ARTICLE

Cite This: J.of Data Sci. and Informa Technol .2025, 2, 55-65

SciForce

Journal of Data Science and Information Technology

Journal homepage: www.sciforce.org

Evaluating IoT Platforms: An Approach Using the COPRAS Method

Satyanarayana Ballamudi*

**SAP Solution Architect, Lennox International Inc., TX, USA*

ARTICLE INFO

Article history:
Received: 20241215
Received in revised form: 20250110
Accepted: 20250110
Available online: 20250118

Keywords:
IoT;
Scalability;
Market longevity;
Security;
Usability;
Unique features and MCDM .

ABSTRACT

IoT platforms act as technological frameworks that provide the foundation for connecting and managing Internet of Things devices and applications. These platforms offer a wide range of services and tools that streamline the development, deployment, and operation of IoT solutions. They enable seamless integration and communication between IoT devices, facilitate data collection and analysis, provide device management capabilities, and facilitate the creation of IoT applications. By offering a centralized and scalable infrastructure, IoT platforms play a crucial role in empowering organizations and developers to fully harness the potential of the IoT, leading to the creation of innovative and efficient IoT solutions. Research dedicated to "the selection of IoT platforms plays a crucial role in the industry". "With the increasing number of IoT applications", the importance of making the right platform choice becomes critical for successful implementation.

The research provides valuable insights that aid organizations and developers "in making informed decisions when selecting an IoT platform that aligns with their specific requirements". By leveraging this knowledge, stakeholders can ensure that they choose the most suitable platform to meet their needs effectively. "The objective of this research paper is to tackle the evaluation of IoT platforms" by approaching it as a problem of multicriteria decision making (MCDM) due to its complexity involving multiple factors. To accomplish this goal, the research develops a system for creating evaluation criteria, facilitating the comprehensive assessment of IoT platforms. In the ranking based on the COPRAS method, Google Cloud IoT emerged as the top-ranked platform, demonstrating its superior performance and highest utility. Amazon AWS IoT Core closely followed in the second position, showcasing its strong performance and positive attributes.

Microsoft Azure IoT Hub secured the third rank, highlighting its competitive performance compared to other platforms. ThingWorx obtained the fourth rank, indicating its relatively good performance according to the COPRAS method. Particle ranked fifth, positioning its performance in the middle range among the evaluated platforms. Oracle IoT obtained the sixth rank, suggesting its performance was relatively lower compared to other platforms. IBM Watson IoT received the seventh rank, indicating its relatively weaker performance in the evaluation. These rankings offer valuable insights for decision-making and platform selection, enabling stakeholders to evaluate the overall performance and relative positions of the IoT platforms based on the COPRAS method.

.

*Corresponding author. Tel.: +1 (954) 592- 4737; e-mail: satya.ballamudi@gmail.com

Introduction

The Internet of Things (IoT) is a network of interconnected physical objects, including devices, animals, machines, buildings, and people, equipped with sensors, software, and other technologies. These objects collect data through sensors, transfer it over the internet, and analyze it using real-time analytics, wireless technologies, machine learning, data visualization technologies, and sensors. The practicality and feasibility of IoT applications are enhanced by the convergence of these technologies [1,2]. The IoT has significant advantages for enterprises, as it enables improvements in productivity, asset utilization, business efficiency, and reduction in labor and maintenance costs. As a result, the IoT has found wide-ranging applications in various fields such as agriculture, manufacturing, transportation, environmental monitoring, and metropolitan-scale development [3].

The knowledge derived from these activities can be leveraged to initiate actions. Over the past few years, numerous IoT platforms have emerged, often developed through international projects and industry initiatives. These platforms are typically designed to support the implementation and design of IoT systems. However, the IoT platform landscape is characterized by its wide and heterogeneous nature, primarily due to the absence of standardization and the prevalent practice of isolated development [4,5]. Multiple IoT platforms offer the necessary programming tools to seamlessly incorporate a wide range of functionalities through numerous APIs. Given the diverse nature of IoT devices, applications, and interests, there is currently a significant number of active IoT platforms. IoT application developers and administrators face the daunting task of selecting the most suitable IoT platform that aligns with their specific requirements. Factors such as cost, the quantity and types of available APIs, programming language compatibility, and supported devices need to be considered during the decision-making process [6].

