization of innovation strategies.

The corporate life cycle theory originates from the field of biology and was first proposed by Adizes (1989), who suggested that enterprises, like organisms, undergo stages from birth, growth, maturity, to decline [1]. Li Ye (2000) pointed out that the corporate life cycle is a dynamic process, and a company's resource endowment, organizational structure, and management strategies at each stage directly influence its innovation capability and efficiency [2]. Qiu Zenghui (2023) examined the relationship between the life cycle of manufacturing firms and technological innovation efficiency,

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finding that innovation efficiency is affected by multiple factors across different stages [3].

The impact of policies and industry regulation on technological innovation efficiency has garnered widespread attention. Yang et al. (2021) found that resource redundancy and environmental management maturity significantly influence innovation efficiency at different life cycle stages [4]. Yu Dianfan and Wang Jiaxi (2024) studied the dynamic effects of government subsidies on innovation across life cycle stages, revealing that subsidies significantly enhance innovation efficiency for growth- and maturity-stage firms [5]. Xue Xiaoshan et al. (2021), using new energy vehicle promotion policies as an antecedent variable, found that inclusion in promotion catalogs positively affects corporate innovation efficiency [6]. Hou et al. (2019) investigated the influence of academia-industry collaboration and government funding on industrial innovation efficiency in China, concluding that both factors significantly improve technological innovation efficiency [7]. Guo Yujing et al. (2020), analyzing Chinese listed companies, found an inverted U-shaped relationship between large shareholder ownership and innovation efficiency, while equity checks negatively impacted efficiency, and institutional investors had a positive effect [8]. Yang Jingshao and Zang Min (2022) discovered that executive team diversity enhances innovation efficiency in uncertain environments [9].

Han Bin et al. (2022) employed a Tobit model to study factors influencing innovation efficiency in new energy vehicle companies, identifying policy support and market demand as significant drivers [10]. Ye and Cheng (2019) explored the relationship between green technology innovation efficiency and financial ecosystems, finding that a well-developed financial environment promotes innovation efficiency [11]. Lu Zhiguo and Meng Fei (2022), using a three-stage DEA model, measured innovation efficiency in strategic emerging industries and highlighted the role of policy support and industry regulation [12]. Wang et al. (2020) applied a two-stage network DEA model to assess innovation efficiency in China's high-tech industries, revealing generally low efficiency with significant inter-industry variations [13].

2 Research Design

2.1 Sample Selection and Data Sources

The sample selection strictly follows *Measures for the Classification of Large, Medium, Small and Micro Enterprises in Statistics (2017)*[1], with adjustments based on the lightweight asset characteristics of the civil UAV industry. This adaptation prevents the exclusion of innovative yet smaller-scale technology leaders. The final sample comprises 74 enterprises with data from 2019 to 2022. Data sources include the Wind database, patent records, and industry reports, with quality ensured through outlier treatment (box-plot method) and missing value imputation.

[1] https://www.stats.gov.cn/sj/tjbz/gjtjbz/202302/t20230213_1902763.html

2.2 Theoretical Model Construction

1. Life Cycle Stage Classification

The research employs a multidimensional set of financial and operational indicators to accurately identify enterprise life cycle stages. These carefully selected metrics capture essential aspects of corporate development, including financial performance trends, human resource allocation patterns, and characteristic risk profiles. Table 1 presents the complete framework of these discriminative indicators, which have been specifically adapted to account for the unique business environment and operational dynamics of the civilian UAV sector. The classification methodology emphasizes both quantitative financial measures and qualitative organizational characteristics to provide a robust assessment framework for enterprise development phases.

Table 1. Financial Characteristics Across Enterprise Life Cycle Stages

Life Cycle Stage	Revenue Growth Rate	Profit Margin	Employee Growth Rate	Operating Cash Flow Growth	Debt-to-Asset Ratio
Startup Phase	High	Low	High	Volatile(potentially negative)	High
Growth Phase	High	Improving	High	Significant improvement	Moderate/Slightly high
Maturity Phase	Stable/Slowing	Relatively high	Stable	Steady	Moderate/Declining
Decline Phase	Low/Negative growth	Declining	Negative growth	Deteriorating(potentially negative)	Potentially increasing

2. Innovation Efficiency Measurement

Technological innovation efficiency serves as a critical indicator for assessing enterprise innovation capabilities, particularly in high-tech industries such as civilian UAVs. This study examines three primary input dimensions: R&D investment intensity, proportion of R&D personnel, and technical equipment investment. Corresponding output metrics include patent quantity, new product revenue share, and technology commercialization rate.

