Evaluating the Effectiveness of Leading Job Portals: A Cross-Platform Analysis

Mettu Siddhartha, M Ramya Sree, Poli Vamsi Vardhan Reddy, Balam Ruchith Balaji, Parlapalli Bhargav Reddy and Radha D*
Department of Computer Science and Engineering, Amrita School of Computing, Bengaluru, Amrita Vishwa Vidyapeetham, India

Keywords: Job Searching Platforms, SEO Analysis, Website Performance, Usability Best Practices, Core Web Vitals, PageSpeed Insights.

Abstract: The modern era has seen widespread adoption of online job platforms, connecting job seekers directly with potential employers. In the proposed work, various key performance evaluation tools—such as Google's PageSpeed Insights, Pingdom, SEMrush, and GTmetrix—have been employed to assess metrics like Performance, SEO(Search Engine Optimization), Accessibility, Best Practices, Load Time, and Traffic, among others. These tools provide insights into platform strengths and limitations, independent of developer influence, thereby ensuring objectivity and offering substantial recommendations for enhancing user experience and technical aspects. The analysis concludes that Job Board-1 demonstrates a high level of competence across nearly all critical factors essential for traffic, audience engagement, and platform availability, and it presents several technological strengths. Job Board-3, while performing reasonably well in terms of accessibility and SEO, faces challenges related to high bounce rates and slow loading speeds, suggesting areas for improvement to increase user engagement.

1 INTRODUCTION

Job seeking in the digital age has transitioned from offline to online, with websites serving as a vital conduit between job seekers and potential employers. These platforms, which now include Job Board-1, Job Board-2, Job Board-3, and Job Board-4, are essential resources for anyone looking to advance in their careers. Each platform offers unique features and services tailored to meet the needs of its diverse user base, ranging from job listings and company ratings to networking opportunities. The effectiveness of these platforms relies not only on the number of job postings but also on their overall performance, usability, and accessibility.

Page load speeds and user interface design were the main emphasis of traditional website performance monitoring. However, a more thorough study is now achievable because to the development of increasingly advanced techniques and technology. Conventional approaches frequently involved basic mobile compatibility tests and broad user satisfaction surveys. Although these approaches offered a wide perspective, they were insufficiently detailed to comprehend the fundamental elements that lead a website to successfully furnish a smooth job search encounter.

Selected job search platforms will be evaluated across a range of parameters using industry-standard tools. Starting the evaluation, the performance, SEO, accessibility, and other best practices are checked with Google PageSpeed Insights. This involves considering factors such as title tags Meta description, server response time, loading speed of both the mobile and the desk top version of the Website. The properties like metadata, mobile-responsiveness, and structured data are analysed in order to understand the websites' visibility and their capability of SEO optimization. Moreover, the issues of usability and accessibility are also verified by such criteria as the existence of alt text for images, keyboard navigation, and color perception violations on the platforms. About performance I use Pingdom by giving tests from a server in Japan to examine performance in the Region of Asia. To analyze the traffic of various platforms, the SEMrush tool is used, including the total visits, visits by unique visitors, bounce rates, and the average time spent by a user on a site. This site goes further in giving different general performance indicators like

Siddhartha, M., Sree, M. R., Reddy, P. V. V., Balaji, B. R., Reddy, P. B. and D, R.
Evaluating the Effectiveness of Leading Job Portals: A Cross-Platform Analysis.
DOI: 10.5220/0013598400004664

In *Proceedings of the 3rd International Conference on Futuristic Technology (INCOFT 2025) - Volume 2*, pages 616-623
ISBN: 978-989-758-763-4

LCP, TBT, CLS, total page weight, and the quantity of requests to give a full report in how well these Plat forms run. By adopting a multi-dimensional perspective to analyze each platform, the strategies for how to optimize them are also shown in detail.

The remaining part of the paper consists of review on the background information and introduction to the topic is discussed in section 1.and Section 2 presents literature of related studies and prior work done in similar field. Section 3 provides the method explaining the method used, methods employed and instruments applied in the study. Section 4 displays the results in form of findings, data and any analysis done on them. Last, Section 5 provides a summary of the findings and the implications of the research for practice.

