LEGAL DOCUMENT GENERATION: HARNESSING LARGE LANGUAGE MODELS FOR DIVERSE LEGAL WORKFLOWS

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ABSTRACT

Creating legal documents like Statement of Work (SoW) Documents, and process documents like Procurement, Treasury, Accounts Payable, Intangible Assets under Development (IAUD), and policies, is a laborious and time-consuming process, which often takes weeks to complete. After the introduction of Large Language Model (LLM), people in the Legal domain have started using it for various tasks. But it is important to note that there is a gap in using LLM's for Automated Document Generation. This paper comes to fill in that gap between the usage of LLMs in various Auto Document generation following certain structures to be compliant. We have used a pioneering approach to automate the generation of diverse legal documents, utilizing the liberty of using the advanced capabilities of LLMs. To craft and generate documents compliant with certain structures and legal criteria, we have designed our methodology that integrates multi-agent systems with iterative prompt refinement. Our innovative framework includes features like specialized agents for semantics identification, information retrieval, and content generation which aims at minimizing user intervention at the same time ensuring document precision and operational efficiency. Through real-world testing, we demonstrate the efficacy of our approach in semi-structured document generation across real-world contexts. To close this gap between the capabilities of LLM and automated legal document generation, our work contributes to the progressive dialogue on LLMs in legal domains and at the same time also holds high importance for revolutionizing the workflows in the legal domain. Our automated document generation solution specifically designed for Legal helps a lot of professionals to drastically reduce the time and manual effort involved in creating legal documents from scratch, thereby significantly improving efficiency and productivity across legal domains.

Keywords: Automated Legal Document Generation, Large Language Models, Statements of Work, NLP, Legal Document scrutinizing.

I. INTRODUCTION

Generating legal documents, such as procurement agreements, Statements of Work (SOW), treasury reports, accounts payable documents, and policies, is a complex and time-consuming task. Prior methods of writing policies or agreements or process documents require laborious manual efforts, also must prepare documents based on some standard templates set forth by their respective company.

Yet, the recent advancements in NLP and LLMs offer the ability to automate this process, streamlining document generation and improving efficiency. Even though LLMs have their footprints in various tasks [3] across different domains including Legal, their application in the legal sphere in auto-generation of documents remains largely uncharted [20].

Existing research primarily focuses on general applications [4], overlooking the nuanced requirements and complexities inherent in legal document generation [6]. This paves the way for urgency to address the precise needs of legal domains by hampering the adoption of automated solutions in the legal sector using LLMs. In response to this gap, this paper presents an innovative approach to automate the automated generation of various legal documents, by making the best use of the advanced capabilities of LLMs.

Our methodology aims to close the gap between LLM capabilities and the intricate requirements of auto-legal document generation by integrating recent advancements in LLMs and iterative prompt engineering. We propose a multi-agent framework that facilitates semantics identification, information retrieval, and content generation, minimizing user intervention while ensuring document precision and compliance with legal imperatives [1].

We demonstrate the efficacy of our approach in semi-structured document generation across real-world contexts through empirical evaluation. By addressing the specific challenges and complexities associated with legal document generation, our work not only contributes to the evolving discourse on LLMs in legal domains but also holds promise for revolutionizing legal workflows.

Our automated document generation solution helps professionals spend little time and effort involved in creating legal documents, thereby enhancing efficiency and productivity across diverse legal domains [2]. Our work not only contributes to the progressive dialogue on LLMs in legal domains but also holds promise for revolutionizing legal workflows. Through empirical evaluation, we showcase the effectiveness of our approach in structured document generation across real-world contexts.

I I . MOTIVATION AND OBJECTIVES

A. Motivation

Manual document preparation involves extensive time and manual efforts which are more prone to delays, errors, and inconsistencies. This requires more scrutinising techniques which again requires manual efforts. Writing documents in some set of predefined templates and standards will also limit flexibility and innovation within organizations.

This is where the inspiration for this research paper originates from. Recognizing these shortcomings, there is a clear need for automated solutions that can streamline document generation processes along with flowcharts which leads to overall improved accuracy, and enhanced efficiency.

