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Economic Value of AI Innovation: An Empirical Exploration of U.S. Patents

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Short Paper

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Abstract

While recent research has established that AI innovations tend to be more incremental and process-oriented than comparable IT innovations, it remains unclear whether these characteristics translate into differential economic value. This emergent research extends the comparative analysis of AI and IT patents by incorporating a stock-market-based economic valuation measure. Using the USPTO AI Patent Dataset and PatentsView data, we construct matched samples of AI and IT patents and compare their estimated private economic values (in 1982 million dollars). Preliminary analysis suggests that despite being less radical, AI patents command higher market valuations than IT patents, potentially reflecting the strategic importance of AI as a source of competitive advantage. This research-in-progress contributes to the emerging discourse on AI innovation management by adding an economic value dimension to the form magnitude framework established in prior work.

Keywords: Artificial intelligence, economic value of innovation, Schumpeterian innovation, patent valuation, general purpose technology

Introduction

Artificial intelligence (AI) is widely regarded as one of the most transformative technologies of our time, attracting unprecedented levels of corporate investment as organizations seek new sources of competitive advantage (Krakowski et al., 2023). From autonomous vehicles to medical diagnostics, AI appears to represent a dramatic departure from prior technological paradigms. Yet this intuition may be misleading. In a landmark study published in MIS Quarterly, Lin and Maruping (2025) provide surprising empirical evidence that challenges conventional wisdom. Analyzing over 283,000 matched pairs of AI and IT patents filed with the U.S. Patent and Trademark Office (USPTO), they demonstrate that AI innovations are significantly less technologically radical and more process-oriented in their functional form than comparable IT innovations. Here, "radical" refers specifically to the degree of technological novelty relative to prior art that is, the extent to which a patent departs from existing knowledge as measured by its citation patterns. By this measure, innovations such as the invention of relational database architectures or the transition from circuit-switched to packet-switched networking represent truly radical IT innovations that fundamentally restructured existing technological trajectories. In contrast, many AI patents build incrementally on established machine learning techniques, applying known algorithms to new domains rather than creating entirely new technological foundations. These findings have reshaped our understanding of how firms should organize and manage AI-driven innovation, and they raise a provocative question: if AI is less radical, why does the market value it so highly?

However, one critical dimension that remains unexplored in this comparative analysis is the economic value that financial markets assign to AI versus IT innovations. While Lin and Maruping (2025) observe in their descriptive statistics that AI patents tend to receive higher market valuations than IT patents based on the Kogan et al. (2017) stock-market-based measure, they do not formally investigate this difference or explore its underlying mechanisms. This gap is consequential for both theory and practice. From a theoretical standpoint, the innovation economics literature has long recognized that the economic value of patents captures information about firm growth and competitive dynamics beyond what citation-based measures alone reveal (Kogan et al., 2017). From a practical standpoint, understanding the market valuation of AI innovations relative to IT innovations is essential for firms' resource allocation decisions, R&D investment strategies, and intellectual property portfolio management. Without this knowledge, managers lack a key input for determining whether and how to shift innovation efforts toward AI.

This emergent research aims to address this gap by posing two research questions: (1) Do AI patents generate higher or lower private economic value than comparable IT patents? (2) How does the economic value of AI patents relate to their comparatively incremental and process-oriented nature? If AI innovations are indeed less radical yet more highly valued, this finding would represent a meaningful boundary condition for the long-standing assumption in innovation economics that greater technological radicalness leads to higher economic value. Such a result would suggest that the core "radicalness-driven value" logic does not generalize to the AI context, requiring scholars to reconsider the mechanisms through which innovation generates economic returns. To investigate these questions, we leverage the USPTO AI Patent Dataset (Giczy et al., 2022), which systematically identifies AI patents across eight component technologies, and the widely adopted patent valuation methodology of Kogan et al. (2017), which estimates the private economic value of each patent from abnormal stock returns around the patent grant date. By linking these datasets to the matched AI–IT patent sample constructed by Lin and Maruping (2025), we are able to compare the economic values of AI and IT patents while controlling for confounding factors through coarsened exact matching. Our preliminary findings suggest that AI patents command approximately 22% higher economic valuations than matched IT patents, despite being less technologically radical, a pattern we explore through the lenses of process innovation theory, general-purpose technology frameworks, and strategic competitive advantage.

