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Leveraging generative artificial intelligence in the FMCG sector for rising maintenance costs

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Abstract

The escalating maintenance expenses in the South African Fast-Moving Consumer Goods (FMCG) industry pose a serious challenge, affecting businesses universally. Numerous studies have aimed to create a framework for evaluating the business effects caused by increasing maintenance costs, aiding in more sustainable decision-making. This study builds upon existing frameworks. The methodological strategies employed include bibliometric analysis, questionnaires, the Analytic Hierarchy Process (AHP), and Generative Artificial Intelligence (GAI). Bibliometric analysis allows for a review of academic literature related to this study. Questionnaires are utilized to pinpoint critical criteria for maintenance costs. AHP facilitates a structured assessment and prioritization of these identified criteria. The GAI method offers initial simulation tests to showcase the real-world application of the decision-support framework and its significance for sustainability. The findings indicate the feasibility of replicating a decision-making framework that incorporates crucial maintenance cost criteria for evaluating scenario impacts, thereby simplifying the process of making more sustainable choices. Managers in FMCG operations can refer to the relevant practical insights derived from this study to explore potential alternatives and take action in line with their existing cost operational guidelines.

Keywords: Analytic Hierarchy Process; Decision-Making; Fast-Moving Consumer Goods; Generative Artificial Intelligence; Maintenance Cost; Sustainability

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1. Introduction

Increasing maintenance expenses represent a major hurdle within the Fast-Moving Consumer Goods (FMCG) sector, arising from fierce competition, revenue pressures, and the ongoing requirement for brand development and growth (Ogah, 2024). These expenses are directly influenced by the operational demands within the sector (Khan et al., 2025). To effectively address escalating maintenance costs in the FMCG arena, a comprehensive strategy that incorporates technology, data analysis, and thoughtful planning is essential (GhanavatiNejad et al., 2025). This strategy should involve the deployment of predictive maintenance systems, the optimization of inventory management, and the promotion of collaboration throughout the supply chain.

To manage and mitigate the increasing maintenance costs in the FMCG field, decision-makers ought to utilize sophisticated tools that harness data analytics, automation, and predictive maintenance (Kumar et al., 2024). These instruments can assist in pinpointing cost contributors, refining maintenance schedules, and forecasting potential equipment failures, resulting in substantial cost reductions. A review of various publications calls for further inquiry into evaluating the effectiveness of these advanced tools. To illustrate this, we can examine several studies demonstrating the importance of advanced tools in managing and lowering rising maintenance costs.

Moreira (2025) has investigated the digital surveillance of heavy machinery to improve cost efficiency and operational performance. The authors undertake a systematic review of existing literature, affirming that the integration of technologies such as the Internet of Things (IoT), advanced sensors, Artificial Intelligence (AI), and Big Data facilitates proactive machine management, which allows for real-time monitoring, early failure detection, and the implementation of predictive maintenance strategies. These innovations lead to significant cuts in downtime, reduce emergency repair expenses, and prolong the lifespan of machinery. The findings affirm that the monitoring of heavy equipment through advanced tools has emerged as a vital strategy for cost efficiency and boosting operational performance in sectors like mining, construction, and infrastructure. The authors recommend future studies to delve deeper into the role of digital technologies in monitoring heavy machinery as a significant breakthrough that provides a clear trajectory facilitating sustainable practices and operational efficiency.

Ankush Keskar (2025) in another body of work tackles rising maintenance expenses by promoting the adoption of Digital Twin technology, which facilitates predictive maintenance via real-time monitoring and data assessment. By transitioning from reactive and time-based maintenance approaches to proactive tactics grounded in analytical insights, organizations can reduce breakdowns and maximize resource utilization. Furthermore, executing pilot programs for crucial assets can demonstrate returns on investment, aiding in securing financing for wider applications and effectively managing costs. The author suggests that future investigations should concentrate on leveraging advanced tools like Digital Twins to enhance predictive maintenance capabilities, thus limiting the growth of maintenance expenses. This encompasses integrating AI and machine learning for real-time data evaluation to detect potential failures in advance, enabling prompt interventions. Additionally, the author proposes the development of interconnected Digital Twins across ecosystems to optimize resource distribution and enhance operational performance, ultimately curtailing unnecessary maintenance costs.

According to Hendradewa and Yin (2025), a focus is directed on addressing rising maintenance costs through the use of advanced tools such as Reinforcement Learning (RL) and Machine Learning (ML) algorithms to refine maintenance strategies. These tools improve decision-making by forecasting the remaining useful life, identifying anomalies, and selecting subsystems, ultimately leading to fewer unnecessary interventions and more effective maintenance schedules. By harmonizing economic gains with environmental factors, the study seeks to reduce maintenance costs while ensuring high system availability. The authors recommend that future research explore the application of advanced tools like Reinforcement Learning (RL) to further enhance maintenance strategies by tackling the unpredictable nature of maintenance requirements. This includes the development of models considering a range of criteria, such as carbon emissions, resource availability, and economic elements, to enable adaptive maintenance decision-making. The objective is to enhance operational efficiency while reducing maintenance expenses and environmental effects, thus offering a sustainable response to increasing maintenance costs.

Ultimately, the primary intention of the authors in reviewing selected publications is to underscore the necessity for additional research on the application of advanced tools to efficiently manage and lower escalating maintenance costs. This study builds on existing literature by employing an Analytic Hierarchy Process (AHP) and Generative Artificial Intelligence (GAI) perspective for its development. This requires identifying both a research gap and a fundamental aim in this study. The gap pertains to comparing and emphasizing the advantages of the AHP-GAI methodology. This is aimed at creating decision-making frameworks to evaluate business impacts arising from the implications of increasing costs and to facilitate more sustainable choices. In light of the defined study gap, the following objectives emerge from the previously mentioned developments.

- RO1: Conduct a bibliometric review to explore academic literature related to the utilization of advanced tools in assessing business impacts due to rising maintenance costs.
- RO2: Determine key maintenance cost criteria that are relevant for evaluating business impacts within the FMCG sector.
- RO3: Execute a systematic assessment and prioritization of the recognized criteria.
- RO4: Perform pilot tests to verify the applicability of the developed decision-support framework in practical settings.
- RO5: Analyze the implications and significance of the established framework for the sustainability of the FMCG industry.

The outlined objectives aim to illustrate the potential to replicate a decision-making framework that integrates vital maintenance cost criteria for the evaluation of scenario impacts, thus facilitating the process of making more sustainable choices.

2. Literature review

2.1. Generative Artificial Intelligence (GAI)

Advanced decision-making tools utilize data, analytical methods, and in certain cases, AI to make better-informed choices (Aad and Hardey, 2025a). These tools typically include approaches such as cost-benefit analysis, decision matrices, SWOT analysis, decision trees, and data visualization techniques. They assist in dissecting intricate problems, assessing alternatives, and formulating more strategic decisions. Generative Artificial Intelligence (GAI) can serve as a valuable asset for decision-making, especially in environments that are complex and rich in data (Kovač, 2024). GAI tools can scrutinize extensive datasets, uncover trends, and deliver recommendations based on evidence, thus facilitating more timely and informed decisions (Aad and

Hardey, 2025b). Nevertheless, it is essential to acknowledge that GAI is intended to enhance human judgment rather than replace it and necessitates thoughtful integration alongside human oversight. This study employs a GAI tool within the FMCG sector to improve decision-making relating to Rising Maintenance Costs.

