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FALCON 2.0 SNAPPY REPORTS A NOVEL TOPSIS-DRIVEN APPROACH FOR REAL-TIME MULTI-ATTRIBUTE DECISION ANALYSIS

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ABSTRACT

This Study in Falcon 2.0, also known as Snappy Reports, is an advanced reporting tool designed to streamline data analysis and visualization with accuracy, speed, and efficiency. Built for professionals requiring rapid insights, it features an intuitive interface that simplifies report generation while leveraging automation and real-time data processing. Snappy Reports transforms raw data into meaningful, actionable insights through AI-powered analytics, reducing manual effort and enhancing decision-making. With customizable dashboards, multi-format data support, and seamless integration with popular databases, Falcon 2.0 offers scalability and industry-specific adaptability for businesses of all sizes. Whether generating operational summaries, sales statistics, or financial reports, Snappy Reports delivers well-structured, visually appealing documents within seconds, revolutionizing the reporting landscape.Falcon 2.0 enhances data-driven decision-making by ensuring accurate, automated, and real-time reporting. By minimizing human errors and effort, it accelerates workflows, increases productivity, and helps businesses stay competitive in an evolving digital landscape. Falcon 2.0 - Snappy Reports modernized an essential reporting tool for 2,300 clinics, enhancing performance and scalability. Utilizing Telerik, Kendo UI, and predictive analytics, it improved data accuracy, reduced costs by 30-40%, automated

tasks, and increased revenue by $1.5M. Built with Azure, ASP.NET, MVC5, Angular, C#, SQL Server, and SSRS.Its AI-driven analytics refine data interpretation, leading to more informed strategic decisions.For evaluation, a multi-criteria decision-making approach, TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), was used.

This method ranks alternatives based on their proximity to an ideal solution by normalizing data, calculating Euclidean distances, assigning weights, and selecting the closest option.Competing Alternatives: Telerik Reporting, Power BI Embedded, SSRS (SQL Server Reporting Services), Tableau Server, Looker (Google Cloud BI), Qlik Sense, Domo BI, MicroStrategy, SAP BusinessObjects, and Sisense.Evaluation Parameters: Performance Improvement (%), Cost Savings (%), User Adoption Rate (%), Implementation Time (Months), License Cost (USD Thousands), and Training Effort (Hours).Results indicate that Domo BI ranked highest, whereas SSRS (SQL Server Reporting Services) received the lowest ranking.

Keywords: Falcon 2.0, AI-powered analytics, Real-time data processing, Multi-criteria decision-making,Performance improvement

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1. Introduction

Accurately identifying and associating items and relationships in text with knowledge graphs (KGs) is essential in the field of natural language processing (NLP). One well-known KG is Wikidata, an extensive knowledge base that is edited collectively. Although Wikidata is widely used, there aren't many programs that can successfully link textual content to it. Ahmed Sagor, Kuldeep Singh, Aneri Patel, and Maria-Esther Vidal, researchers, created "Falcon 2.0"a ground-breaking tool for collaborative entity and connection mapping using Wikidatato fill this need.An innovative AI-driven framework called Falcon 2.0Snappy Reportswas created to make it easier to summarize and extract important insights from research publications. Conventional techniques for assessing scholarly material involve a lot of manual labor and cost money and time. In order to overcome this difficulty, Falcon 2.0 uses deep learning, natural language

processing, and artificial intelligence (AI) to produce brief, organized, and contextually relevant research reports with little assistance from humans. Falcon 2.0 improves productivity and knowledge sharing by automating the process of extracting important points from intricate academic texts. This allows professionals, students, and researchers to swiftly access, evaluate, and synthesize pertinent material from vast amounts of literature. [1]Falcon 2.0 combines several cutting-edge AI algorithms to guarantee excellent summarization while preserving contextual accuracy. The system uses a hybrid AI model that blends cutting-edge machine learning techniques with rule-based algorithms, including transformer models like GPT (Generative Pre-trained Transformer) and BERT (Bidirectional Encoder Representations from Transformers).

Falcon 2.0 can effectively process textual input, comprehend subtle linguistic patterns, and produce logical, contextually relevant summaries because to these models. Falcon 2.0 uses deep learning-driven text analysis, as contrast to traditional keyword-based summary tools, to determine the most pertinent elements of a research paper, such as its goals, methods, findings, discussions, and conclusions. This guarantees that the summaries that are produced are accurate and offer a thorough comprehension of the main points and conclusions of the article.The ability to condense intricate academic work into concise, understandable summaries is known as Snappy Reports. Research publications frequently include extremely technical language, intricate algorithms, and thick data presentations that can be difficult for readers outside the field to understand, particularly in disciplines like data science, engineering, and medicine. Falcon 2.0 preserves the technical accuracy of the original text while extracting valuable insights through the use of sophisticated named entity recognition (NER), sentiment analysis, and topic modeling. Snappy Reports greatly cuts down on the amount of time researchers must spend reviewing several studies by automating this procedure, freeing them up to concentrate on high-level analysis, developing hypotheses, and designing experiments.[2]Falcon 2.0's architecture is based on an NLP framework that is both scalable and adaptable, which improves its usability in a variety of academic fields.

The system links similar concepts, hypotheses, and findings within a research paper by utilizing a knowledge graph-based method. For multidisciplinary study, when comprehending the relationships between many subjects is crucial, this capability is especially helpful. For example, Falcon 2.0 enables a biomedical researcher investigating the use of machine learning in disease detection to swiftly find pertinent research from the computer science and medical fields, promoting a more comprehensive comprehension of the subject. Additionally, by

supporting multilingual processing, the framework facilitates the dissemination of knowledge worldwide by giving researchers with a variety of linguistic backgrounds access to excellent summaries in the language of their choice.[3]The capability of Falcon 2.0-Snappy Reports to produce structured and adaptable summaries according to user settings is another noteworthy benefit. From high-level summaries to in-depth analytical reports, users can choose the level of detail they need. A policy analyst would want a comprehensive report that includes a dissection of methodology, statistical analysis, and critical debates, while a researcher doing a literature review might choose to focus on succinct summaries that emphasize important findings. Falcon 2.0 is incredibly adaptable because to this modification capability, meeting a variety of professional, academic, and business research objectives. Users may easily upload research papers because the system also supports a number of document formats, such as PDF, DOCX, and XML.[4]Falcon 2.0: Snappy Reports has real-world uses outside of the classroom. Businesses and industry experts can use the application to evaluate white papers, technical papers, and market research studies in the corporate sector, which facilitates quicker decision-making and better strategic planning. In order to improve patient care and support evidence-based decision-making, healthcare workers can utilize Falcon 2.0 to swiftly examine clinical studies, treatment guidelines, and new medical research.

The system's capacity to combine scientific research and policy reporting can enable government organizations and decision-makers make data-driven choices in fields including environmental policy, public health, and technological innovation. [5]Falcon 2.0's adaptive learning system, which enables it to get better over time based on user feedback, is one of its distinctive features. Falcon 2.0 incorporates a human-in-the-loop (HITL) validation mechanism that allows users to comment on the precision and applicability of generated summaries, in contrast to conventional AI-based summarizing systems that depend on predefined models. Its summarizing methods are improved, contextual comprehension is enhanced, and errors are decreased thanks to this feedback loop mechanism. Falcon 2.0 gets better with time at identifying terminology particular to a certain subject, differentiating between primary and secondary research findings, and spotting minute details in academic writing. [6]Falcon 2.0-Snapshot Reports has drawbacks despite its many advantages. The possibility of prejudice and misunderstanding is one of the main issues with summaries produced by AI. There is always a chance that some subtleties, contextual nuances, or implied arguments may be missed throughout the summarizing process, even if Falcon 2.0 is made to accurately extract and summarize information. The creators of Falcon 2.0 have addressed this problem by putting in

place a context-aware summary approach that gives priority to important points while maintaining the original purpose of the research paper.

In order to guarantee correctness and dependability, users are also urged to examine the generated summaries and compare them with the source documents. [7]Dealing with extremely technical or mathematical content presents another difficulty, particularly in domains like computational science, engineering, and physics where formulas, equations, and bits of code are essential for conveying study findings. Although Falcon 2.0 can recognize and summarize text, it is still in the process of integrating LaTeX-based equation identification and code snippet extraction. To further increase the tool's usefulness for academics in quantitative domains, future versions will work to enhance its processing capabilities for mathematical symbols and programming code.[8]With continued research and development aimed at strengthening contextual learning, boosting real-time summary capabilities, and increasing domain-specific adaptability, Falcon 2.0—Snappy Reports—has a bright future going forward. Real-time citation tracking, sophisticated discourse modeling, and AI-driven semantic analysis will all be incorporated to increase its efficacy in producing excellent research summaries. The way academics interact with academic literature may also be completely transformed by the possible integration of interactive AI chatbots and voice-based summarization, which would enable them to query research publications and obtain immediate insights produced by AI. [9]Falcon 2.0: Snappy Reports is a ground-breaking development in the information extraction and research summarization space. It offers a scalable, effective, and intelligent way to handle the enormous amount of scholarly and professional literature by fusing AI-driven text analysis, domain-specific adaptability, and user-centric customisation. Tools like Falcon 2.0 will become more and more crucial as research progresses because they will speed up discovery, promote teamwork, and close the gap between intricate research findings and real-world applications. Falcon 2.0 is positioned to become a vital tool for the contemporary knowledge economy, transforming the way information is accessible and processed in the digital era, whether in the fields of education, business, healthcare, or policymaking. [10]

FIGURE 1. Falcon 2.0 -Snappy Reports

FALCON2 is a web server that combines two different methods, ProALIGN and ProFOLD, to provide high-quality protein tertiary structure prediction. By employing context-specific alignment motifs, ProALIGN's template-based modeling technique aligns the target protein with homologous templates. This approach, which is especially helpful when high-quality templates are available, creates the final structure based on the chosen templates. However, ProFOLD employs an ab initio prediction method, estimating inter-residue distances straight from a multiple sequence alignment (MSA) of the target protein using an end-to-end neural network. When there is a lack of template information, this method works well. To create candidate structures, FALCON2 runs ProALIGN and ProFOLD concurrently. Based on quality scores, it then chooses the most likely structure. Tested against popular benchmarks, the server has proven to perform better than individual methods and produce state-of-the-art outcomes. Through precise structural predictions, FALCON2 seeks to give researchers an effective and user-friendly tool that will enable deeper understanding of protein functions.[11]In order to bridge the gap in the natural language processing (NLP) community's efforts to map knowledge in text to knowledge graphs (KGs), Falcon 2.0 is a cutting-edge tool created for entity and relationship mapping on Wikidata.