Conceptual Background

Our research draws on two foundational streams. The first is the Schumpeterian framework of innovation, which distinguishes innovations along two dimensions: form (product vs. process) and magnitude (radical vs. incremental). Lin and Maruping (2025) operationalize this framework using patent text analysis and demonstrate that AI innovations, relative to matched IT innovations, are systematically more process-oriented and less radical. These findings have important managerial implications: because AI innovations emphasize efficiency improvements over breakthrough novelty, firms may benefit from organizing AI R&D around process management practices, formal structural arrangements, and deep rather than broad knowledge search. Yet whether these innovation characteristics also predict differences in economic outcomes remains an open question that the authors identify but do not pursue.

The second stream is the innovation economics literature on measuring the private economic value of patents. Kogan et al. (2017) developed a widely used methodology that infers patent values from stock market reactions to patent grant announcements, capturing the present value of monopoly rents that investors expect the patent to generate. This measure has been validated as positively correlated with forward citations while containing additional predictive information about firm growth and creative destruction dynamics. Notably, Lin and Maruping (2025) report in their descriptive statistics (Table 4) that

AI patents exhibit a higher average economic value (16.80 in 1982 million dollars) than IT patents (13.81 in 1982 million dollars) under the Kogan et al. (2017) measure, but they leave this observation unexamined.

The juxtaposition of these two literatures presents an intriguing puzzle: if AI innovations are less radical than IT innovations, why might they command higher economic valuations from financial markets? Understanding this puzzle requires first considering how financial markets actually price innovation. Research in financial economics suggests that investors evaluate innovations not solely based on technological novelty, but rather through the lens of expected future cash flows, growth options, and competitive positioning (Hall et al., 2005). This market pricing perspective suggests that the radicalness-value link assumed in innovation theory may not directly translate to financial market valuations.

We propose three complementary mechanisms, organized hierarchically across distinct levels of analysis, to explain this paradox:

First, at the innovation level, AI-driven process innovations generate measurable cost-reduction and efficiency benefits that markets can value with relative confidence (Utterback & Abernathy, 1975). Unlike traditional IT process innovations such as ERP-based workflow automation, which follow predefined rules, AI-driven process innovations are distinctive in their capacity for autonomous learning and continuous adaptation—they improve through exposure to data rather than requiring manual reprogramming (Krakowski et al., 2023). However, an exclusive focus on process innovation may limit the scope for market-creating novelty, while purely product-oriented innovations may lack the efficiency anchors that enable reliable market valuation; this logic suggests the relationship between process orientation and economic value may follow an inverted-U shape.

Second, at the technology level, AI's status as a general-purpose technology, one that exhibits pervasive use, inherent potential for improvement, and strong innovation complementarities (Bresnahan & Trajtenberg, 1995) may imbue even incremental AI advances with expectations of broad cross-domain applicability, creating option value that markets price in (Bianchini et al., 2022). While some IT technologies are also general-purpose (e.g., database query optimization), AI is distinctive in its breadth: the same techniques can be deployed across fundamentally different tasks such as image recognition, autonomous navigation, and drug discovery.

Third, at the firm level, AI capabilities may be particularly difficult to imitate because they are embedded in a firm's proprietary data assets, organizational workflows, and tacit knowledge (Krakowski et al., 2023). We note, however, that this mechanism likely operates under specific boundary conditions: algorithmic innovations may be more readily replicated through open-source ecosystems, whereas data-dependent and application-specific AI innovations are more likely to generate durable competitive advantages. These mechanisms collectively suggest that the traditional association between radicalness and value may not hold in the AI domain.

