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Streamlining Supplier Evaluation through Automation: A Lean Six Sigma Approach for Cutting Processing Time

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Abstract

In today's fast-paced procurement environments, organizations face growing pressure to streamline supplier evaluation processes to save time and improve consistency. Manual methods often introduce inefficiencies, errors, and delays, highlighting the need for structured and data-driven improvement strategies. This study applies the DMAIC methodology to enhance the supplier evaluation process within a chemical sourcing team. The original method was highly manual, requiring an average of 5.69 hours to generate evaluation tables and involving repetitive formatting, hardcoded formulas, and inconsistency across projects. The primary objectives were to reduce table creation time to under 30 minutes, automate over 90% of the process, and validate improvements using control charts and process capability analysis. In the Define phase, Voice of the Customer (VOC) data was translated into measurable Critical to Quality (CTQ) targets. The Measure phase revealed high variability in completion times, while the Analyze phase identified key root causes, including non-scalable design and excessive manual effort. Two solutions were tested using PDSA cycles: an Excel-based method and a Python-coded system. The coding solution reduced average creation time to 46 seconds. I-MR charts confirmed process stability, and capability indices supported consistent performance. A Sigma Level of 4.29 further validated long-term capability. The project exceeded its CTQ goals, achieving a 99.77% time reduction and demonstrating the impact of Lean Six Sigma tools in administrative workflows. Future work includes developing a user interface and integrating the system with sourcing platforms to support digital transformation.

Keywords
Lean Six Sigma, DMAIC, Supplier Evaluation, Automation, Process Improvement

1. Introduction
Supplier evaluation is key to making effective sourcing decisions that align with business goals. However, using manual methods like Excel results in a slow and tedious process. For sourcing teams like the Chemical Sourcing Team at a global company, the manual method meant every project had to be rebuilt from scratch. Each new combination of products, suppliers, and locations required redoing the formulas, formats, and structure entirely. The result? A process that takes four to five hours per project, adding stress, increasing the risk of error, and taking time away from more strategic work. As the number of projects grew, this setup became unsustainable. The team was spending hours creating tables and fixing formulas references. The greater the data they handled, the greater the risk of mistakes and late submissions to stakeholders. Thus, it became clear that a better system was needed, one that could reduce repetitive work allowing the team to focus on critical decisions.

To address these challenges, this paper applies the Lean Six Sigma DMAIC framework. The Define and Measure phases captured the team's pain points and quantified performance gaps. In the Analyze phase, tools like 5 Whys and fishbone diagrams were used to identify the root causes of inefficiencies. Two improvement solutions were tested:

one using Excel and another developed in Python. The Python solution was validated through time comparisons, control charts, and process capability metrics. To keep the project focused, only the table generation step was automated; data setup, manual entry, and differences in product-location combinations were considered out of scope. Each phase shows how combining digital tools with Six Sigma can improve efficiency, accuracy, and overall productivity.

1.1 Objectives

The primary objectives of this project were to streamline and optimize the supplier evaluation table creation process, which was previously reliant on time-consuming and error-prone manual methods. The key objectives were to significantly reduce the total time required for generating these tables from over 5 hours to under 30 minutes and automate over 90% of the evaluation steps, including scoring, supplier ranking, and conditional formatting. To ensure the robustness of the new solution, statistical methods such as Individuals-Moving Range (I-MR) control charts and process capability indices (Cp and Cpk) were applied to validate the improvements. Additionally, the project aimed to enhance operational scalability, allowing team members to handle multiple evaluations per day with less stress and reduced non-value-added work. These objectives collectively supported the broader goal of streamlining the sourcing workflow while aligning with Lean Six Sigma principles for sustainable process improvement.

1.2 Current Process: Manual Excel Setup

In the existing manual process, supplier evaluations are conducted in Excel by creating a separate evaluation table for each unique product-location combination. For example, if the same product is required at two locations, two tables are built, each with its own pricing, scores, and rankings tailored to that context.