3. Driving Factor Analysis

Identifying determinants of innovation efficiency constitutes a pivotal research component. The Tobit regression model incorporates three variable categories-external environmental factors, internal organizational factors, and control variables-totaling 18 specific indicators spanning policy support, market demand, R&D investment, and governance structure. These variables collectively influence innovation efficiency through their effects on resource allocation patterns, management decision-making, and market positioning strategies.

3 Empirical Analysis and Validation

3.1 Life Cycle Classification and Verification

The K-means clustering algorithm was employed for life cycle classification, utilizing Euclidean distance as the similarity metric. The distance calculation follows this mathematical expression:

$$d(x, y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (1)$$

This study employed Principal Component Analysis (PCA) to reduce the five-dimensional financial indicators into two-dimensional space. The analysis yielded two principal components: the first component (PC1) captures the economic trade-off between corporate growth potential and debt levels, while the second component primarily reflects the quality of enterprise profitability.

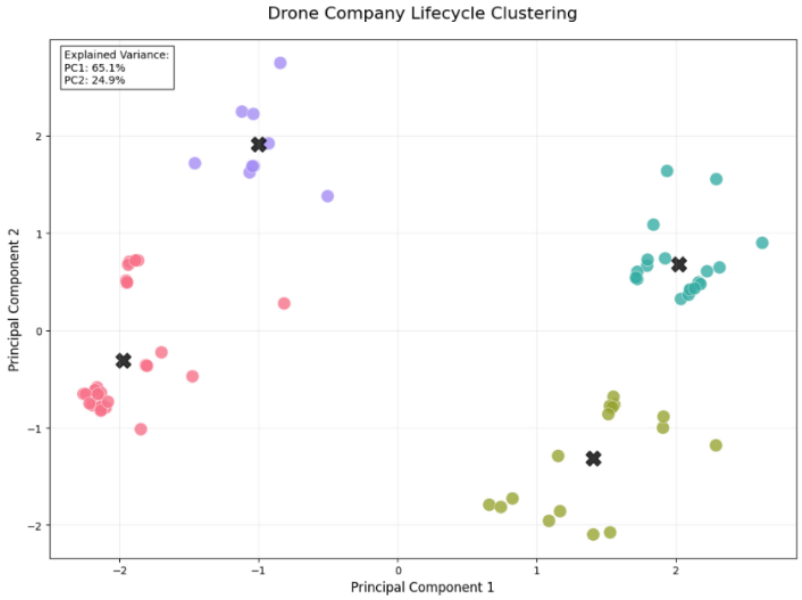

Fig. 1. The visual representation of this clustering analysis for civilian UAV enterprises is presented

As shown in Figure 1, the agglomerative clustering analysis classified 74 civil unmanned aerial vehicle (UAV) enterprises into four categories based on five corporate financial characteristics, namely start-up enterprises (bottom right of Figure 1), growing enterprises (top right of Figure 1), mature enterprises (top left of Figure 1), and declining enterprises (bottom left of Figure 1).The silhouette coefficient serves as a crucial metric for evaluating clustering effectiveness, with values exceeding 0.5 indicating statistically reasonable clustering results and values above 0.7 demonstrating

high reliability. Our silhouette coefficient tests produced a mean value of 0.556, confirming the statistical validity of the life cycle classification.