B. Objectives

Addressing the Gap: The main objective is to close the gap in the usage of LLM capabilities for automated document generation and also to reduce manual efforts and time taken in creating these documents in the Legal Domain [16]. By achieving this we not only create documents in no time but also reduce manual efforts, and improve standard documents with less errors.

By efficiently utilising the advancements in LLMs, Prompt Engineering and recent strides in Natural language Processing (NLP), we can close this gap. Also, there is a huge gap in the implementation of process flow charts in process documents which can be achieved using certain Python libraries.

In addition to automated document creation, we aim to provide flowcharts for process documents as well to achieve end-to-end streamlining of the document generation process. Integrating multi-agent systems and prompt engineering methodologies, we aim to automate critical aspects of document production while ensuring accuracy and adherence to legal standards [12].

Empirical Validation: We assess our methodology's performance by auto-generation fully structured documents for Procurement, Treasury, Accounts Payable and Internal Audit (IAUD) in real real-world environment by strictly adhering to specific templates [13]. This helps us to provide concrete proof of its practical utility and effectiveness.

Contributions to the Field: Our aim is also to let people know about this innovative approach of using Large Language Models (LLMs) along with Prompt engineering and Natural Language Processing (NLP) techniques in the Legal world for auto document generation with flow charts. By highlighting the potential advantages and the specific challenges inherent in legal document creation, we intend to foster innovation and operational efficiency within the legal realm.

III. RESEARCH METHODOLOGIES

Our research method is designed in such a way that it aims to provide meticulously curated end-to-end document generation by utilizing user input. This makes it a novel approach where we control LLM and generate specific documents with specific templates according to user input and company-specific standard templates. It not only helps us to generate curated documents that users need but also achieves error-less and highly standard documents which reduces manual intervention.

A. Template Specification

The first and foremost step is to define standard templates for various legal documents which include process documents like Procurement, Treasury, Accounts Payable, IAUD and policy documents like Statement of Work (SoW). We took the help of our company's legal experts to tailor-stitch the templates specific to our company [1].

B. Prompt Engineering

Now that templates are ready, we next head to tailor prompts for various legal documents. This custom-fit prompt includes information about various terminologies of legal, how the structure and format should be [14]. These custom-crafted prompts instruct LLM on the back end to generate content by following user input and tailor-stitched templates by legal experts across these documents.

C. Multi-Agent System Integration

As prompt engineering is in place now, we now head to our next step for handling various tasks. For Auto Document generation based on user input and standard template, we have to do a series of tasks like information extraction from user input, semantic identification, analysing the template and generating content, for which we have used a multi-agent system in our research. Each agent is used for specific tasks [18].

For example: Information extractor and processor for extracting and processing information from user input, the Semantic Identifier for identifying semantic information [10], the Template analyser for recognizing the template and putting content in that template, Content generator for generating content based on all the above-mentioned criteria. All these agents help us to tailor-stitch our documents according to specific requirements and user input.

D. User Input Processing

As told before, one of our multi-agent Information extractors and processors will extract, analyse and process the relevant information from user input for document generation. We have designed our framework to get specific information from users which would help us to generate user-specific documents.

Point to note is user input differs from one document to another based on the type of document. Company-related information, Vendor related information, timelines, deliverables, pricing, legal clauses, effective dates, etc. are some of the information we will get from users.

E. Content Generation

Now that we have user input, prompts and templates ready, we use LLM to generate the content for the requested document [11]. Our framework is designed in such a way that LLM observes user input along with a specified template and helps to put the generated content in the specified template. It also ensures coherence, accuracy and compliance with legal standards.

F. Section Specific Prompt Refinement

The document contains multiple sections from the Cover page, Table of contents, and Overview, if it is a process document there will be process workflows, if it is a document there will be Payment terms, Risk factors, Concluding terms, etc. As you can see, the section differs from one document to the other. So, to generate tailor-stitched content for each section we need to use user input and company-specific templates along with curating prompt engineering. These prompts will greatly help in optimizing the LLM's performance which will lead to more accurate content generation [5].

The steps we followed involved doing basic prompt engineering for each section, analysing the output to know whether it matches user needs and a standard template, identifying areas of improvement and updating the prompts for desired results in each section.