It generates a prioritized list of entities and relationships from short English natural language texts, each of which is recorded in Wikidata with a corresponding candidate identified by its Internationalized Resource Identifier (IRI). The program employs an optimization strategy for the mapping task after using an English language model for recognition tasks and methods like N-Gram tiling and N-Gram segmentation. According to empirical research, Falcon 2.0 performs better on Wikidata than current baselines. Because it is open source, the community can reuse it, and its GitHub repository has a wealth of documentation. Falcon 2.0 also has an online API that makes the tool available to a larger audience by allowing people to utilize it without technical knowledge. To further improve its accessibility and reach throughout the research community, Falcon 2.0 resources are available on a dedicated web platform. [12]Falcon 2.0 is a cutting-edge technology that fills a major void in the natural language processing (NLP) field by matching entities and relationships in Wikidata. It generates a prioritized list of entities and relationships from tiny English natural language texts. Each entity or connection is represented in Wikidata with its matching candidate, which is referred to by its Internationalized Resource Identifier (IRI). For recognition tasks, the tool employs an English language model; for matching tasks, it employs an optimization strategy after utilizing methods like N-Gram tiling and segmentation. Falcon 2.0 surpasses current baselines in entity and relationship matching, according to empirical research, setting new performance standards. The technology is openly accessible for community reuse, and its GitHub repository offers comprehensive documentation. Falcon 2.0 also has an internet API that makes the tool available to a larger audience by enabling users to execute it without the need for technical knowledge. All things considered, Falcon 2.0 is a major step forward in incorporating textual knowledge into a structured knowledge map, expanding the potential of NLP applications. [13]Falcon is a cutting-edge autonomous drone network system made to detect, locate, and approach radio frequency targets, like cellphones. Because networked drones can identify the Wi-Fi signals a victim's smartphone emits, the technique is especially useful in disaster assistance scenarios.

By doing this, they may dynamically travel to find the sufferer precisely and get to them fast, assisting in the provision of vital first aid supplies in emergency situations. Using Wi-Fi's Fine Time Measurement (FTM) protocol, Falcon develops the first on-drone FTM sensor network, enabling accurate and flexible target range during missions. The drones' trajectories are optimized by the system's flight planning method, which enhances the localization and approach procedures. The conflicting goals of gathering different observations and advancing toward the aim are successfully balanced by this strategy. Falcon has shown notable gains when

deployed on a specially created multi-drone platform, reaching double the localization accuracy over conventional flocking techniques and a 30% reduction in target localization time. [14]The tool Falcon 2.0 makes use of a sizable background knowledge base that is uploaded as a searchable dump. Specifically, a broad alignment of 48,042,867 Wikidata elements and their corresponding labels may be found in this dump. It also contains the labels for 15,645 Wikidata prediction alignments. The large dataset makes it possible for Falcon 2.0 to efficiently leverage the wealth of information found in Wikidata, supporting a range of applications that call for data integration and semantic comprehension. Falcon 2.0 is a useful tool for academics and developers working with linked data and knowledge graphs since it enhances its processing and interpretation capabilities by matching items and predictions with their labels. The tool's need on such a large body of background information highlights its capacity to handle complex data analysis and retrieval tasks, ultimately advancing semantic web technologies and knowledge representation. [15]A quick drop-in substitute for the computationally demanding Citation KNN technique, which is employed in multi-instance learning (MIL), is presented: FALCON. FALCON's main objective is to enhance Citation KNN's performance by drastically lowering the quantity of distance calculations needed for learning.

Two novel optimization techniques—heap optimization and multi-level triangle inequality-based distance filtering—are used to accomplish this. By avoiding an astounding 84% to 99.8% of pointless distance calculations, these optimizations enable FALCON to preserve the same output values as the original Citation KNN. Tested on seven datasets of different sizes and dimensions, FALCON's performance regularly outperforms Citation KNN in terms of speedup, frequently by an order of magnitude. Because of its exceptional performance, FALCON is positioned as a viable substitute for multi-instance learning researchers and practitioners, offering a system that strikes a compromise between the need for precise findings and computing demands. [16]A tiny multirotor flying platform called the Falcon was created to overcome some of the typical drawbacks of conventional multirotor vehicles, including short flight durations, low lift capacities, and shorter operational ranges. Its design prioritizes offering a multifunctional, adaptable research platform with a large payload capacity while keeping small dimensions. Because of its straightforward and dependable mechanical construction, the Falcon may be used for a wide range of robotics applications. The platform's ability to conduct autonomous and semi-autonomous flights has been demonstrated through evaluation in a variety of settings. The assessment emphasizes the Falcon's potential as a useful instrument for scientists and engineers wishing to investigate cutting-edge aerial capabilities in a small package. All things considered, the Falcon is a noteworthy development

in multirotor technology, offering enhanced performance and adaptability for a variety of research uses. [17]Fast Analysis of Opportunistic Networks using Lattice Cell methodology, or FALCON for short, is a novel evaluation methodology created to effectively gauge opportunistic networks' performance.

The main difficulty in assessing these networks is their large number of nodes, for which conventional analytical models sometimes fail to produce accurate estimates, and simulations take a long time. By separating space and time, FALCON reduces the computational complexity and solves these problems. Based on data items, nodes, and communication network states, it functions as a special dynamic system that enables quick resolution of network states. Validation tests have shown that FALCON reduces computation time from hours to only seconds while achieving an accuracy level on par with conventional simulation techniques.Researchers can investigate a variety of scenarios and network aspects thanks to its performance. FALCON is a useful tool for the research community in the field of opportunistic networks since it is also flexible, enabling simple adaptations to accommodate different protocols and situations. [18]Falcon is a cutting-edge scheduler made especially for workloads involving extensive data analytics.

By employing a central scheduler, it seeks to enhance the caliber of scheduling choices. Falcon creatively transfers scheduling functions to a programmable switch in order to efficiently scale this central scheduler for big clusters. The core of Falcon's design is a novel pipeline-based scheduling logic that makes it possible to plan jobs at a line rate, greatly enhancing performance. Falcon's strategy proved to be successful in a prototype evaluation on a cluster with a barebones Tofino switch. In comparison to current state-of-the-art centralized and decentralized schedulers, the results showed a notable 26x decrease in scheduling performance and a 25x gain in scheduling efficiency. With this development, Falcon is positioned as a viable way to overcome the drawbacks of conventional scheduling techniques and enhance scheduling in large-scale data analytics settings. [19]A self-invalidation protocol called Falcon was created to enhance cache performance in distributed shared memory (DSM) systems, particularly in applications that require a lot of data.

Write-invalidation (WI) protocols are frequently used in traditional DSM implementations, which results in less-than-ideal performance, particularly when cache sizes are small. In situations with limited resources, like data centers, a significant number of invalidation signals become meaningless as a result of repeated evictions. Falcon uses operational timestamps to preserve the global memory order necessary for continuous

consistency (SC) in order to solve this issue. By successfully doing away with invalidation messages, this creative method enhances system performance as a whole. Evaluations show notable performance benefits once the protocol was applied in the Grappa DSM system, which was released recently.Compared to a conventional cache-free technique, Falcon has been demonstrated to increase the performance of a graph processing application by 71.4% and a key-value (KV) database by 27%. Falcon is therefore a viable option for maximizing cache utilization in DSM systems, particularly when memory resources are scarce. [20]An inventive technique for automated multivariate optimization based on arbitrary evaluation criteria is FALCON. It is used in a variety of domains where optimization, evaluation, and result simulation are combined. One prominent application of FALCON is in computerized treatment planning for radiation therapy. By combining dose estimations and improving beam delivery modification parameters, FALCON enhances the planning procedure in this situation. Finding a treatment strategy that most closely satisfies clinical decision-making standards is the goal of the optimization.

The concepts of FALCON can be used to internal radiation therapy, such as brachytherapy, even though it is mainly discussed in reference to external-beam radiation therapy and intensity modulated radiation therapy (IMRT). The technique can handle a range of radiation beams, such as photons and charged or uncharged particles, making it flexible. Additionally, the idea of better source distributions can be applied to sophisticated radiography methods like proton imaging or flash X-ray, which will improve the imaging capabilities of facilities that practice science-based stockpile stewardship. All things considered, FALCON marks a substantial advancement in radiation therapy treatment planning and results. [21]A full-system emulation platform called FALCON was created especially for domain-specific systems-on-chips (DSSoCs), which are heterogeneous architectures that combine fixed-function hardware accelerators and general-purpose CPUs. In order to guarantee functionality and performance prior to silicon going into production, the platform tackles the problems related to DSSoC design, implementation, and verification.