3.2 Technological Innovation Measurement and Validation

The study first applies the CCR model to measure technological innovation efficiency in civilian UAV enterprises, followed by the BCC model for verification, adhering to an analytical logic that progresses from holistic to specific examination. Prior to DEA model implementation, the data set underwent Min-Max normalization to standardize variables and eliminate dimensional discrepancies. The mathematical formulation of the CCR model is expressed as:

$$\text{Maximize } \theta_j = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \tag{2}$$

The BCC model is correspondingly defined as:

$$\text{Maximize } \theta_j = \frac{\sum_{r=1}^{s} u_r y_{rj} + u_0}{\sum_{i=1}^{m} v_i x_{ij}} \tag{3}$$

Through these models, we derived comprehensive technical efficiency (TE) and pure technical efficiency (PTE) scores for each enterprise, with scale efficiency (SE) calculated via the ratio SE=TE/PTE. Figure 2 presents the comparative efficiency measurements across different life cycle stages.

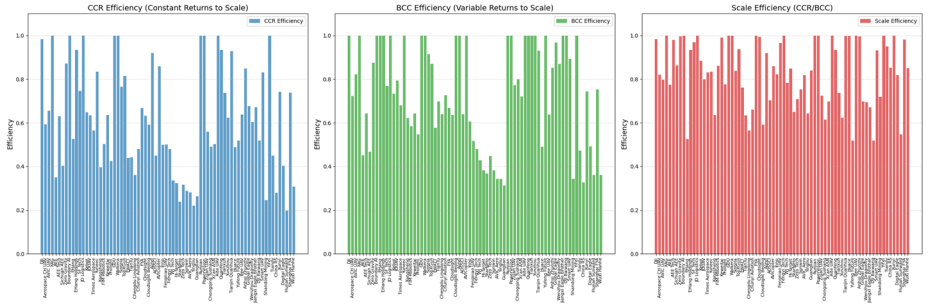

Fig. 2. DEA Model Simulation Results for Civilian UAV Enterprises

This study employed sensitivity analysis as the primary validation approach, systematically constructing multiple alternative models for comparative assessment. The quantitative verification was conducted through three principal methods: The Spearman rank correlation coefficient (ρ>0.7) evaluated the stability of efficiency rankings, paired sample t-tests (p-value>0.1) assessed the significance of efficiency value differences, and efficiency variation magnitude (ΔTE<10% for over 80% of cases) measured individual efficiency fluctuations.

The analytical procedure involved establishing a baseline model using all six original indicators, followed by three modified variants: Model 1 excluded patent quantity, Model 2 replaced total patents with invention patent ratio, and Model 3 removed

technical equipment investment. Comparative analysis using the aforementioned statistical methods confirmed all alternative models satisfied the predetermined triple validation criteria, demonstrating robust consistency across different model specifications. The comprehensive test results validate the fundamental model's reliability in measuring innovation efficiency throughout enterprise life cycles.

3.3 Stage-Specific Driver Analysis and Validation

The study conducted separate regression analyses for each of the four life cycle stages, employing the Tobit model to elucidate the differential impacts of various factors across distinct developmental phases. The fundamental Tobit model specification takes the following form:

$$L(\beta, \sigma) = \prod_{TE_i=0} \Phi\left(\frac{-X_i\beta}{\sigma}\right) * \prod_{TE_i=0} \frac{1}{\sigma} \phi\left(\frac{TE_i - X_i\beta}{\sigma}\right) * \prod_{TE_i=1} \left[1 - \Phi\left(\frac{1-X_i\beta}{\sigma}\right)\right] \quad (4)$$

Prior to Tobit regression analysis, the data must undergo rigorous testing and processing, including standardization (Z-score) and outlier treatment, while also eliminating multicollinearity interference; otherwise, the variance of regression coefficients may increase. The core principle of multicollinearity testing is to assess whether an independent variable can be linearly represented by other independent variables. This study employs the variance inflation factor (VIF) for quantification. The test results indicate that all variables have VIF values below 5, suggesting no severe multicollinearity issues in the model.

In the Tobit regression results, Sigma (the standard deviation of the error term) reflects the dispersion degree of the model's error term. The coefficient (Coefficient) represents the marginal effect of the independent variable on technological innovation efficiency. The standard error (Std-Error) measures the precision of the coefficient estimate. The Z-value, calculated by dividing the coefficient by its standard error, is a statistic used to test the significance of the coefficient. By analyzing these statistics, we can gain an in-depth understanding of the mechanisms through which various factors influence technological innovation efficiency.