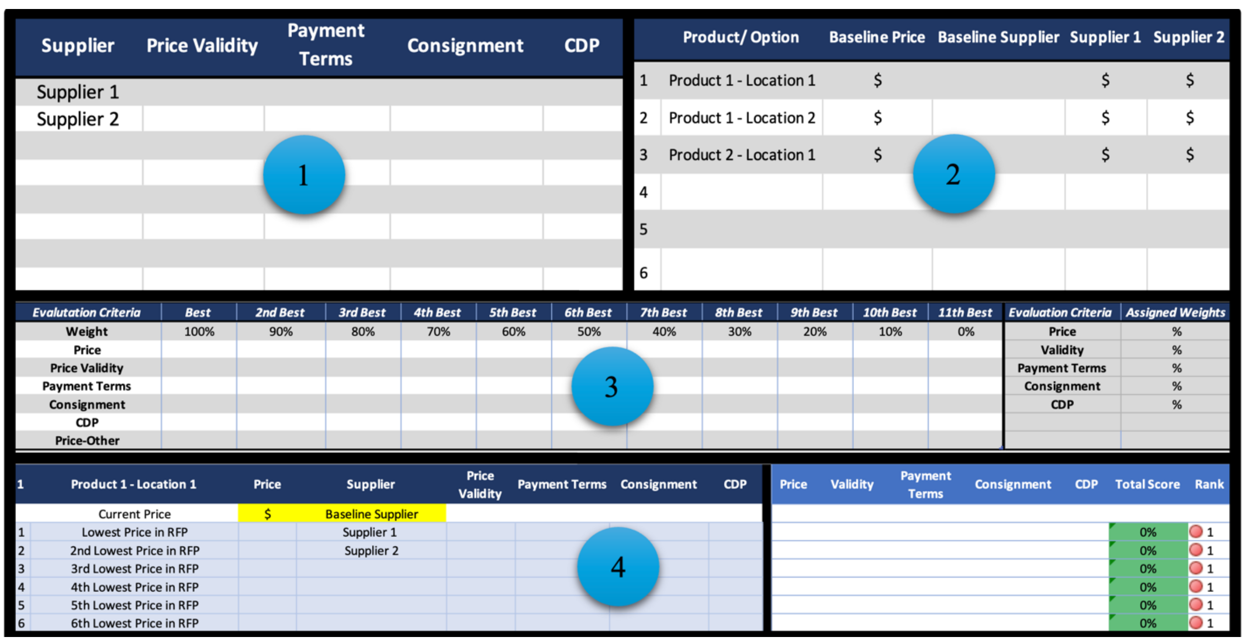

Figure 1. Manual Excel setup sheets

The Excel file shown in Figure 1 contains four linked sheets:

1. **Suppliers' Info**: Stores supplier related details like payment terms, price validity, and other evaluation criteria.
2. **Pricing**: Records the offered prices per supplier for each product-location. Only the relevant row is used to build each table.
3. **Evaluation Criteria**: Holds the scoring logic for all selected criteria. While most criteria have a single set of thresholds, the price criterion may use multiple score brackets to fairly assess supplier offers that differ greatly in value across projects. For example, one product-location may have prices in the range of hundreds, while another may be in the thousands. Using separate brackets ensures fair scoring. Each criterion, including

price, is assigned a weight based on its importance in the evaluation. Scores are then assigned as fixed percentages (e.g., 100%, 90%, etc.) according to the bracketed thresholds.

4. **Evaluation Tables**: Combines all the inputs, calculates total scores, and ranks suppliers for each specific product-location.

Although this manual approach functions well for small projects, it becomes increasingly time-consuming, repetitive, and error prone as the number of combinations and suppliers increases. Even small edits, such as adjusting scoring ranges or adding a supplier, require careful updates across multiple sheets.

2. Literature Review

Supplier evaluation is crucial for efficient sourcing, cost control, and organizational competitiveness. Traditionally, manual supplier evaluations suffer from inefficiency, inconsistency, and high time consumption, which has created a strong need for structured improvement methods. Lean Six Sigma (LSS), especially the DMAIC methodology, has proven effective in addressing these issues. Tay and Aw (2021) used DMAIC to streamline logistics supplier selection, significantly reducing lead time and variability. Similarly, Murtaza et al. (2023) applied DMAIC to administrative processes, showcasing its adaptability beyond manufacturing environments. Nicoletti (2013) also demonstrated that integrating LSS with procurement digitization improves accuracy and cycle time by eliminating manual inefficiencies.

Building on these successes, Gomaa (2025) confirmed the role of LSS in achieving strategic alignment in supply chains. The integration of digital tools within DMAIC applications has become increasingly relevant. Khabbazian (2024) and Bahadori and Li (2023) highlighted the benefits of digital validation and automated scoring, which improve consistency and reduce evaluation time. Fırat et al. (2017) went further by combining DMAIC with AHP and Kano models, emphasizing its flexibility for handling complex supplier evaluations with multiple qualitative and quantitative inputs. DMAIC is also recognized for its clarity, structure, and repeatability in problem-solving contexts (De Mast and Lokkerbol, 2012). Jardim (2013) further demonstrated DMAIC's versatility through a targeted Quality Improvement Plan for supplier performance. Sepúlveda and Derpich (2014) stressed the role of automation in supplier appraisals, and Zope et al. (2025) showed how digital transformation can scale procurement processes efficiently. Beyond procurement, Al-Rifai (2025) applied DMAIC to streamline recruitment cycles, proving its relevance in other business domains.

In the public sector, DMAIC has also demonstrated impact. Kassem and Hamid (2020) reported major cycle time reductions in public services, while Maryadi et al. (2021) applied the methodology to improve lead time in internal supply chains. Číž (2020) highlighted the advantages of digitized evaluations, particularly in improving consistency and speed.

In summary, the literature strongly supports DMAIC as an effective approach for optimizing supplier evaluations, especially when combined with digital tools to improve efficiency, consistency, and reliability. However, while previous studies show how DMAIC and automation can enhance various processes, there is still limited research focused specifically on automating supplier evaluation tables in high-volume sourcing environments. Most existing solutions lack the flexibility and scalability needed to handle complex, dynamic evaluation systems. This study addresses that gap by developing and validating a Python-based automation tool designed for real-world sourcing projects with high complexity and variability.

3. Methodology

To improve the supplier evaluation table creation process, this project adopted the Lean Six Sigma DMAIC methodology, a structured problem-solving approach widely used for process improvement. The DMAIC framework: Define, Measure, Analyze, Improve, and Control, was used to systematically identify inefficiencies, analyze root causes, implement targeted solutions, and ensure long-term stability. Each phase utilized relevant industrial engineering tools to guide decision-making and validate results.

3.1 Define

The Define phase focused on identifying and clarifying the problems in the existing evaluation process. The team conducted structured interviews and meetings to collect feedback from various stakeholders involved in creating supplier evaluation tables. This feedback was translated into the Voice of Customer (VOC) Table 1 below, which revealed recurring complaints such as time-consuming tasks, complex Excel formulas, and repetitive formatting work.

