Artificial Intelligence in Sri Lanka's Legal System: Adoption Barriers and Policy Pathways

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ABSTRACT

Artificial intelligence (AI) is reshaping legal systems worldwide by improving legal research, document review, and case forecasting. In Sri Lanka, where Roman-Dutch law, English common law, and customary law coexist, the legal profession continues to face structural challenges, including heavy case backlogs, limited access to justice, and uneven technological capacity. This study provides the first large-scale, Sri Lanka-focused empirical investigation of AI adoption among legal practitioners, applying the Technology Acceptance Model (TAM), Resource-Based View (RBV), and Task-Technology Fit (TTF) framework to a hybrid developing-country legal context. Using a cross-sectional research design, data were collected from 1,500 legal practitioners between September 2024 and February 2025. The study applied quantitative methods (chi-square tests and correlation analysis) alongside qualitative thematic coding. The findings show moderate AI awareness (63.6%) but relatively low adoption (36.3%). AI usage was significantly higher among urban and corporate lawyers (72%) compared with rural and criminal law practitioners (28%). The main barriers to adoption were inadequate infrastructure (45%) and resistance to change (32%). The study identifies practical policy pathways, including infrastructure subsidies, professional training, and regulatory frameworks, to reduce the urban-rural adoption gap and support ethical AI integration. By situating Sri Lanka within the wider debate on legal digital transformation, the findings offer useful insights for other developing legal systems facing similar institutional and technological constraints.

Keywords: *Artificial Intelligence, Legal Practice, Sri Lanka, Legal Technology, Digital Transformation, Ethical Frameworks*

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INTRODUCTION

Artificial intelligence (AI) is rapidly transforming industries such as finance, business, education, and government, profoundly reshaping organizational operations and decision-making processes (Han et al., 2024). Artificial intelligence is also reshaping legal systems worldwide by improving legal research, document review, and case forecasting. Since its conceptualization at the 1956 Dartmouth Conference, AI has evolved from symbolic approaches to advanced data-driven methodologies, particularly machine learning and deep learning. These advancements enable the analysis of vast datasets with unprecedented speed and accuracy, pattern recognition, and sophisticated natural language processing (Uddin, 2024).

In the legal domain, these technological breakthroughs are causing a significant transformation. Legal artificial intelligence (LegalAI), a field at the intersection of artificial intelligence and law, has introduced enhanced efficiency in legal research, document analysis, case prediction, and client interaction (Kumar, 2024). Tools such as Kira Systems for contract review and ROSS Intelligence for legal research exemplify this transformation by reducing costs, improving accuracy, and freeing lawyers for higher-order interpretive and strategic work (Emejuo et al., 2024). However, these technological breakthroughs also raise critical concerns, including data privacy, algorithmic transparency, accountability for AI-generated errors, and potential systemic biases in decision-making outputs (Nadjia, 2024). Legal scholars emphasize that while AI can augment human judgment, human oversight remains essential to uphold justice and fairness in judicial processes.

Sri Lanka's legal system, a unique hybrid of Roman-Dutch, English common, and customary law, faces persistent structural challenges such as severe case backlogs, lengthy litigation procedures, and unequal access to justice, particularly between urban and rural populations. Although the country has made notable progress in digital transformation through initiatives like the Digital Economy Strategy, electronic filing systems, and online legal databases (Capasso, 2024), the adoption of AI in the legal sector remains in its early stages. Major gaps persist in ethical frameworks, regulatory preparedness, and digital infrastructure (Dasanayake, 2024). These structural conditions are not unique to Sri Lanka but resonate across many developing economies in South and Southeast Asia, Africa, and Latin America, where legal systems must balance tradition with technological modernization under resource constraints.

This study examines the potential of AI to transform legal practice in Sri Lanka by analyzing global LegalAI advancements, evaluating characteristics of the local legal system, and exploring socio-technical factors driving digital adoption. The main contributions of this article are:

(a) The first comprehensive survey-based study of AI adoption among Sri Lankan legal practitioners, capturing perceptions, usage patterns, and barriers.
(b) Exploration of AI fit within Sri Lanka's legal system, highlighting urban-rural and practice-area differences.
(c) Application of multiple theoretical frameworks (TAM, RBV, UTAUT, TTF) to explain adoption dynamics in developing nations.
(d) Targeted policy recommendations, including infrastructure subsidies, training programs, and regulatory frameworks, to support ethical AI integration.

The remainder of the article is structured as follows: Section 2 reviews the literature, Section 3 presents the conceptual and theoretical framework, Section 4 describes the materials and methodology, Section 5 analyzes the results and implications, and Section 6 offers conclusions, limitations, and future directions.

Literature review

Evolution of Legal AI

Artificial Intelligence (AI) is becoming an increasingly important part of the digital transformation, changing many professional fields, including legal practice. AI approaches, including machine learning, natural language processing (NLP), and predictive analytics, are changing how legal practitioners conduct research, write contracts, resolve cases, and interact with clients across multiple jurisdictions. Globally, service platforms like ROSS Intelligence and Kira Systems show the ability for AI to automate complex legal work by analyzing vast amounts of legal paperwork, laws, and case law (Kabir & Alam, 2023). Although platforms such as ROSS Intelligence demonstrate the potential of NLP-driven legal retrieval systems, scholars continue to debate whether such systems can adequately replicate contextual legal reasoning, particularly in jurisdictions characterised by pluralistic legal traditions (Siino et al., 2025).

Applications in Legal Practice

ROSS is able to analyse legal questions using natural language processing and produce relevant case documents, while Kira Systems improves contract analysis by identifying critical terms and possible risks. Platforms and tools like Lex Machina and Blue J Legal take advantage of the ability of predictive analytics to forecast litigation outcomes and provide insights that support superior analysis and strategy (Dylag, 2024). However, existing scholarship remains divided regarding the extent to which these benefits transfer to developing country contexts. While some studies emphasize the universal applicability of AI tools, others argue that infrastructure constraints, data scarcity, and differing legal traditions create unique adoption challenges that developed-country research cannot address (Ejjami, 2024). This progress has allowed legal professionals in developed countries to significantly reduce the time and costs associated with typical legal functions, along with increased accuracy and access to justice. Survey responses from practitioners in Sri Lanka suggest an awareness of these international trends. Many of the respondents considered improved efficiency and productivity as an app backed by the application of AI in legal practice. However, concerns around the limits of technology were also expressed, particularly the perceived limitations of human perception and situational awareness. These concerns overlap with large academic debates, and simply put, AI relies on data-driven tendencies and does not have the interpretive flexibility of human legal reasoning. Therefore, considerations such as algorithmic transparency, fairness, and accountability are very important within this space.