Proposed Methodology

Data and Sample

We utilize three primary data sources: (1) the USPTO AI Patent Dataset, which identifies AI patents using a machine learning classifier across eight AI component technologies (Giczy et al., 2022); (2) the PatentsView database for patent characteristics and the G06 CPC class to identify IT patents; and (3) the Kogan et al. (2017) patent-level economic value estimates based on stock market reactions to patent grants. Following Lin and Maruping (2025), we construct matched pairs of AI and IT patents by filing year, Level-4 CPC code, and text similarity, followed by coarsened exact matching on patent characteristics. Figure 1 illustrates this sample construction procedure.

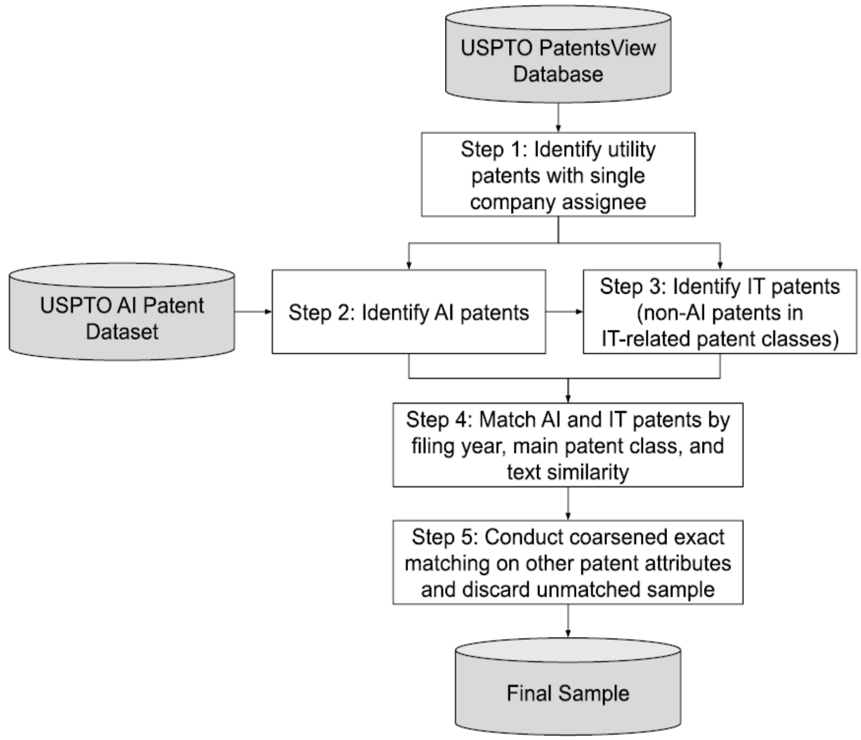

Figure 1. Sample Construction Procedure (Adopted from Lin and Maruping, 2025)

Measures

Our dependent variable is the estimated private economic value of each patent (ξ), constructed following Kogan et al. (2017). This measure isolates the component of the stock price reaction around patent issuance dates attributable to the patent's value. We also retain the radicalness measure R(i) and process orientation measure PO(i) from Lin and Maruping (2025) to examine how these innovation characteristics relate to economic value. Control variables include the number of claims, backward citations, forward citations, and inventors. Table 1 provides formal definitions for all variables.

Table 1. Variable Definitions

Variable	Type	Definition
ξ (Economic Value)	DV	Estimated private economic value of a patent (1982 million dollars), based on stock market reaction to patent grant (Kogan et al., 2017)
AI	IV	Binary indicator equal to 1 if the patent is classified as AI by the USPTO AI Patent Dataset, 0 otherwise
PO (Process Orientation)	Moderator	Proportion of process-oriented claims relative to total claims (Lin & Maruping, 2025)
R (Radicalness)	Moderator	Standardized measure of technological novelty relative to prior art (Lin & Maruping, 2025)
Claims	Control	Number of claims in the patent document

Backward Citations	Control	Number of prior patents cited by the focal patent
Forward Citations	Control	Number of subsequent patents citing the focal patent
Inventors	Control	Number of inventors listed on the patent

Note: Fixed effects include assignee (ω), CPC code (λ), and filing year (π).