Table 1. Voice of customer captured from project stakeholders

Team Member	Complaints
Team Manager	Highlighted that Excel formulas are overly complex and difficult to interpret. Manual updates to maintain cell references are frequent, and generating tables becomes more time-consuming as the number of products, suppliers, and locations increases.
Team Lead	Noted that creating evaluation tables takes up a significant part of the workday. The process involves significant manual work and delays the generation of presentation-ready outputs.
Team Specialist	Pointed out the difficulty of finalizing multiple projects in a day due to the repetitive and tedious nature of the process. Also emphasized increased stress near deadlines and lack of scalability for larger datasets.

To organize these issues, an Affinity Diagram was used to group similar complaints into key categories as mentioned in Figure 2: excessive manual work, lack of automation, inconsistency, and scalability issues.

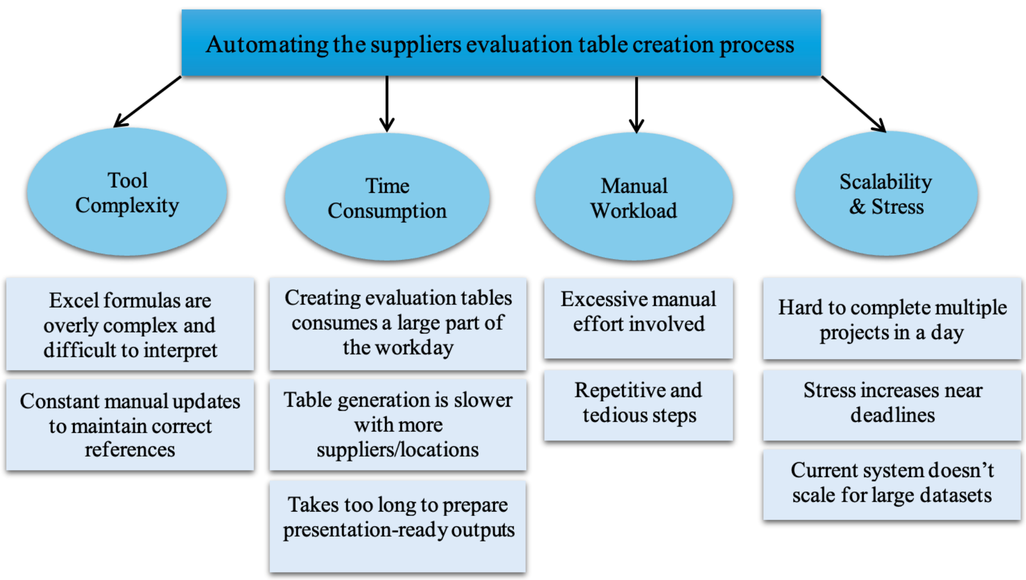

Figure 2. Affinity diagram grouping VOC collected from stakeholders

These categories were then transformed into measurable project goals through a Critical to Quality matrix shown in Figure 3. This helped define clear performance targets, such as reducing table creation time to under 30 minutes and automating over 90% of the workflow steps.

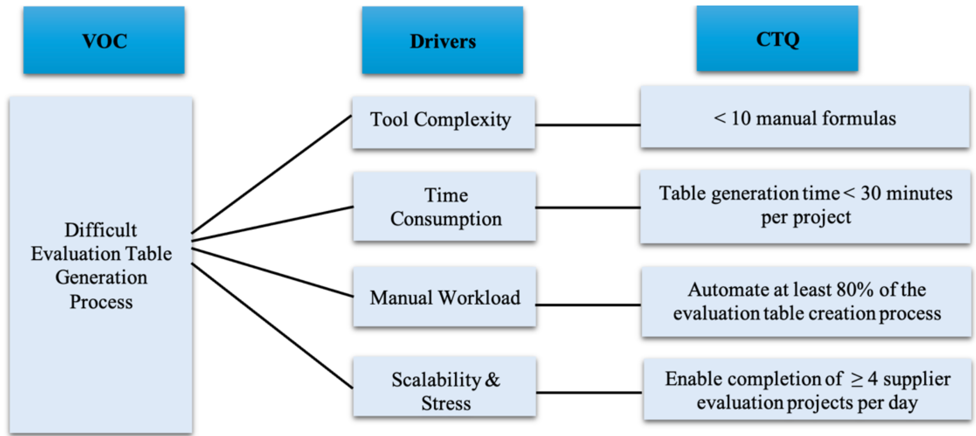

Figure 3. VOC to CTQ matrix translating feedback into project goals

3.2 Measure

The Measure phase focused on further understanding the process and collecting data on how long it took to complete evaluation tables using the manual method. This helped establish a clear idea of how the process is currently performing before any changes are made. The process map (Figure 4) helped break down the manual steps involved in creating evaluation tables. It showed that several steps required repetitive work, including setting up formulas, checking score calculations, formatting the tables, and manually ranking suppliers. These areas were identified as key contributors to delays and inconsistencies across projects.

Each step in the map reflects a task carried out manually by the team. The process begins with gathering supplier pricing and qualitative criteria data, which is entered into Excel. Assigned weights are collected from stakeholders and input alongside the evaluation criteria. Based on the project's pricing range, the scoring brackets are adjusted. From there, scores are calculated for price, validity, payment terms, consignment, and CDP. These individual scores are then combined into a total score used to rank the suppliers. Conditional formatting is applied to highlight the top scoring suppliers and visually distinguish rank levels. Before finalizing the output, the team checks whether all formulas are functioning correctly. If errors are found, adjustments are made, repeating the cycle until the evaluation table is accurate and complete.