Traditionally, IoT developers, administrators, and researchers (referred to as IoT users) have primarily focused on ensuring the proper functioning of their applications and systems. However, there is an increasing concern within the community and among users regarding the security and privacy aspects of IoT [7]. Apart from ensuring the functionality of IoT solutions, an IoT user must either possess expertise in security and privacy or rely on the tools provided by the IoT platform to establish a secure IoT environment. However, obtaining either of these guarantees is not necessarily straightforward. Consequently, numerous security solutions for IoT have been suggested in the past. Nonetheless, these solutions tend to concentrate on IoT architectures and lack the provision of comprehensive measures that simultaneously safeguard devices and applications across different platforms [8,9].

The selection of an IoT platform is a significant challenge, as it involves considering various criteria that influence the decision-making process. The complexity arises from the need to evaluate all the features, capabilities, and application domains of IoT platforms. Therefore, utilizing Multicriteria Decision Making (MCDM) techniques is essential when choosing a specialized IoT platform. Making an incorrect selection can potentially compromise the reliability and safety of IoT systems [10]. When selecting an IoT platform for developing IoT systems, developers typically rely on comparative analysis of the capabilities offered by different IoT platform developers.

However, there is a tendency for IoT developers to prioritize well-known platforms without considering future criteria that may impact “the development, maintenance, updates, reliability, safety, and scalability of the resulting IoT systems”. One approach to addressing this challenge is to define “a reference platform architecture that incorporates the advantages and capabilities of the latest IoT platforms available” [11,12].

Material and methods:

Different IoT platforms exhibit various features, making it necessary to thoroughly assess them based on considerations outlined by a group of developers. This evaluation aims to meet the diverse requirements of IoT applications. Consequently, an evaluation criteria system is established to characterize these considerations, serving as a fundamental requirement for assessing IoT platforms. A company intends to capitalize on the substantial benefits offered by IoT technology by developing its own IoT application. After carefully screening popular IoT platforms, the company has selected seven platforms for further evaluation: “Google Cloud IoT, Oracle IoT, Amazon AWS IoT Core, Microsoft Azure IoT Hub, Particle, IBM Watson IoT, and ThingWorx”. To construct the evaluation criteria system, relevant literature is analyzed, and insights are gathered from experienced software engineers. The evaluation criteria system comprises eight criteria, namely scalability, market longevity, security, usability, unique features, integration flexibility, availability, and pricing.

Scalability: The scalability of IoT platforms is vital since it impacts their capacity to manage the rising number of connected devices and the escalating data volume generated by these devices. To achieve scalability, IoT platforms utilize approaches such as effective device management, distributed data processing, support for diverse communication protocols, horizontal and vertical scaling, and leveraging cloud infrastructure. By implementing these strategies, platforms can adapt to large-scale deployments, maintain optimal performance, and uphold reliability as IoT ecosystems continue to expand.

Market longevity: The growing adoption of IoT technology in diverse industries is expected to contribute to the enduring market longevity of IoT platforms. These platforms play a crucial role in managing and integrating IoT devices and data, empowering organizations to leverage the advantages of connected devices and enhance operational efficiency. As use cases continue to evolve and technological advancements progress, IoT platforms are well-positioned to maintain their relevance and high demand in the market for the foreseeable future.

Security: The security of IoT platforms plays a critical role as connectivity and data exchange between devices continue to grow. Implementing strong security measures, such as device authentication, data encryption, and access control, is necessary to safeguard sensitive data, prevent unauthorized entry, and address potential risks. Securing IoT platforms is vital for upholding the integrity and confidentiality of IoT ecosystems.