Exploratory Data Analysis

Prior to formal hypothesis testing, we conducted exploratory data analysis to examine the distributional properties of key variables and the bivariate relationships among them. Figure 2 presents box plots comparing the distributions of log-transformed economic values for AI and IT patents. Visually, both the median and interquartile range of AI patent values appear shifted upward relative to IT patents, consistent with the mean differences reported in Table 2. A Welch's t-test on the log-transformed values confirms that this difference is statistically significant ($t = 14.73$, $p < 0.001$), as does a non-parametric Mann–Whitney U test ($p < 0.001$). Both distributions exhibit heavy right tails, but the AI group shows a higher concentration of values in the upper quartile. We note, however, that these bivariate tests do not account for the covariates and fixed effects included in our main regression specification; formal results from the WLS model will provide a more rigorous assessment of the AI premium.

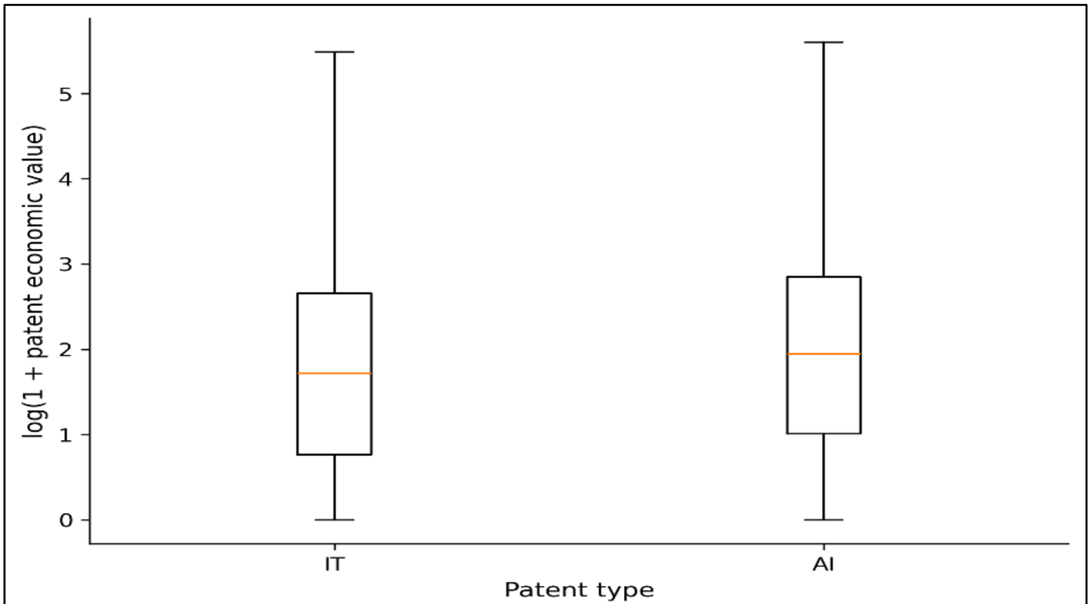

Figure 2. Distribution of Log-Transformed Economic Value by Patent Type

Figure 3 displays a binned scatter plot of forward citations against patent economic value across the pooled sample. The strong, monotonically increasing relationship confirms that the Kogan et al. (2017) market-based valuation measure is positively correlated with citation impact. Crucially, preliminary partial correlation analysis indicates that the positive association between AI status and economic value persists even after conditioning on forward citations, suggesting that the AI valuation premium captures market expectations beyond mere citation-based technological impact.

