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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.

1. INTRODUCTION

Accurately identifying entities and relationships in textual information is an important aspect of Natural Language Processing (NLP) and knowledge graph development. Falcon 2.0, developed by Ahmed Sagor, Kuldeep Singh, Aneri Patel, and Maria-Esther Vidal, is an advanced tool designed to connect textual information with Wikidata, a collaboratively maintained knowledge graph. It identifies entities and relationships from short English texts and generates prioritized

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candidate lists with corresponding Internationalized Resource Identifiers (IRIs). By combining language models, N-gram tiling, N-gram segmentation, and optimization techniques, Falcon 2.0 improves the accuracy of entity and relationship mapping. Its open-source availability, online API, and comprehensive documentation make it accessible to researchers and developers working in semantic web technologies and knowledge representation [12, 13]. The Falcon 2.0 framework also provides opportunities for developing intelligent research summarization systems, particularly through the concept of Snappy Reports. Traditional research analysis requires considerable time and manual effort to examine academic publications, identify important findings, and organize relevant information. An AI-driven summarization approach can reduce this burden by applying Natural Language Processing, machine learning, and deep learning techniques to extract meaningful information from research documents. Transformer-based models, including GPT and BERT, can support the identification of research objectives, methodologies, findings, discussions, and conclusions. Unlike conventional keyword-based summarization, these approaches focus on contextual relationships and linguistic patterns, helping generate concise and meaningful research summaries [1, 2]. An important feature of intelligent summarization is its ability to process complex academic language while maintaining the technical meaning of the original publication. Research articles in engineering, medicine, and data science frequently contain specialized terminology, statistical findings, and detailed methodological descriptions. Techniques such as Named Entity Recognition (NER), sentiment analysis, and topic modeling can help identify significant concepts and relationships within these documents. The Snappy Reports approach aims to transform lengthy research publications into shorter, organized reports that allow students, researchers, and professionals to understand essential findings more efficiently. This reduces the time required for literature reviews and supports further research, hypothesis development, and experimental planning [2]. Knowledge graph integration provides another important advantage by establishing relationships between concepts, research findings, and related topics. Such capabilities are particularly valuable for multidisciplinary research, where information from different academic fields must be connected. For example, research involving machine learning applications in disease detection may require information from both computer science and biomedical literature. Entity and relationship mapping can facilitate the identification of relevant concepts across these disciplines. Furthermore, multilingual processing and flexible summarization settings can improve accessibility for researchers with different linguistic backgrounds and information requirements. Users may require either brief summaries or detailed analytical reports depending on their research objectives. Supporting document formats such as PDF, DOCX, and XML can also simplify the submission and processing of academic materials [3, 4]. The potential applications of AI-based research summarization extend beyond academic institutions. Businesses can use automated reports to examine technical documents, market research, and industry publications, supporting strategic planning and decision-making. Healthcare professionals can benefit from faster examination of clinical studies, treatment guidelines, and emerging medical research. Similarly, government organizations and policymakers can use summarized research findings to support evidence-based decisions in public health, environmental management, and technological development. These applications demonstrate how automated information extraction can improve knowledge accessibility and reduce the effort required to analyze large volumes of professional literature [5]. Human-in-the-loop validation is another important consideration in developing reliable AI summarization systems. User feedback can help identify inaccurate summaries, missing information, and incorrectly interpreted technical concepts. By incorporating feedback into the summarization process, the system can progressively improve its contextual understanding and subject-specific performance.

However, AI-generated summaries may still introduce bias, omit important contextual details, or misinterpret the original author's arguments. Therefore, users should verify generated reports against the original publications before relying on them for academic or professional decisions [6, 7]. Despite these advantages, processing mathematical expressions, programming code, and highly technical information remains challenging. Research publications in physics, computational science, and engineering often depend on equations, algorithms, and code snippets to communicate important findings. Although NLP techniques can process textual information, additional capabilities are necessary to interpret mathematical notation and programming structures accurately. Integrating LaTeX-based equation recognition and code extraction could improve the effectiveness of future summarization systems. Other potential developments include real-time citation tracking, advanced semantic analysis, improved domain-specific learning, and interactive AI-based question-answering capabilities [8, 9]. It is also important to distinguish Falcon 2.0 from other technologies using the Falcon or FALCON



FIGURE 1. Falcon 2.0 -Snappy Reports

name. These include protein structure prediction, autonomous drone networks, multi-instance learning optimization, opportunistic network evaluation, distributed memory systems, and large-scale data analytics scheduling [11, 14–22]. The Snappy Reports application described in the supplied material is also a separate software development project involving Telerik reporting tools, MVC architecture, Kendo UI, and database technologies. Its reported applications include clinical reporting, automated data processing, and operational efficiency improvements [23].