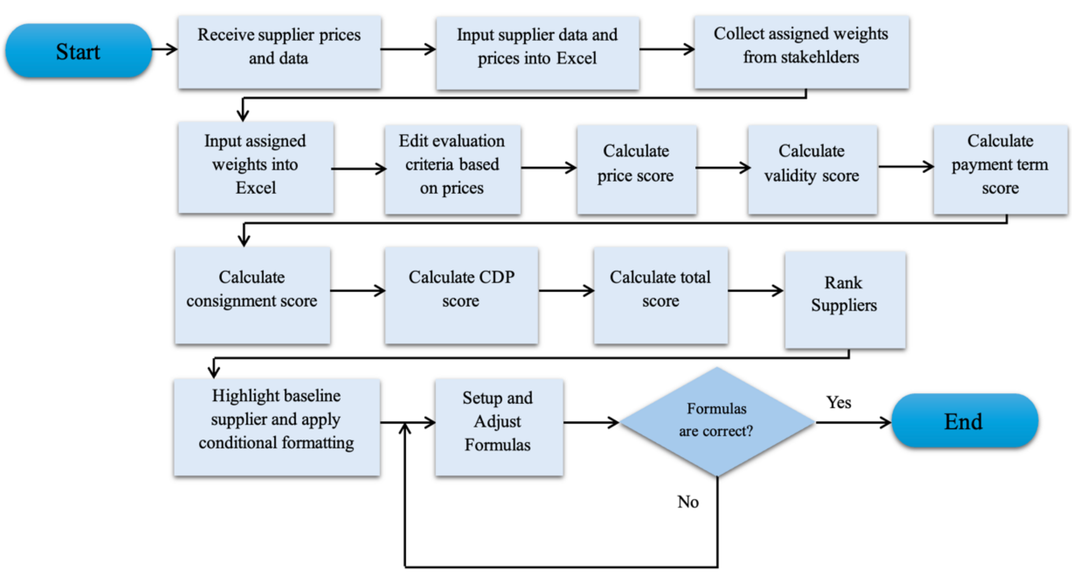

Figure 4. Manual Method Process map

The time to complete this process manually was tracked across multiple projects. While descriptive statistics were calculated in this phase, the full analysis is presented later in Section 5.1.

3.3 Analyze

The Analyze phase focused on identifying the root causes behind the delays and inefficiencies in the current supplier evaluation process after reviewing the data collected in the Measure phase. A 5-why analysis and a fishbone diagram were utilized to find the root causes.

The 5 Whys analysis (Table 2) revealed that the root cause of the problem was the absence of any redesign to support automation or scalability.

Table 2. 5 Whys analysis

Why	Answer
Why does evaluation table creation take too long?	Because every step is done manually
Why is everything done manually?	Because the Excel file isn't automated
Why isn't the Excel file automated?	Because the formulas are hardcoded and not dynamic
Why are the formulas hardcoded and not dynamic?	Because the file was created without a focus on scalability
Why was it created that way?	Because the process was never properly redesigned to support automation or scale

From the fishbone diagram (Figure 5), the major causes include manual table setup, hardcoded and non-automated Excel formulas, and frequent reliance on manual adjustments. Addressing these underlying issues is essential for improving the process in the subsequent phases of the project.

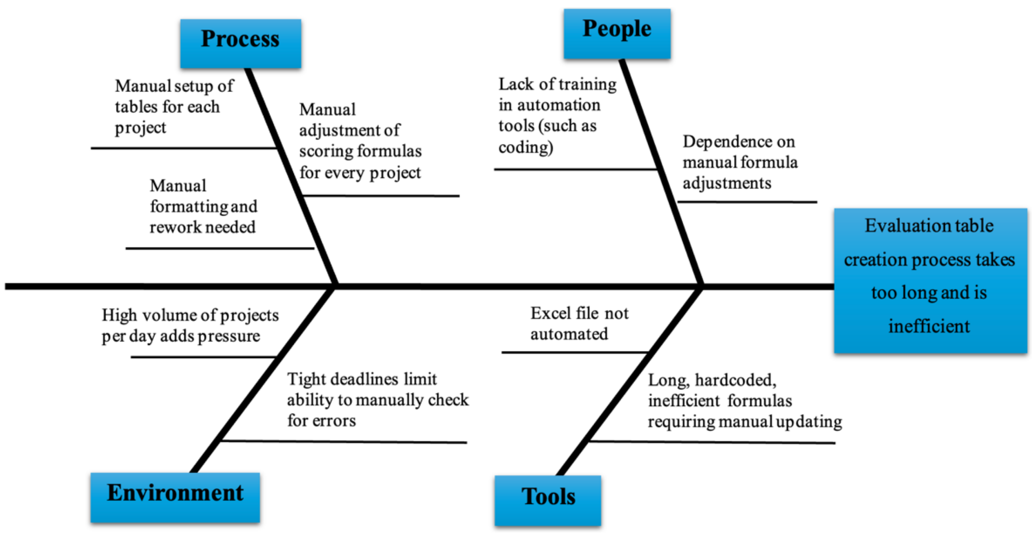

Figure 5. Fishbone diagram

3.4 Improve

The goal of the Improve phase was to create and test solutions to address the root causes found in the Analyze phase. Plan-Do-Study-Act (PDSA) cycles were used to examine two possible solutions (Institute for Healthcare Improvement, 2025). The objective was to satisfy the critical-to-quality (CTQ) objectives of the project while simultaneously using descriptive statistics, as covered in Section 5.1, to validate the changes.

- **PDSA Cycle 1 – Excel-Based Solution:** The first solution involved optimizing the process using Excel, specifically through pivot tables and Power Query.
  - **Plan:** Build an automated solution in Excel using PivotTable and Power Query to generate evaluation tables in under 30 minutes.
  - **Do:** After testing, several limitations were observed in the prototype. Hardcoded headers broke with any changes, multiple price scoring setups were unsupported, and conditional formatting required manual work. Performance lagged with large datasets, and the resulting tables did not match the manual version's visual appearance or structure. While slightly faster, the tool introduced more risks than benefits.
  - **Study:** Although project time was reduced, new inefficiencies emerged.
  - **Act:** The Excel solution was deemed unfit for long-term use. A shift toward a more robust and adaptable coding solution was necessary.

