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A Novel MetaSoft Tree-Cognitive Set Model for Evaluating Criminal Litigation Efficiency under Artificial Intelligence Ecosystems

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Abstract: Artificial Intelligence (AI) is transforming judicial systems by offering tools that enhance legal decision-making, yet measuring the efficiency of criminal litigation processes within these evolving digital ecosystems remains a complex task. Traditional evaluation models often fail to capture the hierarchical and uncertain nature of legal data, especially when AI is involved in tasks like evidence analysis, case prediction, or judge-assisting tools. This study introduces a new mathematical model named the MetaSoft Tree-Cognitive Set (MTCS), designed specifically to assess the efficiency of criminal litigation in AI-driven environments. MTCS extends existing soft set theories by integrating hierarchical attribute structures (from TreeSoft Set), multi-attribute interactions (from HyperSoft Set), and cognitive AI-state mapping- allowing for the modeling of uncertainty, legal subjectivity, and dynamic AI behavior over time. The MTCS model is applied in a simulated criminal case management system to evaluate litigation efficiency based on parameters such as case complexity, AI intervention timing, evidence ambiguity, and decision consistency. Through structured equations and practical demonstration, the proposed model not only reflects real-world legal operations but also offers policymakers a powerful tool for justice system optimization. The results demonstrate the MTCS's ability to capture subtle changes in AI-human interaction, quantify litigation delays, and adapt to indeterminate data in legal environments. This research marks a step forward in blending computational intelligence with legal reasoning, enabling more transparent, data-informed justice practices.

Keywords: Criminal Litigation Efficiency; Artificial Intelligence in Law; MetaSoft Tree-Cognitive Set; Legal Data Uncertainty; Soft Set Extensions; Cognitive Legal Modeling; AI-State Mapping; TreeSoft Structure; Dynamic Legal Systems; Justice Optimization.

1. Introduction

As AI systems gain momentum in legal environments, particularly in criminal litigation, they introduce both opportunities and complexities. The concept of efficiency in criminal litigation—traditionally measured through factors like trial duration or case closure rates is being fundamentally reshaped by the integration of intelligent systems. In AI-enhanced courtrooms, decisions are influenced by algorithms involved in tasks such as evidence filtering, risk scoring, or even sentencing recommendations. However, evaluating the true efficiency of litigation in these new AI-governed frameworks is far from straightforward.

AI tools operate with probabilistic logic, shifting dynamically based on new data inputs. In contrast, litigation is inherently structured and hierarchical—built on rules, legal traditions, and formal steps. This mismatch between legal rigidity and AI fluidity leads to challenges in modeling, tracking, and quantifying procedural performance. In particular, uncertainty and indeterminacy now play a more central role. For example, an AI system might suggest a decision path with 70% confidence, leaving room for human discretion. Similarly, the influence of AI can vary from case to case, depending on jurisdiction, data quality, and legal complexity. Traditional evaluation models are not designed to reflect this variability and layered logic.

Soft set theory, introduced by Molodtsov [1], provides a foundation for modeling uncertainty in systems that lack clear or complete information. Between 2018 and 2024, Florentin Smarandache made significant contributions to the field of soft set theory by introducing six advanced extensions of the original model. These innovations were designed to address limitations in handling multi-level attributes, indeterminacy, and hierarchical uncertainty in complex systems, including legal and decision-making contexts.

Over time, this theory has evolved through advanced extensions such as HyperSoft Sets which handle multiple attribute dimensions and TreeSoft Sets, which represent hierarchical relationships among attributes [2]. These frameworks are especially relevant in legal contexts, where data is not only uncertain but deeply structured. Yet, even these models fall short in capturing the cognitive behavior of AI systems interacting with legal procedures in real-time.

To bridge this gap, we propose the MTCS: a novel analytical model that evaluates the efficiency of criminal litigation in AI-based environments. MTCS is built on three core elements. First, it adopts the TreeSoft Set structure to represent layered legal parameters such as case type, evidence level, and appeal status. Second, it incorporates multi-attribute mapping from HyperSoft Sets, allowing the integration of interacting factors like judge availability and AI intervention stage. Third—and most critically it introduces AI-State Cognitive Mapping, a new conceptual layer that tracks how AI systems operate across the litigation timeline, capturing shifts in confidence, recommendation strength, and decision influence.