GAI encompasses a range of AI algorithms and models that are crafted to produce new and original content similar to examples found in a training dataset (Jackson et al., 2024). Prominent examples of GAI tools include DeepMind's Alpha Code (GoogleLab), LangGraph studio, Dall-E, MidJourney, and Jasper. The literature Kovač (2024) provides extensive examples of GAI tools along with their relevant applications for further exploration. Various industrial implementations of the GAI framework have been documented in fields such as medicine, automotive, manufacturing, textiles, law, aerospace, marketing, customer relations, and logistics.

2.2. Maintenance cost criteria

Maintenance expenses include all costs associated with keeping physical assets functioning optimally, covering both direct and indirect expenditures tied to maintenance, repairs, and replacements (Shamim, 2025). These expenses are vital for preserving operational efficiency, ensuring safety, and prolonging the lifespan of assets (Titilope Tosin Adewale et al., 2024). Criteria for maintenance costs are a key aspect of the decision-making process. These criteria assist businesses in optimizing maintenance approaches, reducing expenses, and guaranteeing the reliability and availability of assets (Vasić et al., 2024). This study identifies key maintenance cost criteria relevant to evaluating business impacts within the FMCG sector. This is essential for enabling informed decisions that reconcile financial factors with operational requirements in the FMCG industry.

2.3. Analytic Hierarchy Process (AHP)

AHP facilitates decisions related to sustainability by offering a systematic, multi-criteria decision-making framework that assists in prioritizing and assessing intricate sustainability challenges (Muller et al., 2025). It allows decision-makers to dismantle sustainability issues into smaller, hierarchical elements, assess their relative significance, and then integrate this information to make well-informed decisions (Singh and Kumar, 2024). It is effective in prioritizing criteria and analyzing options through pairwise comparisons, proving beneficial for collective decision-making across various domains (Nennioğlu et al., 2024). This study performs a thorough assessment and ranking of the specified maintenance cost criteria.

2.4. Decision-making in FMCG industry

The fast-moving consumable goods refer to items that are commonly purchased, relatively low-cost, and typically have a short lifespan. Common examples include food products, beverages, personal hygiene items, and cleaning supplies (Uloma Stella Nwabekee et al., 2024). This study focuses on the FMCG sector in South Africa as a case study. The FMCG industry in South Africa plays a crucial role in the economy, boasting an estimated market value of R593 billion in yearly sales. Although the sector is experiencing expansion, it also faces challenges such as pressure on consumer spending and rising inflation (Moloko and Toendepi, 2025). Current trends show a shift among consumers towards value brands, an increased emphasis on online shopping, and a growing focus on sales to informal retailers. This study utilizes a GAI tool to conduct pilot tests and illustrate the effectiveness of the proposed decision-support framework in practice to advance sustainability-oriented decisions within the FMCG sector.

3. Methodology

The various mixed-method approaches depicted in the diagram are shown in Figure 1.

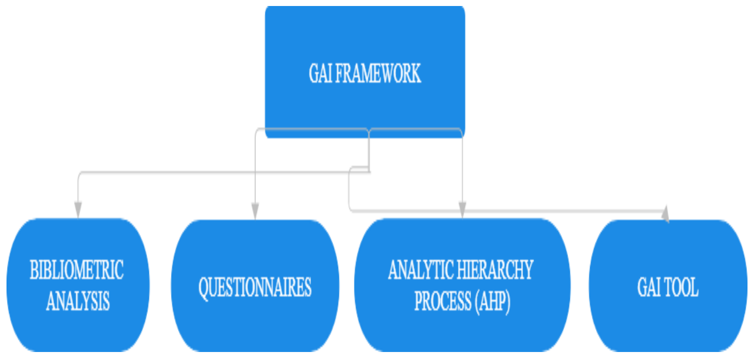

Figure 1. Mixed-method approaches

The subsequent sub-themes demonstrate how the various components of the diagram are interconnected and support the overall study objective.

3.1. Bibliometric analysis

Bibliometric analysis allows for the exploration of academic literature pertinent to this study. The themes identified through this method are represented in Figure 2.

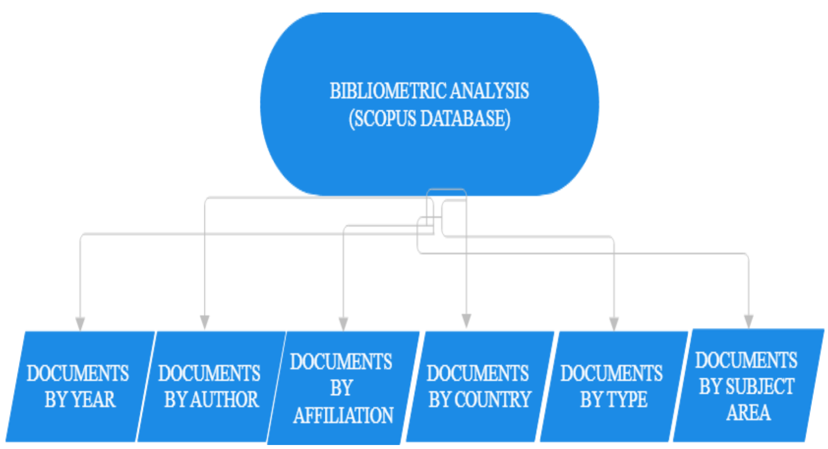

Figure 2. Bibliometric analysis themes

The bibliometric analysis is performed using the Scopus database, which is accessible through the University of South Africa (UNISA) library. This database is a well-recognized international resource for abstracts and citations, containing only peer-reviewed scholarly works. The search is carried out in two stages to allow for comparison. The first stage utilizes a keyword search focused solely on documents containing GAI.

The refined keywords chosen include: "Generative AI*"; "generative* ai*"; "Generative Artificial Intelligence*"; "generative Artificial Intelligence*"; "Generative A.I*"; "generative* a.i*". The second stage involves a keyword search that combines GAI with manufacturing. The term manufacturing is selected since the FMCG sector qualifies as a manufacturing industry, as it entails the production of goods that are rapidly produced and sold at low prices. FMCG companies are involved in creating a wide range of consumer products, such as food and beverages, personal care items, and household cleaning products. The refined keywords for this phase are: "Generative AI*" AND “Manufacturing*” OR “manufacturing*”; "generative* ai*" AND “Manufacturing*” OR “manufacturing*”; "Generative Artificial Intelligence*" AND “Manufacturing*” OR “manufacturing*”; "generative Artificial Intelligence*" AND “Manufacturing*” OR “manufacturing*”; "Generative A.I*" AND “Manufacturing*” OR “manufacturing*”; "generative* a.i*" AND “Manufacturing*” OR “manufacturing*”. The asterisks (*) are employed to ensure that the search captures variations of the phrases. The outcomes of the Scopus search are evaluated according to six categories: “Documents by Year; Documents by Author; Documents by Affiliation; Documents by Country; Documents by Type; and Documents by Subject Area.

3.2. Questionnaire

Questionnaires are utilized to determine critical criteria for maintenance costs. The established criteria function as agents and provide qualitative information for the proposed GAI framework.