- **PDSA Cycle 2 – Python-Based Solution:** The second cycle focused on developing a Python script to fully automate table generation.
  - **Plan:** Create a dynamic Python solution to produce formatted evaluation tables in under 30 minutes.
  - **Do:** The code completed the task in under a minute, preserving layout and applying formatting automatically. It adapted to varying column names, multiple pricing setups, and large datasets without performance issues. Minimal manual intervention was needed.
  - **Study:** The Python solution exceeded expectations, delivering accuracy, speed, flexibility, and consistency (the final output can be seen in Figure 6).
  - **Act:** It was adopted as the final solution. Minor validations were added later to improve error handling. The simplified steps for the automated process are shown in Figure 7.

Product 1 – Location 1

		Supplier	Price	Price Validity	Payment Terms	Consignment	CDP	Price Score	Validity Score	Payment Term Score	Consignment Score	CDP Score	Total Score	Rank
	Current Price	Base.Supplier	$20.00											
1	Lowest Price in RFP	Supplier 2	$5.00	31/12/2025	75	yes	20%	60.0%	10.0%	10.0%	10.0%	6.0%	96.0%	1
2	2nd Lowest Price in RFP	Supplier 3	$7.00	31/12/2025	75	Yes	20%	60.0%	10.0%	10.0%	10.0%	6.0%	96.0%	1
3	3rd Lowest Price in RFP	Supplier 1	$10.00	31/12/2025	90			60.0%	10.0%	10.0%	0.0%	0.0%	80.0%	3
4	4th Lowest Price in RFP	Supplier 4	$15.00	31/12/2025	90	yes	70%	54.0%	10.0%	10.0%	10.0%	8.0%	92.0%	2

Product 2 – Location 2

		Supplier	Price	Price Validity	Payment Terms	Consignment	CDP	Price Score	Validity Score	Payment Term Score	Consignment Score	CDP Score	Total Score	Rank
	Current Price	XYZ	$390.00											
1	Lowest Price in RFP	Supplier 1	$322.00	31/12/2025	90			42.0%	10.0%	10.0%	0.0%	0.0%	62.0%	2
2	2nd Lowest Price in RFP	Supplier 3	$388.00	31/12/2025	75	Yes	20%	6.0%	10.0%	10.0%	10.0%	6.0%	42.0%	4
3	3rd Lowest Price in RFP	Supplier 4	$389.00	31/12/2025	90	yes	70%	6.0%	10.0%	10.0%	10.0%	8.0%	44.0%	3
4	4th Lowest Price in RFP	Supplier 2	$420.00	31/12/2025	75	yes	20%	60.0%	10.0%	10.0%	10.0%	6.0%	96.0%	1

Figure 6. Sample evaluation tables obtained using the Python code

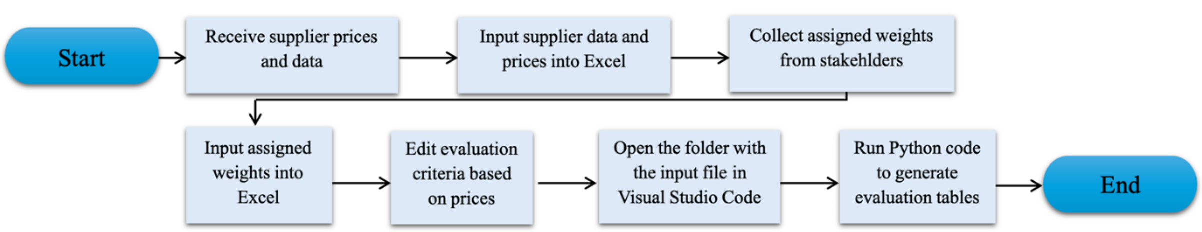

Figure 7. Python solution process map

Simple poka-yoke procedures were incorporated into the code to improve the Python solution (Figure 8). These included pre-checks for columns, including supplier names, the criteria, and location information that were either missing or mislabeled. Additionally, the code validated that every price entry was numeric. If any required input was missing or misconfigured, the code stopped execution and displayed a clear error message for the user to correct the input. The possibility of human error was decreased by these preventative measures, which made sure that table creation would only start when inputs met the requirements.

```
missing_criteria = [col for col in required_criteria_cols if col not in criteria_df.columns]
if missing_criteria:
    raise ValueError(f"Missing column(s) in Criteria sheet: {', '.join(missing_criteria)}")
missing_suppliers = [col for col in required_suppliers_cols if col not in suppliers_df.columns]
if missing_suppliers:
    raise ValueError(f"Missing column(s) in Suppliers sheet: {', '.join(missing_suppliers)}")
missing_pricing = [col for col in required_pricing_cols if col not in pricing_df.columns]
if missing_pricing:
    raise ValueError(f"Missing column(s) in Pricing sheet: {', '.join(missing_pricing)}")

supplier_names = [col for col in pricing_df.columns if col not in required_pricing_cols]
for col in supplier_names:
    if not pd.api.types.is_numeric_dtype(pricing_df[col]):
        raise ValueError(f"Supplier column '{col}' contains invalid or non-numeric price entries.")
```

Figure 8. Code used to validate the data before table creation

3.5 Control

In the Control phase, efforts were focused on sustaining the improvements achieved during the Improve phase and ensuring the long-term stability of the automated supplier evaluation process. A structured control plan was implemented using statistical tools, including Individuals-Moving Range (I-MR) control charts, to monitor stability and detect variation.