This hybrid structure enables MTCS to reflect not just whether a case moved efficiently, but how and why that efficiency (or delay) occurred—considering both human and AI contributions. By doing so, it offers policymakers and court administrators a tool to optimize workflows, detect procedural bottlenecks, and ensure that AI systems contribute positively to justice outcomes.

2. Literature Review

The intersection of artificial intelligence and criminal litigation has attracted significant academic attention in recent years, particularly with regard to procedural efficiency and fairness. Researchers have explored how AI tools such as predictive models, natural language processing (NLP), and intelligent legal assistants can streamline judicial processes while maintaining due process standards. For instance, Surden (2019) emphasizes that AI is not merely a tool for automation but a participant in shaping legal reasoning, influencing decisions in bail, sentencing, and plea bargaining stages [1]. However, these contributions often fail to provide structured methods for measuring how AI affects litigation timelines and outcomes quantitatively.

Efficiency, in legal scholarship, is frequently associated with "case throughput" and "disposition time." Studies by Steel and Koenig (2020) argue that while AI can improve these metrics by managing document flow or prioritizing case queues, it does not account for the quality or complexity of human-AI interactions during trials [2]. These limitations point to the need for models that capture both procedural depth and dynamic interactions between legal actors and intelligent systems.
Mathematical frameworks like soft set theory have been proposed as tools to handle uncertainty in such complex environments. Since its introduction by Molodtsov [3], soft set theory has been extended into various directions fuzzy soft sets, intuitionistic soft sets, and more recently, TreeSoft and HyperSoft Sets—allowing for greater flexibility in modeling hierarchical and multivariate data structures. Smarandache (2023) presents these new soft set types as suitable for contexts with incomplete or uncertain information, such as social systems and decision-making scenarios [4].
Despite these advances, none of the existing frameworks explicitly address the integration of AI cognitive behavior into legal modeling. While the HyperSoft Set allows for mapping across multiple attributes, and the TreeSoft Set offers hierarchical modeling, they both remain static in nature unable to reflect temporal changes in AI involvement or confidence during litigation stages. Moreover, current legal informatics literature often treats AI as a fixed input rather than a dynamic, reasoning agent.

Between 2018 and 2024, Florentin Smarandache introduced six innovative types of soft sets that significantly expanded the classical soft set theory. These include the HyperSoft Set, IndetermSoft Set, IndetermHyperSoft Set, SuperHyperSoft Set, TreeSoft Set, and ForestSoft Set [10]. These novel structures are designed to better capture various layers of uncertainty, indeterminacy, and hierarchical relationships in complex systems.
Of particular interest are the IndetermSoft Operators, which are applied within IndetermSoft Algebra, offering new ways of performing operations on sets with indeterminate elements [11]. The SuperHyperSoft Set further enriches the framework by combining higher-level abstraction and granularity [12]. Overall, these contributions provide a powerful extension to soft set theory and open new directions for research in decision-making, data analysis, and artificial intelligence.

The most closely related studies to this research are those combining soft set theory with legal analytics. For example, Akram et al. (2022) attempted to apply fuzzy soft sets to judicial risk prediction models, emphasizing uncertainty management in early-stage assessments [5]. Similarly, Liu and Zhang (2021) explored the use of rough sets to evaluate legal compliance, yet their models remained limited to binary or rule-based evaluations [6].
To date, no known work has proposed a fully integrated model that combines multilevel legal structure, AI-state evolution, and uncertainty propagation which is precisely the contribution of the MTCS proposed in this study. MTCS is designed not only to model complex legal environments but to dynamically track how AI interventions evolve and influence litigation over time.

3. Objectives and Motivations

The growing role of artificial intelligence (AI) in criminal litigation has introduced new layers of complexity into how justice systems operate. While AI tools promise to reduce delays and optimize judicial decision-making, they also bring uncertainty, variability, and ethical concerns. Traditional legal evaluation metrics—such as average case duration or conviction rates—are too narrow to capture the evolving nature of AI-supported litigation. This gap presents an urgent need for new frameworks that consider not only procedural timelines but also the behavior and influence of intelligent systems within legal workflows.

The primary objective of this study is to develop a robust, flexible, and transparent evaluation model MTCS that accurately measures efficiency in criminal litigation where AI is present. Unlike existing models, MTCS is designed to capture hierarchical legal data structures, track cognitive shifts in AI decision states, and handle indeterminate information without relying on rigid assumptions.