Usability: Ensuring the usability of IoT platforms is vital to the seamless adoption and functionality of IoT solutions. It involves factors like user-friendly interfaces, simplified device setup and customization, and comprehensive documentation and assistance. By prioritizing usability, IoT platforms improve the user experience, streamline device and data management, and encourage the widespread acceptance of IoT technology.unique features: IoT platforms stand out from other technology platforms due to their distinctive features. These features encompass comprehensive device management functionalities, smooth integration and analysis of data, and the ability to facilitate secure and scalable communication between devices and applications. By leveraging these features, businesses can effectively handle connected devices, extract valuable insights from data, and drive innovation in the realm of IoT solutions.

Integration flexibility: The integration flexibility of IoT platforms is a vital attribute that facilitates smooth connectivity and interoperability across a variety of devices, systems, and applications. These platforms are specifically engineered to accommodate diverse devices, protocols, and data sources, enabling efficient aggregation and exchange of data. This adaptability empowers businesses to seamlessly incorporate their existing infrastructure, integrate third-party services, and develop customized applications. As a result, it fosters an ecosystem of interoperability, allowing for diverse IoT use cases to be realized effectively.

Availability: The availability of IoT platforms pertains to their capability to maintain uninterrupted and dependable functionality across diverse environments and scenarios. By employing redundancy, fault tolerance mechanisms, and scalable infrastructure, IoT platforms facilitate seamless connectivity, efficient data processing, and consistent service provision. This heightened availability empowers businesses to deploy resilient IoT solutions that operate reliably and effectively meet the requirements of critical applications.

Pricing: The pricing of IoT platforms can vary based on factors such as the included features, deployment scale, device and user count, and level of support. Typically, IoT platforms follow a subscription-based pricing model, where customers pay regular fees based on their chosen plan or the number of connected devices. Additional costs may arise from data storage, data transfer, or advanced analytics services. Certain IoT platforms offer customizable pricing packages tailored to specific customer needs. The pricing structure of IoT platforms aims to be adaptable and scalable, allowing businesses to select a plan that suits their requirements and budget while accommodating future growth and scalability.

The COPRAS Method: "The COPRAS method, introduced by Zavadskas, Kaklauskas, and Sarka in 1994", is a rating approach that considers "both the best and worst solutions separately". "By identifying the best and ideal worst solutions", it enables the selection of the optimal alternative. This approach is commonly used in the field of engineering for evaluating and choosing different projects. "The main objective of the COPRAS technique is to rank alternatives" by considering the weights assigned to each criterion [13]. Although the COPRAS method has some minor limitations, its numerous strong qualities outweigh them. One of the primary and most significant advantages of COPRAS is its ability to treat beneficial and non-beneficial factors individually, allowing for a more accurate assessment and decision-making process [14].

The COPRAS method employs a set of criteria to determine the importance and utility of the alternatives being evaluated. These criteria include the weights and values assigned to each criterion. COPRAS is considered a significant multiple criteria decision-making (MCDM) technique and a valuable tool for decision-making, as evidenced by its guiding principles [15]. One distinguishing feature of COPRAS is its unified evaluation approach that considers both cost and benefit factors. Unlike other MCDM techniques, COPRAS considers "the utility degree of alternatives, which represents a percentage indicating the extent to which one alternative is superior or inferior to the other alternatives" being evaluated.

This aspect enhances the effectiveness and uniqueness of COPRAS as a decision-making approach [16]. Recent research indicates that decision-making processes utilizing the COPRAS method tend to yield more accurate and less biased judgments compared to approaches such as TOPSIS and WSM. Moreover, COPRAS demonstrates greater stability when confronted with changes in data, particularly when compared to WSM. Additionally, COPRAS offers several advantages over other commonly used multiple criteria decision-making "(MCDM) tools such as PROMETHEE, DEA, VIKOR, AHP, and ELECTRE" [17,18]. One notable advantage is that COPRAS provides a highly straightforward and transparent MCDM approach, requiring less computational effort. This simplicity contributes to a higher likelihood of gaining a visual understanding of the decision-making process. These factors contribute to the growing recognition and preference for the COPRAS method in various decision-making scenarios [19].