To monitor performance over time, I-MR charts were selected as the primary method for visualizing process stability. These charts allowed the team to detect shifts, trends, or unusual variations in table creation time that could indicate process deterioration. Additionally, process capability analysis (Cp and Cpk) was planned to evaluate how well the process outcomes remained within defined specification limits.In addition, the Six Sigma Level was calculated to evaluate long-term process capability, accounting for potential shifts or changes in performance over time. The outcomes of these control measures, including control charts, capability metrics, and the Sigma Level, are presented and discussed in detail in Section 5.2 (Graphical Results) and Section 5.4 (Validation).

4. Data Collection

The time data for 25 sourcing projects was collected to compare the manual and automated methods of creating evaluation tables. The same 25 projects were measured twice: first using the manual Excel method and then using the Python automation tool. For both methods, the timing began at the start of the table creation step, after all input data had already been prepared, as data entry was considered outside the scope of this study. For the automated method, timing started when Visual Studio Code was launched and stopped once the resulting Excel file was generated. Since the manual method required significantly more time, it was measured in hours, whereas the automated method was timed in seconds and later converted to hours to allow for direct comparison.

5. Results and Discussion

5.1 Numerical Results

After collecting the data for both methods, descriptive statistics in Table 3 were compiled to compare the manual and coding methods (both in hours).

The manual method had an average project time of 5.69 hours, with a median of 5.5 hours, indicating that most projects clustered around this mean. Its wide range, from 1.5 to 12.5 hours, highlights the inconsistency in project durations caused by manual and repetitive tasks. This is further supported by the high standard deviation of 2.92 hours, which reflects significant variability across projects.

In contrast, the coding method yielded a significantly lower average project time of 0.0128 hours (approximately 46 seconds), with a median of 0.0127 hours, nearly identical to the mean, demonstrating its consistency. Its tight range of 0.0116 to 0.0137 hours and low standard deviation of 0.0006 hours confirm minimal variation in results. Together, these findings illustrate that the coding solution addressed the core issues identified in the Analyze phase. It eliminated manual work, reduced overall project time, and introduced a more standardized and reliable evaluation process, marking a clear improvement.

Table 3. Descriptive statistics of coding vs. manual method

Statistic	Manual Method (hours)	Coding Method (hours)
Mean	5.6948	0.012836
Median	5.5	0.0127
Minimum	1.5	0.0116
Maximum	12.5	0.0137
Standard Deviation	2.921616448	0.000615684

To quantify the impact of time savings, labor cost reductions were estimated using the median annual wage of a sourcing specialist (AED 308k). Based on a 40-hour workweek, this equates to an hourly rate of AED 148.07. The manual method averaged 5.69 hours per project, while the automated solution required just 0.0128 hours, saving approximately 5.68 hours per project. This translates to a cost saving of AED 841.03 per project and a 99.77% reduction in time.

The numerical results highlight the value of automating the evaluation process. The significant reduction in time, from hours to seconds, not only lowered labor costs but also improved consistency, eliminated repetitive manual tasks, and allowed the focus to shift to more value-added activities. This outcome directly aligns with the project objective and supports the long-term scalability of the solution.

5.2 Graphical Results

Graphical tools were instrumental in visualizing the performance gap between the original manual process and the improved coding-based solution. Among these tools, Individual-Moving Range (I-MR) charts provided the most direct representation of process variability and improvement.

The I-MR control chart for the manual method (see Figure 9) revealed a high degree of variation in project times, with completion times ranging from 1.5 to 12.5 hours. Although most data points fall within the control limits, the wide spread and large moving ranges indicate inconsistent performance and a lack of stability. This reflects a process with high variation and unpredictable execution