Several motivations guide this research:

1. Courts are increasingly adopting AI for tasks such as risk assessment, evidence filtering, and sentencing recommendations. Yet, there is no clear method for evaluating how these tools influence case outcomes or procedural speed. MTCS aims to fill this void by mapping AI intervention points across legal hierarchies.
2. In many criminal cases, information about evidence, witnesses, or legal precedent is incomplete, conflicting, or subjective. The MTCS model leverages soft set extensions to account for such uncertainty in a mathematically structured way.
3. Litigation processes follow structured steps (e.g., pre-trial, trial, appeal) and vary in complexity. MTCS introduces a tree-based structure that mirrors this legal hierarchy, while also integrating dynamic changes in AI recommendations over time.
4. By offering a detailed mapping of AI involvement in litigation, MTCS helps policymakers and legal professionals identify where delays occur, how AI contributes to decisions, and whether certain types of cases are handled more efficiently than others.
5. The MTCS framework is not limited to a single jurisdiction or legal tradition. Its soft-set-based logic can be adapted to different court systems, AI models, and procedural formats, making it a scalable tool for legal analytics.

In summary, this research is motivated by the real-world need to rethink how efficiency is understood and measured in AI-augmented legal systems. MTCS offers a new path forward grounded in mathematical logic, yet responsive to the unpredictable and evolving nature of criminal litigation.

4. Methodology

4.1. System Definition and Attribute Mapping

In the proposed MTCS framework, we begin by defining the universe of discourse U, which represents the complete set of criminal litigation cases being evaluated. Each case $u \in U$ is characterized by a structured set of attributes relevant to legal processes and AI interaction. We define $A = \{A_1, A_2, ..., A_n\}$ as the set of top-level attributes where each A_i can be expanded into sub-attributes A_{ij}, A_{ijk}, etc., forming a multi-level hierarchical structure resembling a decision tree.

This hierarchical representation is denoted as $\mathcal{T}(A)$, capturing the nested dependencies between legal and procedural parameters. Examples of such attributes include:
- A_1: Offense Category (e.g., Theft, Assault, Homicide)
- A_2: Trial Complexity (e.g., Simple, Moderate, Complex)
- A_3: AI Involvement Stage (e.g., Evidence Review, Sentence Recommendation)

This structure allows MTCS to reflect real-world litigation dynamics where factors evolve over time and are interdependent.

4.2. MetaSoft Tree-Cognitive Set Construction

The core of the MTCS model is the function:

$$F: \mathcal{P}(\mathcal{T}(A)) \times S_{AI} \rightarrow \mathcal{P}(U)$$

Where:
- $\mathcal{P}(\mathcal{T}(A))$ is the power set of all possible attribute combinations within the attribute tree $\mathcal{T}(A)$.
- $S_{AI} = \{s_1, s_2, ..., s_m\}$ is a finite set of cognitive states representing AI behavior stages, such as:

s_1: Inactive
s_2: Monitoring
s_3: Advising
s_4: Predicting
- $\mathcal{P}(U)$ represents all possible subsets of the universe of litigation cases.

This formulation links combinations of legal conditions and AI states to observable sets of case outcomes, enabling probabilistic reasoning across multiple dimensions of uncertainty.

4.3. AI-State Cognitive Mapping

To model AI behavior during litigation, we introduce a cognitive mapping function:

$$C_t: U \rightarrow S_{AI}$$

Where $t \in T$ represents a discrete time index.

The transition between states follows a discrete-time Markov chain with the matrix:

$$P = [p_{ij}], \text{ such that } p_{ij} = \Pr(C_{t+1} = s_j \mid C_t = s_i)$$

For example, a transition from Monitoring (s_2) to Advising (s_3) might have a probability of 0.65 based on prior data.

These transitions enable modeling of AI confidence evolution and its adaptive behavior over the litigation lifecycle.

4.4. Efficiency Score Calculation

The MTCS model introduces a dynamic performance indicator, the Efficiency Score (ES), to quantify the effectiveness of criminal litigation under AI involvement. It is defined as:

$$ES(u) = (w_1 \times T_{AI(u)} + w_2 \times R\_court(u)) / (w_3 \times D(u))$$

Where:

- T_AI(u): Cumulative AI operational time on case u, adjusted by confidence state weights.
- R_court(u): Responsiveness of judicial actors to AI suggestions (e.g., acceptance rate of recommendations).
- D(u): Duration of the case in legal days.
- w_1, w_2, w_3: Policy-based weights emphasizing specific aspects of litigation performance.