2 LITERATURE REVIEW

The section outlines prior work done on measuring the performance of the website, search engine optimization, keyword study and usability studies across multiple industries. It underlines the role of recognizing the shifts of keywords and users' behavior and the influence made by SEs' algorithms on the website. Such as SEMrush, PageSpeed Insight, or GTmetrix that is used to review the performance and to determine slips. Largest Contentful Paint and First Input Delay are among the most important metrics configured within the Core Web Vitals to address user experience and site performance needs. Various aspects of the website should be optimized on a continuous basis and the results should be compared with industry targets to ensure that a high efficiency with subsequent improved search engine ranking is attained.

Nanda et al. study is to examine the trend analysis of the keywords, questions, and website domains most frequently associated with melanoma and skin cancer search (Nanda, Hay et al. 2021). All the information was obtained using different search engines and findings indicated higher search terms based on skin cancer as compared to melanoma. The clinicopathologic classification and diagnosis constituted the largest group of the ten most frequently used melanoma keywords. The survival query was the most popular but general/melanoma or diagnosis type query type yielded the highest number of searches per query. To help resolve common issues related to melanoma and skin cancer, the study suggests explaining.

Using the SEMrush analytics tool, Afroz et al. evaluated and analysed the websites of consumer electronics companies (Afroz, Riyazuddin et al. 2023). It evaluates performance indicators like visitor attrs, bounce rate, average stay duration, most popular pages, ctr, backlink, and referring domain. The AIDA model, developed by St. Elmo Lewis, is used to evaluate promotive activities of some brands. The findings help brands understand consumer behavior trends and their digital footprints, guiding their marketing approach. Web analytics have developed rapidly, with SEMrush being a user-friendly tool.

A web-based solution that uses WebpageTest, PageSpeed Insight, and GTmetrix tools to automatically gather and compare e-commerce site performance metrics was presented by Hossain et al.(Hossain, Hassan et al. 2021). The application uses PHP, MYSQL, CSS, and HTML, and allows users to input the URL of a site. Tests on ten Bangladeshi e-commerce sites showed site7 had the lowest Total Blocking Time, while site10 had the lowest Load Time. The application currently supports computer systems, with future research focusing on mobile versions and testing limits.

According to Palacios-Zamora et al. assessing university websites' effectiveness is crucial to enhancing their reputation (Palacios-Zamora, Cordova-Morana et al. 2023). It discusses various quality assessment models and highlights the impact of parameters like response time, throughput, utilization, extensibility, data transfer rate, concurrency, and reliability on website performance. Measures like optimizing images, layouts for desktop, tablet, or mobile devices, and content caching can enhance site efficiency. The research also suggests improving mobile device performance and using the increasing, usability, and accessibility brief.

When evaluating user experience, the authors emphasized importance of PageSpeed Insights (WebPageTest), First Input Delay (FID), and Largest Contentful Paint (LCP) (Dobbala and Lingolu, 2023). It suggests that web developers should focus on improving these parameters to enhance website performance, efficiency, and business results. This will ultimately lead to increased conversion rates, creating a competitive advantage in online business.

Bernine et al. provided an analytical model grounded on Petri nets in assessing the effectiveness of a Web services structure if requests and services adhere to an exponential server (Bernine, Nacer et al. 2020). This mainly applies since the arrival of user as well as the web service requests follows the Poisson distribution only. The model is solved analytically, and the response time and mean number of clients for the system are determined. The limit number of clients in the system is derived from which the system becomes congested.

According to Kumar et al. website performance has a significant impact on user experience, search engine optimisation, and overall business success(Kumar, Kumar et al. 2021). Key automated tools such as Google PageSpeed Insights, GTmetrix, Pingdom, WebPageTest, and Apache JMeter are reviewed by the authors, who highlight their usefulness in locating performance bottlenecks and streamlining web applications. The authors support a methodical approach to performance evaluation that enhances site efficacy and efficiency by using a variety of instruments, ongoing monitoring, and benchmarking against industry norms.

Akgül et al. highlighted the significance of public value, usability, and readability in improving user experience and public service delivery of Turkish government website performance (Akgül, 2024). The authors evaluate how well these websites meet the needs of citizens, encourage participation, and guarantee that all users can access the material. Using a mixed-methods approach and making use of automated technologies such as Google PageSpeed Insights, GTmetrix, and WebPageTest, the study advocates for a user-centred strategy in e-government projects and offers useful suggestions for enhancing government websites.

