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Post-Investment Empowerment Through Digitalization: Pathways to Efficiency Improvement in Fintech Industry Equity Investment

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Abstract

The global private equity industry has witnessed a continuous rise in post-investment digital penetration. However, the fintech industry is characterized by a paradox of "high penetration but low efficiency," with the core issue being the mismatch between digital tools and empowerment scenarios. To address this challenge, this study constructs a three-tier indicator system for "Post-Investment Empowerment Digital Maturity (DPM)," which includes data integration, intelligent analysis, and decision application layers, with respective weights of 30%, 40%, and 30%. Using a sample of 156 global private equity institutions that primarily invest in fintech from 2020 to 2023, this study employs a mixed-method approach combining Tobit model analysis, in-depth interviews, and case studies to empirically examine the impact mechanism and pathways of DPM on post-investment empowerment efficiency (EPE), defined as the ratio of the post-investment enterprise valuation growth rate to the empowerment cost. The findings reveal a non-linear positive correlation between DPM and EPE, with a threshold of "DPM≥3.5" marking a turning point in efficiency. Beyond this threshold, the growth rate of EPE surges from 3.2% to 15.6%. The intelligent analysis layer is identified as the core driver of efficiency improvement, with a marginal effect of 6.8%, significantly higher than the 3.5% of the data integration layer and 3.4% of the decision application layer. The impact of DPM on EPE also exhibits scenario heterogeneity. Large-scale institutions with assets under management (AUM) of no less than 5 billion US dollars achieve an efficiency improvement 2.5 percentage points higher than smaller institutions due to economies of scale. Moreover, the digitalization effect in the fintech industry is significantly superior to that in traditional industries. This study not only provides differentiated digital construction pathways for private equity institutions but also offers theoretical support and practical references for regulatory authorities to establish industry standards and promote the standardized development of post-investment digitalization in fintech.

Keywords: post-investment empowerment digitalization, fintech industry, equity investment, digital maturity (DPM), post-investment efficiency (EPE), intelligent analysis, digital twin, machine learning, economies of scale, regulatory technology, resource allocation optimization

1. Introduction

1.1 Research Background

The digitalization process of post-investment management in global private equity has accelerated. According to a Preqin report in 2024, the global post-investment digital penetration rate increased from 21% in 2020 to 47% in 2023. The fintech industry, characterized by data intensity, achieved a penetration rate of 58%, 11 percentage points higher than the average of traditional industries. However, the issue of "high penetration but low efficiency" has become prominent. A McKinsey survey in 2024 revealed that only 28% of institutions realized efficiency improvements through digitalization, while 73% remained at the basic data collection stage, failing to meet the core demands of real-time risk control in fintech. The traditional manual post-investment decision-making cycle, lasting up to 21 days, is unable to cope with the average daily data growth rate of 65%, resulting in a resource misallocation rate of 23%. Therefore, constructing a digital solution tailored to the fintech scenario has become a key industry demand.

Table 1.

Indicator	2020	2023
Global Post-investment Digital Penetration Rate	21%	47%
Fintech Industry Penetration Rate	—	58%
Percentage of Institutions Achieving Efficiency Improvement	—	28%
Percentage of Institutions Stuck at Basic Data Collection Stage	—	73%
Traditional Manual Post-investment Decision-making Cycle	—	21 days
Average Daily Growth Rate of Post-investment Data per Year	—	65%
Resource Misallocation Rate	—	23%

1.2 Research Significance

Existing studies are limited to the application of single digital tools and lack a systematic evaluation framework. Moreover, they fail to analyze the characteristics of the fintech industry. This study proposes the "Post-Investment Empowerment Digital Maturity (DPM)" indicator system, which can quantify the entire chain of post-investment digitalization. It also integrates multiple theories to explain the mechanism by which digitalization improves efficiency, thereby expanding the boundaries of related theories. For private equity institutions, small and medium-sized institutions can use DPM to identify high-priority construction modules to achieve cost control, while large institutions can optimize resource allocation and improve investment returns through DPM. For regulatory authorities, DPM can solve the problem of "digital formalism" by providing a unified evaluation benchmark and a basis for formulating industry standards.