2. MATERIAL AND METHODS

Business Intelligence (BI) tools play an important role in improving organizational performance through efficient data analysis, reporting, and decision-making. Several BI solutions are available, including Telerik Reporting, Power BI Embedded, SQL Server Reporting Services (SSRS), Tableau Server, Looker, Qlik Sense, Domo BI, MicroStrategy, SAP BusinessObjects, and Sisense. These platforms provide different capabilities, such as interactive dashboards, automated reporting, data visualization, predictive analytics, and integration with enterprise applications. The effectiveness of these tools can be evaluated using six parameters: performance improvement, cost savings, user adoption rate, implementation time, license cost, and training effort. Performance improvement measures reporting efficiency and analytical accuracy, while cost savings indicate reductions in operational and IT expenses. User adoption reflects employee acceptance and ease of use, whereas implementation time measures deployment complexity. License cost determines the financial investment required, and training effort evaluates the time needed to develop employee proficiency. Cloud-based platforms such as Domo, Looker, and Sisense offer flexible deployment and integration capabilities, while Tableau, Qlik Sense, and Power BI provide user-friendly visualization and self-service analytics. Enterprise solutions such as MicroStrategy and

SAP BusinessObjects support complex reporting requirements. Therefore, selecting an appropriate BI solution requires balancing technical capabilities, implementation complexity, cost efficiency, and organizational requirements.

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

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is an effective multi-criteria decision-making (MCDM) method used to evaluate and rank alternatives across different fields. Its applications include tourism, education, business development, healthcare, supplier selection, and financial investment. In tourism, TOPSIS helps identify suitable travel destinations by considering factors such as affordability, accessibility, safety, cleanliness, and available facilities [24]. In higher education, it supports university competitiveness by evaluating factors such as accreditation, student selection, alumni quality, and institutional services [25]. The integration of TOPSIS with other decision-making techniques further improves its effectiveness. For example, combining TOPSIS with the Entropy Weighting Method (EWM) provides objective criteria weights and reduces subjective bias in decision-making [26]. Similarly, integrating SWOT analysis with TOPSIS helps businesses identify and prioritize appropriate development strategies based on internal strengths and external opportunities [27]. In healthcare, TOPSIS supports employee performance evaluation using criteria such as discipline, responsibility, attendance, and service orientation [28]. It also improves teacher assessment by reducing evaluation time and generating systematic performance reports [29]. Supplier selection is another important application of TOPSIS. Its integration with the Analytical Hierarchy Process (AHP) helps organizations identify suitable suppliers based on quality, price, and delivery reliability [30, 31]. In financial investment, TOPSIS evaluates securities using indicators such as debt-to-equity ratio, return on assets, earnings per share, and price-to-book value [32]. Furthermore, it supports mineral water supplier evaluation by considering physical, chemical, and microbiological quality parameters [33]. Overall, TOPSIS provides a systematic, flexible, and reliable framework for ranking alternatives, improving decision-making accuracy, and supporting efficient resource allocation across diverse applications.

3. RESULT AND DISCUSSION

TABLE 1. Falcon 2.0 – Snappy Reports

BI Tool	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 presents a comparative analysis of various Business Intelligence (BI) and reporting tools based on key performance indicators, including performance improvement, cost savings, user adoption rate, implementation time, license cost, and training effort. In terms of performance improvement, Tableau Server achieves the highest value of 70%, followed by MicroStrategy (68%), Sisense (66%), and Power BI Embedded (65%), making them suitable choices for organizations seeking improved operational efficiency. Regarding cost savings, MicroStrategy records the highest value of 42%, followed by Telerik Reporting (40%), while Tableau Server shows the lowest value of 25%. User adoption is highest for Tableau Server at 90%, indicating strong user acceptance, followed by Power BI Embedded and MicroStrategy, both achieving 85%. Regarding implementation time, SSRS requires the shortest deployment period of 4 months, whereas MicroStrategy takes the longest at 9 months. In terms of license cost, MicroStrategy is the most expensive solution at USD 90,000, followed by SAP BusinessObjects at USD 85,000, while SSRS is the most affordable at USD 45,000. Finally, training effort is highest for MicroStrategy (50 hours) and lowest for Power BI Embedded (15 hours), highlighting differences in learning requirements. Overall, the comparative analysis supports informed BI tool selection by balancing performance, cost efficiency, implementation requirements, and user-friendliness.