Step 1: The decision matrix X, which displays how assorted options perform in relation to certain criteria, is created.

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

Step 2: Weights for the criteria are expressed as

$$w_j = [w_1 \cdots w_n], \quad (2)$$

$$\sum_{j=1}^{n}(w_1 \ \cdots \ w_n) = 1$$

sum of the weight distributed among the evaluation parameters must be one.

Step 3: The matrix x_{ij}'s normalized values are computed as

$$n_{ij} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} \quad (3)$$

Step 4: Weighted normalized matrix N_{ij} is calculated by following formula.

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

Step 5: sum of benefit criteria and the sum of cost criterion are calculated by following equations 5 and 6, respectively.

$$B_i = \sum_{j=1}^{k} N_{ij} \quad (5)$$

$$C_i = \sum_{j=k+1}^{m} N_{ij} \quad (6)$$

Step 6: Decide the relative significance of the alternatives. Significance of alternatives are calculated based on Q_i. The greater the solution if greater the value of Q_i. Alternatives having the highest value of Qi is $Q_{(max)}$. Formula to find Qi is given below:

$$Q_i = B_i + \frac{min\,(C_i) \times \sum_{i=1}^{n} C_i}{C_i \times \sum_{i=1}^{n}(\frac{min\,(C_i)}{C_i})} \quad (7)$$

Step 7: Next U_i is calculated.

$$U_i = \frac{Q_i}{max\,(Q_i)} \times 100\% \quad (8)$$

The highest relative level of significance is C_{max}. An alternative's utility function rises or falls as the relative importance value for that choice does. From 0% to 100%, the utility value is possible. In a decision-making dilemma where multiple criteria are present, "this approach enables the evaluation of immediate and relative significance, usefulness degrees of weight, and operational values" [20,21].

Analysis and Discussion

Table 1. Assessment of IoT platforms

IoT Platforms	scalability	market longevity	security	usability	unique features	integration flexibility	availability	pricing
Google Cloud IoT	7	8	8	9	8	9	5	8
Oracle IoT	8	7	6	7	9	6	7	8
Amazon AWS IoT Core	8	9	7	8	8	7	6	7
Microsoft Azure IoT Hub	8	6	6	7	5	9	9	6
Particle	6	9	7	8	9	5	7	7
IBM Watson IoT	7	8	6	8	8	6	7	8
ThingWo	8	6	8	9	7	8	6	8

rx								

Table 1 provides a comprehensive evaluation of different IoT platforms, considering factors such as “scalability, market longevity, security, usability, unique features, integration flexibility, availability, and pricing”. The table presents the scores assigned to each platform for each criterion. Google Cloud IoT: Strong in “scalability, market longevity, security, usability, and unique features”, but lower in “integration flexibility, availability, and pricing”. Oracle IoT: Performs well in scalability, market longevity, usability, unique features, and pricing, but lower in security, integration flexibility, and availability. Amazon AWS IoT Core: Excels in “market longevity, usability, unique features, and availability”, but has average scores in scalability, security, integration flexibility, and pricing. Microsoft Azure IoT Hub: Decent scores in “scalability, usability, integration flexibility, and availability”, but lower in “market longevity, security, unique features, and pricing”. Particle: Scores well in “market longevity, usability, unique features, and integration flexibility”, but average in “scalability, security, availability, and pricing”. IBM Watson IoT: Performs well in “market longevity, usability, unique features, and integration flexibility”, but lower in scalability, security, availability, and pricing. ThingWorx: Excels in usability, unique features, scalability, and pricing, but lower in market longevity, security, integration flexibility and availability.