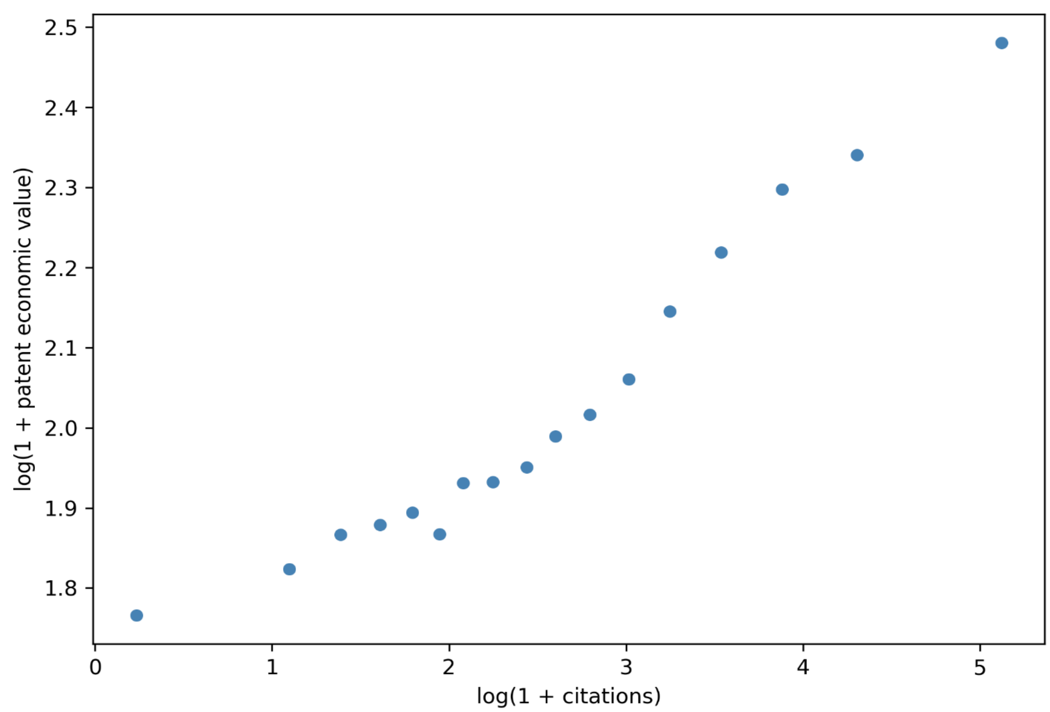

Figure 3. Binned Scatter Plot of Forward Citations vs. Patent Economic Value

Analytical Approach

We employ a weighted least squares (WLS) regression framework consistent with Lin and Maruping (2025) as follows

$$\log(\xi_i) = \beta_0 + \beta_1 AI_i + \beta_2 Controls + \omega_i + \lambda_i + \pi_t + \varepsilon_i$$

where ξ_i is the economic value of patent i (in 1982 million dollars), AI_i indicates whether the patent is an AI patent, and we include assignee (ω), CPC code (λ), and filing year (π) fixed effects. Crucially, the inclusion of assignee fixed effects means that the AI coefficient is identified from within-firm variation—comparing AI and IT patents granted to the same firm—which mitigates concerns that the AI premium merely reflects firm-level characteristics such as investor sentiment toward AI-active firms. We extend this model by incorporating interaction terms between AI status and process orientation or radicalness to test whether these innovation characteristics moderate the economic value differential. To further address potential confounds, we include firm size (log of total assets) and R&D intensity (R&D expenditure scaled by total assets) as additional control variables in robustness specifications, given that these firm-level factors may independently influence market valuations (Hall et al., 2005).

Preliminary Findings and Expected Contributions

Table 2 summarizes the descriptive statistics from our preliminary sample construction, drawing on values reported in Lin and Maruping (2025, Table 4) and our initial data linkage with Kogan et al. (2017).

Table 2. Preliminary Descriptive Comparison		
Characteristic	**AI Patents**	**IT Patents**

Average Economic Value (1982 Million Dollars)	17.39	14.95
Process Orientation (PO)	0.502	0.476
Radicalness (R, Standardized)	0.073	−0.073
N (Matched Pairs)	283,688	283,688

Note: Economic value based on Kogan et al. (2017); other measures from Lin and Maruping (2025).

The preliminary data indicate that AI patents command approximately 22% higher average economic value than matched IT patents (17.39 vs. 14.95 in 1982 million dollars). This difference is economically substantial and warrants formal testing. To further probe the mechanisms underlying this value differential, Figures 4 and 5 provide additional exploratory evidence.