G. Tabular Data & Visual Aids

To continue our exploration, we have also used Python libraries to bring some tables as per requirement. Legal documents often require tables to showcase certain calculations like cost, expenses, budget breakdown, etc. To accommodate that, we tried to build a basic table using Python libraries. Also, Flow charts are bread and butter for professionals dealing with process documents. It takes hours to create one but we have also brought this flowchart in our process document. This gives a complete detailed flow of that particular process in short.

H. Evaluation and Validation

Now that our end-to-end framework is ready, our next step is to evaluate our methodology. We compared our auto-generated documents against human-authored counterparts to evaluate our documents. The key factors like following a standard template, the content generated based on user input, coherence and compliance with legal standards are considered in evaluating our methodology.

I. Real-world Deployment

Our automated document generation with flowchart solution is now successfully deployed in our company's real-world legal workflows. As this is purely Python-based coding with the implementation of Prompt engineering and LLMs and certain NLP techniques [9], deployment of this solution across the platform is super easy and adapts to changes. As this has a simple UI, we don't require much training people on this. All that is required to be shared with them is what kind of user input is given for each document.

J. Continuous Improvement

Finally, we prioritize continuous improvement through ongoing monitoring, feedback collection, and refinement of the document generation process. We adapt our methodology based on user experiences and evolving legal requirements to ensure that our solution remains effective and relevant over time.

Here is the overall architect of our methodology

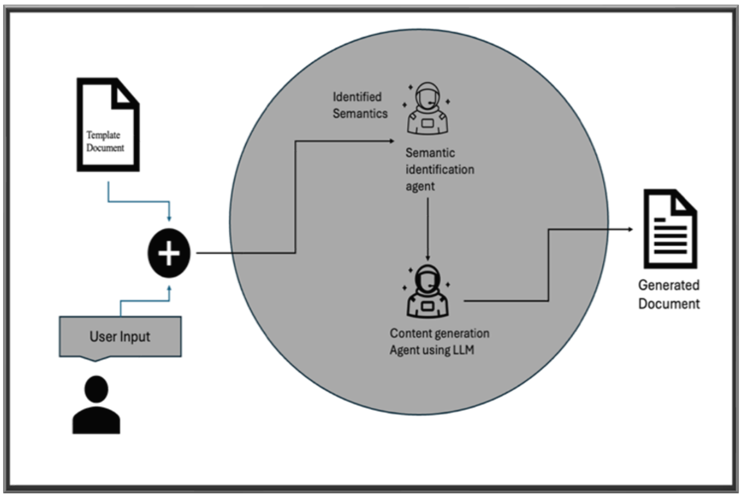

Figure 1: Architecture of Legal Document Generation

Here is our Solution Approach

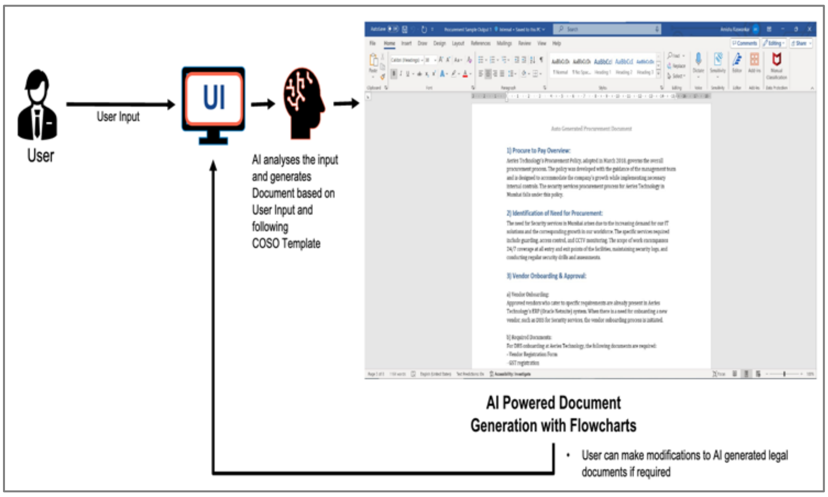

Figure 2: Solution Approach

The formula for Basic Prompt Engineering:

Prompt = User Input + Legal Terminology + Document Structure Guidelines

IV. RESULTS

A meticulously curated approach for auto-generation of documents with flow charts gave promising results. As a result of this, it was implemented for generating various types of documents in our company. When compared to the manual way of writing these documents, there was a significant improvement in efficiency and accuracy and at the same time compliance with legal terms.