- The target audience comprises experienced professionals from the maintenance division in the FMCG sector, which serves as a case study.
- The development of the questionnaire is grounded in the selection of maintenance strategies, decision-making processes, and sustainability considerations.
- The questions are formulated based on a combination of Likert scale items which are both closed-ended and open-ended questions using a Microsoft form.
- Open-ended questions are analyzed through content analysis to identify themes and patterns.
- The reviews of the questionnaires include computational analysis, demographic information, and cross-tabulation.
- Cronbach’s alpha is a statistical metric used to evaluate the internal consistency or reliability of a questionnaire or survey instrument. The reliability of the responses is assessed through Cronbach’s alpha in Microsoft Excel.

3.3. Analytic Hierarchy Process (AHP)

The AHP (Analytic Hierarchy Process) systematically assesses and ranks the identified criteria. This step in AHP provides quantitative information (numerical values for each criterion) for the proposed GAI (Generalized Artificial Intelligence) framework. The AHP method allows the framework to make multiple decisions based on the evaluation and prioritization of criteria. It establishes a hierarchy of criteria in relation to the context. The AHP methodology, which is part of a mixed-method approach, is utilized to delineate a hierarchy of the identified criteria through pairwise comparisons. The authors present a summarized five-step overview of the AHP process, which includes:

- Organizing the hierarchy
- Conducting pairwise comparisons to assess the mean differences between pairs of criteria that are statistically significant.

- Determining criterion weights to ascertain the contribution of each criterion to the overall decision-making process.
- Assessing alternatives to evaluate the relative significance of the criteria identified in the previous step.
- Calculating the consistency ratio, which integrates weights and scores to rank the alternatives. The consistency ratio is crucial for evaluating the reliability and precision of the pairwise comparisons.

3.4. Generative Artificial Intelligence (GAI)

The GAI methodology offers pilot tests to showcase the applicability of the decision-support framework in practical scenarios and its significance for sustainability. GAI stands for computational methods capable of creating seemingly innovative or meaningful content derived from training data (Liu, 2025). The foundational principles of GAI are currently reshaping education and business operational procedures (Koroleva and Jogezai, 2025). This encompasses supporting individuals in making decisions more easily, such as through intelligent question-answering systems. Leong et al. (2025) present a concise workflow for creating the GAI framework.

- Defining the problem, objectives, and business justification
- Formulating a solution method for the identified issue
- Creating a deployment strategy that incorporates the AI component into current workflows
- Establishing and executing a continuous evaluation system

The actions outlined in the aforementioned subthemes validate the operationalization of the suggested GAI framework and illustrate how this integration impacts the sustainability of the decision-making process in the FMCG sector, which is utilized as a case study. A bibliometric analysis investigates relevant scholarly literature associated with this study. Surveys help identify crucial maintenance cost criteria. The prioritized maintenance cost criteria and their corresponding numeric values derived from the AHP methodology are utilized as inputs for the proposed GAI framework and are modeled to support a data-to-decision scenario. The authors employ the LangGraph workflow and Stream-lit user interface to construct the GAI framework, aiming for outcomes such as maintenance cost reductions.

4. Results

4.1. Literature scan

The outcomes of the Scopus search are examined according to six categories: "Documents by Year; Documents by Author; Documents by Affiliation; Documents by Country; Documents by Type; and Documents by Subject Area." In the initial phase, a total of 6,553 document results were obtained, while the second phase yielded 75 documents. The results of the analysis are emphasized based on the established themes outlined below.

4.1.1. Documents by year

Figure 3 illustrates the findings from both phases. Phase one shows that discussions on GAI began around 2008, but there was only a notable rise in publications starting in 2022. In contrast, phase two, which integrates GAI and manufacturing, had its publications start in 2023 with 16 documents, and for 2024, 59 documents have already been released. A substantial gap remains in the utilization of GAI within a manufacturing setting, as demonstrated by the significant difference in results between phase one (6,553 documents) and phase two (75 documents).

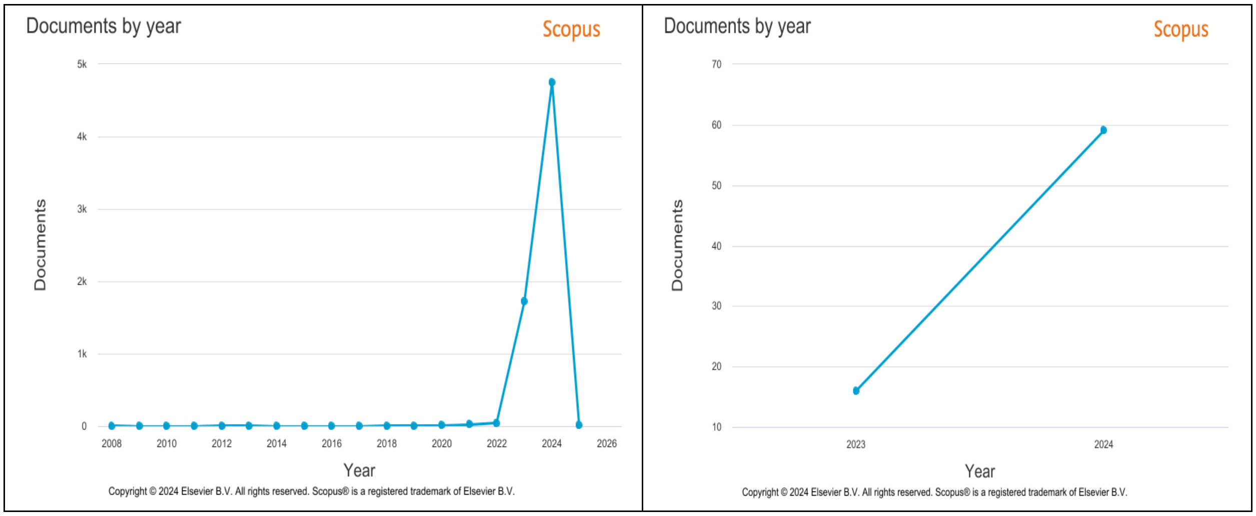

Figure 3. Documents by year phase one and phase two

4.1.2. Documents by author

Figure 4 illustrates the results from the first and second phases. A comparison between these two search phases reveals that the ten leading authors in the GAI field have not published any works connecting GAI with manufacturing.

Figure 4. Documents by author phase one and two

4.1.3. Documents by affiliation

Figure 5 displays the results from both phase one and phase two. An analysis of the two search phases reveals that the top ten most notable affiliations in the GAI field have not published any works that connect GAI with manufacturing.