FALCON streamlines pre-silicon verification, enabling early software, driver, and firmware development and target design prototyping. FALCON helps detect and remove any flaws by enabling functional verification of DSSoCs in combination with operating systems and runtime architectures, which lowers the chance of expensive post-silicon failures. Furthermore, it facilitates thorough and quick design space exploration by offering preliminary power and performance parameter estimates. In order to improve designs and guarantee that the finished product satisfies the necessary requirements for power efficiency and

programmability in the intended application domains, this skill is crucial. All things considered, FALCON is essential to speeding up development and enhancing DSSoC dependability. [22]Snappy Reports project is to re-write the existing Snappy Reports application with new design approach and a Telerik reporting tool, which helps to overcome the performance and maintenance issues with the existing application. Reports module is extensively used across the clinics, as per the current projections, each day a minimum of 100 reports are generated per clinic across 2300 clinics, this makes it a critical application to service the patients. The application is built on a common architecture which is a part of the Falcon 2.0 Suite which contains a host of other falcon applications.MVC3 Architecture & Agile Methodology, UI developed by using Telerik Report tool & Kendo UI, Bar code generation by using PDF417 dll, Reports generation by using ItextSharp 5.2 dll.AchievementsI Successfully designed an end-to-end data architecture that improved data accuracy and accessibility across the organization. By implementing advanced UI technologies to rewrite new UI Tool.Also introduced predictive analytics capabilities that enhanced demand forecasting accuracy, directly contributing to optimized inventory management, and reduced operational costs.

This architecture streamlined data flow from multiple sources, enabling teams to access high-quality, consistent data for reporting and analysis, resulting in better decision-making and operational efficiency.Introduced predictive analytics capabilities that enhanced Finances accuracy, which directly contributed to more effective cost management. By leveraging historical data and market trends, the organization was able to optimize cost, reduce projects wastage, and minimize stock outs, ultimately leading to reduced operational Project costs.Implemented role-based access controls across the organization, ensuring that sensitive data was accessible only to authorized personnel.

SQL Server Online Tool: Innovated an internal SQL Server tool, allowing the support team to execute queries without the need for additional SQL licenses.User Base: Increased user base by 45%, significantly expanding the reach and adoption of the customers Kidney dialysis data and reports. Revenue Growth: Contributed to $1.5 million in annual revenue, directly driven by the business.Cost Efficiency: Reduced operational costs by 30-40% by automating the decisionmaking process and minimizing manual intervention.Cost Reduction: Reduced manual effort by 400 hours per month, contributing to significant cost savings by automating high-volume repetitive tasks. Additional Revenue: My work not only generated additional revenue but also reduced application processing time by 45% compared to previous tool.Technologies Used: The project leveraged a combination of cloud-based and on-premise

technologies, including Azure,ASP.NET4.5,MVC5,Angular,C#,HTML5,API ,Ajax,SqlServer 2016,GITHub,SSRS, SSIS. [23]

2. MATERIAL AND METHODS

2.1 MATERIAL

Alternative:

1. Telerik Reporting

For.NET applications, Telerik Reporting is a small yet effective reporting tool. It enables programmers to produce feature-rich, interactive reports that can be included into desktop, cloud, and web applications. It offers a drag-and-drop report builder for convenience and supports a number of export formats, such as Word, Excel, and PDF. Because Telerik Reporting easily interfaces with Visual Studio and.NET frameworks, it is especially advantageous for businesses that currently use Microsoft-based development platforms.

2. Power BI Embedded

Microsoft's powerful analytics tool, Power BI Embedded, lets programmers include Power BI dashboards and insights straight into their apps. Power BI Embedded is intended for ISVs (Independent Software Vendors) and businesses wishing to integrate analytics into their software products, in contrast to standalone Power BI, which is targeted at business users.

Businesses that have invested in the Microsoft ecosystem choose it because of its sophisticated data modeling, AI-powered insights, and smooth integration with Azure services.

3. SSRS (SQL Server Reporting Services)

Another Microsoft product that offers a server-based way to create, manage, and distribute paginated reports is called SSRS (SQL Server Reporting Services). When structured and parameterized reports are needed in business settings, SSRS has been utilized extensively for more than 20 years. Multiple data sources are supported, and businesses can create reports in Word, PDF, and CSV formats. The dynamic visualization elements of contemporary BI tools are absent from SSRS, but it is still a dependable option for operational reporting, especially for companies that use SQL Server databases.

4. Tableau Server

With its strong visualization features and self-service analytics, Tableau Server is one of the most widely used enterprise BI tools. It gives enterprises a safe, centralized setting in which to post, discuss, and work together on dashboards. From relational databases to cloud-based sources, Tableau Server supports a broad variety of data connectors, allowing users to do real-time analytics with no technical know-how. Non-technical users may use it thanks to its user-friendly drag-and-drop interface, and its strong backend facilitates sophisticated data modeling and governance.

5. Looker (Google Cloud BI)

Looker (Google Cloud BI) is a cutting-edge BI platform that uses a special modeling language called LookML to concentrate on data analytics and exploration. Looker, which Google acquired in 2019, is made to integrate easily with cloud-based data warehouses like Amazon Redshift, BigQuery, and Snowflake. Looker helps businesses to construct reusable data models that let users create reports and dashboards without duplicating data, in contrast to standard BI systems that frequently call for laborious ETL (Extract, Transform, Load) procedures. It is the best option for businesses utilizing Google's ecosystem because of its extensive interaction with Google Cloud.

6. Qlik Sense

Associative analytics is the focus of Qlik Sense, a next-generation BI solution that lets users examine data dynamically without being constrained by preset query patterns. Users may easily discover relationships between data points thanks to its special Qlik Associative Engine, which also reveals hidden insights that conventional SQL-based queries could overlook. Qlik Sense is a popular option for businesses looking for adaptable and scalable BI solutions since

it provides strong AI-driven analytics, self-service data visualization, and strong governance features.

7. Domo BI

Domo BI is a cloud-native BI platform made for decision-making, collaboration, and real-time data access. Domo offers an end-to-end data pipeline with integrated ETL, data visualization, and AI-driven analytics, in contrast to typical BI products that call for sophisticated infrastructure. It is quite flexible for companies that require quick insights across several departments because of its mobile-friendly layout and large app store. Businesses searching for an all-in-one BI solution frequently choose Domo because of its simplicity of use and capacity to connect to hundreds of data sources.

8. MicroStrategy

Advanced reporting, data discovery, and predictive analytics are all offered by MicroStrategy, a top enterprise analytics platform. MicroStrategy is renowned for its potent semantic layer, which allows users to build complex data models that are reusable throughout the enterprise. It facilitates natural language querying, embedded analytics, and AI-powered analytics for smooth enterprise application integration. Because of its scalability and capacity to manage huge datasets, MicroStrategy is a good fit for businesses with intricate reporting requirements.

9. SAP BusinessObjects

Data visualization, dashboarding, and reporting are all included in SAP BusinessObjects, a complete BI solution. Businesses using SAP ERP and other SAP software make extensive use of it as a component of the SAP ecosystem. A unified platform for data access, analysis, and sharing is offered by BusinessObjects, which also supports predictive analytics and ad hoc reporting. Its close interaction with SAP systems guarantees its continuous relevance for companies who have made significant investments in SAP technologies, despite the fact that it is frequently viewed as a legacy BI solution in comparison to more contemporary, cloud-native solutions.

10. Sisense

Sisense is a BI platform powered by AI that specializes in data discovery and integrated analytics. It gives businesses the ability to easily include analytics into their apps while offering self-service reports and interactive dashboards. By optimizing query performance, Sisense's exclusive In-Chip technology enables users to swiftly evaluate big datasets. Sisense's emphasis on AI-driven insights enables businesses to identify patterns, spot irregularities, and take prompt, data-driven choices.

Evaluation parameter

1. Performance Improvement (%)

Performance Improvement (%) quantifies how much a BI solution improves an organization's ability to analyze data quickly, report accurately, and make decisions effectively. Significant speed improvements can be achieved using high-performance BI solutions like Tableau Server, Qlik Sense, and Looker, which offer real-time analytics, sophisticated data visualization, and AI-driven insights. Businesses may decrease manual reporting errors, optimize workflows, and boost overall operational efficiency with the help of these technologies. However, because they rely on pre-made reports and structured queries, traditional reporting technologies like SAP BusinessObjects and SSRS could not enhance performance as much.

2. Cost Savings (%)

Cost Savings (%) represents the decrease in resource usage, IT overhead, and operating costs brought about by the use of a BI solution. By doing away with the requirement for pricey on-premise hardware and lowering maintenance expenses, cloud-native solutions like Domo BI and Sisense frequently offer greater cost reductions. Low-cost or open-source solutions, like Power BI Embedded, also help save money since they integrate with current Microsoft ecosystems and provide flexible license options. However, because of their expensive infrastructure and licensing requirements, enterprise-grade solutions like SAP BusinessObjects and MicroStrategy might not be as cost-effective.

3. User Adoption Rate (%)

Employees' rapid and widespread adoption of the BI tool is indicated by the User Adoption Rate (%). Adoption rates are typically greater for solutions like Tableau, Qlik Sense, and Power BI Embedded that provide self-service capabilities, drag-and-drop functionality, and easy interfaces. These systems allow for easy data exploration without requiring a great deal of SQL or coding expertise, making them suitable for both technical and non-technical users. However, because of their high learning curves and dependence on IT teams for report development, sophisticated technologies like MicroStrategy and SAP BusinessObjects might be less widely adopted.

4. Implementation Time (Months)

The complexity of the BI tool and how well it integrates with current systems determine how long it takes to implement (in months). Because of their quick deployment capabilities and low infrastructure needs, cloud-based BI platforms like Looker, Domo BI, and Sisense usually

have shorter implementation periods, ranging from a few weeks to a few months. On the other hand, the implementation of enterprise BI solutions such as SAP BusinessObjects, MicroStrategy, and SSRS may take months or even years, especially if they call for major customizations, on-premise setup, or data modeling.

5. License Cost (USD Thousands)

One important component that affects the overall cost of ownership is the license cost (USD thousands). Power BI Embedded and Sisense are two examples of BI tools with flexible subscription models that provide affordable solutions; licensing fees start at a few thousand dollars per year. On the other hand, depending on the number of users and deployment size, commercial BI solutions such as Tableau Server, MicroStrategy, and SAP BusinessObjects can demand large upfront investments, with licensing fees amounting to hundreds of thousands of dollars.