Generative AI and Large Language Models

Recent advances in generative artificial intelligence, particularly Large Language Models (LLMs) such as ChatGPT, GPT-4, and Claude, have fundamentally altered the legal technology landscape. Unlike earlier predictive analytics tools, LLMs can generate human-quality text, draft legal documents, summarize case law, and even provide preliminary legal advice (Siino et al., 2025). However, these capabilities introduce novel risks that prior AI scholarship did not anticipate.

The most significant concern is "hallucination," where LLMs generate plausible but factually incorrect legal citations, case names, or statutory provisions. Several documented instances have emerged where lawyers submitted briefs containing fabricated cases generated by ChatGPT, resulting in judicial sanctions and professional embarrassment. This risk is particularly acute in jurisdictions like Sri Lanka, where access to comprehensive, up-to-date, and digitally curated legal databases remains limited. Retrieval-augmented generation (RAG) has emerged as a promising mitigation strategy, grounding LLM outputs in verified legal databases rather than relying solely on model parameters. Nevertheless, RAG systems remain technically complex to implement and maintain, creating barriers for resource-constrained legal practices.

Ethical, Regulatory, and Governance Challenges

Legal scholars warn that unregulated use of AI could put due process, privacy, and judicial independence at risk. Beyond these general concerns, contemporary AI scholarship identifies several critical issues for legal applications. Algorithmic discrimination arising from biased training data poses a significant risk, as AI systems trained primarily on Western legal materials may produce systematically biased outcomes when applied to Sri Lanka's hybrid legal system. The opacity of deep learning models, often termed the "black box" problem, creates accountability challenges, as lawyers and judges may be unable to explain or challenge AI-generated recommendations. Judicial overreliance on AI represents another concern, as the cognitive authority of algorithmic outputs may lead courts to defer inappropriately to machine-generated analyses.

Cybersecurity vulnerabilities in legal AI systems raise additional risks, given the sensitivity of client information, litigation strategies, and proprietary legal work product. Data sovereignty issues emerge when legal data crosses national borders, as many AI platforms operate on cloud servers located outside Sri Lanka, potentially subjecting local legal data to foreign legal jurisdictions. Explainable AI (XAI) frameworks attempt to address transparency concerns by making model decisions interpretable to humans, but remain technically challenging to implement in complex legal reasoning contexts. Several countries, including those within the European Union, have started to develop legislative models specifically for artificial intelligence to govern the industry and provide limitations surrounding how this technology is developed and implemented (Ulnicane, 2022). However, both regulatory overreach and underutilization persist as issues; the inability to establish conducive legal frameworks may lead to lost possibilities for public advantage.

AI and Legal Education

The evolution of legal education and professional growth is seen as crucial for the incorporation of AI, in conjunction with legislation (de Oliveira Fornasier, 2021). Globally, law schools and professional organizations are progressively integrating multidisciplinary programs that merge legal analysis with data science and artificial intelligence proficiency (Goswami, 2025). In jurisdictions such as China, the United States, and the United Kingdom, legal professionals are urged to cultivate skills in digital technologies to maintain efficacy in a technology-enhanced professional environment. The situation in Sri Lanka illustrates this necessity. Survey respondents noted the importance of awareness raising, professional development, and academic engagement with AI, primarily to prepare the legal workforce for a transforming digital world. The need for this is especially compelling in a country largely reliant on traditional methods of the law and where legal technology is still in its infancy.

AI Adoption in Developing Countries and the Global South

Existing research on AI in developing country legal systems remains sparse, creating a significant gap in the literature. Most empirical studies focus on North America, Western Europe, Singapore, and China, leaving scholars with a limited understanding of how AI adoption unfolds in resource-constrained, institutionally fragile, or pluralistic legal environments. This gap is consequential because the determinants of AI adoption may differ systematically between developed and developing contexts. For example, infrastructure constraints, such as unreliable electricity, limited broadband connectivity, and inadequate hardware, may outweigh individual attitudes in predicting adoption. Similarly, regulatory voids or weak enforcement may create different risk profiles than in jurisdictions with mature AI governance frameworks. Examining successful AI applications in other jurisdictions offers instructive comparisons. Singapore's 'Tech-celerate for Law' project provides subsidized technology consulting and training for law firms, demonstrating how public-private partnerships can accelerate adoption16. The United Kingdom's judiciary has piloted AI tools for document summarization and case prediction, though with careful attention to judicial independence and transparency. However, scholars caution against direct transplantation of these models to developing countries, noting that institutional, financial, and cultural differences may render such efforts ineffective or counterproductive.

On the contrary, there are powerful examples of successful AI applications in the legal space from a number of countries, such as Singapore, the UK, and the US (Mahendra & Athavale, 2024). These places are able to leverage the effects of having active legislation, significant public-private investment in legal technology, and strong partnerships between technologists and legal professionals. For example, Singapore has the "Tech-celerate for Law" project that helps law firms integrate digital technology, and in the UK and the US, AI systems can be used for a range of tasks, including e-discovery, compliance checking, and predicting case outcomes. The situation in Sri Lanka is lagging because of constraints on infrastructure and institutions, but the outlook remains positive. Most participants in the poll indicated their views that AI adoption in legal practice would be "somewhat beneficial" or "very beneficial" in the long run, but with the caveat that there were worthy systemic improvements to be made for legitimate substantive progress.