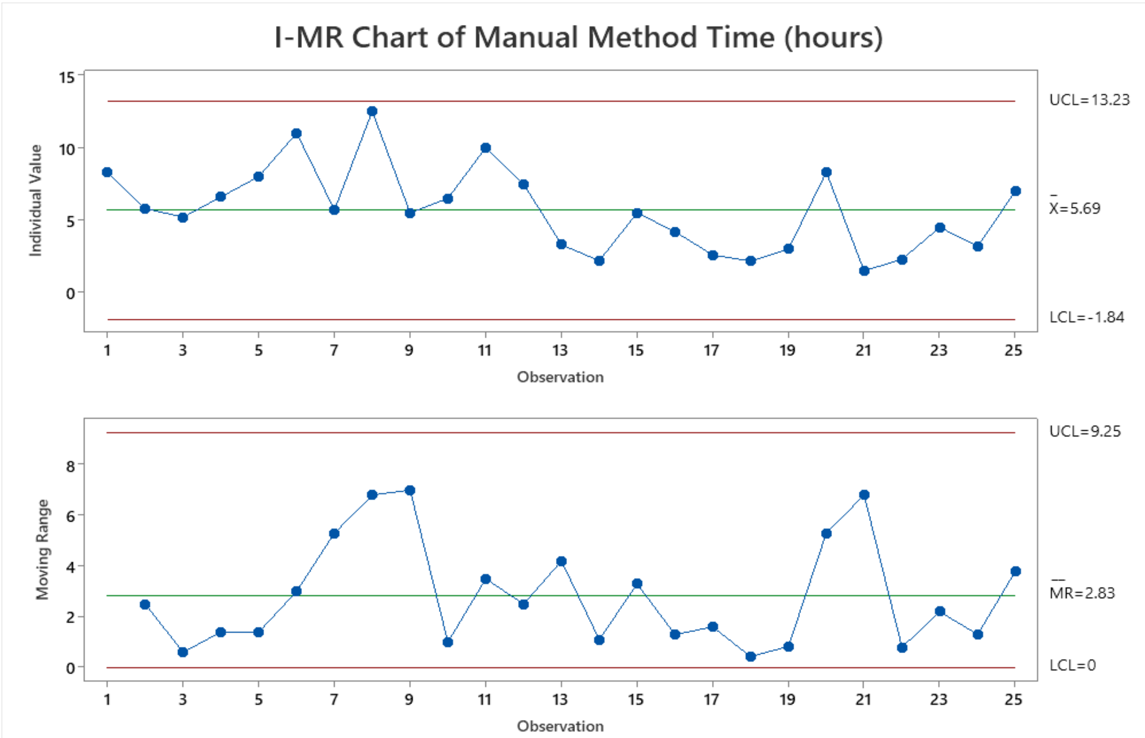

Figure 9. Individual and Moving Range (I-MR) Chart for Manual Method Time (hours)

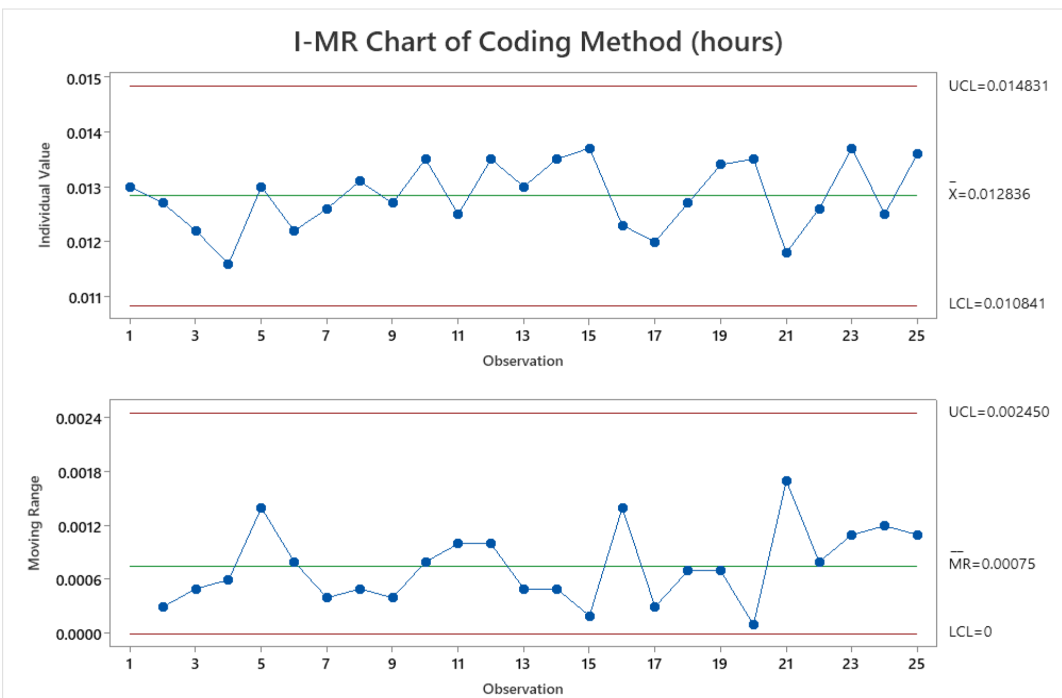

Figure 10. Individual and Moving Range (I-MR) Chart for Coding Method Time (hours)

In contrast, the coding method's I-MR chart (Figure 10) demonstrates a highly consistent and stable process. The individual times remain tightly clustered around the mean of approximately 0.0128 hours (or 46 seconds), with minimal variation in the moving range values. The completion times consistently fall well within the control limits, indicating that the new system is not only faster but also highly predictable.

These graphical comparisons strongly reinforce the effectiveness of the automated solution. The shift from a scattered, manually intensive process to a tightly controlled, automated one directly aligns with the project's goals of reducing average table creation time and enhancing process stability.

5.3 Proposed Improvements

The key improvement in this project was the development of a Python-based tool that automated supplier evaluation table creation. It resolved major inefficiencies in the manual method by standardizing formatting, scoring, and layout, cutting processing time from hours to under a minute, regardless of project size or complexity. One future enhancement could be developing a simple user interface so that team members without coding experience can run the tool without opening the code directly. This would improve and simplify daily operation. However, adding an interface could increase project costs and would require additional testing to ensure it works efficiently with changing input files. For these reasons, this improvement is noted as a potential next step but remains outside the scope of this project.

5.4 Validation

To confirm the effectiveness and long-term reliability of the improved supplier evaluation process, several validation tools were applied in alignment with Six Sigma methodology. These included process capability indices, Sigma Level analysis, and I-MR charts. As shown in Table 4, a process capability analysis was conducted to assess how consistently the automated process stayed within the defined specification limits of 40 to 60 seconds; this was supported by the I-MR chart, which showed no points outside the control limits and minimal variation across observations. The average completion time using the coding method was 46.21 seconds, with a standard deviation of 2.22 seconds. This resulted in a Cp value of 1.50, indicating the process spread was well within the range. The Cpk value was 0.93, meaning the process was capable, though slightly skewed toward the lower limit. Despite this, all values remained within the acceptable range, confirming the process's reliability (Hessing, 2023).