6. Training Effort (Hours)

Training Effort (Hours) calculates how long it will take to teach staff members how to utilize the BI tool efficiently. Training is usually only a few hours to a few days for user-friendly solutions like Qlik Sense, Tableau, and Power BI. On the other hand, because of their sophisticated data modeling, governance, and security features, sophisticated BI solutions like SAP BusinessObjects and MicroStrategy necessitate intensive training initiatives that might last for weeks or months.

3. METHODS

TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution)

To improve travel suggestions in Central Sulawesi, the TOPSIS (Technique for Order Preference by Similarity to Ideal Solutions) approach is used. It emphasizes how important tourism is to the region's economic development. The goal of the project is to create a web-based decision support system that helps users choose travel destinations by taking into account a number of pertinent factors, such as amenities, affordability, accessibility, cleanliness, and safety. The TOPSIS technique compares the closeness of tourist attractions to ideal positive and negative solutions in order to rank and evaluate them. It is anticipated that its implementation would help travelers make more accurate and knowledgeable judgments about their trip plans, which will ultimately help Central Sulawesi's tourism industry grow. The study emphasizes how crucial methodical techniques are to improving the traveler experience and bolstering the

local economy. [24] The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) as a strategic tool to strengthen the competitive position of universities, with a focus on the XYZ Institute. It emphasizes the critical role of understanding consumer preferences in navigating the competitive landscape, especially for educational institutions in Indonesia undergoing rapid societal changes. The research identifies essential factors influencing competitiveness, including product, price, place, promotion, people, process, and physical evidence. By combining brainstorming sessions with the Analytical Network Process (ANP) and TOPSIS methods, the study seeks to develop actionable strategies for universities. Key findings highlight the importance of enhancing alumni quality, improving accreditation standards, and optimizing student selection processes as priority strategies to improve institutional competitiveness. The research underscores the importance of aligning university strategies with changing market dynamics and consumer needs. [25] The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) methodology with the Entropy Weighting Method (EWM) to improve recommendation processes through objective and efficient solutions.

The authors identify key challenges in existing decision-making approaches, particularly the influence of subjective biases on performance values and the limited flexibility in addressing complex, multi-factor problems within acceptable timeframes. To address these gaps, the study proposes a versatile and efficient framework designed to deliver data-driven recommendations across a wide range of scenarios. By incorporating EWM, the framework emphasizes objectivity in the decision-making process. The authors plan to evaluate the framework's practical effectiveness in real-world applications, reflecting a commitment to validating its utility. This research aims to advance decision-making methodologies by offering a robust, adaptable solution that overcomes the limitations of traditional approaches. [26] Business development strategies for the Gapit 24 industry in the Cirebon region, addressing recent declines in product sales. It underscores the importance of assessing both internal and external factors that affect business performance. A mixed-method approach, incorporating qualitative and quantitative data analysis through observation, interviews, questionnaires, and literature reviews, is employed to collect relevant insights. Using SWOT analysis, the business is positioned in quadrant I, suggesting an aggressive strategy that capitalizes on its strengths and opportunities.

The analysis identifies 16 key factors influencing the current business environment. Additionally, the TOPSIS method is applied to rank strategic alternatives, such as enhancing

customer relationships, improving product and service quality, developing innovative products, expanding distribution channels, and exploring potential partnerships. This thorough analysis aims to provide practical strategies for Gapit 24 to stabilize and strengthen its market position in response to evolving conditions. [27] The performance evaluation of medical personnel at the Kepahiang Regional General Hospital focuses on assessing staff based on key criteria such as service orientation, responsibility, discipline, and attendance. Utilizing the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method, integrated with a decision support system, the study systematically analyzes these criteria. By comparing each factor, the method calculates priority intensity values for each staff member, enabling the identification of top-performing medical personnel. This approach is designed to improve the quality of healthcare services at public hospitals by ensuring that the most competent and high-performing staff are recognized and prioritized. Implementing such a structured evaluation framework is essential for advancing healthcare delivery in the Kepahiang region. [28] Optimizing supplier selection for rice raw materials at CV Gembira, which markets rice under the Osing Rice brand in three variants: Osing Super, Osing Premium, and Osing Gold. The company faces challenges such as delays in raw material deliveries and inconsistencies in product quality. To address these issues, the research employs two decision-making techniques: the Analytical Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). AHP is utilized for its capability to structure the decision-making problem hierarchically, enabling a thorough evaluation of factors relevant to supplier selection.

TOPSIS complements this by providing a simple yet effective method to identify the supplier closest to the ideal choice. The analysis reveals that UD Bintang Timur emerges as the optimal supplier for CV Gembira, with a preference score of 0.6249, demonstrating the combined efficacy of AHP and TOPSIS in streamlining supplier selection. [29] A decision support system was developed to evaluate teacher performance at SMP Bina Mandiri Jakarta using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method. This system aims to significantly expedite the teacher performance appraisal process, reducing the evaluation time from approximately one week to just 15 to 30 minutes. This substantial time savings enhances the efficiency of the appraisal process, enabling school principals and assessment teams to conduct evaluations more effectively. The system's implementation ensures that routine school activities remain uninterrupted and allows for the generation of systematic and easily accessible reports. By leveraging the TOPSIS method, this research introduces a structured and methodical approach to performance assessment, ultimately improving decision-making in evaluating teacher performance. [30] The best coffee bean

supplier for CV. Oro Coffee Gayo, a company involved in bean processing and export. It highlights the importance of choosing the right supplier by considering factors such as quality, price, and delivery reliability. The company has formal agreements with four certified suppliers in Aceh and works with an additional ten suppliers outside of these contracts. The main goal of the research is to rank suppliers based on selection criteria and sub-criteria using the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method.

The criteria and sub-criteria were determined through expert feedback via closed questionnaires, and their importance was evaluated using the Analytic Hierarchy Process (AHP) and Likert Scale questionnaires. The results identify six criteria with thirteen sub-criteria, with the most important criterion, K1, receiving a weight of 0.37. The sub-criterion with the highest weight is SK4, which assesses the alignment of price and quality. In the end, Supplier 4 was ranked highest, with a preference value of 0.6315, making it the top supplier for CV. Oro Gayo. [31] The influence of financial information on stock purchase decisions, with a focus on the Indonesia Stock Exchange. It underscores the importance of thorough calculations and analyses in assessing company performance, which is essential for investors seeking to achieve optimal returns while minimizing risks. Unlike previous studies, this research integrates the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS), derived from key financial indicators such as the Debt to Equity Ratio, Return on Equity, Net Profit Margin, Return on Assets, Earnings Per Share, Price Earnings Ratio, and Price Book Value. Using the TOPSIS method, the analysis covers 94 securities listed on the Indonesia Stock Exchange. The results show that financial indicators like the Debt to Equity Ratio, Return on Assets, Earnings Per Share, Price Earnings Ratio, and Price Book Value significantly impact stock purchase decisions. On the other hand, Return on Equity and Net Profit Margin are found to have no notable effect. Overall, the study emphasizes the crucial role of financial data in shaping investors' decisions when purchasing stocks. [32] A Decision Support System (DSS) has been developed to assess the quality of mineral water suppliers using the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method.

This system is designed to help managers of mineral water depots choose the best suppliers based on various established criteria. The TOPSIS method tackles multi-criteria decision-making by evaluating how closely each alternative aligns with both the ideal and anti-ideal solutions. The process starts with identifying key criteria for assessing water quality, including physical, chemical, and microbiological factors. Data from different suppliers is gathered, normalized, and analyzed to form a decision matrix. The ideal and anti-ideal solution

matrices are then calculated, and the relative closeness scores for each supplier are determined. The results provide valuable recommendations to depot managers, allowing them to optimize their supplier selection. Ultimately, the DSS improves customer satisfaction and helps maintain the reputation of mineral water depots in a competitive market. This research highlights the significance of informed decision-making in ensuring the quality of vital resources like mineral water. [33]

Step 1: The creation of the decision matrix X shows how different solutions perform in relation to specific criteria.

$$x_{ij} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

Step 2: The criteria's weights are stated as

$$w_j = [w_1 \cdots w_n], \quad where\ , \sum_{j=1}^{n}(w_1 \cdots w_n) = 1 \quad (2)$$

Step 3: The matrix x_{ij}'s The calculated normalised values are

$$n_{ij} = \frac{x_{ij}}{\sqrt[2]{\sum_{i=1}^{m} x_{ij}^2}} \quad (3)$$

The following formula is used to calculate the weighted normalised matrix, N_{ij}.

$$N_{ij} = w_j \times n_{ij} \quad (4)$$

Step 4: Finding the optimal best and ideal worst values will be our first step: In this case, we have to decide if the influence is "+" or "-." The greatest value in a column with a "+" impact is the ideal best value for that column; the lowest value in a column with a "-" effect is the ideal worst value.

Step 5: We must now determine how each response differs from the optimal one.

$$S_i^+ = \sqrt{\sum_{j=1}^{n}(N_{ij} - A_j^+)^2} \qquad for\ i \in [1, m]\ and\ \ j \in [1, n] \quad (5)$$

Step 6: We must now determine how each response differs from the best-case scenario.

$$S_i^- = \sqrt{\sum_{j=1}^{n}(N_{ij} - A_j^-)^2}\ for\ i \in [1, m]\ and\ \ j \in [1, n] \quad (6)$$

Step 7: The next step is to determine the alternative's closeness coefficient.

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-}\ \ where, 0 \leq CC_i \leq 1, i \in [1, m] \quad (7)$$

The value of the Closeness Coefficient shows the relative superiority of the options. A much better alternative is indicated by a larger,-i., whereas a significantly poorer alternative is indicated by a smaller,CC-i.