The idea of SEO and the methods by which standard tools can be used to evaluate a website's search engine optimisation were described by Simec et al. (Simec and Križanić, 2023). As an example, it proposes to apply three tools to evaluate the same site and compare their functions and options. In the same token, SEO is a very fluid field where one is always in assimilating new information in the field. Semrush is an online tool that helps analyze SEO, content, a market, web advertising, and social networking. It gives a percentage bound to each item where the important mistakes fixed and the warnings given are said in terms of a percentage.

Simunic et al. conducted a study on SEO factors to improve internet visibility (Šimunić, Stifanich et al. 2023). The research involved literature analysis and an analysis model. The study found no significant correlation between website quality and search query points. However, there were qualitative deficits in variable optimization. The study suggests that detecting and optimizing important Google factors for ranking can lead to higher online direct sales, enriching new scientific data knowledge and creating potential for further research.

The authors Considers the rise in traffic from services like HTTP, FTP, and SMTP, network traffic classification is crucial for monitoring and managing data flow in networks (Archanaa, Athulya et al. 2017). In this work, the performance of using different sorts of supervised learning algorithms: Ensemble learning, Decision tree and Bayesian classifiers for detecting network traffic. When applying the wrapper method in feature selection, then the research highlights that the Decorate Algorithm an ensemble classifier is efficient and reliable than other algorithms.

Sujee et al. explained Modern educational databases have expanded, and it is possible to find many hidden resources that can contribute to improving the results achieved by students (Sujee, Padmavathi et al. 2021). This work explains how predictive modeling, grouping, and association rule mining can be employed in order to discover information beneficial to students and tutors. RBF model enables one to predict which students are performing well and which group could benefit from a boost in instructions. It helps the instructors in the settings to present teaching methodologies that fits every student's needs successfully.

The domain, domain age, web impact variables, and Alexa traffic rank of Indian universities were compared with the NIRF ranking 2021 by Meghwal et al. (Meghwal, Joshi et al. 2022). It discovered that all the websites in the study employed SEO tools. Out of the universities, Amrita Vishwa Vidyapeetham university had the oldest domain registration in December 1988 and the Indian Institute of Science university had the highest Domain Authority score of 62. A National level survey found it that three Universities of Karnataka were in the top ten Universities in India.

Subbulakshmi et al. explained how a framework for extending the assessment of Web portal pertinence can be used to measure the reliability of Web portals and to calculate their credibility score (Subbulakshmi, Gopika et al. 2019). Main parameters taken into account include the content, links, spam information, the frequency of updating the web portals under concern. The credibility score is determined using metrics such as page rank, blacklist status, average page hits, and two key quality factors: , namely credibility and relevance. A web crawler collects page links from different websites in response to specific queries and in the end, presents the Web sites in order of reliability so that users can easily determine which sources contain reliable information.

The Deep Cyber Threat Situational Awareness Framework (DCTSAF), developed by Soman et al. uses deep learning to detect malicious domains and URLs . Traditional methods like blacklisting and signature-based strategies don't work, especially when faced with fresh or more sophisticated threats. Deep learning is the foundation of the framework, which uses character-level embeddings to work with the raw data and automatically determine the most relevant features. The use of both hierarchical features and long-distance linkages in domain names/URLs makes CNN-LSTM networks better than other models. The system is extremely powerful and can handle two million events per second, which leads to early threat detection and an alert.

Malathi et al. pointed out In the current generation to form social network they must family social network site such as Linked In, Google Plus and face book (Malathi and Radha, 2016). Social networks can be represented by graphs and their most significant figures, connections, and interaction. Other uses of graphs include the representation of relations and processes of different systems, chemical and physical, biological, information as well. This work examines a database of US politics books as a network with such elements as betweenness, eigen vector, degree and closeness.

3 EXPERIMENT

In conducting the analysis of website performance, several industry-standard tools were used to gather insights across key metrics such as Performance, SEO, Accessibility, Best Practices, Load Time, and Traffic

To assess performance, SEO, accessibility, and best practices, **Google PageSpeed Insights** was used. This tool provides detailed insights into the speed characteristics of a website, scoring and offering suggestions for improvements on both desktop and mobile versions.