The Key findings include:

A. Reduction in Document Generation Time:

With the help of professionals in our company, we did a time and motion study. According to our study, writing documents such as SoW, Accounts Payable, Procurement, Treasury, IAUD from scratch requires substantial time and manual efforts. On an average, time required by a single professional to create Statement of Work (SoW) is 30 hours. Say a need arises for a Professional to prepare 10 more SoW's for different clients in next 5 working days. To prepare 1 SoW document will take close to 3 and half days on an average (30 Hours).

So, for the Professional to prepare 10 such SoW's will require 35 days on an average to complete all 10 documents. The Company can't wait for so long as SoW's need to be signed soon. Solution 1 is company will hire additional professionals in future to handle growing needs, but it will cost the company and Solution 2 is to ask for extra time. Both of which is a loss to the company. So, if need arises, time and cost also increase.

Our solution paved the way for professionals to create documents in no time. They now don't have to spend days to weeks to months to create one document. In a minute, our innovative approach will provide multiple(60) documents. There is a 99% increase in speed based on our time and motion study.

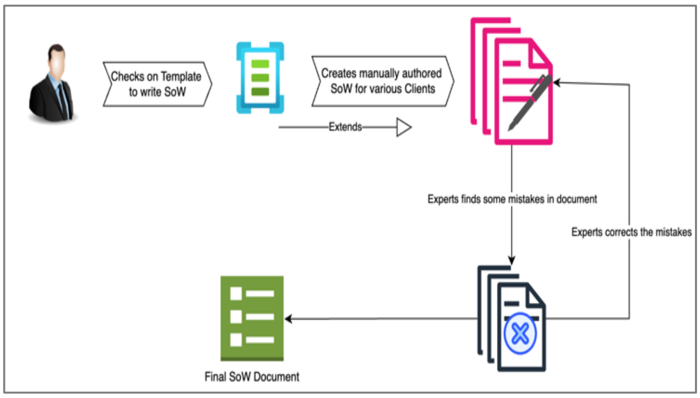

Figure 3: Manually Authored Document Creation Process

Document Type	Average Manual Time (in Hours)	Average Time taken by Legal Document generation (in Minutes)
Statement of Work	30	1
IAUD	40	1
Procurement	20	1
Treasury	15	1
Accounts Payable	10	1

Table 1: Average Manual Time (in Hours) vs Average Time take by Legal Document generation (in Minutes)

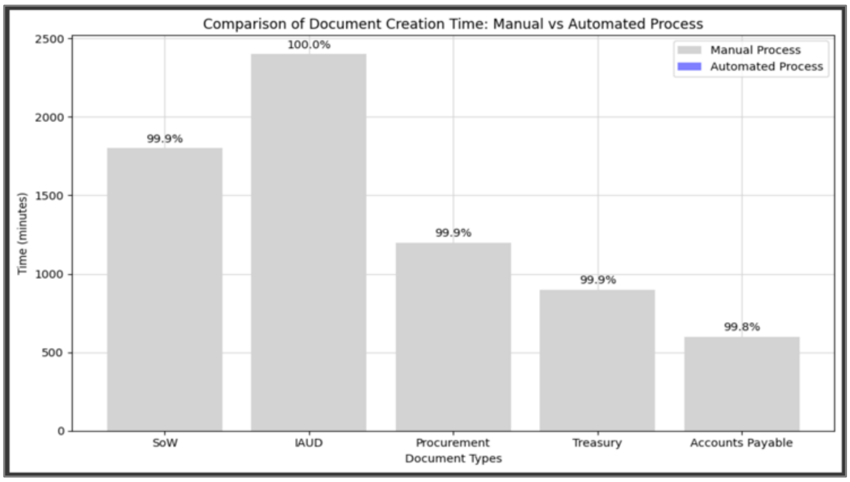

Figure 4: Comparison of Document creation time: Manual vs Legal Document generation

B. Enhanced Precision and Compliance:

Based on our time and motion study we also observed that although Professionals take extra care in preparing the documents like SoW, IAUD, Procurement, Treasury, Accounts payable, etc, there were always some errors. Professionals need to revisit the documents multiple times to find and correct mistakes. On average, it would take a single professional about 1 week to achieve minimal to no errors.