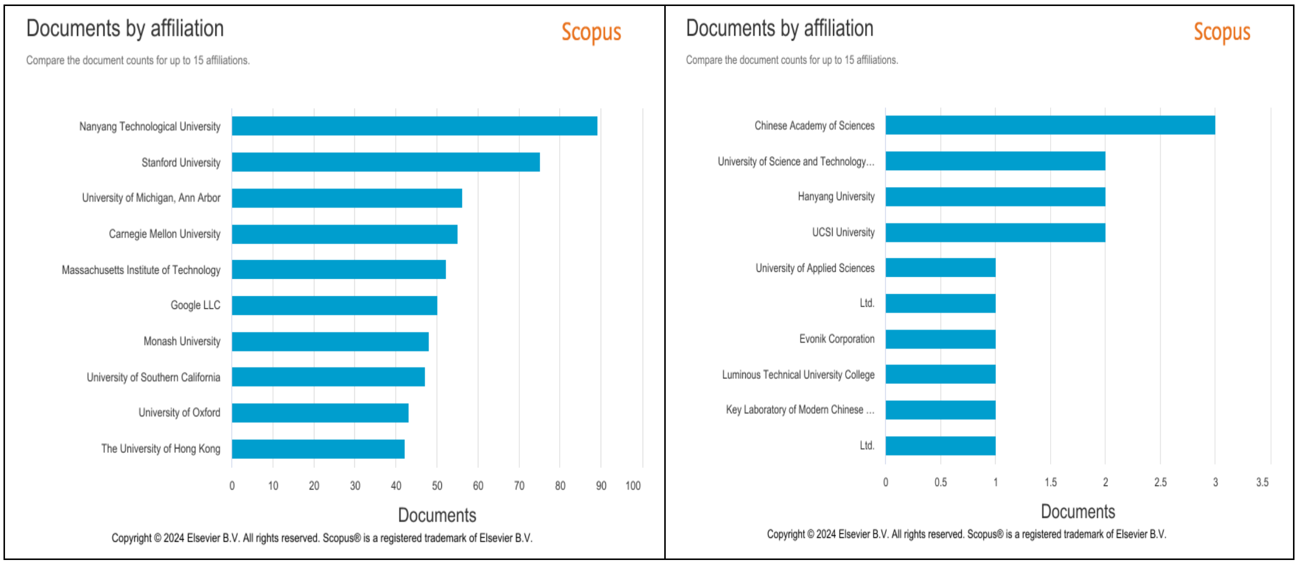

Figure 5. Documents by affiliation phase one and phase two

4.1.4. Documents by country

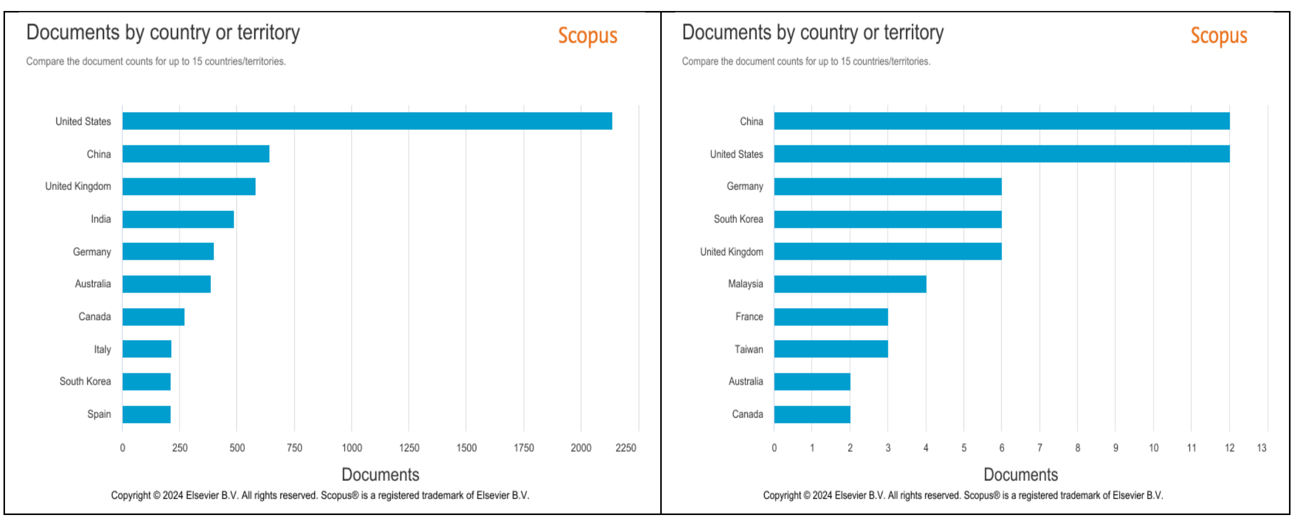

Figure 6. Documents by country phase one and phase two

Figure 6 illustrates the results from both phase one and phase two. A comparison between the two search phases reveals the ten most significant documents by country. The United States leads in the number of published documents on current discussions regarding GAI, closely followed by China, the United Kingdom, Germany, India, and South Korea. The countries present in both search phases are largely consistent, with the exception of three. In phase one, "India, Italy, and Spain" are prominent, while in phase two, they are replaced by Malaysia, Taiwan, and France. The analysis also shows that no African country is included among the ten most prominent authors in this field.

4.1.5. Documents by type

Figure 7 summarizes the results from both phase one and phase two. When comparing the two search phases, it is evident that most publications were contributed by authors in the form of Research Articles. This is closely followed by contributions from conference papers and review articles.

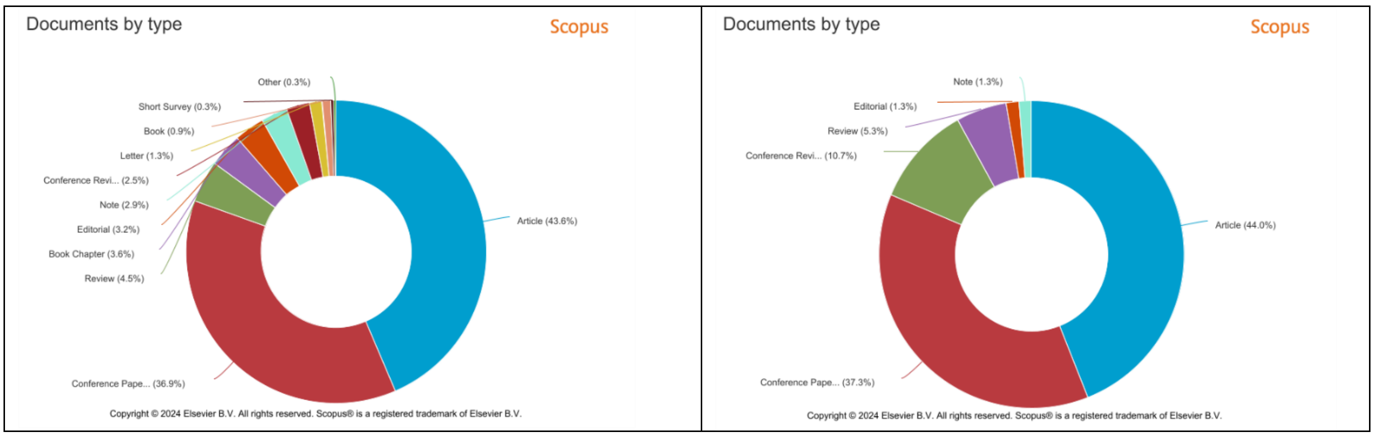

Figure 7. Documents by type phase one and phase two

4.1.6. Documents by subject area

Figure 8 illustrates the results from both phase one and phase two. An examination of the two search phases shows that the predominant areas of study for authors are primarily in computer science and engineering, closely followed by social and material sciences.