3.1 Performance

This metric complies with how quickly and active the website is once opened. The tool breaks down features such as response time of the server, resource loading and rendering speed.

3.2 SEO

SEO score is defined as the capability of the website to appear in search engines results and evaluate metadata, mobile-friendliness, and structured data.

3.3 Accessibility

This metric deals with the accessibility of users with complications for example; this measures the number of images that have the alt text; users who can only use the keyboard to get round the website; users who have problems with color perception.

3.4 Best Practices

Google PageSpeed Insights assess the current state of website according to modern web technologies and standards like security, response, and coding.

3.5 Load Time

The loading time for this website was determined by **Pingdom Tool**. Namely, the tests were performed from an Asia-Japan-Tokyo server to consider the load effect in this region. when using Pingdom, which delivers specific results based on several aspects such as server response time, resource loading time, and total page loading time. This assists in finding out some of the constraints in performance that might hamper on user experience within certain espoused zones.

3.6 Traffic Analysis

For the assessment purpose of monitoring website traffic and its behavior index, the **SEMrush Tool** was used. It also offers additional traffic details such as the visits, the visitors, the bounce rates and the average session time. The following metrics were analyzed:

3.6.1 Total Visits

The over all the number of time the site was visited in the given time of the study.

3.6.2 Unique Visitors

The number of people who visit this website without repetition of any user.

3.6.3 Purchase Conversion Rate

This was measured wherever possible showing the rate which visitors made a purchase or achieved a desired end result.

3.6.4 Pages per Visit

The quantity of unique web page visits by each user on average per session.

3.6.5 Average Visit Duration

The specific time that the users stay connected to the site/ portal.

3.6.6 Bounce Rate

The rate at which visitors leave the site after visiting only one of its pages.

GTmetrix [] was also used, offering additional performance insights. The tool includes metrics such as GTmetrix Grade, Performance Score, Structure Score, Largest Contentful Paint (LCP), Total Blocking Time (TBT), Cumulative Layout Shift (CLS), Total Page Size, and Total Number of Requests.

3.7.1 GTmetrix Grade

This is a composite score that reflects the overall performance and structure of your website. It's broken into two components:

Performance Score (70% of the grade) Reflects how well the website performs based on loading speed and interactivity, derived from Core Web Vitals metrics.

Structure Score (30% of the grade) Measures how well your site follows best coding and optimization practices to ensure faster load times.

3.7.2 Performance Score

This is the segment of the GTmetrix Grade that looks at how effectively users can access and interact with what your website has to offer. While it also incorporates data from other performance indicators such as Core Web Vitals to provide a transparent indication of user experience scores.

3.7.3 Structure Score

This metric emphasizes various aspects of a website's architecture or design. Often it shows how well your site can actually perform and details like too much JavaScript, ineffective CSS, and uncompressed images discover. The greater the structure score, the more your site prepares appropriately regarding loading speed and maintainability.

3.7.4 Largest Contentful Paint (LCP)

LCP determines the page load time on the screen taking the biggest factor that is the size of the largest visible content element (image, video or large text block) into consideration. This is an essential UX value, as increased LCP can give a user a sensation that a site is slow. Google advises LCP should happen within a time frame of 2.5 seconds from the page time.

3.7.5 Total Blocking Time (TBT)

TBT quantifies the time the browser is occupied by tasks that hinder or completely halt user interaction (such as script loading). It measures the time a website's JavaScript or any other resource takes to hamper interactivity and quantify the amount of interactivity lost due to a specific resource. The site's TBT values must be lower since this represents a more responsive website.

3.7.6 Cumulative Layout Shift (CLS)

CLS gives the total scrambled layout/flush that happens inadvertently when you load a site. For instance, if images or ads take time to load that they across text and make it shift about it will contribute to the CLS score. A CLS score below 0.1 guarantees that users have reliable and consistent client-side experience.

3.7.7 Total Page Size

This metric demonstrates the sum of the sizes of all files required for rendering the webpage – images, scripts, stylesheets and others. Factoring for larger page sizes is that greater page size decreases the loading time, particularly for internet users with low bandwidth. Therefore the best page size is derived from minimizing its resources since a decrease in page size has a positive effect on page performance.