Our solution has drastically minimised the errors, inconsistencies and omissions in legal documents when compared to traditional document writing where professionals need to go through a complete document to correct part of the document with specific usage of words or sentences following legal standards. This consumes a significant amount of time. Using our solution, professionals only take a day to correct errors, if any, because our automated legal document generation follows a standard template and compliance, making it rigid against errors. Hence, professionals don't have to spend a week but just a day to correct errors. Hence, based on our time and motion study, this represents an improvement in work efficiency of approximately 85.71%.

C. Improved User Experience:

Users are happy with this solution. What majorly attracts them is Ease of use, generating a whole document in a fraction of a second, an editable document that can also be used to make minor changes if required, compliant with legal standards. They also reported that it saves their time and allows them to focus more on their work.

D. Scalability and Adaptability:

Our innovative approach of using LLM for auto document generation is designed in a way to adapt itself to growing changes. This allows smooth integration into existing workflows and also fits in well with evolving requirements.

On the whole, our approach in addressing the challenges of legal document generation and improving efficiency within the legal sector bridges the gap between LLM and auto legal document generation in today's era with pretty good precision and at the same time compliant with legal standards.

V. DISCUSSION OF RESULTS/BENEFITS

A. Practical Implications:

In our company's legal sector, professionals were greatly impressed with our automated generation of legal documents with flow charts solution. In the real world, they started using our solution for various legal documents like Procurement process documents, Treasury process documents, Accounts Payable process documents and IAUD documents and also used for generating Statement of Work (SoW).

B. Impact on Workflows

Statement of Work (SoW) Documents: SoWs are so important when dealing with multiple clients and our solution serves the best here. Professionals don't have to depend on templates where they need to modify certain placeholders for each client which is generally followed in the manual process of writing SoW Documents. By using our novel solution, they just need to provide a set of user inputs, which will generate a complete SoW document following the standard template and most importantly user inputs are also placed in the right place. And the same applies for other types of documents as well.

C. Process Documents:

The need and importance of explaining each step in detail when it comes to processing documents like Procurement, Treasury, Accounts Payable, and IAUD is a cumbersome and laborious process. The tough part here is attention to every step in the process document has to be accurate and specific to companies and to come up with a process flow chart, the team needs to spend days to get it done.

Our solution which auto-generates these documents has completely removed the pain on professionals who need to come up with these documents. As the standard templates are in place, with just a few user inputs, it will generate complete process documents with flow charts ensuring accuracy with manually authored process documents or even beyond that.

D. Cost and Time savings:

Be it agreement documents like Statement of Work(SoW), or process documents like Procurement, Treasury, Accounts Payable, or IAUD, the company relies on multiple professionals to get these documents ready and in case of rework. This would cost the company a lot. Instead by using our solution, they can reduce headcount by half which saves them more money.

As these are time-consuming tasks company needs to wait until these documents get ready which can take weeks to months to get completed. If there are some mistakes in man-written documents, it will take a few more weeks to review and course correct them. In this frame, the company will lose time, money, etc [10].

Our solution will be a huge help for professionals as it auto-generates documents like Statement of Work(SoW), and processes documents like Procurement, Treasury, Accounts Payable, and IAUD in a fraction of a second in Word format. So in a minute, they can generate n number of these documents and the company doesn't need to wait for weeks to get these documents.

E. Increased Efficiency:

Automation reduces the time and effort required to generate legal documents, enabling organizations to allocate resources more effectively and accelerate decision-making processes.

F. Enhanced Accuracy and Compliance:

Automated systems ensure consistency, accuracy, and compliance with legal standards, minimizing the risk of errors, discrepancies, and regulatory violations [19].

G. Improved Productivity:

By freeing up human resources from mundane document generation tasks, automation allows legal professionals to focus on higher-value activities such as legal analysis, strategy development, and client engagement.