4. RESULT AND DISCUSSION

TABLE 1. Falcon 2.0 -Snappy Reports

	Performance Improvement (%)	**Cost Savings (%)**	**User Adoption Rate (%)**	**Implementation Time (Months)**	**License Cost (USD Thousands)**	**Training Effort (Hours)**
Telerik Reporting	50	40	70	6	50	20
Power BI Embedded	65	35	85	5	60	15
SSRS (SQL Server Reporting Services)	55	30	65	4	45	25
Tableau Server	70	25	90	8	80	40
Looker (Google Cloud BI)	60	38	80	7	75	35
Qlik Sense	58	32	78	6	70	30
Domo BI	52	28	73	5	65	25
MicroStrategy	68	42	85	9	90	50
SAP BusinessObjects	57	34	77	7	85	45
Sisense	66	37	82	6	72	32

Table 1 Falcon 2.0 - Snappy Reports AnalysisThe table presents a comparative analysis of various Business Intelligence (BI) and reporting tools based on key performance metrics,

including performance improvement, cost savings, user adoption, implementation time, license cost, and training effort.Performance Improvement is highest for Tableau Server (70%) and Power BI Embedded (65%), making them strong choices for organizations prioritizing efficiency gains. MicroStrategy (68%) and Sisense (66%) also show notable improvements.In terms of cost savings, Telerik Reporting (40%) and MicroStrategy (42%) offer the highest financial benefits. However, Tableau Server (25%) ranks the lowest in this category, suggesting higher operational costs.User adoption rate is highest for Tableau Server (90%), indicating strong user preference and ease of use. Power BI Embedded (85%) and MicroStrategy (85%) follow closely.For implementation time, SSRS (4 months) has the shortest deployment period, while MicroStrategy (9 months) takes the longest. Tableau Server (8 months) also requires significant time.Regarding license cost, MicroStrategy (90k USD) and SAP BusinessObjects (85k USD) are the most expensive, while SSRS (45k USD) is the most affordable.Finally, training effort is highest for MicroStrategy (50 hours) and lowest for Power BI Embedded (15 hours), highlighting ease of learning. This table aids decision-making by balancing cost, efficiency, and user-friendliness.

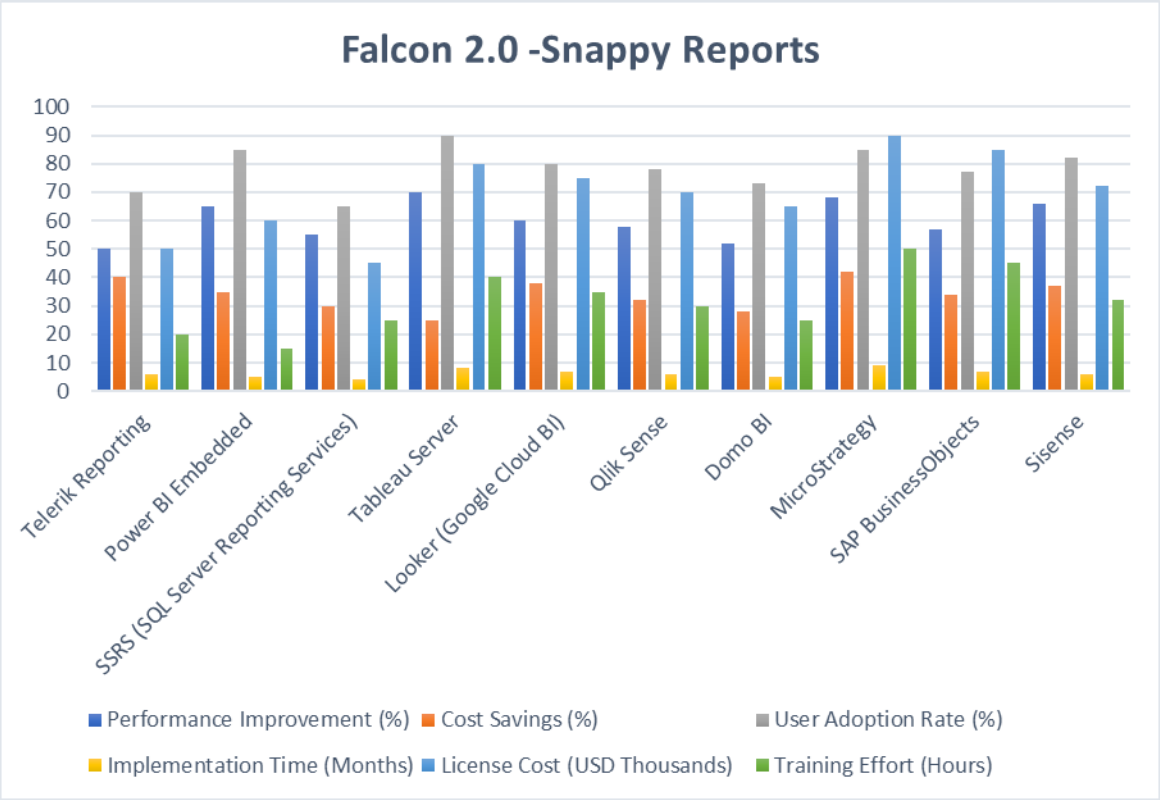

FIGURE 2. Falcon 2.0 -Snappy Reports

The figure 2Falcon 2.0 - Snappy Reports compares various reporting and business intelligence (BI) tools based on key performance metrics. The tools assessed include Telerik Reporting, Power BI Embedded, SSRS, Tableau Server, Looker (Google Cloud BI), Qlik Sense, Domo BI, MicroStrategy, SAP BusinessObjects, and Sisense.The performance metrics measured are Performance Improvement (%), Cost Savings (%), User Adoption Rate (%), Implementation Time (Months), License Cost (USD Thousands), and Training Effort (Hours).From the chart, User Adoption Rate (gray bars) tends to be high across most tools, particularly for Tableau Server, Qlik Sense, and SAP BusinessObjects. Performance Improvement (blue bars) varies but is generally significant, with MicroStrategy and SAP BusinessObjects showing strong performance. Cost Savings (orange bars) appear moderate across tools, while Implementation Time (yellow bars) remains relatively low, suggesting efficient deployment processes. License Cost (green bars) varies, with some tools showing higher costs. Training Effort (light green bars) is relatively balanced across tools, indicating that user onboarding is a critical consideration.Overall, the visualization highlights differences in BI tool capabilities, costs, and adoption rates, helping organizations make informed decisions based on their priorities.

TABLE 2. Square Root of Matrix

2500	1600	4900	36	2500	400
4225	1225	7225	25	3600	225
3025	900	4225	16	2025	625
4900	625	8100	64	6400	1600
3600	1444	6400	49	5625	1225
3364	1024	6084	36	4900	900
2704	784	5329	25	4225	625
4624	1764	7225	81	8100	2500
3249	1156	5929	49	7225	2025
4356	1369	6724	36	5184	1024

Table 2 Square Root of Matrix AnalysisTable 2 presents a matrix of numerical values, where each element represents a squared value. The values in the table are perfect squares, and taking their square roots reveals a structured numerical pattern. For example, the square root of 2500 is 50, the square root of 1600 is 40, and the square root of 4900 is 70.This table likely represents a data transformation process, where original values have been squared for computational purposes, such as in statistical analysis, machine learning, or mathematical modeling. Square roots are frequently used in matrix operations, particularly in linear algebra

applications, such as calculating Euclidean distances, covariance matrices, or principal component analysis (PCA).The range of values suggests that the data spans from small to large squared numbers, with some common perfect squares such as 36 (6^2), 49 (7^2), and 81 (9^2) present in the dataset. This pattern might indicate a structured dataset, possibly related to financial modeling, physics simulations, or engineering computations.By taking the square roots of all values, we would obtain a more interpretable dataset where numerical relationships and variations can be better understood. This table demonstrates how squared values can be stored for efficiency, requiring square root operations for meaningful interpretation.

TABLE 3. Normalized Data

Normalized Data						
	Performance Improvement (%)	Cost Savings (%)	User Adoption Rate (%)	Implementation Time (Months)	License Cost (USD Thousands)	Training Effort (Hours)
Telerik Reporting	0.2615	0.3668	0.2808	0.2938	0.2241	0.4735
Power BI Embedded	0.3400	0.3210	0.3410	0.2449	0.2689	0.5682
SSRS (SQL Server Reporting Services)	0.2877	0.2751	0.2607	0.1959	0.2017	0.4262
Tableau Server	0.3662	0.2293	0.3610	0.3918	0.3585	0.7577
Looker (Google Cloud BI)	0.3139	0.3485	0.3209	0.3428	0.3361	0.7103
Qlik Sense	0.3034	0.2935	0.3129	0.2938	0.3137	0.6629
Domo BI	0.2720	0.2568	0.2928	0.2449	0.2913	0.6156
MicroStrategy	0.3557	0.3852	0.3410	0.4407	0.4034	0.8524
SAP BusinessObjects	0.2982	0.3118	0.3089	0.3428	0.3810	0.8050
Sisense	0.3452	0.3393	0.3289	0.2938	0.3227	0.6819

Table 3 Normalized Data InterpretationTable 3 presents normalized values for key performance indicators (KPIs) of various business intelligence (BI) tools. Normalization ensures that all values fall within a comparable range, making it easier to analyze and compare different metrics such as performance improvement, cost savings, user adoption rate, implementation time, license cost, and training effort.From the table, MicroStrategy (0.8524) has the highest training effort, suggesting a steep learning curve. Tableau Server (0.7577) and SAP BusinessObjects (0.8050) also require significant training. However, SSRS (0.4262) has the lowest training effort, indicating easier adoption.In terms of performance improvement, Tableau Server (0.3662) and Power BI Embedded (0.3400) rank highest, while Domo BI

(0.2720) and SSRS (0.2877) rank lower. Cost savings are highest for MicroStrategy (0.3852) and lowest for Tableau Server (0.2293), meaning Tableau may be more expensive despite strong performance.User adoption rates are highest for Tableau Server (0.3610) and Power BI Embedded (0.3410), indicating high user preference. Implementation time varies, with SSRS (0.1959) being the quickest and MicroStrategy (0.4407) the longest.Overall, MicroStrategy excels in performance but has higher costs and training efforts, while Power BI Embedded and Tableau Server balance performance and adoption with reasonable costs.