3.7.8 Total Number of Requests

The number of HTTP requests or browser clicks an HTML page makes to load all required elements, including images, java, css, and fonts, is shown by this measure. The longer it takes for a website to load, the more requests the page receives. The website loading time can be extended if script requests can be made more frequently or at a later time.

Several objective tools were chosen because they are universal and can give more or less exhaustive information about various aspects of a website taking into account technical parameters and users' experiences. These metrics provide a birds-eye view of the website and this not only considers such factors as speed of loading of the website, ease of use of the website, availability of Search Engine Optimization and identified best practices but also factors such as structure or organization of the website, responsiveness of the website, and optimum use of resources amongst others. In any case, it integrates supports the identification of specific areas of improvement, providing a fair assessment based on both, technology and users.

4 EXPERIMENTAL RESULTS

Analyzing the performance of four job board websites, their strengths and weaknesses differ significantly. However, Job Board-1 stands out by excelling in multiple categories, performing superbly with high scores in traffic, audience engagement, and easy access. It claims the highest visit count, unique visitors, and pages per visit, which are strong indicators of higher user engagement and a lower bounce rate. Job Board-2 receives an average number of visitors but experiences slow loading times, which may lead to potential user loss. Job Board-4 shows good performance in terms of accessibility and compliance, but overall visits have decreased, which could be improved by enhancing SEO and reducing load times. Job Board-3, the smallest platform by traffic, boasts the highest accessibility and best practice rates. However, it has a relatively high bounce rate and lower interaction rates, indicating room for improvement in user experience (UX). The findings from this analysis highlight the importance of technical performance, search engine optimization, and user-centric metrics for driving effective traffic flow.

According to the data presented in Table 1, the following important aspects of website performance can be evaluated. Regarding performance, both Job Board-1 and Job Board-3 posted faster loading times, allowing customers to engage in quicker interactions, unlike Job Board-2, which took 3.30 seconds to load. The overall SEO report is almost perfect for most sites, with Job Board-1 and Job Board-3 scoring 100 points, while Job Board-4 and Job Board-2 scored relatively lower. In terms of accessibility, Job Board-1 achieved a perfect score of 100%, indicating full compliance with accessibility standards for disabled users, while Job Board-4 received the lowest score. Job Board-3 performed moderately well. For best practices, Job Board-1 had the lowest score of 74, whereas other platforms, such as Job Board-4, Job Board-3, and Job Board-2, scored above 90. When considering visits, Job Board-1 led with 1.8 billion visits, followed by Job Board-2 with 43.9 million, Job Board-4 with 29.5 million, and Job Board-3 with 7.1 million. Engagement rates show that Job Board-1 had the highest page views per visit at 8.8, with an average visit duration of 12 minutes and 1 second. However, Job Board-3 had the highest bounce rate at 58.41%, indicating that users leave the site quickly.

Fig 1 represents the traffic analysis of Job Board-1, Job Board-2, Job Board-3, and Job Board-4, revealing distinct performance metrics. Job Board-1 leads significantly with 1.88 billion visits (up 3.62%) and 423.6 million unique visitors (up 6.44%). Job Board-2 follows with 43.9 million visits (up 9.14%) and 24.7 million unique visitors (down 4.49%).

Table 2 provides a comparative analysis of four job boards (Job Board-1 to Job Board-4) based on performance and structure metrics from GTmetrix, covering six key aspects: GTmetrix Grade, Performance Score, Structure Score, Largest Contentful Paint (LCP), Total Blocking Time (TBT), Cumulative Layout Shift (CLS), and Total Page Size. Job Board-1 achieved the highest overall performance with an 'A' GTmetrix Grade (91%), the best Performance Score (89%), and a strong Structure Score (93%). It also had the fastest LCP (770ms), minimal blocking time (260ms), and the smallest page size (585KB), indicating quick load times and efficient resource usage. In contrast, Job Board-3 performed the worst, with the lowest GTmetrix Grade ('D', 61%), the slowest LCP (4.5s), the highest TBT (1.2s), and relatively large page size (2.43MB). Job Board-4 also lagged in some areas, but performed well in blocking time (172ms). Overall, Job Board-1 stands out as the best-performing website in terms of both speed and user experience.