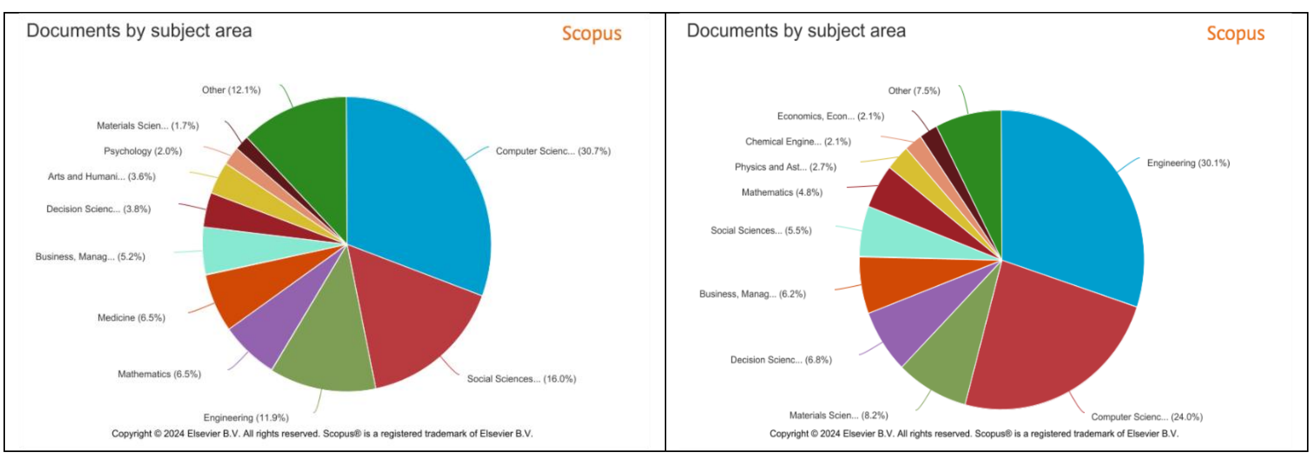

Figure 8. Documents by subject area phase one and phase two

4.2. Questionnaire insights

- A total of 40 skilled professionals from the maintenance unit are selected, and questionnaires are distributed. However, only 29 of these questionnaires were completed, resulting in a response rate of approximately 70%, which is deemed suitable for analysis according to the literature (Kazzazi et al., 2018).
- A Cronbach's alpha value of 0.72 was found, indicating good internal consistency as confirmed by the literature (Vann Yaroson et al., 2024).

The feedback obtained from the analyzed questionnaires is shown in Table 1.

Table 1. Feedback from the questionnaires

Questionnaire constructs	Review
Working experience	38% of those surveyed had between 0 and 2 years of experience in the workforce, 24% had between 3 and 5 years, 21% possessed between 6 and 10 years, and 17% had more than 11 years of work experience.
Maintenance frameworks	14% of those surveyed expressed uncertainty in their answers, indicating that certain businesses might not have clearly or consistently selected their maintenance frameworks. Various factors, including the implementation of maintenance tasks using different methods, a gap in knowledge, or differing organizational practices, are identified as the reasons for this uncertainty among 14% of the respondents.
Formal training	59% of the participants who identified Reliability Centered Maintenance (RCM) as the framework used also belong to the 62% majority that confirmed they have received formal training. This reinforces the validity of the responses obtained for analysis. 42% of the participants think that training is offered solely when new equipment is introduced.
Equipment failure	A total of 55% of participants highlighted several reasons for equipment failures, primarily linked to wear and tear as well as insufficient maintenance. This combination of factors indicates the importance of implementing both proactive (preventive and predictive) and reactive (corrective) maintenance strategies. The explanations for equipment malfunctions or failures shared in the responses reflect the complex nature of challenges associated with equipment reliability.
Skills development	75% of the participants indicate a moderate relationship between skills development and training. The difference between training that occurs solely when new equipment is introduced, and regular training sessions highlights a disparity in the organization's strategy. The former method is reactive and addresses immediate requirements, whereas the latter approach is proactive, focusing on ongoing improvement and skill enhancement. The training strategy can affect the choice of maintenance methods. The absence of a formal training program may suggest a budget-conscious mindset. However, it's crucial to take into account, the potential consequences of insufficient training on maintenance efficiency and equipment reliability, which could influence maintenance expenses.

An analysis of the questionnaire outcomes reveals four criteria for maintenance costs: safety, RCM, skills and training, and budget management. These four maintenance cost criteria are incorporated into an AHP model to perform a structured assessment and prioritization of the specified criteria.

4.3. Analytical Hierarchy Process (AHP)

The pairwise distribution, which is an element of the AHP methodology, evaluates the extent to which each specified criterion impacts maintenance costs relative to other criteria. Numerical values are allocated based on a scale ranging from 1 to 9, where 1 represents equal significance and 9 denotes extremely strong significance. The findings derived from the AHP method are elaborated.

4.3.1. Safety

Became an essential aspect in the investigation, indicating the significant impact of safety-related practices and measures on maintenance expenses. Safety surfaced as a critical issue, highlighting the necessity of fostering a secure work environment to reduce risks and accidents.

4.3.2. RCM

The evaluation highlights the anticipatory aspects of RCM methods aimed at improving equipment dependability. Utilizing data-driven RCM guarantees that maintenance occurs exactly when necessary, boosting equipment reliability. This strategy prioritizes predictive and condition-based maintenance, tackling problems before they lead to serious failures.

4.3.3. Skills and training

Individuals who indicated that they have undergone formal training in maintenance management demonstrated a correlation with enhanced efficiency. This factor highlights the importance of having a skilled workforce to lower maintenance expenses. Increasing the emphasis on skills and training during the decision-making process is a strategic approach to develop a more capable and adept maintenance workforce. Competent maintenance staff have a more comprehensive understanding of equipment, which leads to more precise fault identification. Accurate fault detection is crucial for minimizing downtime, ensuring that the correct problems are resolved, and that spare parts are used effectively. The enhancement of skills and training directly results in a more effective implementation of maintenance tasks. Well-trained staff are more prepared to identify and resolve issues, thereby decreasing the time required for repairs.

4.3.4. Budget management

Effective management of the budget is emphasized as crucial for managing maintenance costs. The ongoing rise in the maintenance budget, along with actual spending exceeding the budget, underscores the necessity of cost control and optimal budget allocation. Feedback from the survey highlighted the financial aspects related to maintenance.

Following the AHP steps detailed in the Methodology section, the pairwise comparison matrix is presented in Table 2.

Table 2. Pairwise comparison matrix

Criteria	Safety	RCM	Skills & training	Budget management
Safety	1	5	4	7
RCM	0.2	1	0.5	3
Skills & training	0.25	2	1	3
Budget management	0.14	0.33	0.33	1
Sum	1.59	8.33	5.83	14

The normalized pairwise comparison matrix is captured in Table 3.

Table 3. Normalised pairwise comparison matrix

Criteria	Safety	RCM	Skills & training	Budget management	Criteria weights
Safety	0.629	0.600	0.686	0.500	0.604
RCM	0.126	0.120	0.086	0.214	0.137
Skills & training	0.157	0.240	0.172	0.214	0.196
Budget management	0.090	0.040	0.057	0.071	0.065

The weighted sum value is captured in Table 4.

Table 4. Weighted sum value

Criteria	Weighted sum value	Criteria weights	Ratio
Safety	2.522	0.604	4.176
RCM	0.549	0.137	4.023
Skills & training	0.814	0.196	4.155
Budget management	0.262	0.065	4.049

The verification of consistency and the determination of criteria weights are performed, leading to a structured hierarchy of the established criteria. This process begins with the assessment of the consistency index, which yields a value of 0.034. Next, the consistency ratio is computed, resulting in a value of 0.037. A consistency ratio of 0.037 indicates that the pairwise comparisons are reasonably consistent. According to the hierarchical analysis from AHP, the proposed hierarchy of the chosen maintenance cost criteria is presented in Table 5.

Table 5. Recommended hierarchy of selected maintenance cost criteria

Criteria	Weights
Safety	0.604
Reliability centered maintenance	0.196
Skills & training	0.137
Budget management	0.065

The prioritized maintenance cost criteria and their corresponding numeric values derived from the AHP method act as inputs for the suggested GAI framework and are modeled to support a data-to-decisions context.