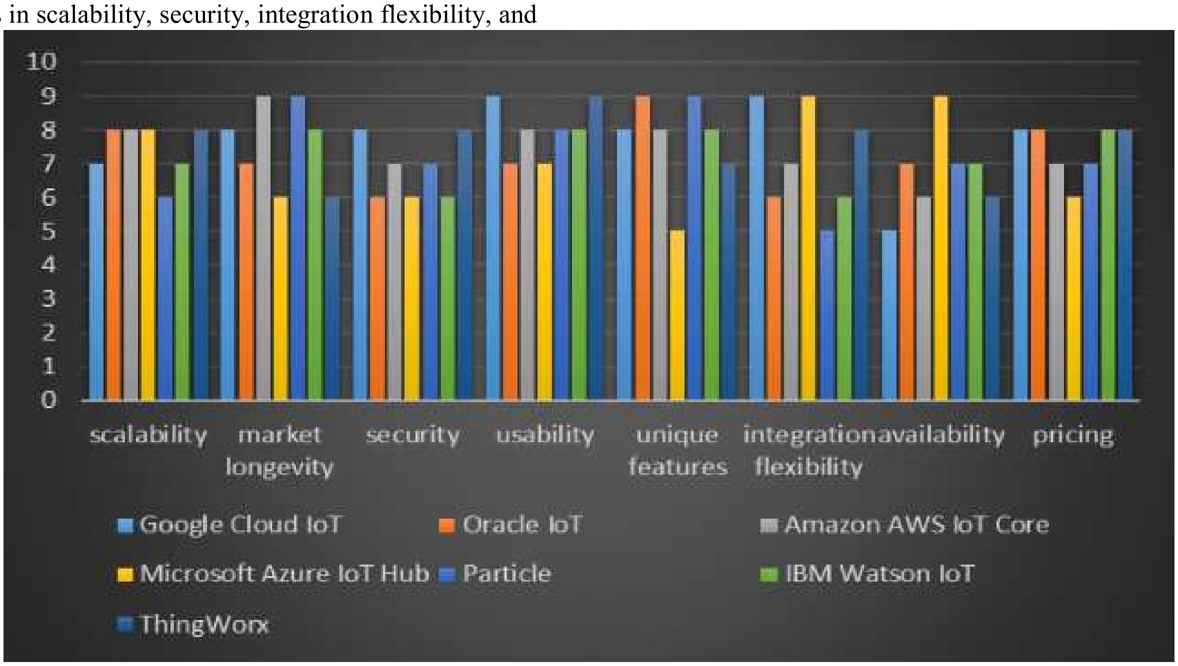

Figure 1. Assessment of IoT platforms

Figure 1 provides a comprehensive evaluation of IoT platforms, considering various factors such as “scalability, market longevity, security, ease of use, unique features, integration flexibility, availability, and pricing”. Google Cloud IoT displays strengths in multiple areas but has weaknesses in integration flexibility, availability, and pricing. Oracle IoT performs well in several criteria but falls short in security, integration flexibility, and availability. Amazon AWS IoT Core receives high ratings for longevity, ease of use, unique features, and availability, but has average scores in scalability, security, integration flexibility, and pricing.

Microsoft Azure IoT Hub demonstrates decent performance in some respects but lacks in terms of longevity, security, unique features, and pricing. Particle receives high ratings for longevity, ease of use, unique features, and integration flexibility, with average scores in scalability, security, availability, and pricing. IBM Watson IoT excels in longevity, ease of use, unique features, and integration flexibility, but falls short in scalability, security, availability, and pricing. ThingWorx stands out in terms of ease of use, unique features, scalability, and pricing, but has lower scores in longevity, security, integration flexibility, and availability.

Table 2. Normalized Data

0.1346	0.1509	0.1667	0.1607	0.1481	0.1800	0.1064	0.1538
0.1538	0.1321	0.1250	0.1250	0.1667	0.1200	0.1489	0.1538
0.1538	0.1698	0.1458	0.1429	0.1481	0.1400	0.1277	0.1346
0.1538	0.1132	0.1250	0.1250	0.0926	0.1800	0.1915	0.1154
0.1154	0.1698	0.1458	0.1429	0.1667	0.1000	0.1489	0.1346
0.1346	0.1509	0.1250	0.1429	0.1481	0.1200	0.1489	0.1538
0.1538	0.1132	0.1667	0.1607	0.1296	0.1600	0.1277	0.1538

Table 2 presents the normalized data obtained through the COPRAS method for the assessed IoT platforms. Notably, Google Cloud IoT and Amazon AWS IoT Core demonstrate strengths in market longevity, security, and usability. Oracle IoT performs well in market longevity and unique features. Microsoft Azure IoT Hub and ThingWorx display mixed performance across various criteria. Particle stands out in market longevity and unique features. These normalized scores facilitate a comparison of the platforms' relative performance, aiding in decision-making processes related to IoT platform selection.