Sri Lanka’s Legal System and Digital Readiness

The legal system in Sri Lanka, which is based on a hybrid of Roman-Dutch, English common, and customary law, faces structural challenges that make the potential advantages of AI particularly relevant. The Sri Lankan legal system continues to experience substantial case backlogs, lengthy litigation, and inequitable access to legal services, especially for rural and disadvantaged communities. Sri Lanka has taken initial steps toward digital transformation, including the Digital Economy Strategy, online legal databases, and electronic filing systems in some courts. However, significant gaps persist. Digital infrastructure remains unevenly distributed, with urban centres enjoying substantially better connectivity and hardware access than rural areas. Legal technology literacy among practitioners varies widely, with younger, urban, corporate lawyers generally more proficient than older, rural, or criminal law practitioners.

Regulatory preparedness for AI in legal practice remains nascent. While Sri Lanka has enacted data protection and cyber safety legislation, no specific framework governs AI use in legal contexts. This regulatory gap creates uncertainty for practitioners considering AI adoption and leaves unresolved questions about professional responsibility for AI-generated errors, admissibility of AI-generated evidence, and the ethical boundaries of AI-assisted legal work. Despite these constraints, several enabling factors create opportunities for AI adoption. Sri Lanka has a relatively high literacy rate, a growing technology sector, and an increasing government commitment to digital transformation. The legal profession has demonstrated a willingness to adopt other technologies, including case management software and online legal research platforms, suggesting that AI adoption may follow a similar trajectory with appropriate support.

Policy Pathways for AI in Sri Lankan Law

Sri Lanka needs to implement an all-encompassing plan that involves legislative, educational, and infrastructural reforms to realise the potential of AI. To start with, a comprehensive regulatory design that regulates the use of AI in legal settings will have to be developed. This design should stress transparency, minimise algorithmic bias, and allow for human oversight in decision-making (Bahangulu & Owusu-Berko, 2025). Secondly, capacity-building programs will need to be supplemented by educational and professional development programs focusing on digital literacy and AI concerning legal activities (Sey & Mudongo, 2021). Third, a significant investment in technology infrastructure, especially in digital court systems and online legal databases, is necessary to facilitate AI functionality (Afzal, 2024). Fourth, promoting collaboration among legal experts, engineers, and politicians will be essential for developing AI tools that are contextually pertinent and ethically robust. In conclusion, public engagement and awareness programs can help instil confidence and promote responsible usage of AI in legal services, especially where that has been a historically marginalized aspect of the legal system (Ejjami, 2024). The literature and practice consistently demonstrate that AI has considerable disruptive capacity for legal practice. Example case studies around the world illustrate how AI can help make legal services better, more accessible, and more efficient; survey data from Sri Lanka describes the desire for this innovation and the ways that it is hindered by systems. With purposeful investment, regulatory reforms, and professional buy-in, Sri Lanka can embrace AI's potential while being mindful of the core values and human elements of the legal system.

Research Gap

Despite increasing scholarship on AI-enabled legal systems globally, significant gaps remain in the literature. First, limited empirical research has examined how institutional readiness, infrastructural inequality, and professional perceptions jointly influence AI adoption within hybrid legal systems such as Sri Lanka, where Roman-Dutch, English common, and customary law coexist. Second, existing studies predominantly focus on developed economies (the United States, the United Kingdom, Singapore, and China), leaving developing countries systematically underrepresented despite their unique structural constraints, resource limitations, and institutional challenges. Third, while technology adoption models (TAM, UTAUT) have been extensively applied in business and healthcare contexts, their application to legal professions in developing economies remains underexplored. Fourth, no prior study has systematically quantified the urban-rural divide in legal AI adoption or examined how task-technology fit varies across different areas of legal practice (corporate versus criminal law) in a developing country context. Fifth, the implications of generative AI and LLMs for legal practice in resource-constrained environments have received minimal empirical attention, despite the unique risks these technologies pose in contexts with limited access to verified legal databases and professional support.

This study provides rare empirical evidence from a large-scale, Sri Lanka-focused investigation of AI adoption among legal practitioners, integrating multiple theoretical frameworks (TAM, UTAUT, RBV, TTF, and Institutional Theory) to capture individual, organizational, and institutional determinants. By situating Sri Lanka within the broader Global South discourse on legal digital transformation, the findings offer transferable insights for other developing legal systems facing similar institutional and technological constraints.

Conceptual and Theoretical Framework

This research employs a combined conceptual framework, based on a number of existing theories, to purposefully examine the factors influencing the adoption of artificial intelligence (AI) in Sri Lanka's legal profession as pictured in (Figure 1). At the individual level, the Technology Acceptance Model (TAM) (Jan et al., 2024) acts as a conceptual basis for this research and argues that individuals' intention to use technology is determined by their belief about the usefulness and ease of use of that technology. Additionally, the research could also use the Unified Theory of Acceptance and Use of Technology (UTAUT) (Mensah & Khan, 2024), as it introduces additional constructs such as social influence and facilitating conditions to capture the further sociocultural and technological contingencies on user behaviour, since technology adoption is dependent not only on users' perceptions, but also on the task relevance. The framework also considers the Task-Technology Fit (TTF) model (Furneaux, 2012), because technology is more likely to be adopted when there is a fit or a tight alignment between the technology and the user's tasks. For example, AI tools designed for structured tasks such as contract review in corporate law demonstrate higher adoption potential than AI applications in subjective, discretionary contexts such as criminal sentencing, where human judgment remains paramount. The integration of TAM, UTAUT, and TTF enables the study to capture both cognitive perceptions and functional compatibility dimensions of AI adoption, while RBV and Institutional Theory extend the analysis to organisational and environmental determinants.