4.4. GAI simulation outputs

The authors utilize the LangGraph workflow along with the Stream-lit user interface to establish the GAI framework, aiming to achieve savings in maintenance costs as a result. LangGraph is incorporated as a Python package that enables users to define, synchronize, and implement various Large Language Models (LLMs). In the current study, the examples of GAI model development calculate cost savings (output) based on the identified criteria of increasing maintenance costs along with their corresponding numeric values (inputs). The steps involved in developing the GAI model are illustrated in Figure 9.

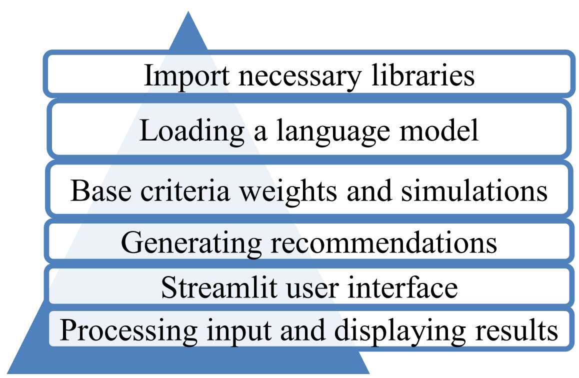

Figure 9: GAI model development steps

The subsequent information outlines how the various components in the GAI model development stages are interconnected and support the overall study objective.

4.4.1. Import necessary libraries

This step installs the necessary libraries within the virtual environment to support the workflow. Stream-lit is employed to create an interactive web interface. Torch is used for performing numerical operations and tensor calculations. The Transformers library offers pre-trained models for generating recommendations. Additional imported packages that aid in building the decision-making workflow and ensure data validation and structure through models include Pandas, Numpy, Matplotlib, Seaborn, Scipy, and the transformer library. A page configuration is performed on the Stream-lit user interface. This adjustment sets the Stream-lit page to a wide layout, optimizing the use of screen space. Inline CSS is incorporated to enhance the appearance of the Stream-lit app by minimizing padding and margins, resulting in a more compact layout.

4.4.2. Loading a language model

This function utilizes transformers to load a pre-trained Flan-T5 language model. It employs st.cache_resource to cache the model, preventing the need to reload it during each interaction. The tokenization also takes place in this section by initializing both the tokenizer and the model. Depending on the selected simulation analysis method employed, it receives the method (either WSA or Variation Minimization) as input. With the generated result, it formulates a prompt that requests the Flan-T5 model to produce a recommendation based on the analysis findings. It utilizes the `tokenizer` to transform the prompt into tokens and calls the model.generate() function to retrieve the language model's response. Finally, it refines the output text to ensure it is properly formatted and coherent.

4.4.3. Base criteria weights and simulations

This dictionary establishes the default weights for the criteria (safety, reliability, skills, cost) as determined by AHP. It also produces multiple weight combinations by iterating and modifying the weights by ±0.01 within various criterion groups. Finally, it constructs a Pandas Data Frame that encapsulates the simulations, including details on the adjusted weights and additional attributes.

4.4.4. Generating recommendations

This function identifies the best solution by considering both the overall weight sum and the variation. It organizes the analysis data that will be utilized for generating the recommendation. The visualization functions create various charts with Matplot-lib and Seaborn to display the data, such as a histogram representing the distribution of total weight, a radar chart illustrating criteria weights, violin plots categorized by case type, and an exploded pie chart showing the distribution of case types.

4.4.5. Stream-lit user interface

The primary function creates the user interface, featuring a title and an introductory description. The sidebar collects user inputs for the base weights and optimization method, along with a button to initiate the simulation. When the button is clicked, the simulation data is produced (accompanied by a loading spinner) and shown as a data frame. Charts are then presented in a two-column layout to illustrate the simulation results. Ultimately, the application evaluates the optimal configuration based on the selected method and showcases, a professional recommendation generated by the language model.

4.4.6. Processing input and displaying results

The gathered inputs are analyzed to illustrate and examine the structure, patterns, color variations, and deviations, as well as the similarities and differences present in the inherent properties of the data being studied. A graphical depiction is created from a sample of 80 distinct alterations drawn from a total of 240 potential alterations obtained through the fuzzy simulation of the four identified criteria, each assigned specific numeric weights. Out of the various graphing styles available in the Python framework, three graphical representations are selected. Figure 10 displays a histogram accompanied by a normal curve.

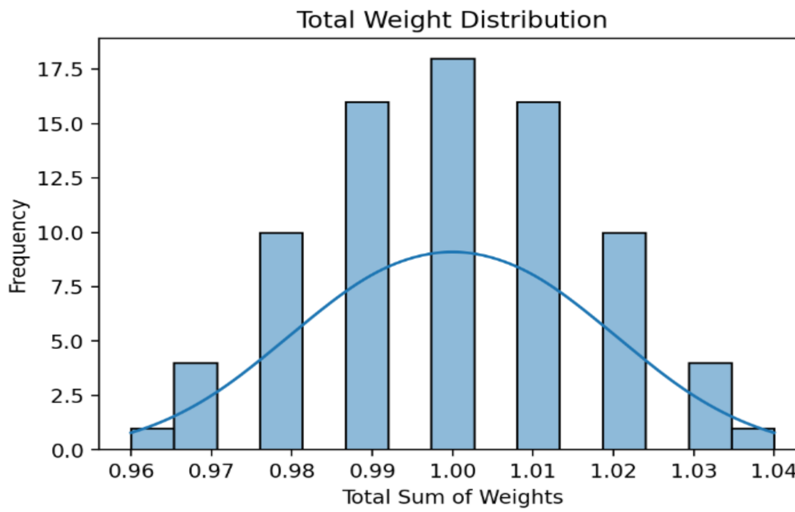

Figure 10. Histogram with normal curve

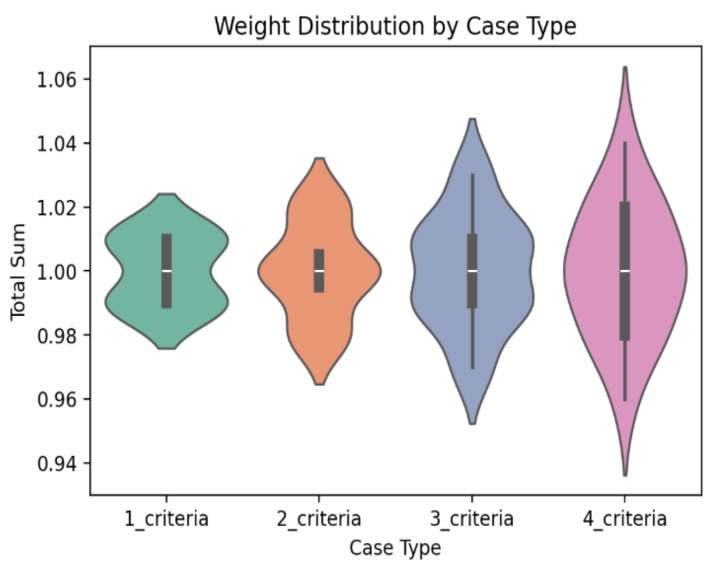

Figure 11. Violin plot of the total sum by case type

This graph illustrates the overall distribution of the total weights, indicating the frequency (number of occurrences) of different weight totals, along with a normal curve for evaluating central tendency and variability. It is clear from the graph that the most common total weight is 1.0, which appears 18 times; this is followed closely by 0.99 and 1.01, each occurring 16 times. The frequency distribution is rounded out by the total weights 0.96 and 1.04, which each occur only once, positioned at the far left and right ends of the histogram with the normal curve. These last two totals carry significant insights, as they represent the minimum and maximum totals possible within the ±0.01 range generated by the fuzzy simulation. The histogram, together with the normal curve, gives a clear impression of how the simulated totals are distributed and if they conform to a bell-shaped pattern, which they do. Figure 11 showcases the violin plot depicting the total sum by case type.