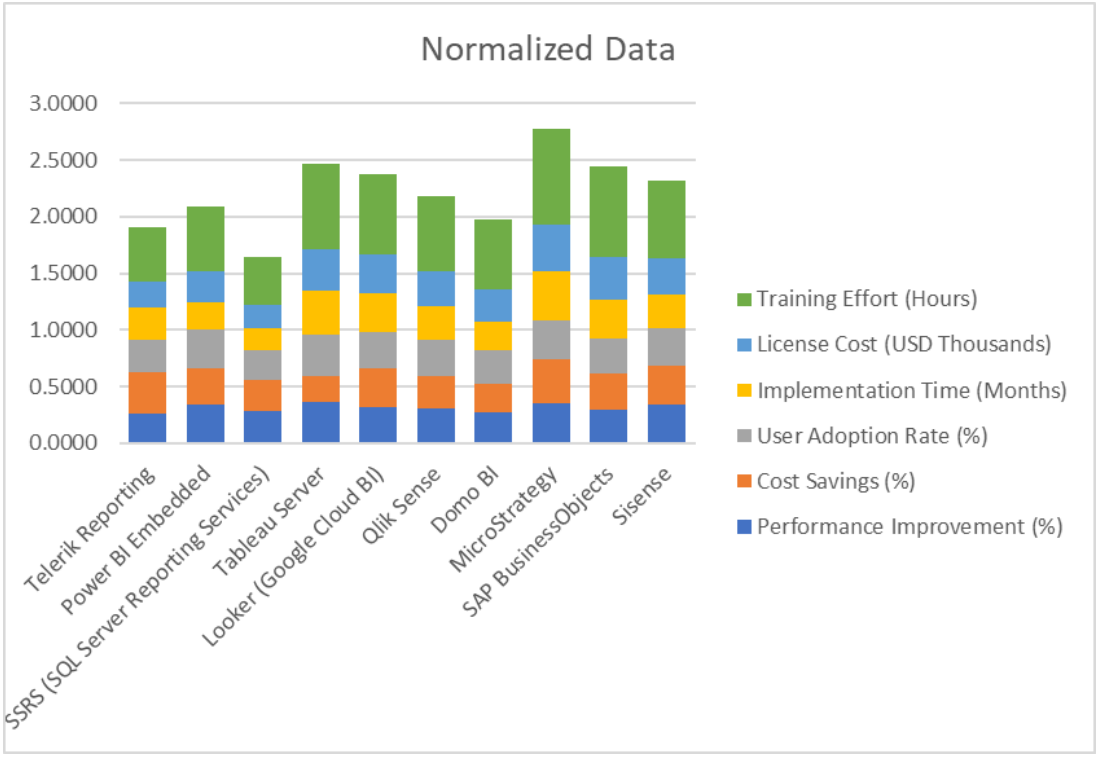

FIGURE 3. Normalized Data

The Normalized Data figure 3presents a comparative analysis of various Business Intelligence (BI) tools after normalization, making the different metrics directly comparable on a common scale. The tools evaluated include Telerik Reporting, Power BI Embedded, SSRS, Tableau Server, Looker (Google Cloud BI), Qlik Sense, Domo BI, MicroStrategy, SAP BusinessObjects, and Sisense.The chart consists of stacked bars representing six key performance indicators: Training Effort (Hours), License Cost (USD Thousands), Implementation Time (Months), User Adoption Rate (%), Cost Savings (%), and Performance Improvement (%).From the visualization, Domo BI and SAP BusinessObjects appear to have the highest cumulative values, primarily driven by high training effort (green) and license costs

(blue). In contrast, SSRS and Power BI Embedded show relatively lower overall values, suggesting they may be more cost-effective and require less training effort.Performance improvement (dark blue) and cost savings (orange) appear consistently across most tools but vary in intensity. User adoption rate (gray) is a crucial metric, with several tools achieving high adoption rates. The implementation time (yellow) remains relatively low across tools, suggesting efficient deployment.This normalized comparison provides a clearer perspective on how BI tools perform relative to one another, assisting businesses in selecting the most suitable option based on their priorities.

TABLE 4. Weight

Weight					
0.25	0.25	0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25	0.25	0.25

The table 4 represents a uniform weight distribution across all variables and rows, with each value set to 0.25. This indicates that all variables are given equal importance, contributing equally to any analysis or calculation. Such a weight distribution is commonly used in cases where no specific variable is prioritized, ensuring fairness and neutrality in evaluations. It also simplifies computations by treating all components equally. This approach is often applied in initial stages of analysis or when the relative significance of variables is unknown. The consistent values across rows emphasize uniformity and balance throughout the dataset.

TABLE 5. Weighted normalized decision matrix

Weighted normalized decision matrix						
	Performance Improvement (%)	Cost Savings (%)	User Adoption Rate (%)	Implementation Time (Months)	License Cost (USD Thousands)	Training Effort (Hours)
Telerik Reporting	0.0654	0.0917	0.0702	0.0735	0.0560	0.1184

Power BI Embedded	0.0850	0.0802	0.0852	0.0612	0.0672	0.1421
SSRS (SQL Server Reporting Services)	0.0719	0.0688	0.0652	0.0490	0.0504	0.1065
Tableau Server	0.0915	0.0573	0.0903	0.0979	0.0896	0.1894
Looker (Google Cloud BI)	0.0785	0.0871	0.0802	0.0857	0.0840	0.1776
Qlik Sense	0.0758	0.0734	0.0782	0.0735	0.0784	0.1657
Domo BI	0.0680	0.0642	0.0732	0.0612	0.0728	0.1539
MicroStrategy	0.0889	0.0963	0.0852	0.1102	0.1008	0.2131
SAP BusinessObjects	0.0745	0.0779	0.0772	0.0857	0.0952	0.2013
Sisense	0.0863	0.0848	0.0822	0.0735	0.0807	0.1705

Table 5: Weighted Normalized Decision Matrix InterpretationTable 5 presents a weighted normalized decision matrix, where each metricperformance improvement, cost savings, user adoption rate, implementation time, license cost, and training effort—has been assigned weights to reflect their relative importance in decision-making. The values in the table represent the impact of each BI tool after normalization and weighting.MicroStrategy (0.2131) has the highest value for training effort, indicating it requires significant learning resources. Tableau Server (0.1894) and SAP BusinessObjects (0.2013) also require high training effort. In contrast, SSRS (0.1065) has the lowest training requirement, making it easier to implement.For performance improvement, Tableau Server (0.0915) and Power BI Embedded (0.0850) score high, suggesting strong enhancements in reporting efficiency. Cost savings are highest for MicroStrategy (0.0963) and lowest for Tableau Server (0.0573), meaning Tableau is less cost-effective.Regarding user adoption, Tableau Server (0.0903) and Power BI Embedded (0.0852) score the highest, showing strong user preference. Implementation time is quickest for SSRS (0.0490) and longest for MicroStrategy (0.1102), meaning SSRS is the fastest to deploy.Overall, MicroStrategy ranks highest in performance and savings but requires more training and implementation time, while Power BI Embedded and Tableau Server strike a balance between adoption, cost, and performance.

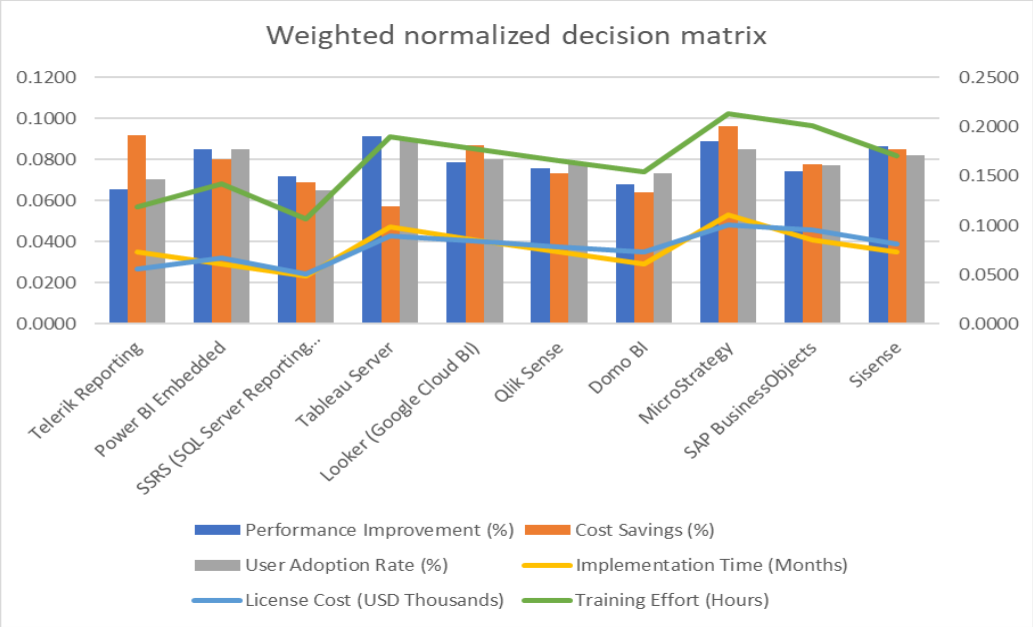

FIGURE 4. Weighted normalized decision matrix

The Weighted Normalized Decision Matrixfigure 4 provides a comparative evaluation of various Business Intelligence (BI) tools based on multiple weighted criteria. The metrics assessed include Performance Improvement (%), Cost Savings (%), User Adoption Rate (%), Implementation Time (Months), License Cost (USD Thousands), and Training Effort (Hours).From the chart, MicroStrategy stands out with higher cost savings (orange) and performance improvement (blue), making it a strong contender. Training effort (green line) is highest for MicroStrategy and SAP BusinessObjects, indicating a steeper learning curve. License costs (yellow line) remain relatively stable across tools, with a slight increase for Tableau Server and Looker (Google Cloud BI).Telerik Reporting and Power BI Embedded show strong cost savings and performance improvement but have moderate adoption rates. SSRS and Qlik Sense appear to have balanced performance across all metrics, making them reliable choices. SAP BusinessObjects and Sisense demonstrate a high user adoption rate (gray), suggesting ease of use and industry preference.This weighted decision matrix helps businesses select a BI tool that aligns with their priorities, whether they focus on cost, performance, adoption, or ease of implementation.