Figure 4 plots process orientation against log-transformed patent economic value in a binned scatter. The relationship follows an inverted-U shape: patents with moderate levels of process orientation (approximately 0.3–0.6) tend to exhibit the highest economic values, while patents at the extremes—those that are almost entirely product-oriented or almost entirely process-oriented—receive lower market valuations. This pattern is consistent with the theoretical logic developed in our conceptual framework: purely product-oriented innovations may lack the measurable efficiency gains that give investors confidence in near-term returns, while purely process-oriented innovations may lack sufficient novelty to generate growth expectations and option value. The optimal balance at moderate levels of process orientation reflects the point at which innovations combine credible efficiency benefits with sufficient scope for market expansion.

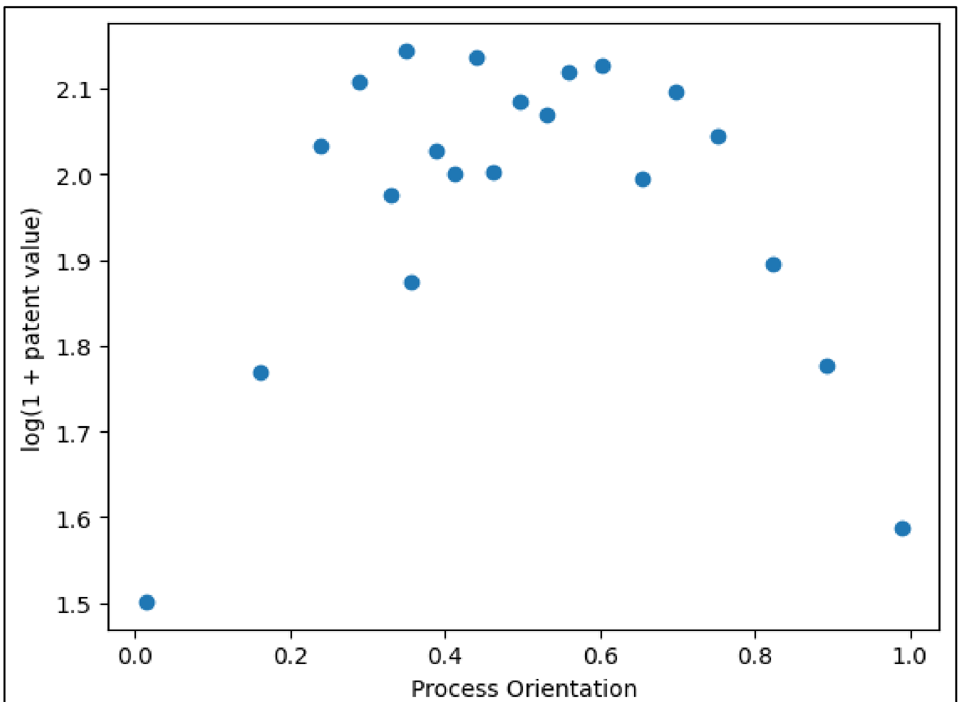

Figure 4. Process O rientation vs. Log-Transformed Patent

Figure 5 displays the raw (non-log-transformed) economic value distributions for AI patents (AI Indicator = 1) and non-AI IT patents (AI Indicator = 0) using a strip plot with box plot overlay. We acknowledge that this visualization is difficult to interpret given the extreme right-skew; in the final version, we plan to replace it with kernel density estimates on log-transformed values for a more informative distributional comparison. Notwithstanding, the AI patent group exhibits a thicker upper tail with more extreme high-value outliers, some exceeding 2,500 in 1982 million dollars. This visual evidence suggests that the AI premium is driven not only by a higher mean but also by a fatter right tail of exceptionally valuable patents, a feature that may reflect the option-value characteristics of AI as a general-purpose technology.