The violin plot provides an in-depth view of the distribution of total sums for each case type, illustrating the complete density and variability of the data. It enhances the bar chart by depicting not just the average but also the range and shape of the distribution within each category, emphasizing outliers and variations in distribution shapes. The progression from green to purple illustrates the distribution of each specific case type or alternation case. The single alternation violin shows that the values are relatively close to the mean value, resulting in a shape that resembles a wide bottle, whereas the 2-criteria alternation case exhibits some tips compared to the flat ends of the single alternation violin. This change in spread becomes even more pronounced in the 3-criteria violin but reaches a peak at the 4-criteria alternation violin, which demonstrates a significant dispersion of the total weight distribution away from the mean value. Figure 12 presents the exploded pie chart depicting the distribution of case types.

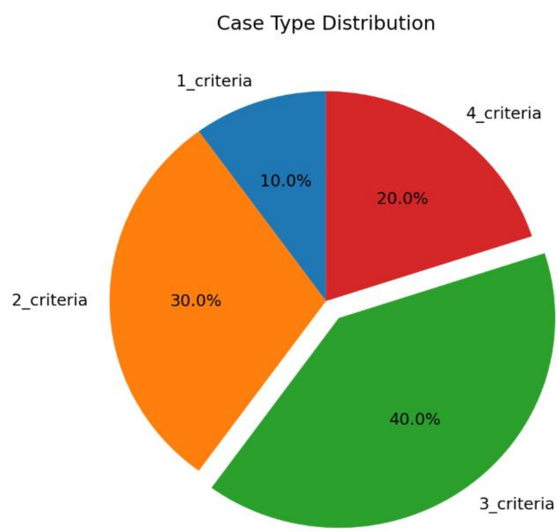

Figure 12. Exploded pie chart of case type distribution

This chart illustrates the percentage contribution of each case type, to the overall total sum. By "exploding" the segment related to the case type with the highest total, it highlights the primary category and offers a clear view of the relative significance of each group. As depicted in the image, the 3-criteria case accounts for 40% of the total value distribution, indicating that there are 32 out of 80 unique mixes present in this sample set. With this insight, decision-makers can easily identify the case where they have the greatest potential for flexibility regarding possible combinations. The remaining portions consist of 30% for the 2-criteria alternation case, 20% for the 4-criteria alternation case, while the 1-criteria alternation case makes up 10% of the 80 unique cases chosen for this analysis.

The three graphical representations offer a comprehensive overview of the simulation data, facilitating informed decision-making. The histogram presents the overall distribution, the violin plot contrasts and elaborates on the performance of different case types, and the exploded pie chart offers a quick, intuitive grasp of the contribution each case type makes. Two decision criteria, namely weighted average and variation minimization, are utilized to analyze the simulation results.

4.4.7. Weighted average

To reach a conclusion, the weighted average identifies the highest total from the samples and presents it as the best possible combination, as this represents the maximum sum of criteria for which the entire system operates optimally, significantly surpassing the default operational outcomes. The Weighted Average determines the highest total from the sample, enhancing system performance beyond its standard results.

4.4.8. Variation minimization

Variation minimization identifies the highest sum (1.01) that is nearest to the default value (1.0) to ensure stability. If the aim is to minimize, the system could yield 0.96 as the lowest sum, thus reducing investment. Presently, the system emphasizes discovering the optimal maximum mix. Variation minimization focuses on achieving the highest feasible sum (1.01) of criteria that remain closest to the default sum (1.0). Depending on the desired decision target, the system is capable of providing its recommendation based on these two decision paths. Another potential scenario arises when minimization is prioritized, in which case we could have the system return 0.96 as the minimum sum value within the simulation parameters, representing the least investment in the sample space. This could be a factor to consider for upgrading this system; however, the current direction of this system is to pursue the highest possible and reasonable mix sum.

This decision-making system utilizes Google/flan-t5-base for managing workflows and Stream-lit for a user-friendly interactive interface. By assessing weighted scores and employing a lightweight language model to generate professional recommendations, the system serves as a tool for decision-making across various applications. The modular design using this model guarantees data integrity, while the incorporation of transformers enhances advanced language generation abilities. The endpoint URL for the GAI model architecture, which is hosted by the Stream-lit interface, can be shared upon request.

5. Discussion

5.1. Key deductions

The decision-making framework outlined in this study offers valuable insights that emphasize the necessity for FMCG stakeholders to enhance operational procedures that reduce escalating maintenance expenses. Furthermore, it is crucial to comprehend the business repercussions of increasing maintenance costs and to make decisions that are more sustainable. The primary conclusions are underscored by an in-depth explanation of how the study tackled the objectives.

RO1: Conduct a bibliometric review to explore academic literature related to the utilization of advanced tools in assessing business impacts due to rising maintenance costs.

The literature review in “section 4.1” highlighted various studies that have incorporated advanced tools to analyze business impacts stemming from escalating maintenance costs. This study provides an analysis of the literature review across six themes: “Documents by Year; Documents by Author; Documents by Affiliation; Documents by Country; Documents by Type; and Documents by Subject Area.” The key takeaway from this analysis is the need for further research on advanced tools that enhance decision-making pertaining to rising maintenance costs. The compilation and review of literature offer insights into crucial parameters for developing the questionnaire constructs.

RO2: Determine key maintenance cost criteria that are relevant for evaluating business impacts within the FMCG sector.

The analysis of the questionnaire insights in “section 4.2” identified four essential maintenance cost criteria: safety, RCM, skills & training, and budget management. These four criteria are vital for facilitating sustainable decision-making in relation to increasing maintenance costs within the FMCG sector. The identified maintenance cost criteria inform the development of the proposed AHP model.

RO3: Execute a systematic assessment and prioritization of the recognized criteria.

An AHP model serves as a tool to emulate real-world FMCG systems, allowing for analysis and ranking in a simulated environment. The AHP model in “section 4.3” performs a systematic evaluation and ranks the identified maintenance cost criteria. The outputs generated from the AHP model yield numeric results that act as inputs for the proposed GAI framework.

RO4: Perform pilot tests to verify the applicability of the developed decision-support framework in practical settings.

The pilot tests aim to validate the practical applicability of the GAI experimental framework in facilitating a data-to-decisions scenario. The experimental framework depicted in “section 4.4” illustrated a simulated decision-making structure utilizing a GAI tool. This framework is founded on graphical representations of scenario impacts that showcase general distributions, compare different case types, and detail their performances, providing a straightforward and intuitive grasp of the contributions made by each case type. Two primary impact metrics, namely weighted average and variation minimization, serve as quantifiable outcomes. The simulation results indicated that it is feasible to model and assess rising maintenance cost criteria and evaluate the implications of each on maintenance expenses.

RO5: Analyze the implications and significance of the established framework for the sustainability of the FMCG industry.