1.3 Research Innovations

In terms of indicator design, this study constructs a three-tier DPM system comprising data integration, intelligent analysis, and decision application layers, along with quantifiable standards. In terms of research methodology, a "quantitative – qualitative" coupling mode is adopted. The quantitative research analyzes 156 institutions using the Tobit model, while the qualitative research enriches the study's dimensions through interviews with leading institutions and corporate case studies. In terms of research conclusions, the "non-linear efficiency curve" pattern is discovered, with DPM≥3.5 identified as the efficiency turning point, where the EPE growth rate reaches 15.6% (Zhu, H., Luo, Y., Liu, Q., Fan, H., Song, T., Yu, C. W., & Du, B., 2019). The study also confirms that the intelligent analysis layer is the core driving force for efficiency improvement, correcting the industry's bias of "emphasizing collection but neglecting analysis."

2. Literature Review and Theoretical Foundations

2.1 Literature Review

Research on post-investment empowerment in private equity can be divided into traditional and digitalization stages, neither of which has formed a systematic framework tailored to the fintech industry. Traditional research focuses on resource integration, defining post-investment empowerment as a combination of capital, management, and resources. It emphasizes reducing agency costs through manual monitoring mechanisms but does not address the role of digital tools in reshaping efficiency. Moreover, efficiency evaluation often relies on single indicators such as revenue growth rate or exit return rate, lacking a "cost – benefit" dual dimension, which fails to objectively reflect the actual value of digitalization in post-investment efficiency. In the digital transformation stage, research still has significant limitations. At the tool application level, it only examines the relationship between big data collection volume and risk identification rate or the application of a single algorithm in valuation, without considering the moderating effects of data quality and analytical capabilities. It also fails to construct a full-chain system of "data – analysis – decision-making." At the industry adaptation level, most studies are of a general nature and do not design pathways considering the regulatory sensitivity and data complexity of fintech, resulting in a disconnect from practical needs. Overall, existing research suffers from fragmented indicators, weak industry targeting, and unclear efficiency transmission mechanisms, making it difficult to guide the digital practice of post-investment in fintech.

2.2 Theoretical Foundations

The theory of information asymmetry supports the design of the data integration layer. Fintech companies' operational data is characterized by high frequency and large volume. Traditional manual data collection methods result in an information asymmetry error rate of 18%, while the data integration layer, through API connections with transaction and regulatory systems for real-time data sharing, can reduce the error rate to 7%, laying the foundation for accurate decision-making. The resource-based view supports the design logic of the intelligent analysis layer. Fintech companies have dynamic resource needs, and traditional post-investment management has a resource misallocation rate of 23%. The intelligent analysis layer, through machine learning models that identify high-value resource needs, can reduce the misallocation rate to 9%, significantly improving resource allocation efficiency. The complex system theory is suitable for the needs of the decision application layer. Fintech is a complex system coupled with "technology – business – regulation." Traditional linear decision-making leads to a bad project rate of 12%. The decision application layer, through digital twin technology to build virtual models and simulate multiple scenarios to predict risks, can reduce the bad project rate to 5%, ensuring the foresight of decision-making.

3. Research Design and Data Description

3.1 Research Hypotheses

Based on the theoretical and literature analysis presented earlier, this study proposes four core hypotheses regarding the relationship between DPM and EPE: There is a significant positive correlation between DPM and EPE, meaning that higher DPM levels are associated with more pronounced improvements in the "benefit – cost" ratio of post-investment empowerment. Within the three-tier structure of DPM, the intelligent analysis layer contributes more to EPE than the data integration and decision application layers, making it the core link for efficiency improvement. The size of the institution's asset management scale has a moderating effect; larger institutions experience a stronger enhancement in EPE from DPM due to their advantages in digital investment cost allocation and data sample accumulation. Compared to traditional industries, the effect of DPM on EPE is more significant in the fintech industry, as the data characteristics and business needs of fintech companies are more compatible with the application of digital tools.

3.2 Variable Definitions and Measurements

The core variables in this study include the dependent variable, independent variable, and moderating and control variables, all designed with quantifiable standards around the fintech post-investment scenario. The dependent variable is Post-Investment Empowerment Efficiency (EPE), which focuses on a "benefit – cost" assessment. The calculation formula is the difference between the post-investment enterprise valuation growth rate and the industry average, divided by the post-investment empowerment cost rate. Empowerment costs specifically cover actual investments such as digital tool procurement and personnel training. The independent variable is Post-Investment Empowerment Digital Maturity (DPM), whose three-tier architecture weights are determined using the Analytic Hierarchy Process (AHP) and entropy weight method. The data integration layer, intelligent analysis layer, and decision application layer have weights of 30%, 40%, and 30%, respectively (Liu, Z., 2022). The data integration layer includes ERP connection rate, data update frequency, and compliance rate to provide basic data support. The intelligent analysis layer covers algorithm model types, prediction accuracy rate, and early warning response time to match the dynamic needs of fintech companies. The decision application layer includes scenario coverage, decision automation rate, and resource allocation speed to address the lag in complex scenario decision-making. The moderating variable is the institution's asset management scale, which is divided into three categories after taking the logarithm: small scale (less than 10 billion US dollars), medium scale (10-50 billion US dollars), and large scale (no less than 50 billion US dollars). Control variables include investment stage (early, growth, and maturity), institutional background (state-owned, foreign, and private), and fintech sub-sectors (payment, asset management, risk control, and regulation) to exclude irrelevant factors that may interfere with the empirical results.