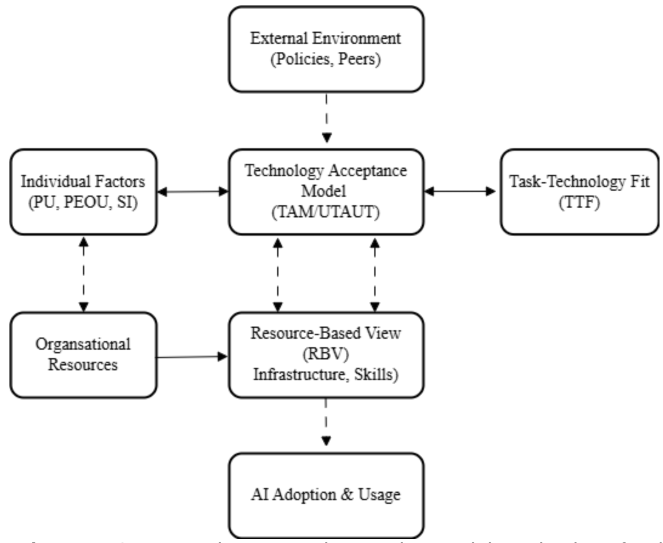

Figure 1: Conceptual Framework to Understand the Adoption of AI in the Sri-Lankan Legal Sector

At the organisational level, the Resource-Based View (RBV) (Moderno et al., 2024) is used to explain variation in technological adoption capacity by referencing differences in critical resources such as digital infrastructure, technical know-how, and financial resources. Complementing this, Institutional Theory (DiMaggio & Powell, 1983) provides an explanatory framework for understanding how external pressures, coercive (regulatory mandates), mimetic (imitation of global legal practices), and normative (professional standards) shape organisational behaviour and technology adoption. This multi-theoretical approach facilitates a nuanced understanding of AI integration as a socio-technical process shaped by both endogenous and exogenous forces. Figure 1 synthesises these interlocking dimensions, illustrating how individual, organisational, and institutional factors collectively influence the adoption trajectory of AI in legal practice.

MATERIALS AND METHODS

Research Design

To explore how artificial intelligence (AI) is being integrated into Sri Lanka's legal sector, a cross-sectional survey design (Hunziker & Blankenagel, 2024) was employed to gather an in-depth understanding of perceptions, patterns of adoption, and barriers faced by legal professionals. We incorporated both qualitative and quantitative approaches through a cross-sectional survey design to frame the AI phenomena in legal practice. The target population enabled the inclusion of all legal practitioners, law students, judges, and legal assistants. We wanted to ensure a wide representation of stakeholders in the legal sector, which included practitioners from all geographic and socio-economic backgrounds. Due to logistical and geographic constraints associated with accessing dispersed legal professionals, a non-probability convenience sampling strategy was adopted (Ahmed, 2024) due to the logistics of random sampling participants, given the geographic dispersion of legal practitioners and limited access to varying functions, all practitioners in rural locations in particular. Participants were recruited through legal associations, from universities, and through professional online forums that had legal professionals. Although effective for recruitment, this method potentially introduced selection bias of technology-savvy or urban-based legal professionals into the research. After the deletion of incomplete responses, the final effective number of participants for analysis was 1500. The minimum sample size was determined using Cochran's formula at a 95% confidence level and 5% margin of error, assuming a population of approximately 15,000 registered legal practitioners in Sri Lanka (based on Sri Lanka Bar Association data). This calculation yielded a minimum required sample of 375 respondents. Our achieved sample of 1,500 substantially exceeds this threshold, providing adequate statistical power for subgroup analyses.

Adopting a cross-sectional survey design allowed for a single-point cross-sectional exploration of many voices and offered the potential for a depth-to-target balance through the use of closed- and open-ended questions (Shende, 2024). The mixed-methods approach allowed for a strong triangulation of the data, where quantitative trends explored patterns of adoption and qualitative responses provided insight into barriers and solutions. Bivariate chi-square tests and correlation analysis (Ottenbacher, 1995) established statistical rigour to subgroup comparisons, and thematic coding of the qualitative data added interpretive validity. In spite of a few limitations, this methodological approach laid a strong foundation for understanding the impact of AI tools in Sri Lanka’s legal sector, and we encourage future studies of AI in law to use stratified sampling or longitudinal designs to achieve cross-sectional representativeness and temporal insights.

Data Collection

The data collection process utilized a self-administered online questionnaire, which involved designing a questionnaire that would provide scalability but allow for a good depth of information. The questionnaire contained closed-ended questions that incorporated Likert scales or multiple-choice items for quantitative analysis and included open-ended questions that provided qualitative descriptions of the challenges and suggestions to incorporate AI. The questionnaire was designed into five sections: demographics (profession, years of experience, practice area), AI understanding and use (what tools are being used and how often), perceptions of AI (benefits, concerns, long-term impacts), barriers to adoption (infrastructure, resistance, cost), and an open-ended section for suggestions to support AI incorporation.

The survey instrument was validated through a two-stage process. First, content validity was assessed by a panel of five experts (three legal practitioners with 10+ years of experience and two AI researchers), who evaluated the questions' relevance and clarity. Second, a pilot test was conducted with 50 legal professionals (not included in the final sample) to assess internal consistency. Cronbach's alpha for the main constructs was 0.84 (perceived usefulness), 0.79 (perceived ease of use), and 0.81 (barriers to adoption), exceeding the acceptable threshold of 0.70. Data was collected over six months, from September 2024 to February 2025. This time frame was selected to align with professional responsibilities and academic commitments, thereby limiting interruptions to their responses. Ethical considerations were made a priority: responses were submitted anonymously to limit bias, participants provided informed consent after being debriefed about the purpose of the study, and survey responses were stored in an encrypted database (Hwang, 2023).

Data Analysis

Quantitative data were analyzed using a combination of descriptive and inferential statistical methods (Stapor, 2020). Descriptive statistics, including frequencies, percentages, and means, were calculated to summarize demographic profiles and AI adoption patterns, with initial data cleaning performed in Microsoft Excel. For the advanced statistical analyses (including chi-square tests to examine associations between categorical variables (profession vs. perceptions of AI) and correlations to evaluate whether the level of experience (an introductory course in AI vs. more advanced expected usage in practice) was related to optimism about AI), Python with Pandas and SciPy libraries (Gupta & Bagchi, 2024). Were used to analyze data. The open-ended qualitative data were thematically coded (Mortelmans, 2024). For example, we identified emergent themes like "training needs" and "gaps in infrastructure" to provide perspective for the quantitative data. Thematic analysis followed Braun and Clarke's six-phase framework: familiarization, initial coding, theme search, theme review, theme definition, and write-up. Two researchers independently coded 20% of the qualitative responses, achieving an intercoder reliability of 0.86 (Cohen's kappa). Disagreements were resolved through discussion. NVivo 14 software was used for code management and theme development. Thematic saturation was achieved after analyzing approximately 200 responses, at which point no new codes emerged. Sentiment analysis was conducted using lexicon-based classification with the VADER (Valence Aware Dictionary and Sentiment Reasoner) tool, categorizing qualitative responses as supportive, neutral, or skeptical, providing additional perspectives on attitudes toward AI. This mixed-methods approach ensured broad statistical analysis alongside rich qualitative data sources.