TABLE 6. Positive Matrix

Positive Matrix						
	Performance Improvement (%)	Cost Savings (%)	User Adoption Rate (%)	Implementation Time (Months)	License Cost (USD Thousands)	Training Effort (Hours)
Telerik Reporting	0.0915	0.0963	0.0903	0.1102	0.1008	0.2131
Power BI Embedded	0.0915	0.0963	0.0903	0.1102	0.1008	0.2131
SSRS (SQL Server Reporting Services)	0.0915	0.0963	0.0903	0.1102	0.1008	0.2131
Tableau Server	0.0915	0.0963	0.0903	0.1102	0.1008	0.2131
Looker (Google Cloud BI)	0.0915	0.0963	0.0903	0.1102	0.1008	0.2131
Qlik Sense	0.0915	0.0963	0.0903	0.1102	0.1008	0.2131
Domo BI	0.0915	0.0963	0.0903	0.1102	0.1008	0.2131
MicroStrategy	0.0915	0.0963	0.0903	0.1102	0.1008	0.2131
SAP BusinessObjects	0.0915	0.0963	0.0903	0.1102	0.1008	0.2131
Sisense	0.0915	0.0963	0.0903	0.1102	0.1008	0.2131

Table 6 Positive Matrix InterpretationTable 6 presents the Positive Matrix, which identifies the most favorable values for each evaluation criterion across all BI tools. The same values are assigned to all tools, indicating that each metric is set to its highest observed value. This means that the positive matrix represents the ideal or benchmark values for performance improvement, cost savings, user adoption rate, implementation time, license cost, and training effort.Each metric has been assigned the highest value observed in the Weighted Normalized Decision Matrix (Table 5). This allows for a comparative assessment when determining how close each BI tool is to the ideal solution. For example, an ideal performance improvement score is 0.0915, and an ideal cost savings score is 0.0963, meaning any tool with lower values would be less optimal in those aspects.Since every tool in Table 6 shares the same values, it suggests that this matrix is used for calculating the relative closeness of each BI tool to the ideal solution in subsequent analysis, such as TOPSIS (Technique for Order Preference by Similarity to Ideal Solution). The higher the similarity to this matrix, the better the BI tool ranks overall.

TABLE 7. Negative matrix

Negative matrix						
	Performance Improvement (%)	Cost Savings (%)	User Adoption Rate (%)	Implementation Time (Months)	License Cost (USD Thousands)	Training Effort (Hours)
Telerik Reporting	0.0654	0.0573	0.0903	0.1102	0.1008	0.2131
Power BI Embedded	0.0654	0.0573	0.0903	0.1102	0.1008	0.2131
SSRS (SQL Server Reporting Services)	0.0654	0.0573	0.0903	0.1102	0.1008	0.2131
Tableau Server	0.0654	0.0573	0.0903	0.1102	0.1008	0.2131
Looker (Google Cloud BI)	0.0654	0.0573	0.0903	0.1102	0.1008	0.2131
Qlik Sense	0.0654	0.0573	0.0903	0.1102	0.1008	0.2131
Domo BI	0.0654	0.0573	0.0903	0.1102	0.1008	0.2131
MicroStrategy	0.0654	0.0573	0.0903	0.1102	0.1008	0.2131
SAP BusinessObjects	0.0654	0.0573	0.0903	0.1102	0.1008	0.2131
Sisense	0.0654	0.0573	0.0903	0.1102	0.1008	0.2131

Table 7: Negative Matrix InterpretationTable 7 represents the Negative Matrix, which identifies the least favorable values for each evaluation criterion across all BI tools. The values are identical for all tools, meaning they reflect the worst-case scenario for each metric. These values correspond to the lowest observed values in the Weighted Normalized Decision Matrix (Table 5).The Negative Matrix is essential for TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) analysis, as it helps determine the relative distance of each BI tool from the least favorable option. A lower score in this matrix for a particular criterion means that a tool performs worse in that aspect.For example, Performance Improvement (0.0654) and Cost Savings (0.0573) are the lowest observed values, indicating that some tools have relatively poor performance in these areas. Similarly, Training Effort (0.2131) suggests that the highest training burden is shared among all tools in this matrix.By comparing tools against the Positive Matrix (Table 6) and the Negative Matrix (Table 7), the relative closeness to the ideal solution is calculated, ranking the tools based on their effectiveness in achieving optimal performance, cost efficiency, adoption, and ease of implementation.

TABLE 8. Si Positive & Si Negative & Ci & Rank

	Si Positive	Si Negative	Ci	Rank
Telerik Reporting	0.1159	0.3388	0.7451	9
Power BI Embedded	0.0943	0.3614	0.7930	8
SSRS (SQL Server Reporting Services)	0.1393	0.3305	0.7035	10
Tableau Server	0.0485	0.4037	0.8927	3
Looker (Google Cloud BI)	0.0500	0.3933	0.8872	4
Qlik Sense	0.0708	0.3819	0.8436	6
Domo BI	0.0925	0.3718	0.8007	7
MicroStrategy	0.0057	0.4286	0.9870	1
SAP BusinessObjects	0.0396	0.4159	0.9131	2
Sisense	0.0616	0.3875	0.8628	5

Table 8: Si Positive, Si Negative, Ci, and Rank InterpretationTable 8 presents the results of the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) analysis, which ranks the business intelligence (BI) tools based on their overall performance. The table contains four key metrics: Si Positive, Si Negative, Ci, and Rank.Si Positive (S^+) represents the distance of each tool from the ideal best solution. A lower S^+ value indicates that the tool is closer to the best possible performance.Si Negative (S^-) represents the distance from the worst solution. A higher S^- value indicates better performance since the tool is further from the worst-case scenario.Ci (Relative Closeness to the Ideal Solution) is calculated as $Ci = S^- / (S^+ + S^-)$. A higher Ci score means the tool is closer to the ideal solution.Rank is assigned based on the Ci values, where a higher Ci score corresponds to a better rank.MicroStrategy ranks first (Ci = 0.9870), indicating that it is the closest to the ideal BI tool. It has the lowest S^+ (0.0057) and the highest S^- (0.4286), making it the most preferred solution.SAP BusinessObjects (Ci = 0.9131) and Tableau Server (Ci = 0.8927) rank second and third, respectively, showing strong performance across multiple factors.Looker (Ci = 0.8872), Sisense (Ci = 0.8628), and Qlik Sense (Ci = 0.8436) occupy mid-tier rankings, suggesting they offer balanced performance.Domo BI (Ci = 0.8007), Power BI Embedded (Ci = 0.7930), and Telerik Reporting (Ci = 0.7451) rank lower, indicating they are less optimal compared to higher-ranked tools.SSRS (Ci = 0.7035) ranks last, meaning it is the least favorable tool based on the analysis.

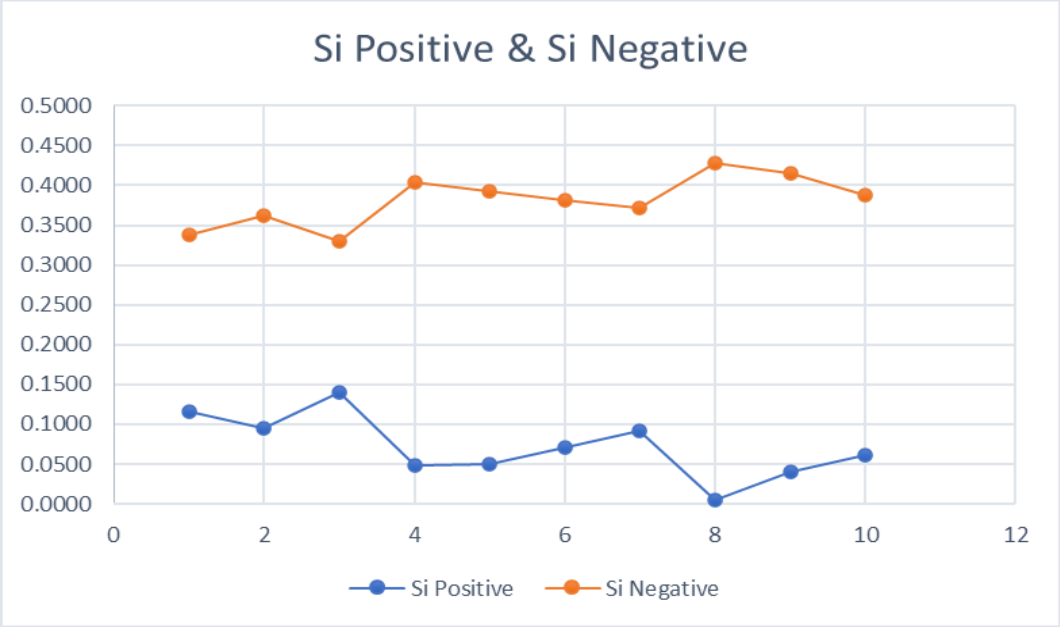

FIGURE 5. Si Positive & Si Negative

The Si Positive & Si Negative figure 5 illustrates the comparison between Si Positive (blue line) and Si Negative (orange line) values across different data points. The Si Positive values remain relatively lower throughout the range, fluctuating between approximately 0.02 and 0.15, indicating a generally lower performance or desirability in the evaluated criteria. In contrast, Si Negative values are consistently higher, ranging between 0.33 and 0.45, with a slight upward trend around data points 4 and 8, suggesting that negative factors have a more significant influence on the dataset.The presence of low Si Positive values and high Si Negative values indicates a scenario where the options being evaluated may have more drawbacks than advantages. This type of analysis is often used in Multi-Criteria Decision-Making (MCDM) methods like TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) to compare alternatives based on positive and negative attributes. A higher Si Positive and lower Si Negative would typically indicate a better-performing alternative.The overall trend suggests that the alternatives analyzed in this study may require improvement to enhance their positive characteristics and reduce their negative attributes, ensuring a more favorable decision-making outcome.