H. Greater Flexibility and Innovation:

Automation eliminates the constraints imposed by predefined templates and allows for greater flexibility and innovation in document design and content, enabling organizations to adapt to changing legal requirements and business needs. Overall, the discussion highlights the potential of automated document generation to revolutionize legal workflows, enhance operational efficiency, and drive value creation across diverse legal domains. We have also done Time and Motion study to benchmark our research work which is been shared in later part of this paper.

VI. FAILURES AND BOTTLENECKS

Some of the bottlenecks include:

A. Language barrier:

This was developed majorly for English-based users. So people who don't know English will need to translate each section to understand the content completely [8].

B. Complexity of Legal Language:

Legal documents often contain complex language, terminology, and structures. Though our framework is designed to generate complete documents based on user input and a standard template, if the type of document changes, we need to tweak our code a bit to get a more reliable, compliant document. Hence we need to tailor stitch according to each document only in case you require it to follow a certain template.

C. Document specific:

Legal documents often contain complex language, terminology, and structures. So we need to know the structure, and template of each document to generate a compliant document. Insufficient information can result in suboptimal performance and reduced accuracy.

Addressing these failures and bottlenecks requires further research and development efforts to enhance the robustness, accuracy, and usability of automated document generation solutions in legal domains.

VII. SAFETY CONSIDERATIONS

If organizations follow below said safety measures, they can easily minimize the risks and deploy automated document generation solutions in their platform.

Key safety considerations to include for responsible use of technology and to mitigate risks:

A. Risk of Bias and Fairness:

Auto document generator will only look at what's been given in the template. Hence we have to be careful with the template and each section in it as the model's performance might vary depending on it [15].

B. Data Privacy and Security:

To prevent unnecessary manual intervention to sensitive data, we should encrypt, and anonymise data and user access. This will prevent unnecessary breaching of sensitive data.

C. Legal and Ethical Compliance:

Our Automated document generation systems must comply with legal and ethical standards. As we deal with the legal domain where sensitive information for the company lies, we must be cautious in the usage of data and at the same time we follow and comply with legal conditions [7].

D. Transparency and Being Accountable:

In case of errors or disputes, we must establish a clear mechanism for accountability. With Transparent communication about system capabilities, limitations, and potential risks we can gain trust among users.

VIII. ENVIRONMENTAL ISSUES CONSIDERED

Our Automated document generation solutions in legal workflows can have environmental implications, both positive and negative.

Key Environmental issues include:

A. Paper Reduction:

As we know, deforestation has been a big issue nowadays leading to pollution. Our Automated document generation solution gives output in a Word document. So professionals can just save it as Word or PDF and send it across. They don't have to waste paper by printing. Even if it is required to print, our solution gives more accurate output in one go where professionals can only print that copy and this surpasses the manual method which requires multiple printouts and corrections before getting the final draft.

B. Energy Consumption:

Deploying our solution requires higher computation as it involves LLM's. To bring resource consumption down, we also tried to use quantized LLM's which has drastically reduced resource, energy and time.

C. Electronic Waste:

Recycling of resources specifically servers is highly important to adapt to advancements in LLM usage.

IX. BENCHMARK OF RESEARCH

To benchmark the effectiveness of our research methodology, We compare the performance of our solution against manually authored documents using time and motion study Key benchmark criteria include:

A. Document creation and quality:

Our time and motion study resulted that by using our Legal Document generation has drastically reduced the time taken to generate documents like SoW, IAUD, Procurement, Treasury, Accounts Payable, etc by 99%. For instance: To create one SoW document manually it takes 30 hours on an average. But with Legal document creation, we can generate one document in a minute. Since this is automated document generation, we have made sure document generated is compliant and with minimal to no errors.

B. Error Reduction

Error rate has also decreased drastically. On an average, Professionals take minimum 1 week to find and rectify errors in these documents using manual approach.

Using our Legal Document generation, time spent on correcting errors have decreased to 1 day or even less than that [20]. Professional doesn't have to spend another 1 week to find and rectify the errors.