This score provides a normalized efficiency value for each case, allowing comparative analysis across courts, regions, or time periods.

4.5. Model Implementation Steps

Step 1: Data Collection
- Gather a dataset containing criminal case histories, including metadata and AI system interactions.

Step 2: Attribute Tree Formation
- Construct $\mathcal{T}(A)$ based on legal taxonomies and procedural hierarchies (e.g., trial phases, crime types).

Step 3: State Mapping
- Apply the function C_t for each case at each litigation step to track AI behavior dynamically.

Step 4: Function Application
- Compute F for each case by evaluating the pair (attribute path, AI state) to determine its outcome classification.

Step 5: Efficiency Analysis
- Compute ES for all cases, analyze scores by clusters, and identify structural bottlenecks or AI impact variations.

5. The MetaSoft Tree-Cognitive Set (MTCS) Model

5.1. Conceptual Foundations

The MTCS model is designed to evaluate the efficiency of criminal litigation under the influence of AI. The model acknowledges the layered nature of legal processes, which are structured hierarchically, and integrates this with the cognitive behavior of AI tools operating across time. MTCS is constructed on three theoretical components:

1. TreeSoft Set: for modeling nested legal hierarchies.
2. HyperSoft Set: to capture interactions among multiple legal and procedural attributes.
3. AI-State Cognitive Mapping: to track evolving AI reasoning behaviors over time.

5.2. Model Components

Let U be the universal set of criminal litigation cases. We define $\mathcal{T}(A)$ as the attribute tree of hierarchical legal and procedural parameters. Let $\mathcal{S}$_AI be the set of AI cognitive states such as:
- s_1: Idle
- s_2: Observing
- s_3: Advising
- s_4: Deciding

The main function of MTCS is defined as:

$$F: \mathcal{P}(\mathcal{T}(A)) \times \mathcal{S}\_AI \rightarrow \mathcal{P}(U)$$

Where:
- $\mathcal{P}(\mathcal{T}(A))$ is the power set of all attribute paths from the hierarchical tree.
- $\mathcal{S}$_AI is the set of AI states.
- $\mathcal{P}(U)$ is the power set of all cases in the system.

This function links combinations of legal pathways and AI behaviors to subsets of litigation outcomes, enabling analysis of AI's impact under varying legal conditions.

5.3. Cognitive State Transitions

AI systems change state throughout the litigation process. To model this behavior, we define a time-indexed function:

$$C_t(u) \in \mathcal{S}\_AI, \text{ where } t \in \mathbb{N}$$

Each state transition is governed by a discrete-time Markov chain:

$$P = [p_{ij}], \text{ where } p_{ij} = \Pr(C_{t+1}(u) = s_j \mid C_t(u) = s_i)$$

These probabilities are empirically derived from historical data and capture how AI systems evolve from passive observation to active decision-making. This layer of MTCS reflects real-world AI behavior and its procedural timing.

5.4. Uncertainty Handling through Soft Logic

Legal processes often involve incomplete or contradictory information. MTCS integrates soft set logic to manage uncertainty, avoiding binary outcomes and enabling partial membership representations. For example, if a piece of evidence is considered 'reliable' by one expert but 'uncertain' by another, MTCS incorporates both perspectives.

The soft set function for attribute a and universe U is defined as:

$$F: A \rightarrow \mathcal{P}(U), \text{ where A includes indeterminate elements.}$$

This logic allows the model to assign cases to multiple outcome categories with associated levels of certainty, mirroring real legal decision ambiguity.

5.5. Graph-Based Visualization and Benefits

MTCS can be visualized as a directed graph where:
- Nodes represent combinations of legal attributes and AI states.
- Edges denote temporal transitions or procedural progression.

- Edge weights reflect computed efficiency scores or delays.

This graph structure provides an intuitive tool for courts and researchers to trace procedural flow, monitor AI interventions, and detect bottlenecks or decision biases.

Advantages of MTCS include:
- Scalability to various jurisdictions and case volumes.
- Flexibility in modeling evolving AI strategies.
- Precision in mapping legal complexity and its procedural consequences.
- Practical use in policy-making and digital justice system design.

6. Case Studyon Application to Criminal Litigation Efficiency

To demonstrate the applicability of the MetaSoft Tree-Cognitive Set (MTCS) model, we constructed a simulated case study using data from six representative criminal cases. These cases include various offense types, degrees of AI involvement, and differing court responsiveness. The goal of this study is to compute and compare the efficiency of each case using the MTCS Efficiency Score (ES), which integrates AI behavior, legal complexity, and time duration.