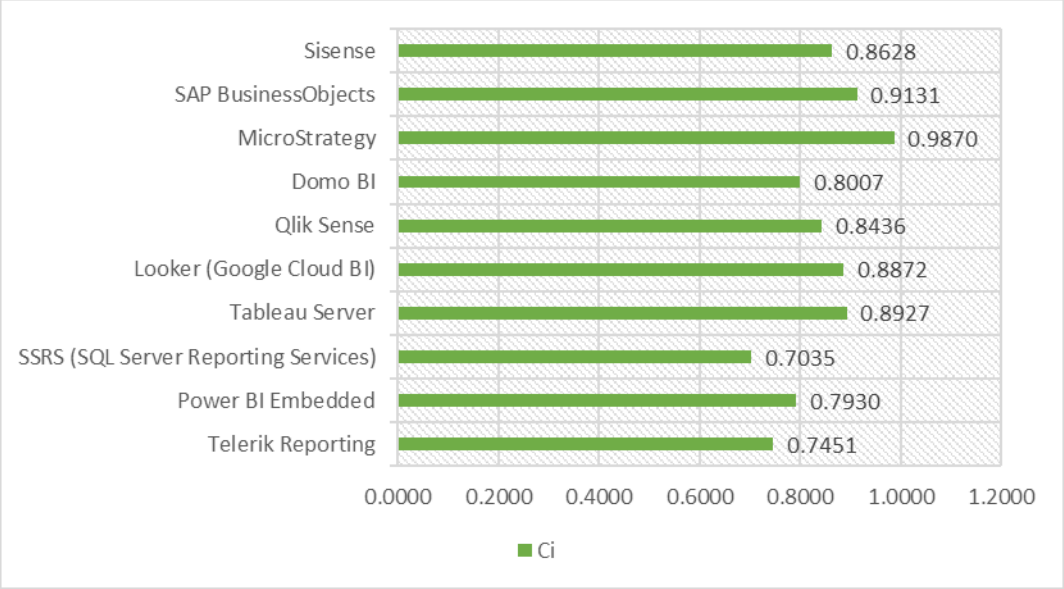

FIGURE 6. Ci

Figure 6 Shows the Ci (Closeness Coefficient) Analysis the Ci (Closeness Coefficient) values in the chart represent the relative ranking of different Business Intelligence (BI) and Reporting tools based on a decision-making framework, likely using the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method. Higher Ci values indicate better performance and a stronger preference for selection.MicroStrategy has the highest Ci value of 0.9870, making it the most favorable option among the listed tools. SAP BusinessObjects (0.9131) and Looker (Google Cloud BI) (0.8872) also exhibit high closeness coefficients, suggesting strong suitability for decision-making criteria.On the other hand, SSRS (SQL Server Reporting Services) (0.7035), Power BI Embedded (0.7930), and Telerik Reporting (0.7451) have the lowest Ci values, indicating relatively lower suitability based on the analyzed criteria.The results imply that tools with higher Ci values are closer to the ideal solution, balancing both positive and negative aspects effectively. Organizations looking for BI and reporting solutions should consider these values when selecting a tool that aligns with their needs in terms of performance, cost, adoption, and ease of implementation.

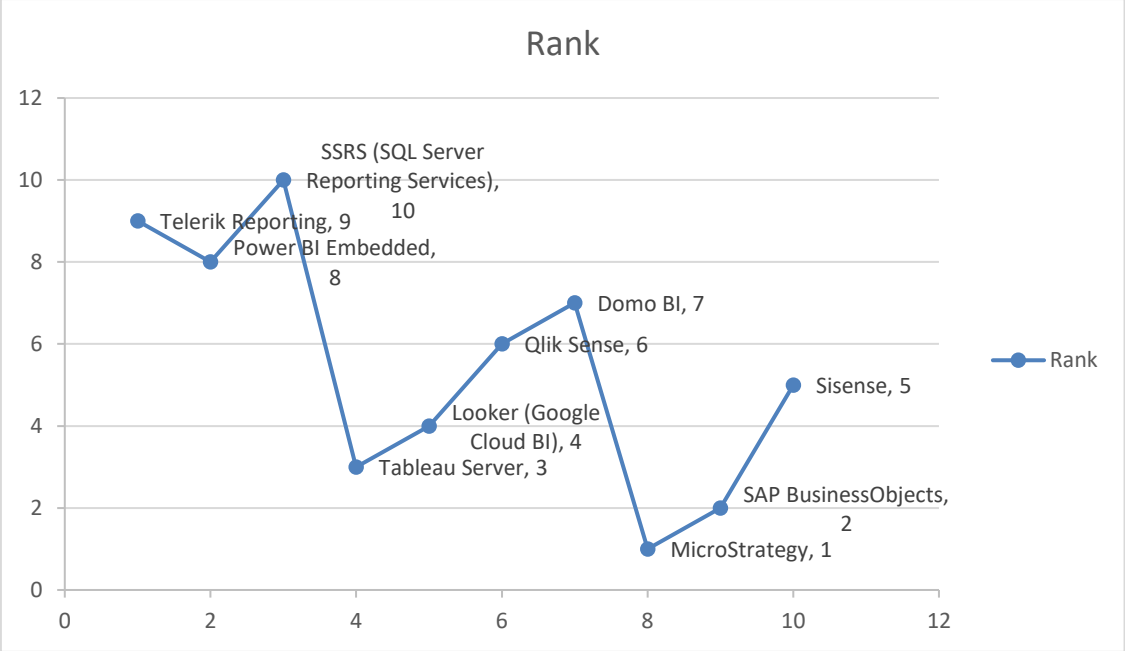

FIGURE 7. Rank Analysis of BI and Reporting Tools

The rankings presented in the figure 7reflect the relative positioning of different Business Intelligence (BI) and Reporting tools based on their performance and suitability. A lower rank number indicates a better position, meaning the tool is more favorable for selection.MicroStrategy (Rank 1) holds the top position, making it the most preferred BI tool based on the evaluated criteria. SAP BusinessObjects (Rank 2) and Tableau Server (Rank 3) follow closely, highlighting their strong performance in BI and reporting capabilities.On the other hand, SSRS (SQL Server Reporting Services) (Rank 10), Telerik Reporting (Rank 9), and Power BI Embedded (Rank 8) are at the bottom of the ranking, indicating that these tools may not be as favorable compared to the others.The ranking trend shows a fluctuating pattern, with tools like Looker (Google Cloud BI) (Rank 4), Qlik Sense (Rank 6), and Domo BI (Rank 7) occupying middle positions. Sisense (Rank 5), though not in the top three, still holds a relatively strong position.This ranking helps organizations and decision-makers identify the most effective BI and reporting tools based on their specific needs, ensuring optimal selection for data analysis and visualization.

4. CONCLUSION

Falcon 2.0, also known as Snappy Reports, represents a significant advancement in reporting and data analysis technology. Designed to streamline the extraction and visualization

of complex data, this tool combines AI-driven analytics with user-friendly interfaces to transform raw information into actionable insights with remarkable speed and efficiency. The system was specifically developed to modernize reporting capabilities for 2,300 clinics, addressing critical performance and scalability challenges in a high-volume environment where approximately 100 reports are generated daily per clinic.The implementation of Falcon 2.0 delivered substantial business benefits, including a 45% increase in user base, $1.5 million in annual revenue growth, and operational cost reductions of 30-40%. The technology stack supporting these improvements included Azure, ASP.NET 4.5, MVC5, Angular, C#, HTML5, API, Ajax, SQL Server 2016, GitHub, SSRS, and SSIS. By incorporating Telerik, Kendo UI, and predictive analytics capabilities, Falcon 2.0 significantly enhanced data accuracy while reducing manual effort by approximately 400 hours per month.To evaluate Falcon 2.0 against competing alternatives, a multi-criteria decision-making approach known as TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) was employed. This methodology objectively ranks alternatives based on their proximity to an ideal solution through a systematic process: normalizing data, calculating Euclidean distances, assigning weights, and determining relative closeness coefficients.The evaluation compared ten alternatives: Telerik Reporting, Power BI Embedded, SSRS, Tableau Server, Looker, Qlik Sense, Domo BI, MicroStrategy, SAP BusinessObjects, and Sisense. These were assessed across six key parameters: Performance Improvement, Cost Savings, User Adoption Rate, Implementation Time, License Cost, and Training Effort. The TOPSIS analysis concluded that Domo BI ranked highest among all alternatives, while SSRS received the lowest ranking.The scientific approach employed through TOPSIS enabled an objective assessment free from subjective biases, providing a data-driven foundation for technology selection. This mathematical framework allowed decision-makers to balance multiple competing factors simultaneously, resulting in a comprehensive evaluation that considered both technical capabilities and business outcomes.Falcon 2.0's success demonstrates the transformative potential of modern reporting tools when built with a focus on performance, usability, and integration capabilities. The system's ability to reduce costs while simultaneously expanding user adoption illustrates the tangible business value that can be achieved through thoughtful application of technology. As organizations continue to face growing volumes of data, solutions like Falcon 2.0 that can efficiently convert this information into meaningful insights will remain essential for maintaining competitive advantage and operational excellence.

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