Table 3. Weight Distribution

0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125

Table 3 displays the uniform distribution of weights among the evaluated IoT platforms. Each criterion receives an equal weight of 0.125 for all platforms, suggesting that equal significance is assigned to each criterion during the evaluation process.

Table 4. Weighted Normalized Data

0.0168	0.0189	0.0208	0.0201	0.0185	0.0225	0.0133	0.0192
0.0192	0.0165	0.0156	0.0156	0.0208	0.0150	0.0186	0.0192
0.0192	0.0212	0.0182	0.0179	0.0185	0.0175	0.0160	0.0168
0.0192	0.0142	0.0156	0.0156	0.0116	0.0225	0.0239	0.0144
0.0144	0.0212	0.0182	0.0179	0.0208	0.0125	0.0186	0.0168
0.0168	0.0189	0.0156	0.0179	0.0185	0.0150	0.0186	0.0192
0.0192	0.0142	0.0208	0.0201	0.0162	0.0200	0.0160	0.0192

Table 4 showcases the weighted and normalized data acquired through the COPRAS method for the evaluated IoT platforms. The scores represent the weighted and normalized performance of each platform across various criteria. This data allows for a comparison of the relative performance of the platforms, aiding in informed decision-making when selecting an IoT platform based on specific criteria and their assigned weights.

Table 5. Sum of benefit (Bi) and Cost Criteria (Ci)

IoT Platforms	Bi	Ci
Google Cloud IoT	0.13093	0.01923
Oracle IoT	0.12144	0.01923
Amazon AWS IoT Core	0.12852	0.01683
Microsoft Azure IoT Hub	0.12264	0.01442
Particle	0.12369	0.01683
IBM Watson IoT	0.12131	0.01923
ThingWorx	0.12647	0.01923

Table 5 presents the calculated sum of benefit (Bi) and cost criteria (Ci) using the COPRAS method for the evaluated IoT platforms. The Bi scores represent the overall benefit derived from each platform, while the Ci scores indicate the associated costs. Notably, Google Cloud IoT obtains the highest sum of benefit score (0.13093) with a relatively low-cost criteria score (0.01923). In contrast, Microsoft Azure IoT Hub achieves a slightly lower sum of benefit score (0.12264) but exhibits the lowest cost criteria score (0.01442).

Other platforms such as Oracle IoT, Particle, IBM Watson IoT, and ThingWorx fall within comparable ranges for both benefit and cost criteria. These scores “play a significant role in the decision-making process” as they consider the benefits and costs associated with each platform, thereby facilitating the selection of an IoT platform based on individual priorities and considerations.

Table 6. Significance Value (Qi) and Utility Function (Ui)

IoT Platforms	Qi	Ui	Rank
Google Cloud IoT	0.14734	1	1
Oracle IoT	0.13785	0.93557	6
Amazon AWS IoT Core	0.14727	0.99952	2
Microsoft Azure IoT Hub	0.14452	0.98084	3
Particle	0.14244	0.96672	5
IBM Watson IoT	0.13772	0.93470	7
ThingWorx	0.14287	0.96967	4

Table 6 presents the significance value (Qi) and utility function (Ui) derived from the COPRAS method for the evaluated IoT platforms. The Qi values reflect the significance or importance of each platform, while the Ui values represent their overall utility or desirability. Google Cloud IoT stands out with the highest Qi value of 0.14734 and a Ui value of 1, indicating the highest level of utility and desirability. Oracle IoT and IBM Watson IoT follow closely with slightly lower Qi values of 0.13785 and 0.13772, respectively, and respectable Ui values of 0.93557 and 0.93470. Amazon AWS IoT Core demonstrates a high Qi value of 0.14727 and a Ui value of 0.99952. Microsoft Azure IoT Hub and ThingWorx also perform well with Qi values of 0.14452 and 0.14287, respectively, along with Ui values of 0.98084 and 0.96967.