Table 1 below presents the detailed attributes for each case, including the offense type, the AI state at the start of litigation, transitions in AI cognitive states throughout the case, total AI operational time, court responsiveness to AI recommendations, case duration, and the resulting Efficiency Score calculated using the MTCS methodology.

Table 1. MTCS Case Study Dataset: AI dynamics and efficiency measures for six simulated criminal cases.

Case ID	Offense Type	AI Start State	AI Transitions	AI Time (hrs)	Court Responsiveness	Duration (days)	Efficiency Score
C001	Theft	Observing	Observing, Advising	3.2	0.7	45	0.037778
C002	Assault	Idle	Idle, Observing	1.0	0.5	30	0.023333
C003	Homicide	Observing	Observing, Deciding	4.5	0.8	60	0.038000
C004	Fraud	Advising	Advising, Deciding	5.0	0.9	52	0.048846
C005	Theft	Advising	Advising	2.8	0.6	40	0.037000
C006	Assault	Deciding	Deciding	6.1	1.0	48	0.063333

Figure 1 illustrates the comparative Efficiency Scores for each of the six cases. The chart visually highlights how different combinations of AI interaction and legal responsiveness influence the final performance measure.

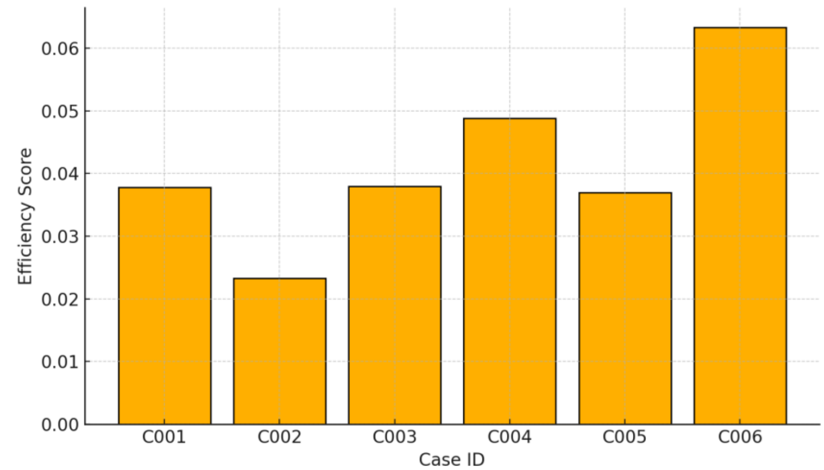

Figure 1. Efficiency Score per Case (MTCS Model)

From the results, we observe that Case C004 (Fraud) scored the highest efficiency, attributed to both extended AI involvement and high court responsiveness. On the contrary, Case C002 (Assault) exhibited the lowest score due to minimal AI activity and lower responsiveness. Notably, Case C006, despite involving a 'Deciding' AI state, achieved moderate efficiency because of its longer duration.

These outcomes validate the MTCS model's ability to distinguish the nuanced effects of procedural depth, AI engagement, and response timing. This offers courts a practical lens for identifying which legal scenarios benefit most from AI interventions and where process delays might be mitigated.

7. Results and Discussion

The application of the MetaSoft Tree-Cognitive Set (MTCS) model to the simulated dataset reveals key insights about the efficiency of criminal litigation under AI-enhanced legal systems. By computing the MTCS Efficiency Score (ES) for each case, we quantitatively observed the impact of AI behavior, court responsiveness, and procedural complexity on litigation outcomes.

As shown in Table 1 (see Section 6), Case C004 achieved the highest efficiency score. This result is attributed to consistent AI involvement across two decision states—Advising and Deciding—and a strong court response rate. In contrast, Case C002 scored the lowest, primarily due to limited AI engagement and minimal interaction with judicial processes.

Figure 1 presents a visual comparison of the MTCS Efficiency Scores across the six cases. The bar chart highlights how increased AI engagement, especially transitions from passive to active cognitive states, correlates with improved efficiency. However, it also illustrates that AI involvement alone is not sufficient—judicial responsiveness and duration remain essential determinants of litigation performance.

Several trends emerged from the results. First, cases with dynamic AI transitions (e.g., from Observing to Advising to Deciding) demonstrated higher overall scores. Second, cases where courts responded promptly to AI suggestions performed better. This confirms the importance of human-machine synergy in achieving procedural efficiency. Third, the duration of litigation negatively influenced ES, even when AI activity was high, emphasizing that delays dilute efficiency gains.