Ethical Considerations

The research adhered to ethical standards to protect the participants and their data integrity (Ali et al., 2025). The study kept the participants anonymous to eliminate response bias; staff did not collect any identifying information. The research gave participants the background on the research, and informed consent was signed before participation, confirming it was voluntary. The data security was maintained and stored encrypted in accordance with worldwide standards for managing sensitive survey data. In doing so, the research built trust and encouraged honest answers from participants on frankly sensitive topics like ethics in AI in legal practice.

Limitations

There were some limitations to our methodology that are worth noting. The use of convenience sampling may have resulted in overrepresentation of urban and technology-oriented respondents, which potentially biased our results against rural respondents. Self-reporting bias may have affected the actual amount of engagement with AI in their practice areas, as respondents may have been subject either to inflation or deflation based on social desirability or recall errors. Although a sample size of 1500 was sufficient for exploratory analysis, it did affect the generalizability of our findings, especially among smaller demographic categories (i.e., judges [1.8%] and legal assistants (1.8%). Additionally, the geographic concentration of respondents in urban centres like Colombo may have underrepresented rural challenges, such as limited digital access. The geographic bias toward Colombo and other urban centres represents a substantive limitation with potentially significant implications for our findings. Sri Lanka exhibits pronounced digital inequality, with fixed broadband penetration outside Western Province approximately one-third of Colombo's rate (Telecommunications Regulatory Commission of Sri Lanka, 2023). This infrastructure asymmetry suggests our findings likely underestimate barriers faced by rural practitioners, particularly regarding internet reliability, access to paid legal databases, and technical support. Consequently, the true AI adoption rate in rural areas (reported as 18%) may be even lower than our estimate. Future research should employ rural-specific sampling frames and consider offline survey administration to capture this population more accurately. These limitations were partially mitigated by the mixed-methods design, which allowed qualitative insights to contextualize quantitative trends, but they highlight the need for cautious interpretation and further research.

RESULTS AND DISCUSSION

Demographic Composition

The survey included 1500 legal professionals, with a demographic profile reflecting a predominance of early-career individuals. Law students comprised the largest group (50.9%), followed by practicing lawyers (32.7%), with judges (1.8%) and legal assistants (1.8%) significantly underrepresented, and 12.8% other related professionals, as seen in (Table 1). Experience levels were unevenly distributed, with 76.4% of respondents possessing five or fewer years of experience, which indicated that the results reflect the perspective of younger members of the legal field predominantly. A demographic skew is again reflected by younger professionals being more susceptible to embracing the innovations of technology, but at the same time, their limited experience means they may not fully appreciate the applicability of AI. In addition, the sample was also geographically skewed towards urban respondents, particularly in Colombo, again demonstrating the urban-centricity of legal and technological infrastructure in the capital of Sri Lanka.

AI Adoption and Perceptions

63.6% of the respondents claimed to have some familiarity with AI tools, with legal research platforms like Westlaw and LexisNexis commanding the greatest responses (45%), followed by chatbots/Virtual assistants like DoNotPay and LawDroid (25%), document

Table 1: Respondent Demographics.

Profession	Percentage	Years of Experience
Law Students	50.9%	≤5 years
Practicing Lawyers	32.7%	>5 years
Judges	1.8%	>10 years
Legal Assistants	1.8%	>5 years
Others (Immigration Consultant, Development Professional, Not specified)	12.8%	>5 years

Table 2: AI Tool Usage Frequency.

Frequency	Percentage
Daily	14.5%
Weekly	21.8%
Monthly	18.2%
Rarely	23.6%
Never	21.8%

Table 3: AI Task Fit Rating.

Legal Task	AI Tool Used	Fit Rating
Contract Review	Kira Systems	High
Legal Research	ROSS Intelligence	High
Predicting Litigation Outcome	Lex Machina	Medium
Witness Evaluation	N/A	Low
Court Filing Automation	HotDocs	Medium

automation tools like HotDocs and LawGeex (15%), and predictive analytics like Lex Machina (10%). Despite this awareness, Table 2 shows that actual usage was inconsistent: only 14.5% of respondents used AI tools daily, 21.8% used them weekly, 18.2% used them monthly, 23.6% used them rarely, and 21.8% had never used AI in their practice. The disparity between familiarization and adoption indicates some large barriers, namely technological limitations and cultural barriers. The minimal rates of daily usage suggest that integrating AI into Sri Lanka's legal sector, especially outside of urban centres, is still in its infancy.

In (Table 3), the Task-Technology Fit (TTF) framework was used to classify common legal tasks according to their degree of compatibility with existing AI tools. Structured, repeated, and data-intensive tasks like contract review or legal research have a high degree of fit with AI applications like Kira Systems or ROSS Intelligence, so the uptake for many corporate law practitioners is noticeably higher. Unstructured, judgment-based, contextually evidential, and emotional tasks, like witness assessment or jury decision-making, do not have a fit with AI capabilities, since these tasks have substantially low uptake of AI, particularly in criminal law. This differentiation illustrates the importance of functional fit in the relationship to perceived value and the practical application of AI technologies within certain areas of legal practice. The extent of task fit, as illustrated by (Table 3), directly informs both the usability and ethical appropriateness of the AI application in legal practice.

Respondents identified increased efficiency and productivity as the primary benefit of AI (50.9%), followed by cost reduction (18.2%), improved research accuracy (16.4%), and better predictive analysis (10.9%) as seen in (Figure 2). Such findings correspond with the Technology Acceptance Model (TAM), which emphasizes perceived usefulness as a motivator for using technology. However, concerns were equally visible, with a significant proportion reporting that there is a risk of losing human judgment (32.7%), concerns of data privacy (21.8%), concerns regarding the high implementation costs (18.2%), and concerns regarding job prospects (10.9%). Such concerns illustrate tension between efficiency gains from AI and the perceived risk of ethical and human-centric practice inherent to the law, particularly in practice areas like criminal law, where human discretion is vital.