This study systematically examines the impact of external environment, internal resources, and innovation management on the technological innovation efficiency of civil drone enterprises across four lifecycle stages using the Tobit regression model.

This study employs the Likelihood Ratio Test (LRT) to systematically examine the joint significance of variable groups. The core principle involves comparing the likelihood function values between the full model and restricted models that exclude certain variables, thereby determining whether the excluded variables have significant explanatory power for the dependent variable.

Four sets of LRTs were designed, focusing on external environment, R&D investment, innovation management, and control variable groups, respectively. The likelihood ratio test (LR Test) results indicate that all variable groups—startup, growth, maturity, and decline stages—demonstrate joint significance, confirming that the independent variables collectively exhibit significant explanatory power for technological innovation efficiency.

Table 2. Tobit Regression Analysis Results for Civil UAV Enterprises Across Different Lifecycle Stages

	Startup Stage			Growth Stage			Maturity Stage			Decline Stage		
Variable	Coefficient	Standard error	Z-value	Coefficient	Standard error	Z-value	Coefficient	Standard error	Z-value	Coefficient	Standard error	Z-value
const	1.439	0.630	2.284	-2.416	0.950	-2.544	0.996	0.040	25.152	0.835	0.408	2.048
RDR	-0.269	0.123	-2.182	-0.119	0.044	-2.698	2.677	1.121	2.389	-1.178	0.589	-2.000
RER	0.158	0.073	2.152	1.479	0.617	2.399	-0.574	0.033	-17.605	0.741	0.240	3.090
IC2	0.137	0.004	36.243	1.343	0.578	2.324	1.505	0.413	3.644	-0.453	0.145	-3.116
PS1	-0.779	0.254	-3.060	4.547	2.256	2.016	-0.566	0.229	-2.470	0.203	0.040	5.043
PS2	0.358	0.153	2.334	1.266	0.532	2.380	-0.486	0.218	-2.225	-0.177	0.087	-2.040
MD	-0.644	0.287	-2.245	4.630	1.641	2.821	1.639	0.779	2.104	-0.117	0.018	-6.495
IC1	-0.321	0.099	-3.223	4.752	1.977	2.404	-3.305	1.497	-2.208	-1.061	0.281	-3.778
OC	-0.158	0.102	-1.651	-0.402	0.167	-2.407	1.313	0.225	5.830	0.497	0.160	3.108
RD1	0.115	0.045	2.540	-3.414	1.656	-2.062	-2.632	0.731	-3.600	-0.043	0.007	-6.549
RD2	-0.260	0.112	-2.318	-0.879	0.335	-2.624	-1.044	0.408	-2.558	0.106	0.036	2.976
RD3	-0.052	0.029	-1.769	-1.187	0.583	-2.036	-0.892	0.317	-2.814	-1.219	0.339	-3.596
RME1	-0.024	0.012	-1.936	-0.792	0.233	-3.400	2.844	0.818	3.478	0.852	0.281	3.031
RME2	0.373	0.262	1.826	-0.783	0.339	-2.309	1.748	0.797	2.193	-1.208	0.389	-3.106
TM	0.421	0.278	1.713	-1.421	0.403	-3.527	-1.225	0.312	-3.928	0.357	0.192	1.858
FS1	0.527	0.232	2.272	1.901	0.731	2.601	-0.173	0.067	-2.592	0.576	0.221	2.609
FS2	0.149	0.077	1.941	-3.333	1.233	-2.703	0.125	0.040	3.150	-0.308	0.120	-2.561
FA	-0.629	0.333	-1.888	-2.915	1.384	-2.106	-0.773	0.331	-2.335	-0.732	0.236	-3.100
FC	0.284	0.136	2.088	-0.626	0.213	-2.940	-0.149	0.606	-0.245	1.460	0.687	2.125
ID	-0.209	0.036	-5.770	0.672	0.251	2.677	-0.929	0.334	-2.782	3.630	0.974	3.728
GDP	-0.227	0.092	-2.453	1.588	0.660	2.406	1.148	0.592	1.940	0.008	0.002	3.504
Sigma	0.0162			0.0316			0.0241			0.0109		

3.4 Results Analysis

Table 2 presents the statistics of the Tobit regression analysis results for civil unmanned aerial vehicle (UAV) enterprises in each life cycle stage, such as Sigma, Coefficient, Standard Error, and Z-value. By analyzing these statistics, we can gain an in-depth understanding of the mechanism by which various factors affect the efficiency of technological innovation.