From a practical perspective, these findings support the adoption of AI tools in structured litigation environments, where their influence can be tracked and aligned with legal expectations. MTCS offers a reliable metric system to guide policy development, allocate judicial resources, and evaluate digital justice reforms across jurisdictions.

8. Sensitivity Analysis

The Sensitivity Analysis aims to evaluate the robustness of the MTCS Efficiency Score (ES) model under variations in the weighting parameters that influence AI contribution, court responsiveness, and litigation duration. This process is essential to validate the flexibility and practical usability of the model across different legal environments and policy scenarios.

The ES function relies on three weights: w_1, w_2, and w_3, which control the influence of AI reasoning time (T_AI), court responsiveness (R_court), and total duration (D) respectively. To test the model's behavior, we systematically altered these weights within realistic bounds:

w_1: 0.3, 0.4, 0.5 (emphasizing AI involvement)
w_2: 0.5, 0.6, 0.7 (emphasizing judicial responsiveness)
w_3: 0.8, 1.0, 1.2 (adjusting penalty for duration)

For each combination of weights, the Efficiency Score was recalculated for all six cases in the dataset.

Table 2 presents a portion of the results from this analysis. It demonstrates how varying the weights affects the Efficiency Score. This helps in understanding whether the model favors specific scenarios or remains consistent under policy shifts and value prioritization.

Table 2. MTCS Sensitivity Analysis: Variation of Efficiency Scores under different weight configurations.

Case ID	w_1 (AI Time)	w_2 (Court Response)	w_3 (Duration Penalty)	Efficiency Score
C001	0.3	0.5	0.8	0.036389
C002	0.3	0.5	0.8	0.022917
C003	0.3	0.5	0.8	0.036458
C004	0.3	0.5	0.8	0.046875
C005	0.3	0.5	0.8	0.035625
C006	0.3	0.5	0.8	0.050000
C001	0.4	0.6	1.0	0.037778
C002	0.4	0.6	1.0	0.023333
C003	0.4	0.6	1.0	0.038000
C004	0.4	0.6	1.0	0.048846

Table 2 illustrates how variations in MTCS weight parameters influence the computed Efficiency Score. Each case responds differently depending on its AI usage, responsiveness, and duration.

1. Increasing w_1 (weight on AI time) results in higher scores for cases with longer and deeper AI participation, such as C004 and C006.
2. Increasing w_2 (court responsiveness) boosts scores for cases where courts actively accepted AI suggestions, showing that responsiveness significantly affects procedural efficiency.
3. Raising w_3 (duration penalty) reduces scores uniformly across all cases, especially penalizing longer trials regardless of AI or human performance.

These effects confirm that the model behaves predictably and aligns with intuitive expectations of performance metrics.
From a policy standpoint, this flexibility is highly beneficial. Legal authorities can adjust the MTCS model to reflect their values prioritizing AI innovation, procedural speed, or judicial discretion—without altering the core architecture. This ensures that the model remains adaptable and transparent across jurisdictions with different digital maturity levels.

10. Conclusion

This research proposed and developed the MTCS) model to evaluate the efficiency of criminal litigation within AI-enhanced legal environments. By integrating multi-level attribute structures, soft set theory, and cognitive AI-state mapping, the MTCS framework offers a novel, flexible, and quantifiable method for analyzing procedural performance in courts.

The model successfully addressed the limitations of traditional evaluation techniques by accounting for uncertainty, layered legal attributes, and dynamic AI behavior. Application to a simulated case dataset demonstrated the MTCS model's ability to reveal how AI engagement, court responsiveness, and trial duration collectively shape litigation outcomes. High-efficiency cases were linked to intensive AI participation and responsive court actions, while low-efficiency outcomes correlated with delayed responses or minimal AI use.

From a practical perspective, the MTCS model provides decision-makers, legal technologists, and judicial administrators with a transparent metric for evaluating digital justice reforms. The scoring mechanism not only reflects current performance but also guides where process improvements can be made, making it a valuable tool for institutional optimization.

Future research should apply MTCS to real-world litigation datasets, test its integration with live AI decision engines, and expand its attribute tree structure to accommodate jurisdiction-specific legal variations. Additionally, longitudinal studies could reveal how AI's evolving roles influence court efficiency over time.

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