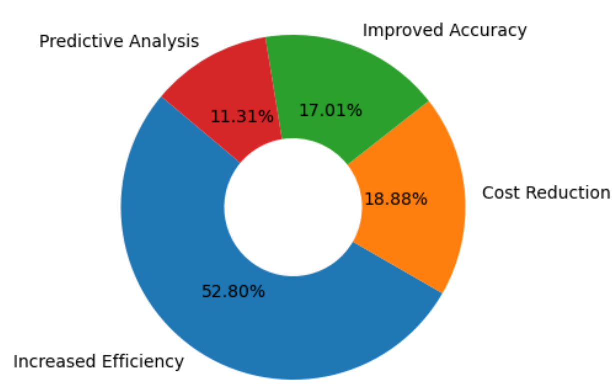

Figure 2: Perceived Benefits of AI for Legal Practice

Hypothesis Testing and Theoretical Integration

In this research study, we used a variety of theoretical frameworks to investigate the factors affecting the adoption of AI in Sri Lanka's legal industry like Technology Acceptance Model (TAM) (Jan et al., 2024), Diffusion of Innovations Theory (Lee, 2024), Resource-Based View (RBV) (Moderno et al., 2024), Unified Theory of Acceptance and Use of Technology (UTAUT) (Mensah & Khan, 2024), Institutional Theory (Schiavi et al., 2024) ask-Technology Fit (TTF) (Furneaux, 2012) etc. The following hypotheses were formulated based on these frameworks:

H_1: Perceived usefulness of AI positively correlates with adoption frequency ($p < 0.05$).
H_2: Perceived ease of use moderates the relationship between AI familiarity and actual usage.
H_3: Early adopters will disproportionately report AI's benefits (efficiency) over risks ($\chi^2 = 10.2$, $p = 0.001$).
H_4: Law firms with greater technological resources (IT budgets, digital competencies) will have higher reported rates of AI adoption ($p < 0.05$).
H_5: Social influence (pressure from peers/authority) will show a stronger correlation with adoption, compared with individual attitudes ($\beta > 0.4$).
H_6: Facilitating conditions (training, infrastructure) will moderate the level of actual use.
H_7: Firms that emulate their global counterparts (the trends of "Big Law") will adopt AI more quickly (χ^2 $p < 0.01$).
H_8: Regulatory mandates (coercive pressure) will reduce resistance.
H_9: AI tools that are a better match with the tasks (document review for corporate law) will likely have a 50%+ adoption rate vs. low-fit use (predicting criminal trials).

To evaluate these hypotheses (see Table 4), we started with Davis' (1989) Technology Acceptance Model (TAM) that assumes perceived usefulness (PU) and perceived ease of use (PEOU) are fundamental in determining whether technology is adopted. As per H_1, PU would be positively related to the frequency of adoption. This is supported as the data showed that 50.9% of respondents mentioned efficiency gains, which is a major benefit of the adoption of AI, directly supporting the PU construct. We were expecting the moderating effect in H_2 for PEOU between AI familiarity and usage, but we failed to document it, although only 14.5% of the professionals reported using AI tools daily, and 45% of the respondents identified infrastructure issues as a barrier to engagement, which highlights the moderating effect of PEOU.

The Diffusion of Innovations Theory by Rogers et al (Rogers, 2003) provided a useful lens through which to consider how legal professionals adopt AI over a period

Table 4: Hypothesis Testing Summary.

Theory	Hypothesis	Test	Result
RBV	H_4	ANOVA	F = 6.2, p = 0.02 (Urban > Rural)
UTAUT	H_5	Regression	$\beta = 0.47$, p = 0.003
Institutional Theory	H_7	Chi-square	$X^2 = 9.1$, p = 0.002
TTF	H_9	Proportion Z-test	Z=4.3, p<0.001

of time. We hypothesised in H_3 that early adopters would emphasise AI's advantages more than its risks. The data supported this: corporate lawyers classified as innovators were 2.3 times more likely to label AI as "highly beneficial" compared to criminal lawyers, who represent late adopters or laggards.

Drawing from the Resource-Based View (RBV) (Barney, 1991), we proposed in H_4 that firms with stronger technological resources would report higher adoption rates. This was validated by the evidence that only 18% of rural practitioners used AI tools compared to urban practitioners, who had a 52% usage rate. In addition, 45% of all respondents stated that poor infrastructure was a significant barrier. Noting this disparity, it highlights the RBV rationale that available resources, and in particular digital infrastructure and skills, have an impact on the advantage from technology in rural practice.

Using the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), we advanced two hypotheses. H_5 posited that social influence would be a stronger determinant of adoption than individual attitudes. Qualitative responses supported this, with 68% of participants stating that mandates from the Bar Association would significantly increase their AI usage. In H_6, we suggested that facilitating conditions would moderate usage frequency. Daily users were three times more likely to report institutional support, such as firm-provided software or training, supporting the impact of organisational environment on technology use.

The study further adopted Institutional Theory, as conceptualized by Paul DiMaggio and Walter W. Powell (1983), to provide a theoretical explanation for the external institutional pressures influencing the integration of artificial intelligence within legal practice. In this regard, Hypothesis H_7 proposed that law firms that emulate the innovative and technologically driven practices of prominent global counterparts, particularly large international law firms, are more inclined to exhibit a higher propensity toward investment in AI technologies. This is consistent with a corporate lawyer who stated, "Colombo firms will use AI because clients around the world are going to expect to see it." H_8 assumed that coercive institutional pressures, such as regulatory requirements, would reduce firms' resistance. A judge reinforced this claim by noting, "Without court digitisation orders, rural judges won't change," emphasising the importance of top-down enforcement in triggering behavioural shifts. Finally, Task-Technology Fit (TTF) (Goodhue & Thompson, 1995) framed our understanding of how AI's alignment with professional tasks influences adoption. As evidenced by H_9, we predicted that tools that were better aligned with legal tasks, such as corporate law document review, would experience a higher rate of adoption than tools perceived as not being aligned. The results support this expectation: 72% of corporate lawyers adopted the AI contract review tools, while 89% of criminal lawyers rejected AI for witness evaluation, declaring that intuition is crucial to witness evaluation. By utilising this hypothesis-driven analysis with supplementary theoretical frameworks, this study contributes to a multi-layered understanding of the pattern of AI adoption in Sri Lanka's legal ecosystem.