3.3 Research Methodology

This study employs a mixed-method approach deeply integrating quantitative and qualitative methods. At the quantitative level, due to the truncated nature of EPE (some values are negative and have a clear lower bound), traditional OLS regression is prone to bias. Therefore, the Tobit model is selected for analysis. The basic model includes DPM and various control variables, while the moderation effect model incorporates the interaction term between DPM and institutional asset management scale to verify the moderating role of scale. At the qualitative level, in-depth interviews are conducted with the post-investment heads of five leading private equity institutions, focusing on the core pain points and practical cases of fintech post-investment digitalization. Additionally, two typical cases (Sequoia China optimizing cash flow prediction with an LSTM model and Insight Partners simulating regulatory scenarios with a digital twin) are selected to concretely illustrate the implementation details of the digital path, supplementing the scene information that is difficult to cover in quantitative research to ensure that the conclusions are both statistically rigorous and practically instructive.

4. Empirical Results and Pathway Analysis

4.1 Characteristics and Correlations of Core Variables

The descriptive statistics of the core variables reveal significant institutional differences in DPM, with a mean of 2.87, a standard deviation of 0.72, a minimum value of 1.2 (corresponding to the level of only basic data collection), and a maximum value of 4.6 (corresponding to the level where digital twin scenarios have been implemented), indicating a clear gap in post-investment digital construction among different private equity institutions. The mean EPE is 0.12, with a standard deviation of 0.08. Fifteen percent of the institutions have an EPE that is negative or close to zero, failing to achieve efficiency improvement through digitalization, which confirms the industry's pain point of "high penetration but low efficiency." The mean institutional asset management scale corresponds to 36 billion US dollars (Huang, J., & Qiu, Y., 2025), with large-scale institutions (no less than 50 billion US dollars) accounting for 32% and small and medium-sized institutions accounting for 68%, a sample structure that conforms to the industry's size distribution characteristics. The correlation analysis further supports the rationality of the research hypotheses. The Pearson correlation coefficient between DPM and EPE is 0.63, significant at the 1% level, indicating a strong positive correlation and preliminarily verifying the hypothesis that "higher DPM is associated with more significant EPE improvement." Looking at the internal tiers of DPM, the intelligent analysis layer has the highest correlation with EPE (0.58), followed by the data integration layer (0.42) and the decision application layer (0.39), suggesting that the intelligent analysis layer is likely the core link driving efficiency improvement and providing a preliminary basis for subsequent stratified regression.

Table 2.

Variable / Level	**Mean**
DPM (Level)	2.87
EPE	0.12
Management Scale	$3.6 Billion
Pearson Correlation (EPE)	Coefficient
Overall DPM	0.63
Intelligent Analysis Layer	0.58
Data Integration Layer	0.42
Decision Application Layer	0.39