Table 4. Process capability and process capability index

Parameter	Value
Lower Specification Limit (LSL)	40.00
Upper Specification Limit (USL)	60.00
Average Completion Time	46.21
Standard Deviation	2.22
Process Capability (Cp)	1.50
Process Capability Index (Cpk)	0.93

To further support the validation of the improved process, a Sigma Level analysis was conducted using standard Six Sigma methodology. The first step was to compute the short-term Sigma Level, which reflects the process capability under stable, controlled conditions:

$$\text{Short-Term Sigma Level} = 3 \times \text{Cpk} = 3 \times 0.93 = 2.79$$

While this indicates how the process performs in the short run, Six Sigma methodology recognizes that real-world processes are subject to long-term shifts caused by various factors. To account for this, a standard shift is added:

$$\text{Long-Term Sigma Level} = 3 \times \text{Cpk} + 1.5 = 2.79 + 1.5 = 4.29$$

This improvement is clear when compared to the manual method, which showed high variability and frequent time overruns. In contrast, the automated method consistently met the < 60-second target with minimal deviation. Moving from a non-capable process to over 4 Sigma performance reflects the strength of properly applied Lean Six Sigma tools (Terek, 2023). A Sigma Level of 4.29 indicates the process can withstand day-to-day variation while delivering reliable, consistent, and defect-free output, making it well-suited for repeat use across projects.

5.5 Comparative Discussion and Applicability

The Python automation tool and DMAIC approach can also be utilized beyond chemical sourcing to support other teams and industries facing similar repetitive evaluation tasks. For example, logistics teams could use it to compare transport quotes across different routes and service levels. Facilities or admin teams could adapt it to rank service providers like maintenance or cleaning contracts. Even HR teams could use a version of this to score job applicants when there are many changing criteria. Because the scoring and ranking logic is flexible, the tool can be applied wherever evaluations need to be done accurately and consistently without manual rework.

When comparing this Lean Six Sigma-based approach to alternative frameworks, such as Robotic Process Automation (RPA), Business Process Management (BPM) platforms, or direct digital transformation strategies, it becomes clear why this method was chosen. RPA excels at automating repetitive tasks but lacks the analytical depth to improve flawed processes. It simply mimics existing actions, which may reinforce inefficiencies rather than eliminate them. BPM platforms, while useful for mapping and managing workflows at scale, often require significant investment, technical expertise, and long implementation timelines. Moreover, BPM tools rarely include statistical validation methods, making it difficult to measure or control variation in output quality.

In contrast, the DMAIC-Python approach offers a more focused and flexible alternative. It begins with understanding the process, identifying root causes, and applying statistical tools to validate improvements, ensuring that automation is applied only after the process is optimized. Python enables customization and fast deployment without the licensing or infrastructure demands of larger platforms. The integration of poka-yoke features, validation logic, and performance tracking ensures both efficiency and reliability. Unlike other tools that prioritize speed or scale alone, this method balances automation with continuous improvement.

Ultimately, the choice of DMAIC with Python allowed for measurable gains, low cost, and scalability across teams and functions. By combining structured problem-solving with lightweight automation, this approach not only streamlines work but sustains improvements, making it academically rigorous and practically effective.

6. Conclusion and Future Recommendations

This study successfully applied the Lean Six Sigma DMAIC methodology to eliminate inefficiencies in the supplier evaluation table creation process. By systematically identifying root causes, measuring process variability, and implementing a fully automated coding solution, the team achieved significant improvements in both speed and reliability. All project objectives were fully met. The average table creation time was reduced from 5.69 hours to approximately 46 seconds, representing a 99.77% time reduction. Over 90% of the manual steps, including scoring, ranking, and formatting, were automated. The improved process demonstrated high consistency, with minimal variation, as confirmed by I-MR charts. Process capability indices ($C_p = 1.50$, $C_{pk} = 0.93$) and a long-term Sigma Level of 4.29 validated that the solution was statistically capable, stable, and aligned with the defined specification limits. Beyond technical metrics, the improvement also enhanced operational scalability, reduced employee workload, and generated measurable cost savings per project. These results reflect a successful integration of Lean Six Sigma principles into a real-world administrative process, delivering both quantitative and qualitative value.

Although the main goals were achieved, a few improvements could further strengthen the solution for future use. One option is to develop a simple user interface so that team members without coding experience can run the tool without opening the Python script directly. This would improve and simplify daily operation. However, adding an interface could increase project costs and would require additional testing to ensure it works efficiently with changing input files. Automating the final report output could also help maintain result consistency and save additional time. These steps would support ongoing digital improvements and help keep the process practical and scalable as the team's needs grow.

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Biographies

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Joud Abuobid is currently a senior Industrial Engineering student at RIT Dubai. Her academic interests include Lean Six Sigma methodologies, process optimization, project management, and quality improvement. Joud has actively contributed to several practical projects involving data-driven process enhancement and formula car design. Joud gained hands-on experience in project management during her time with Schneider Electric and worked as a Quality Intern in the manufacturing sector at Emerson. In her recent project on automating supplier evaluation tables, Joud played a key role in applying statistical analysis and data validation to ensure process accuracy and effectiveness.

Dr. Muhammad Imran is an Assistant Professor of Industrial Engineering in the Department of Mechanical and Industrial Engineering at RIT Dubai. He earned his Ph.D. in Digital Manufacturing from Loughborough University, UK, where his research focused on manufacturing system modeling. He also holds a Master's degree in Advanced Manufacturing Engineering and Management from the same university. With over 12 years of experience in higher education, Dr. Imran has contributed to curriculum development, accreditation, and the instruction of a wide range of undergraduate and graduate courses. His teaching and research interests include digital manufacturing, digital twin technologies, process improvement, Lean Six Sigma, sustainability, and human factors engineering. At RIT Dubai, he actively supervises student projects that apply industrial engineering tools to real-world challenges.