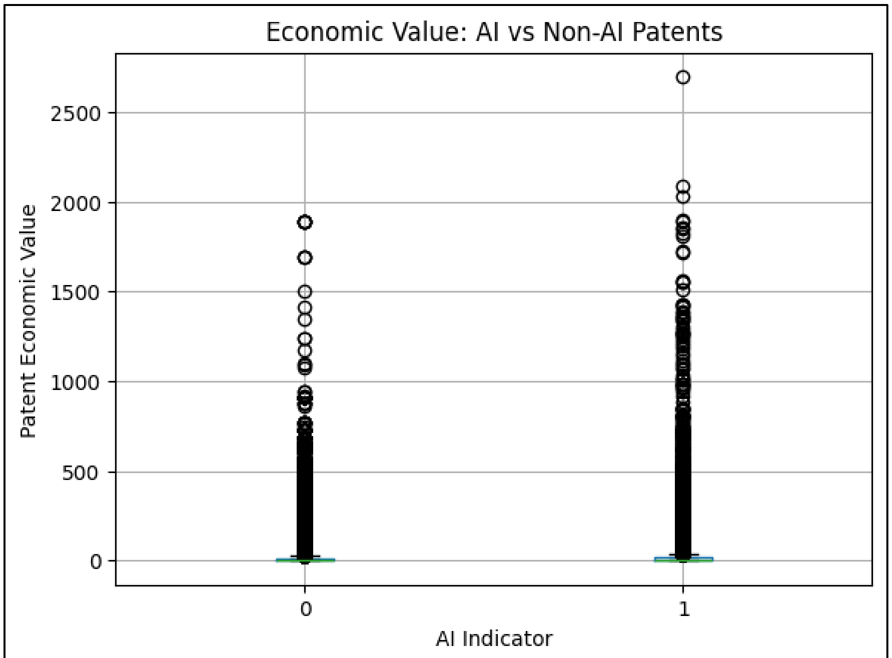

Figure 5. Economic Value Distribution: AI vs. Non-AI Patents

This research-in-progress is expected to make three contributions to the IS literature. First, it extends the comparative AI–IT innovation framework introduced by Lin and Maruping (2025) by adding an economic value dimension, providing researchers with a more holistic understanding of how AI innovations differ from IT innovations not only in form and magnitude but also in market valuation. Second, it offers theoretical insight into the seeming paradox that incremental, process-oriented innovations can command premium economic valuations. By examining how process orientation and radicalness moderate the AI value premium, this study contributes to ongoing debates about AI as a general-purpose technology (Bresnahan & Trajtenberg, 1995; Cockburn et al., 2019) whose value may derive more from broad applicability and strategic optionality than from radical novelty. Third, it provides actionable guidance for practitioners by quantifying the economic returns to AI innovation relative to IT innovation, informing R&D portfolio allocation and intellectual property management decisions.

Future Work

Several steps remain before this research is complete. First, we will execute the formal WLS regression analysis with the full set of fixed effects and interaction terms to establish whether the AI economic value premium is statistically significant and to quantify the moderating roles of process orientation and radicalness. Second, we will conduct robustness checks using alternative matching criteria (e.g., varying the text similarity threshold), alternative value measures (e.g., citation-weighted counts), and different model specifications (e.g., OLS with clustered standard errors). We will also explore an event study framework that treats each patent grant announcement as the event of interest, specifying the patent grant date as the event date and examining abnormal returns in a narrow window (e.g., [0, +2] trading days) to more precisely link patent-level constructs to firm-level outcomes, while controlling for concurrent events through market model adjustments. Third, we plan subsample analyses by AI component type (learning, sensing, reasoning, and hardware) and by time period to assess whether the premium has grown following the post-2012 deep learning revolution; this is important because the valuation environment for AI has evolved substantially over time and the observed premium may be concentrated in more recent years. Fourth, we will examine boundary conditions related to firm size, R&D intensity, and industry characteristics, incorporating these as control variables and potential moderators in the main specification. Finally, we plan to investigate whether the creative destruction dynamics documented by Kogan et al. (2017), whereby competitor innovation negatively affects incumbent firm growth, differ in magnitude or direction for AI versus IT innovations.

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