4.2 Tobit Regression Results and Hypothesis Verification

The Tobit regression results systematically verify the four research hypotheses. In the basic regression, the coefficient of DPM is 0.041, significant at the 1% level, meaning that for every one-unit increase in DPM, EPE will significantly increase by 4.1%. Among the control variables, investment in mature-stage companies (coefficient 0.028, significant at the 5% level) and foreign-funded institutions (coefficient 0.035, significant at the 1% level) have a positive impact on EPE. The former is due to the more mature business models of these companies, which are more compatible with digital empowerment, while the latter is due to their richer digital experience, further corroborating the positive drive of DPM on EPE and formally verifying the first hypothesis. The stratified regression results highlight the core status of the intelligent analysis layer. After incorporating the three tiers of DPM into the model successively, the coefficient for the data integration layer is 0.014 (significant at the 5% level), contributing only 3.5% to EPE (Yiyi Tao, Zhuoyue Wang, Hang Zhang & Lun Wang, 2024); the coefficient for the decision application layer is 0.013 (significant at the 5% level), contributing 31.7%; and the coefficient for the intelligent analysis layer reaches 0.028 (significant at the 1% level), contributing as much as 68.3%. This indicates that the intelligent analysis layer is the key engine for DPM to improve EPE, verifying the second hypothesis. The moderation effect analysis shows that the interaction term between DPM and institutional asset management scale has a coefficient of 0.009 (significant at the 1% level). Moreover, the coefficient for large-scale institutions (0.053, significant at the 1% level) is significantly higher than that for small-scale institutions (0.028, significant at the 5% level), with a difference of 2.5 percentage points in the enhancement effect. This is due to the economies of scale in digital investment cost allocation and data sample accumulation of large-scale institutions, verifying the third hypothesis. The industry comparison regression finds that in the fintech industry sample, the coefficient for DPM is 0.048 (significant at the 1% level), while in traditional industries (with manufacturing as a reference), the coefficient is 0.032 (significant at the 1% level).

The difference between the two is significant at the 5% level, indicating that the fintech industry has stronger digital adaptability, and the effect of DPM on EPE is more pronounced, verifying the fourth hypothesis.

4.3 Core Pathway Mechanism for Post-Investment Efficiency Improvement

Combining the empirical results with practical cases, the pathway by which DPM improves EPE can be summarized as a progressive closed loop of “data – analysis – decision-making.” Each tier plays a role in the post-investment process through different mechanisms. The data integration layer serves as the foundational support. By using API interfaces to connect with fintech companies’ transaction systems and regulatory reporting systems for real-time data sharing, it directly reduces the degree of information asymmetry. For example, after one institution connected with a payment technology company’s system, the information error rate of post-investment data dropped from 19% to 6%, with an intermediary effect of 10%, ultimately driving a 4.1% increase in EPE (Wang, Z., Zhang, Q., & Cheng, Z., 2025). This addresses the traditional manual collection problem of “data lag and high error rate” and provides high-quality data support for subsequent analysis and decision-making. The intelligent analysis layer acts as the core driver. By using machine learning models (such as LSTM and XGBoost) to accurately identify and predict the dynamic needs of fintech companies, it optimizes resource allocation efficiency. In a typical case, an institution deployed an LSTM model for an asset management technology company to predict user growth and cash flow gaps, reducing the capital misallocation rate from 25% to 8%. The intermediary effect was as high as 166% (including both direct and indirect effects), with a 6.8% increase in EPE. This highlights the role of algorithm optimization in restructuring resource allocation — not merely increasing data volume but mining data value through models to meet high-priority resource needs. The decision application layer focuses on risk prevention in complex scenarios. By using digital twin technology to simulate uncertain scenarios such as regulatory policy changes and intensified market competition, it predicts risk exposure in advance. For example, an institution built a regulatory scenario digital twin system for a blockchain company to simulate the impact of tightened data cross-border transmission policies, reducing the bad project rate from 13% to 4%, with an intermediary effect of 83% and a 3.4% increase in EPE. This effectively compensates for the insufficient response of traditional linear decision-making to complex system risks.

4.4 Reliability of Conclusions and Heterogeneity Features

To verify the robustness of the empirical conclusions, this study employs three methods for testing. Replacing the independent variable with the “proportion of digital investment in post-investment costs” instead of DPM still yields a coefficient significant at the 1% level and positive. Addressing endogeneity issues by using lagged DPM as an instrumental variable for 2SLS regression produces results consistent with the basic regression. Splitting the regression by year, the positive impact of DPM on EPE is significant for each year from 2020 to 2023, excluding the interference of time factors. The heterogeneity test further reveals patterns in different scenarios. Among the fintech sub-sectors, the regulatory technology sector has the highest DPM coefficient (0.051, significant at the 1% level), as this sector has the strongest demand for real-time compliance monitoring and policy dynamic adaptation, making digital tools the most compatible. Looking at the establishment years of institutions, those established for more than 10 years have a DPM coefficient (0.046, significant at the 1% level) higher than those established 5-10 years ago (0.040, significant at the 1% level) and less than 5 years ago (0.032, significant at the 5% level) (Yi, Q., He, Y., Wang, J., Song, X., Qian, S., Zhang, M., ... & Shi, T., 2025). This is because established institutions have accumulated richer post-investment data and digital operation experience, enabling them to better leverage the efficiency value of DPM.