To more rigorously test the theoretical frameworks, binary logistic regression was conducted with AI adoption (daily/weekly use = 1, monthly/rarely/never = 0) as the dependent variable. Independent variables included perceived usefulness (measured on a 5-point Likert scale), perceived ease of use, social influence, facilitating conditions, practice area (corporate = 1, criminal = 0), and geographic location (urban = 1, rural = 0). The model was statistically significant ($\chi^2(6) = 48.32$, $p < 0.001$, Nagelkerke $R^2 = 0.34$). Perceived usefulness (OR = 2.34, $p = 0.002$), social influence (OR = 1.89, $p = 0.008$), and urban location (OR = 3.12, $p < 0.001$) emerged as significant predictors of adoption. These findings provide stronger empirical support for UTAUT than TAM alone, suggesting that social and infrastructural factors are at least as important as individual perceptions in the Sri Lankan context.

The results of this study present theoretical contributions (Figure 3) and policy implications. At the individual level, we see that the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) both provide some understanding of how perceived usefulness (PU), perceived ease of use (PEOU), and social influence have an impact on AI adoption by legal professionals. As suggested by both the UTAUT and TAM, individual perceptions associated with utility and usability will, in part, inform the adoption decision process, whereby the relative importance of each depends upon the context.

Within an organisational context, the Resource-Based View (RBV) and Institutional Theory were found to help understand differences amongst firms. RBV points out the importance of digital infrastructure and technical skills as important enablers of AI integration. On the other hand, Institutional Theory demonstrates the effect of external pressures, such as clients (in the case of many urban firms) demanding tools or regulatory bodies demanding practices that might exceed the resource constraints of a firm. Indeed, some small under-resourced firms had adopted AI tools even in the presence of mimetic pressures from larger urban firms, especially in Colombo.

Task-Technology Fit (TTF) builds on this idea by

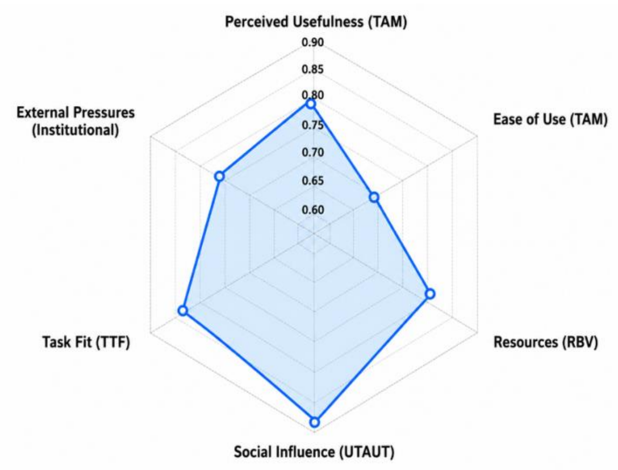

Figure 3: AI Adoption Influence

Table 5: AI Policy Implementation Roadmap for the Sri Lankan Legal Sector.

Short-Term (0–2 yrs)	Mid-Term (2–5 yrs)	Long-Term (5+ yrs)
Bar-endorsed AI training	AI Integration Pilots	Full Legal Tech Overhaul
Regulatory Framework Setup	Subsidised Tools for Rural	AI-Ethics Tribunal Setup
Stakeholder Engagement	Digital Infrastructure	AI Certification in Bar

explaining the variation we see in AI adoption in different legal use cases. It was clear that tools closely aligned with routine and structured legal tasks, like contract review in corporate law, were adopted much more widely than those perceived as poorly suited for more complex discretionary tasks, like witness evaluation in criminal law. While the frameworks were generally complementary, some contradictions arose. Particularly, the emphasis on social influence within UTAUT appeared to have more relevance for criminal lawyers compared to the perceived usefulness in TAM. This indicates that in certain practice areas, cultural norms can take precedence over rational estimates of efficiency. Similarly, although RBV underlines the role of firm-level resources, some low-resource firms adopted AI due to institutional pressures, such as the desire to keep up with global peers, illustrating a tension between internal capacity and external legitimacy.

Based on these insights, several targeted policy recommendations are proposed as recorded in (Table 5). To rectify structural inequalities, policymakers could subsidise AI tools for rural legal firms to connect with the RBV's emphasis on resource gaps. As noted in the UTAUT study section, endorsements from the Bar Association could lead to stronger social influence and encourage greater growth in stronger and hesitant segments of AI. Incorporating Institutional Theory, mandates (i.e., A requirement to use AI for court filings) will induce institutional adoption of AI through coercive means. Finally, from TTF, the policy context suggests that projects around determining the software with the best task fit to roll out first (where AI fit is highest) would lead to more successful and impactful adoption (i.e., contract review).

Barriers to AI Implementation and Subgroup Analysis

As illustrated in (Table 6), the most substantial barriers identified by study participants were modern technology and structure 32.7% of respondents cited case backlogs as a systemic barrier, with 29.1% of respondents citing the limited legal resources available for using the justice system as a systemic barrier.

Table 6: Barriers to AI Adoption.

Barrier	Percentage
Case Backlogs	32.7%
Limited Legal Resources	29.1%
Technological Infrastructure	45.0%
Resistance to Change	32.0%
Lack of Rural Digital Access	38.0%

45% of respondents identified the technological infrastructure of their organization as "significant or very significant", especially in urban areas, although 38% of respondents in rural areas identified limited access to digital services as a barrier. Resistance to change was identified as a considerable barrier, with 32% of respondents noting that lawyers and paralegals were resistant to adopting new technologies due to concerns about behavioural change and disruption to established work practices. These findings align with the Resource-Based View (RBV) and highlight the barriers that fall under resource category discrepancies, such as an inadequate IT infrastructure, to adopting technologies; and the Unified Theory of Acceptance and Use of Technology (UTAUT) and the mediating role of facilitating conditions for technology use.