The figure 2 Falcon 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

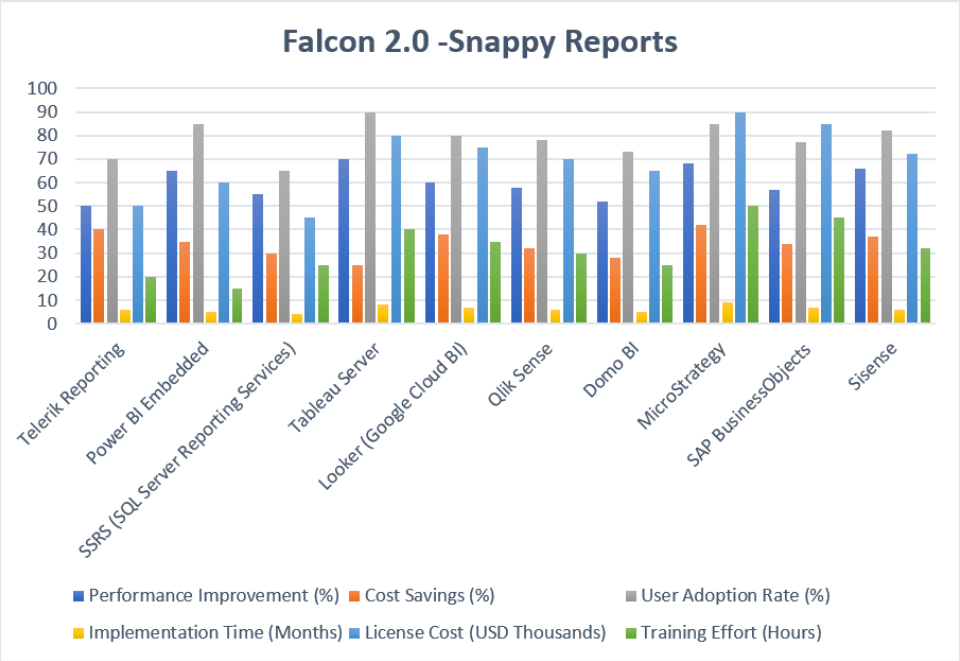


FIGURE 2. Enter Caption

(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

Row	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
R1	2500	1600	4900	36	2500	400	4225	1225	7225	25
R2	3600	225	3025	900	4225	16	2025	625	4900	625
R3	8100	64	6400	1600	3600	1444	6400	49	5625	1225
R4	3364	1024	6084	36	4900	900	2704	784	5329	25
R5	4225	625	4624	1764	7225	81	8100	2500	3249	1156
R6	5929	49	7225	2025	4356	1369	6724	36	5184	1024

Table 2 Square Root of Matrix Analysis Table 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 dataset spans from small to large squared numbers, with several common perfect squares, such as 36 (6^2), 49 (7^2), and 81 (9^2). This pattern may indicate a structured dataset associated with financial modeling, physics simulations, or engineering computations. By calculating the square roots of all the values, the original numerical scale can be recovered, making relationships and variations easier to interpret.

Thus, the table illustrates how squared values can be represented in a dataset and how square root operations can be applied to obtain more meaningful numerical interpretations.

TABLE 3. Normalized Data

Alternative	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 **??** Normalized Data Interpretation Table 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.