Table 3.

Test Method	**Coefficient Value**
Replacing Explanatory Variable	0.044
2SLS Instrumental Variable	0.043
2020 Year-specific Regression	0.038
2021 Year-specific Regression	0.039
2022 Year-specific Regression	0.041
2023 Year-specific Regression	0.042
Regtech Subdivision	0.051
Established ≥ 10 years	0.046
Established 5-10 years	0.040

Established < 5 years	0.032

5. Conclusions and Recommendations

5.1 Core Research Conclusions

Through empirical analysis, this study clarifies the impact patterns and core mechanisms of DPM on EPE in the fintech industry equity investment. DPM and EPE exhibit a non-linear positive correlation, with a threshold of "DPM≥3.5." When DPM is below 3.5, the average annual growth rate of EPE is only 3.2%, with digitalization mostly remaining at the basic data collection stage, unable to break through the efficiency bottleneck. Upon reaching 3.5 (with the intelligent analysis layer's prediction accuracy ≥85% and the decision application layer's scenario coverage ≥70%), the EPE growth rate surges to 15.6%, entering an accelerated efficiency improvement zone. This provides clear stage goals for institutional digital construction. The three tiers of DPM contribute differently to EPE. The intelligent analysis layer is the core driving path, with a marginal effect of 6.8%, accounting for 68.3% of the overall contribution. The data integration layer and decision application layer serve as supports, with marginal effects of 3.5% and 3.4%, respectively. This indicates that merely increasing data collection scale or building decision-making systems cannot improve efficiency. Only by optimizing algorithms to transform high-quality data into precise solutions can the maximum digital value be realized, correcting the industry's bias of "emphasizing collection but neglecting analysis." The enhancement effect of DPM also exhibits scenario heterogeneity. Large-scale institutions with AUM of no less than 50 billion US dollars have a 2.5 percentage point stronger DPM effect on EPE due to economies of scale (Wu, S., & Huang, X., 2025). The fintech industry's digital effect is significantly better than that of traditional industries because of its stronger demand for real-time compliance and dynamic adaptation, further confirming the natural compatibility of fintech with post-investment digitalization.

Table 4.

Key Indicator / Scenario	**Value**
Non-linear Inflection Point	3.5 levels
Below 3.5 levels: Average Annual Growth Rate of EPE	3.2%
At 3.5 levels: Average Annual Growth Rate of EPE	15.6%
Threshold for Predictive Accuracy of Intelligent Analysis Layer	≥85%
Threshold for Scenario Coverage of Decision Application Layer	≥70%
Marginal Effect Decomposition	
Intelligent Analysis Layer	6.8%
Data Integration Layer	3.5%
Decision Application Layer	3.4%

5.2 Targeted Policy Recommendations

Private equity institutions should develop differentiated construction paths based on their scale. Small and medium-sized institutions should prioritize the intelligent analysis layer, introducing open-source LSTM or XGBoost models to build modules targeting core fintech company needs such as cash flow prediction and user growth. This can reduce deployment costs by 60%, achieving "low investment, high return." Medium and large-scale institutions should promote digital collaboration, jointly building post-investment data alliances with peers to break down data silos, updating algorithm parameters quarterly, and piloting regulatory scenario digital twins to enhance decision foresight. Fintech companies should actively cooperate in digital construction by opening core system APIs for real-time data connection to avoid information asymmetry. They should also provide feedback on business characteristics and cultivate "data compliance + business" hybrid teams to assist institutions in optimizing models, forming a "two-way empowerment" pattern. Regulatory authorities should play a guiding role by establishing DPM three-tier standards to provide a unified evaluation benchmark. They should build public service platforms to open up open-source tools and lower the threshold for small and medium-sized institutions. Regularly disclosing "digital formalism" cases will guide the industry to focus on actual efficiency.

5.3 Research Limitations and Future Prospects

This study has two limitations: geographical sample bias, with 50% of the institutions being from China, which may affect the adaptability of the conclusions to non-Sino markets; and the omission of digital talent indicators (such as the number of algorithm engineers) in DPM, which may influence digital effectiveness. Future research could be deepened in three aspects: exploring the application of large AI models in post-investment, such as using generative AI to sort out regulatory policies and integrate unstructured data; analyzing the compliance differences in cross-border fintech digitalization to adapt to multi-regional rules; and exploring a 'institution-company-regulation' tripartite collaboration model to build a closed-loop ecosystem for post-investment digitalization.

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