These significance and utility function values play a crucial role in decision-making processes by assessing the relative importance and desirability of each platform, facilitating the selection of the most suitable IoT platform based on their significance and utility. In the ranking based on the COPRAS method, Google Cloud IoT emerged as the top-ranked platform, demonstrating its superior performance and highest utility. Amazon AWS IoT Core closely followed in the second position, showcasing its strong performance and positive attributes. Microsoft Azure IoT Hub secured the third rank, highlighting its competitive performance compared to other platforms.

ThingWorx obtained the fourth rank, indicating its relatively good performance according to the COPRAS method. Particle ranked fifth, positioning its performance in the middle range among the evaluated platforms. Oracle IoT obtained the sixth rank, suggesting its performance was relatively lower compared to other platforms. IBM Watson IoT received the seventh rank, indicating its relatively weaker performance in the evaluation. These rankings offer valuable insights for decision-making and platform selection, enabling stakeholders to evaluate the overall performance and relative positions of the IoT platforms based on the COPRAS method.

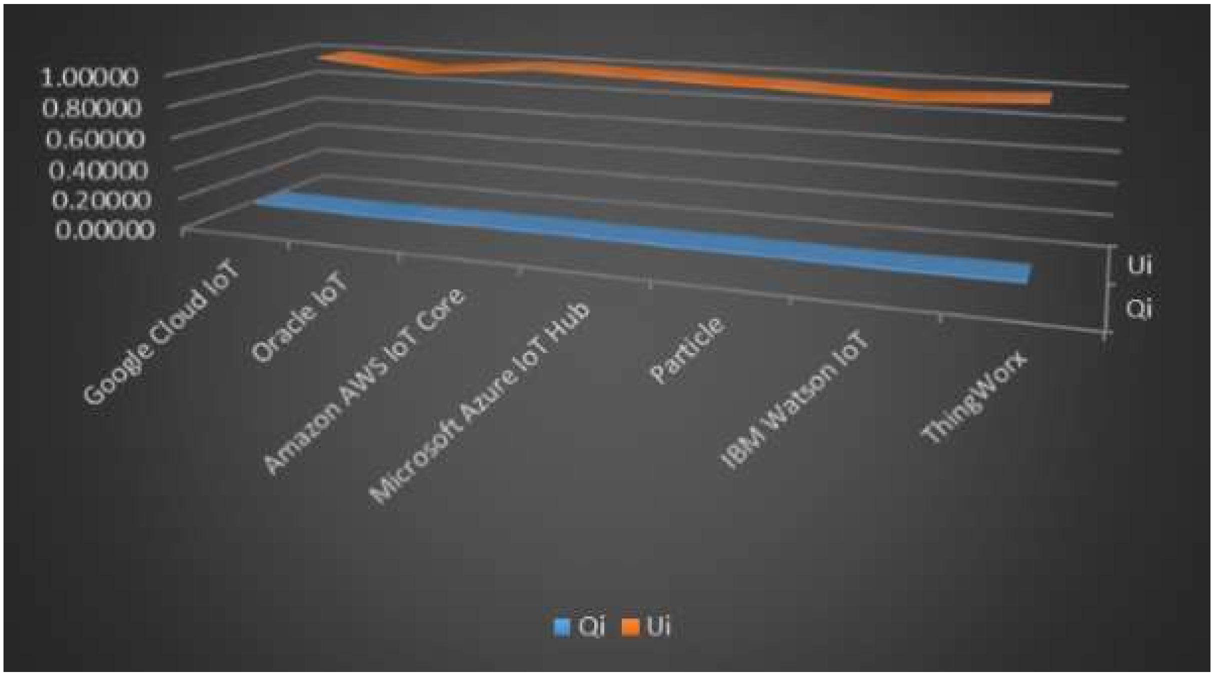

Figure 2. Significance value (qi) and utility function (ui)