TABLE 4. Weights Assigned to Criteria for Evaluating Business Intelligence and Reporting Platforms

Alternative	Performance Improvement (%)	Cost Savings (%)	User Adoption Rate (%)	Implementation Time (Months)	License Cost (USD Thousands)	Training Effort (Hours)
Telerik Reporting	0.25	0.25	0.25	0.25	0.25	0.25
Power BI Embedded	0.25	0.25	0.25	0.25	0.25	0.25
SSRS (SQL Server Reporting Services)	0.25	0.25	0.25	0.25	0.25	0.25
Tableau Server	0.25	0.25	0.25	0.25	0.25	0.25
Looker (Google Cloud BI)	0.25	0.25	0.25	0.25	0.25	0.25
Qlik Sense	0.25	0.25	0.25	0.25	0.25	0.25
Domo BI	0.25	0.25	0.25	0.25	0.25	0.25
MicroStrategy	0.25	0.25	0.25	0.25	0.25	0.25
SAP BusinessObjects	0.25	0.25	0.25	0.25	0.25	0.25
Sisense	0.25	0.25	0.25	0.25	0.25	0.25

The table **??** 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

Alternative	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 Interpretation Table 5 presents a weighted normalized decision matrix, where each metric performance 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.

TABLE 6. Positive Matrix

Alternative	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 Interpretation Table 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.

TABLE 7. Negative Matrix

Alternative	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 **??**: Negative Matrix Interpretation Table 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 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

TABLE 8. Si Positive, Si Negative, Ci, and Rank

Alternative	S_i^+	S_i^-	C_i	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

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 follows:

$$C_i = \frac{S^-}{S^+ + S^-}$$

A higher C_i score means that the tool is closer to the ideal solution. Rank is assigned based on the C_i values, where a higher C_i score corresponds to a better rank.

MicroStrategy ranks first ($C_i = 0.9870$), 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 ($C_i = 0.9131$) and Tableau Server ($C_i = 0.8927$) rank second and third, respectively, showing strong performance across multiple factors.

Looker ($C_i = 0.8872$), Sisense ($C_i = 0.8628$), and Qlik Sense ($C_i = 0.8436$) occupy mid-tier rankings, suggesting that they offer balanced performance. Domo BI ($C_i = 0.8007$), Power BI Embedded ($C_i = 0.7930$), and Telerik Reporting ($C_i = 0.7451$) rank lower, indicating that they are less optimal compared to higher-ranked tools. SSRS ($C_i = 0.7035$) ranks last, meaning that it is the least favorable tool based on the analysis.

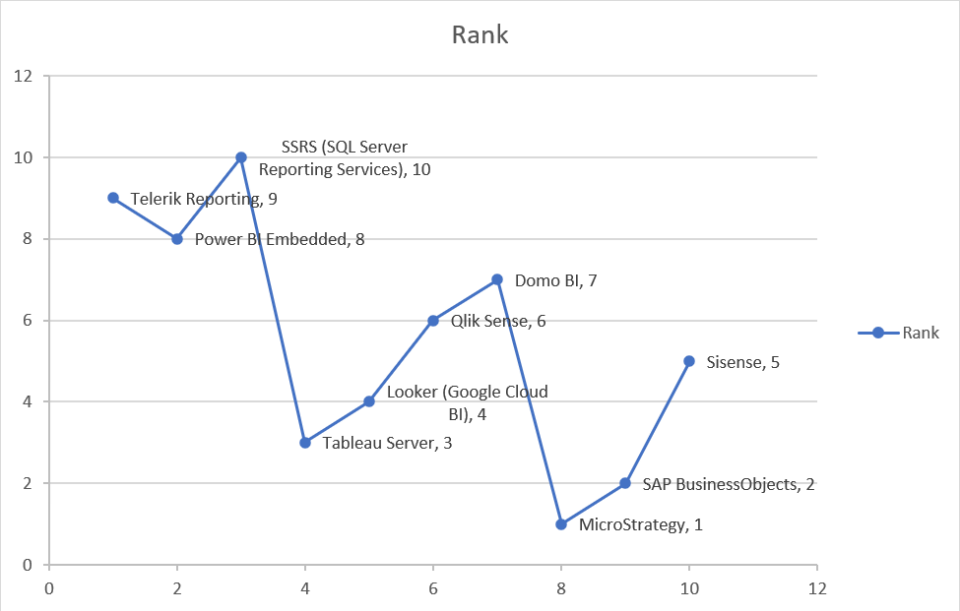


FIGURE 3. Rank

The rankings presented in the figure 3 reflect 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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