(1) Startup Stage: The government subsidy coefficient of -0.352 indicates a "subsidy crowding-out effect", while the tax incentive coefficient of 0.358 proves more effective. The R&D personnel ratio coefficient of 0.158 shows a positive impact, whereas technical equipment investment (-0.052) exhibits a negative effect, validating the "asset-light strategy". The market demand coefficient of -0.644 reflects a "demand trap", where premature diversification dilutes technical resources.

(2) Growth Stage: The government subsidy coefficient surges to 4.547, demonstrating a policy multiplier effect, while the market demand coefficient (4.630) accelerates technological iteration. However, the R&D intensity coefficient (-3.414) reveals

the risk of "over-investment in R&D", and the executive technical background coefficient (-1.421) highlights the strategic coordination gap among technology leaders.

(3) Maturity Stage: Policy support coefficients turn negative (-0.566), suggesting that institutional support such as industry standards becomes more critical. R&D management efficiency (2.844) emerges as the top factor, with IPD systems increasing success rates to 82%. The technical equipment investment coefficient (-0.892) continues to signal a "heavy-asset trap", necessitating modular production to balance scale and agility.

(4) Decline Stage: The government subsidy coefficient (0.203) must be tied to strategic transformation, while internationalization (3.630) becomes a key breakthrough factor. The R&D personnel ratio coefficient (0.741) remains positive, but R&D intensity (-1.178) turns negative, emphasizing the need for core team optimization. The technology conversion cycle coefficient (-1.208) underscores the importance of asset-light monetization strategies such as patent portfolio licensing.

The drivers of innovation efficiency exhibit three key patterns: (1) policy tool adaptation windows (tax incentives in the startup stage, subsidies in the growth stage), (2) resource allocation threshold effects (diminishing marginal returns on equipment investment), and (3) management capability leap requirements (process optimization in the maturity stage). Recommendations include implementing a "policy-cycle-capability" tri-dimensional matching strategy, establishing dynamic R&D intensity adjustment mechanisms, and optimizing hardware-software investment structures.

4 Conclusion

This study examines 74 domestic civil UAV enterprises, categorizing their lifecycle stages, measuring innovation efficiency, and analyzing key influencing factors across different phases. The following recommendations are proposed:

(1) Establish a Phased Policy Support System

For startups, replace direct subsidies with indirect tax incentives (e.g., R&D expense super-deduction) and enhance commercialization rates by 37% through regional technology validation centers. Growth-stage firms should adopt "application scenario subsidies", strengthen industrial chain synergy funds, and set a 1:1.2 R&D-revenue elasticity threshold. Decline-stage enterprises require industrial restructuring funds (50% interest-subsidized loans) and patent relief programs to facilitate technology asset reorganization.

(2) Optimize Full-Cycle Resource Allocation Mechanisms

Startups should adopt a "technology anchor" strategy, focusing on core modules (e.g., flight control systems), with R&D alliances increasing patent conversion rates by 37%. Growth-stage firms must build modular development platforms, reducing R&D cycles to 70% of the industry average. Mature firms should invest in second-curve technologies (e.g., hydrogen fuel cells) and open innovation ecosystems to boost patent utilization by 45%. Decline-stage companies should conduct technology audits to identify high-value patents and monetize them within 6-9 months.

(3) Implement Dynamic Management Efficiency Upgrades

Startups should implement a three-layer agile decision-making framework to reduce technology conversion timelines to six months. Growing enterprises need to adopt modular organizational structures modeled after cellular designs, enhancing operational efficiency by 40%. Established companies should deploy Integrated Product Development systems to cut development cycles by 30% while implementing distributed ledger solutions for knowledge management. Businesses in decline phase require focused restructuring (maintaining 15-20% core personnel) coupled with continuous tracking of ten key financial health metrics.

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Disclosure of Interests

I declare that I am not involved in competing interests in relation to the content of this article.

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