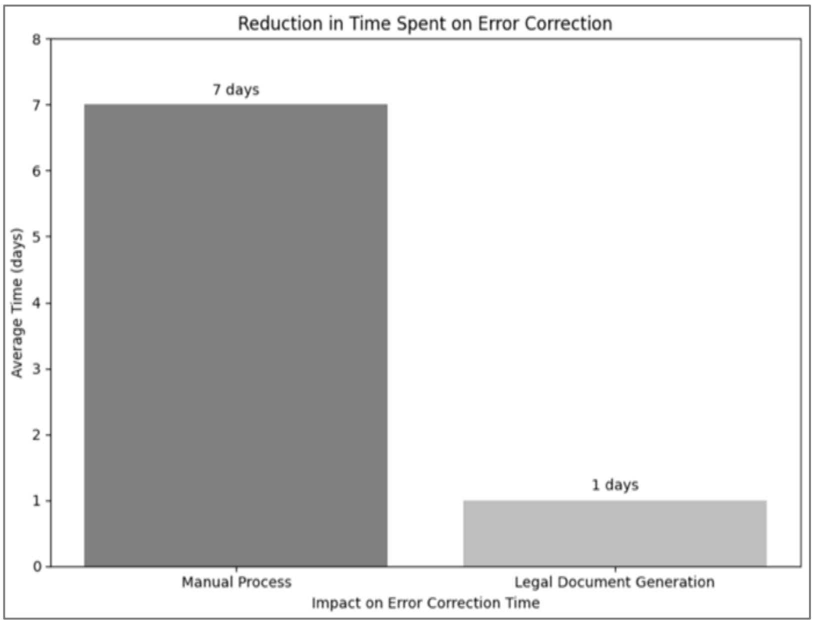

Figure 5: Reduction in Time spent on Error Correction: Manual vs Legal Document generation

C. Faster Turnaround:

Manual Turnaround time was more which led to slower processing time. Based on time and motion study,

Turnaround time using Manual document creation and Error correction:

Document	**Manual Creation Time (Average Hours)**	**Manual Error Correction Time (Hours)**	**Total Turnaround Time (Hours)**
Statement of Work	30	56	86
IAUD	40	56	96
Procurement	20	56	76
Treasury	15	56	71
Accounts Payable	10	56	66
Average Time	23	56	79

Table 2: Total Turnaround time based on Manual creation and Error Correction Time

Turnaround time using Legal Document generation:

Document	**Legal Document generation Time (Minutes)**	**Automated Error Correction Time (Hours)**	**Total Turnaround Time (Hours)**
Statement of Work	1	8	8.02
IAUD	1	8	8.02
Procurement	1	8	8.02

Treasury	1	8	8.02
Accounts Payable	1	8	8.02
Average Time	1	8	8.02

Table 3: Total Turnaround time using Legal Document generation

Comparing Turnaround time for both Manual time and Legal document generation:

Document	**Turnaround Time – Manual (Average Hours)**	**Turnaround Time - Legal Document generation (in Hours)**
Statement of Work	86	8.02
IAUD	96	8.02
Procurement	76	8.02
Treasury	71	8.02
Accounts Payable	66	8.02
Average Efficiency Improvement		89.66%

Table 4: Total Turnaround Comparison (Manual Vs Legal Document generation)

On an average, turnaround time have improved by 89.66% which lead to quicker project kick-offs and faster completion times, enhancing client satisfaction and competitive advantage.

D. User Satisfaction:

We solicit feedback from users and stakeholders to gauge satisfaction with the document generation process, usability of the system, and overall experience, comparing it to baseline levels.

X. CONCLUSION

In summary, our research presents a pioneering approach to automate the generation of diverse legal documents, addressing the specific challenges and complexities inherent in legal workflows. Leveraging the advanced capabilities of Large Language Models (LLMs) and recent advancements in Natural Language Processing (NLP), our methodology streamlines the document generation process, improves efficiency, and ensures compliance with legal standards.

Through time and motion study and real-world deployment, we demonstrate the effectiveness and practical applicability of our approach in diverse legal domains. By considering safety, environmental, and ethical considerations, we promote responsible use and sustainable adoption of automated document generation solutions in legal workflows. Overall, our research contributes to the evolving discourse on LLMs in legal domains and holds promise for revolutionizing legal workflows.

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