Fig 2 presents a comparison of key performance metrics across five different platforms, focusing on areas such as Performance, SEO, Accessibility, and Best Practices. Two platforms show the highest performance scores, reflecting quicker load times, while one lags behind with the lowest performance score and a longer load time of 3.30 seconds. In the SEO category, two platforms achieve a perfect score, indicating strong optimization, while others have room for improvement. Accessibility is another area where one platform excels with a perfect score, suggesting full accessibility for disabled users, while another has the lowest score. Regarding best practices, three platforms consistently score high, but one unexpectedly has the lowest score in this category. The chart offers a visual comparison that highlights strengths and areas for improvement, particularly in SEO and best practices for some platforms.

Job Board-4 sees a decline in visits to 29.5 million (down 13.36%) and 13.1 million unique visitors (down 5.61%). Job Board-3 shows modest growth with 7.1 million visits (up 2.38%) and 3.5 million unique visitors (down 3.63%). In terms of engagement, Job Board-1 has the highest pages per visit at 8.8 and an average visit duration of 12:01 minutes. Job Board-4 and Job Board-2 show increases in pages per visit, while Job Board-3's metrics decline. The bounce rate is highest for Job Board-3 at 58.41%, while Job Board-1 has the lowest at 41.11%. Overall, Job Board-1 outperforms its competitors across all key metrics, highlighting its effectiveness and user

Table 1: Performance analysis of various webpages

	Job Board-1	Job Board-2	Job Board-3	Job Board-4
Performance	100	64	60	93
SEO	100	85	100	77
Accessibility	100	90	90	75
Best practices	74	96	100	93
Load Time	767ms	3.30 s	853 ms	112 ms

Table 2: Performance and Structure Metrics of Various Job Boards as Analyzed by GTmetrix

	Job Board-1	Job Board-2	Job Board-3	Job Board-4
GTmetrix Grade	A (91%)	C (76%)	D (61%)	C (78%)
Performance Score	89%	71%	39%	76%
Structure Score	93%	83%	93%	82%
Largest Contentful Paint	770ms	686ms -83ms	4.5s +3.7s	3.0s +2.2s
Total Blocking Time	260ms	1.0s +775ms	1.2s +919ms	172ms -88ms
Cumulative Layout Shift	0	0.01 +0.01	0	0.01 +0.01
Total Page Size	585KB	3.98MB +3.41MB	2.43MB +1.86MB	2.98MB +2.41MB

engagement.

5 CONCLUSION

In conclusion, analysis indicates that Job Board-1 surpasses other job platforms in performance, user engagement, SEO, and accessibility, positioning it as a benchmark job platform. Another popular platform, Job Board-2, exhibits slower loading times, suggesting potential improvements in user experience. Job Board-4, recognized for strong accessibility and adherence to best practices, may enhance traffic through targeted SEO optimizations. Job Board-3 ranks highly in accessibility and best practices, though its bounce rate remains elevated, with moderate user engagement relative to larger platforms. Consistent with prior findings, this study emphasizes that a balance of efficiency, user satisfaction, and findability is essential for the success of online platforms.

REFERENCES

Nanda, J.K., Hay, J.L. and Marchetti, M.A., 2021. Analysis of keywords used in Internet searches for melanoma information: observational study. JMIR dermatology, 4(1), p.e25720.

Afroz, S., Riyazuddin, Y.M. and Jadda, V., 2023, December. Website Traffic Trends and Performance Evaluation of Selected Consumer Electronic Company Websites. In 2023 Global Conference on Information Technologies and Communications (GCITC) (pp. 1-4). IEEE.

Hossain, M.T., Hassan, R., Amjad, M. and Rahman, M.A., 2021. Web performance analysis: an empirical analysis of e-commerce sites in Bangladesh. International Journal of Information Engineering and Electronic Business, 11(4), p.47.

Palacios-Zamora, K., Cordova-Morana, J., Mendoza-Cabrera, D. and Pacheco-Mendoza, S., 2023. Measurement on University Websites: A Perspective of Effectiveness. JOIV: International Journal on Informatics Visualization, 7(3-2), pp.1995-2006.

Dobbala, M.K. and Lingolu, M.S.S., 2022. Web Performance Tooling and the Importance of Web Vitals. Journal of Technological Innovations, 3(3).

Bernine, N., Nacer, H., Aissani, D. and Alla, H., 2020. Towards a performance analysis of composite web services using Petri nets. International Journal of Mathematics in Operational Research, 17(4), pp.467-491.