Simulation protocols fundamentally employ digital methodologies to replicate real-world operations and provide a digital view of the underlying processes. Simulation frameworks can effectively mimic real-life scenarios, especially when utilized for training or testing purposes. While simulations may not always be flawless, they offer significant insights and prepare industries or systems for actual circumstances. The simulation framework can greatly impact sustainability initiatives. By enabling the examination of various scenarios, it aids in identifying the most effective and efficient criteria to enhance decision-making. The broader implications and significance of the developed framework will be elaborated upon in the subsequent section.

6. Theoretical and practical implications

6.1. Theoretical implications

The theoretical implications emphasize the evolution of the model framework alongside the combination of the AHP and GAI protocols. In many business organizations, it is common for the decision-making process to rely on assumptions. The established decision-making framework provides a forward-looking tool that merges research and practical application, making it applicable in real-world operational contexts. Although the model framework is conceptual, it delivers a structured and systematic method through simulation for the FMCG sectors to evaluate practical maintenance scenarios while considering various maintenance cost criteria.

This model framework derives from the amalgamation of the AHP and GAI protocols. To reduce bias in the AHP approach, the authors ensure that a consistency index and ratio determined from the pairwise comparisons of decision-makers are conducted. Similarly, to mitigate bias within the GAI approach, the authors make sure that large, diverse sample sizes are employed for the training data.

The authors recognize that the study may present some limitations stemming from theoretical perspectives. For instance, Aad and Hardey (2025c) outline several challenges in applying GAI procedures, such as poor data quality, data security concerns regarding privacy, complexity of AI algorithms, technical challenges, and ethical issues. Nevertheless, the model framework can be duplicated to enhance the sustainability of rising maintenance costs within the FMCG sector. It supports the creation of new sustainability risk assessment standards (from qualitative to quantitative), including systematic data collection that assists in identifying the most effective and efficient maintenance cost criteria to address escalating maintenance expenses in the FMCG sector. Managers in the FMCG sector are encouraged to re-assess their current operational protocols to bolster the integration with their maintenance processes and to understand or mitigate sustainability risks.

6.2. Practical implications

The practical applications emphasize the utility of the framework as a decision-making resource for managers in the FMCG sector.

- Forecasting behavior: The decision-making framework provides a foundation to anticipate how the FMCG industry reacts to increasing maintenance costs based on various criteria. This allows for streamlined analysis and potential interventions to enhance decision quality concerning surging maintenance expenses.
- Reasoned decision-making: The decision-making framework acts as a normative instrument for FMCG managers, enabling them to make decisions rooted in optimal logical reasoning. This tool offers an organized method that can help reduce the impact of personal biases (both real and ideal behavior) that could sway decision-making regarding rising maintenance costs. This ensures that all parties involved are aware of the decision-making process, reducing uncertainty.
- Recognizing biases: The decision-making framework can reveal cognitive biases that might affect sustainable decision-making by pinpointing areas where the FMCG sector may stray from logical choices.

- Evaluating and enhancing: The decision-making framework functions as a tool that can be assessed for accuracy, clarity, and consistency, while also identifying opportunities for enhancement. This tool aids in recognizing and managing risks linked to differing maintenance cost criteria by analyzing possible outcomes and repercussions.

The authors suggest that FMCG managers examine relevant practical insights derived from this study to explore alternative options and take measures based on existing maintenance operational procedures.

7. Limitations and future work

The authors acknowledge that creating a decision-making framework based on advanced tools might be more complex or time-intensive compared to traditional approaches. Nonetheless, the importance of this framework is significant. Despite certain challenges and limitations inherent in the study, the proposed interventions aid stakeholders, particularly those in the FMCG sector, in making informed decisions. This study includes a case study highlighting maintenance cost criteria as measurable outcomes. Several limitations of this study and prospective avenues for future investigation are noted.

- This article concentrated specifically on the FMCG sector. It is crucial to broaden the examination of rising maintenance costs to encompass a wider context that transcends industry-specific constraints. Future research could explore how the developments presented can be applied across various business sectors, with further emphasis on comparing previous integrations across different industries.
- A case study focusing on four criteria for maintenance costs is presented to evaluate the effectiveness of the framework. Future research might investigate more advanced tools for systematic data gathering and the results of additional maintenance cost criteria. This could include barriers to implementation, economic limitations, strategies for stakeholder engagement, trade-offs, and the technical know-how necessary to apply theory in practical settings. Such efforts will improve the general applicability of the decision-making GAI model.
- The authors encountered challenges related to data privacy, ethical issues, power relations, and the risk of biased interpretations in their investigation of the FMCG sector. Nevertheless, simulation fundamentally employs digital protocols to mirror real-world operations and offer a digital viewpoint of the underlying context. Upcoming outcomes may focus on showcasing the simulated framework with numeric scenario data derived from actual industry situations.

8. Conclusion

This study is driven by growing concerns regarding the long-term viability of quality maintenance practices amidst rising costs. A thorough review of literature reveals that no peer-reviewed studies have established a GAI model for managing increasing maintenance costs within the FMCG sector in Southern Africa. To illustrate this investigation, the study aims to enhance the existing knowledge base by exploring the creation of a decision-making model grounded in the principles of AHP and GAI. This also supports emerging research on the effectiveness of GAI initiatives in significantly enhancing decision-making and operational procedures within the FMCG sector.

The study underscores AHP and GAI as vital sustainable methodologies in decision-making processes. There exists a lack of evidence in previous studies that combine both AHP and GAI approaches. In this study, AHP systematically ranks the criteria associated with maintenance costs. The GAI method conducts preliminary tests to demonstrate the practical application of the decision-support system in real-world situations and highlights the system's relevance to sustainability. The findings showcase the potential to replicate a decision-making framework that integrates key maintenance cost criteria to evaluate scenario impacts, facilitating the adoption of more sustainable decisions.

Identifying the use of both AHP and GAI as essential sustainable methods for addressing increased maintenance costs in the FMCG sector stands out as an important area of research. The significant contributions of this study to the existing body of knowledge are summarized as follows:

- The review assesses and contrasts outcomes from previous applications of advanced tools to rising maintenance costs. The findings further establish the feasibility of developing a decision-making framework based on maintenance cost criteria, along with its practical applicability in real-world scenarios and its relationship to sustainability.
- The importance of maintenance cost criteria as measurable factors in dialogues aimed at reducing escalating maintenance expenses is discussed. An overview of maintenance criteria with numerical values is also provided to support illustrative testing in a simulated environment.
- The simulation results offer insights, to FMCG stakeholders about the potential to integrate and simulate a variety of maintenance cost criteria, quantifying the impacts based on scenario assessments.
- It emphasizes the necessity of incorporating advanced tools and underscores the demand for further study into methods that promote sustainability in addressing rising maintenance costs. This sets the stage for future inquiries within the domain of GAI research.
- The analysis presents insights into how the specified maintenance cost criteria rank concerning increasing maintenance expenses.

Conclusively, implementing sustainable decision-making in manufacturing companies is crucial as it fosters lasting economic success, minimizes ecological harm, and improves societal responsibility. By incorporating key elements that can be measured in real-time for decision-making that supports sustainable practices, managers can enhance resource efficiency, reduce waste, and contribute positively.

Data availability

I acknowledge the data-sharing policy of this journal, which allows access upon reasonable request, and the authors assure that all critical data is included in the manuscript, with the raw data available upon reasonable request.

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