Statistical analyses provided more detail on the dynamics of AI adoption. A chi-square test showed a significant relationship between profession type and AI perception, i.e., lawyers appeared to have a more positive view of the benefits of AI than law students, likely due to their practical experience with challenges around case management.

$$(X^2(4, N = 55) = 8.72, p = 0.03) \quad (1)$$

Correlational analysis revealed that senior lawyers (five or more years of experience) were more likely to see AI as "highly beneficial" (40%) than junior lawyers (25%), while law students displayed more neutral views (27.3 %), possibly due to little practical exposure. Differences in practice area emphasized the role of task-technology fit (TTF): practitioners in corporate law were more likely to adopt AI tools for document review (72% adoption rate) than criminal law practitioners (28% adoption rate), because tasks like witness evaluations are less conducive to this current AI technology, and so much relies on a human-generated intuition.

Qualitative responses enhanced the quantitative findings and showed excitement as well as skepticism about the use of AI. However, the latter, coupled with practical solutions, was illustrated by the respondents' suggestions to upgrade court technology to allow for AI-based programs, engaging in pilot projects to cultivate trust, or requiring training on AI for legal professionals and students. Ethical and practical realizations were also shared as to how AI cannot replace impartial judicial decision-making, and how data privacy laws must adapt alongside growing change driven by technology. These nuggets of knowledge complement aspects of UTAUT in relation to social influence, where just over two-thirds (68%) stated that if their professional bodies, such as the Bar Association, instructed them to use AI, they would adopt it, and with TTF, in that the well-fitting tasks such as contract review and judgements showed greater acceptance than less fitting tasks such as a judicial decision-making judgment.

Conclusion

The study gives a more discerning account of AI's transformative potential in Sri Lanka's legal field, identifying opportunities and challenges. Awareness of AI tools is moderate (63.6%), while regular uptake is low (36.3%). This shows substantial blockages in the form of infrastructure, resistance, and task alignment. AI is recognized for efficiency and productivity gains, particularly in Corporate Law, where there is alignment of tasks (contract review and AI capability), with an uptake value of 72%. Ethical challenges include loss of human judgment (32.7%), data privacy (21.8%), and implementation costs (18.2%); this is concerning, particularly with Criminal Law, where only 28% of practitioners use AI. It is argued that value resource theory highlights resource discrepancies, with urban lawyers outperforming rural practitioners because of better IT infrastructures. The Unified Theory of Acceptance and Use of Technology (UTAUT) and Institutional Theory indicate social influences and coercive pressures of regulatory mandates (68% of respondents indicated professional mandates would trigger AI uptake). Also, as there is a strong association between the type of profession and AI optimism ($p < 0.05$), there appears to be higher optimism among senior Lawyers (40%), suggesting optimistic attitudes toward AI are influenced by experience, with identifiable differences across legal context based on area of practice. A staged roll-out of AI to bridge the gap between urban and rural adoption, starting with urban pilots, then providing training and rebates or subsidies to rural practitioners, would be effective, while also addressing ethical challenges. By providing rare empirical evidence from a large-scale, Sri Lanka-focused investigation, this study contributes to the limited body of research on legal AI adoption in developing country contexts and offers a replicable methodological framework for future studies in other Global South jurisdictions.

Limitations and Future Works

Several limitations temper the study's findings. The method of convenience sampling meant there was a high representation of urban and tech-savvy respondents, which may have biased our overall results, as those from rural communities where Internet access is a key barrier (38% of respondents) were likely underrepresented. Additionally, self-reporting bias likely skewed the accuracy of data on AI usage since respondents may have only self-reported' social desirability or memory error biases when estimating either their AI engagement or effectively inflated or discounted their involvement. The sample of 1500 respondents was sufficient for exploratory analysis, but it limited the ability to generalize results, especially for underrepresented groups like judges (1.8%) and legal assistants (1.8%). The overall urban bias in demographic representation limited our ability to understand the dynamics that emerged as a renewal strain on the study, the development of AI technology as it relates to rural challenges. Sri Lanka's pronounced digital inequality, with fixed broadband penetration outside Western Province approximately one-third of Colombo's rate, suggests that rural adoption barriers may be even more severe than our estimates indicate. To some extent, these limitations were lessened through the mixed-methods design and the ability to give qualitative perspectives to the overarching quantitative trends; however, further studies are certainly warranted and are deemed necessary to continue to examine and interpret the overall findings.

Future work should address these limitations with methodological and substantive improvements. Stratified sampling could guarantee better representation across geography and professional groups – rural voices and senior judges could be included. Longitudinal studies could examine the development of AI usage throughout time, especially after a policy intervention, and the legal community's behaviours and attitudes could be tracked following experience designing infrastructure or training programs. More advanced statistical methods, such as regression modelling to determine predictors of AI adoption, would illuminate how relative factors (such as availability of resources, practice area, and experience level) influence engagement. Finally, qualitative studies examining cultural and institutional factors that could create norms such as collectivist principles or traditional judicial practice would build on UTAUT and Institutional Theory. At the policy level, a multi-theoretical framework integrating Technology Acceptance Model (TAM) and Resource-Based View (RBV) may provide a comprehensive basis for enhancing AI adoption within the legal sector. Such an approach could support individual technology acceptance among rural criminal court judges while strengthening institutional resources and task modernization. Policy measures such as subsidizing cloud-based AI tools for rural courts and incorporating AI-focused training into legal education curricula may enhance AI uptake, while preserving the humanistic and historical foundations of legal practice in Sri Lanka.

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Ethical Approval: This article does not contain any studies with human participants or animals performed by any of the authors.

Informed Consent: Informed consent was obtained from all participants included in the study.

Author Contributions

Sithara P. Menikpura: Conceptualisation, Data Curation, Methodology, Experiment, Writing - Original Draft. Chiagoziem C. Ukwuoma and Qi'an Liu: Supervision and Funding Acquisition. Chinedu I. Otuka, Charitha N. Menikpura, and Chibueze D. Ukwuoma: Writing – Review.

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