Kumar, N., Kumar, S. and Rajak, R., 2021, December. Website Performance Analysis and Evaluation using Automated Tools. In 2021 5th International Conference on Electrical, Electronics, Communication, Computer Technologies and Optimization Techniques (ICEECCOT) (pp. 210-214). IEEE.

Akgül, Y., 2024. Evaluating the performance of websites from a public value, usability, and readability perspectives: a review of Turkish national government websites. Universal Access in the Information Society, 23(2), pp.975-990.

Simec, A. and Križanić, M., 2022. Comparison of tools for analyzing the degree of optimization of website search engines.

Šimunić, M., Stifanich, L.P. and Car, T., 2023. Hotel web site SEO analysis: Segmentation and valorization as a precondition for discovering and understanding insights to improve online visibility. Ekonomski vjesnik/Econviews-Review of Contemporary Business, Entrepreneurship and Economic Issues, 36(2), pp.299-311.

Archanaa, R., Athulya, V., Rajasundari, T. and Kiran, M.V.K., 2017, January. A comparative performance analysis on network traffic classification using supervised learning algorithms. In 2017 4th International

Target	Visits	Unique Visitors	Purchase Conver...	Pages / Visit	Avg. Visit Duration	Bounce Rate
Job Board -3	29.5M ↓13.36%	13.1M ↓5.61%		5.5 ↑5.81%	10:20 ↓8.82%	46.14% ↓7.48%
Job Board -2	43.9M ↓9.14%	24.7M ↓4.49%		3.3 ↑3.39%	06:43 ↓1.95%	52.02% ↓1.85%
Job Board - 4	7.1M ↑2.38%	3.5M ↓3.36%		3 ↑1%	07:13 ↓5.87%	58.41% ↑2.31%
Job Board -1	1.8B ↓6.32%	423.6M ↓6.44%	0.08% ↑7.93%	8.8 ↑3.28%	12:01 ↓0.83%	41.11% ↑2.57%

Figure 1: Traffic analysis of various platforms

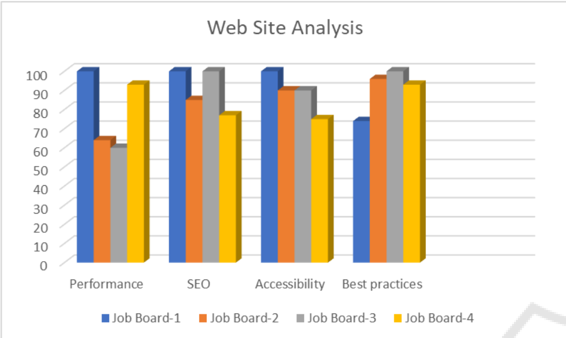

Figure 2: Visualization plot for website analysis

Conference on Advanced Computing and Communication Systems (ICACCS) (pp. 1-5). IEEE.

Sujee, R. and Padmavathi, S., 2021, October. Performance Analysis and Prediction of Students Results Using RBF Networks. In 2021 2nd International Conference on Smart Electronics and Communication (ICOSEC) (pp. 333-338). IEEE.

Meghwal, J., Joshi, K., Chaparwal, N. and Rajput, P.S., 2022. NIRF Ranking 2021: A Webometric Analysis of Top 10 University Websites of India. International Journal of Research in Library Science (IJRLS), 8(2), pp.191-205.

Subbulakshmi, S., Gopika, A. and Thomson, L., 2019, July. Enhanced Ranking of Websites Based on Credibility Evaluation. In 2019 International Conference on Communication and Electronics Systems (ICCES) (pp. 2035-2040). IEEE.

Soman, K.P., Poornachandran, P. and Menon, V.K., Vinayakumar R Center for Computational Engineering and Networking (CEN), Amrita School of Engineering, Coimbatore Amrita Vishwa Vidyapeetham, India vinayakumarr77@ gmail. com.

Malathi, A. and Radha, D., 2016, October. Analysis and visualization of social media networks. In 2016 International Conference on Computation System and Information Technology for Sustainable Solutions (CSITSS) (pp. 58-63). IEEE.

Google PageSpeed Insights

SEMrush

Pingdom Tool

GTMatrix