Figure 2 depicts the results obtained from the COPRAS method, showcasing the significance value (Qi) and utility function (Ui) for the evaluated IoT platforms. The Qi values signify the significance or importance of each platform, while the Ui values represent their overall utility or desirability. Notably, Google Cloud IoT emerges as the frontrunner with the highest Qi value of 0.14734 and a Ui value of 1, denoting the highest level of utility and desirability.

Oracle IoT and IBM Watson IoT closely follow with slightly lower Qi values of 0.13785 and 0.13772, respectively, along with respectable Ui values of 0.93557 and 0.93470. Amazon AWS IoT Core showcases a significant Qi value of 0.14727 and a Ui value of 0.99952. Microsoft Azure IoT Hub and ThingWorx also perform well, with Qi values of 0.14452 and 0.14287, respectively, coupled with Ui values of 0.98084 and 0.96967. These Qi and Ui values play a pivotal role in decision-making processes as they evaluate the relative importance and desirability of each platform, thereby facilitating the selection of the most suitable IoT platform based on their significance and utility.

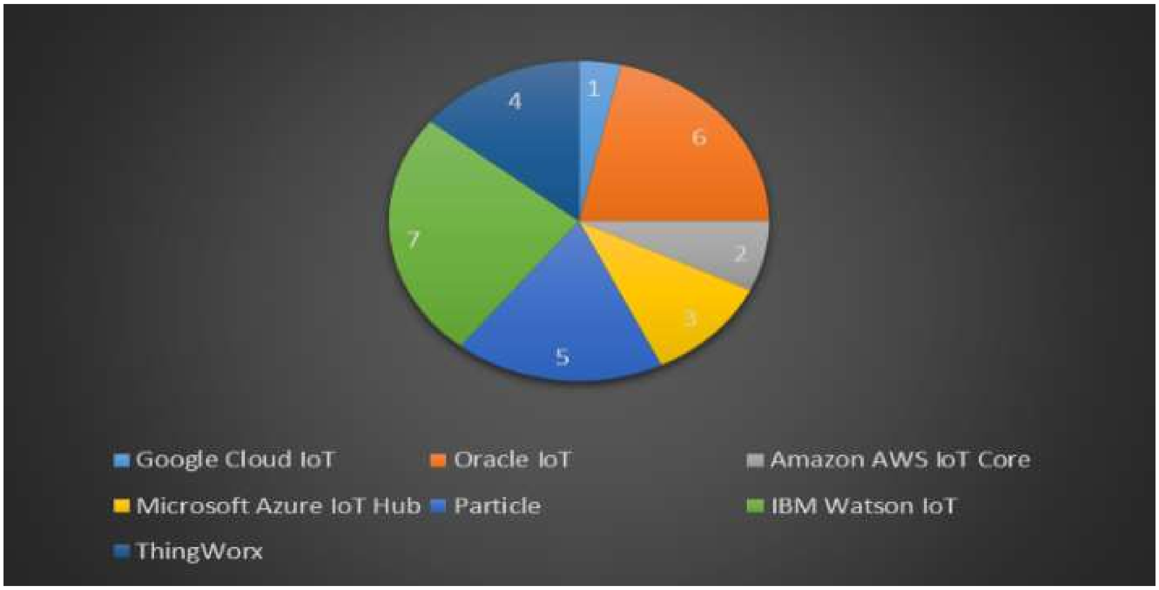

Figure 3. Rank

Figure 3 illustrates the rankings of the evaluated IoT platforms using the COPRAS method. Google Cloud IoT emerged as the top-ranked platform, showcasing its superior performance and highest utility. Amazon AWS IoT Core closely followed in the second rank, highlighting its strong performance and favorable attributes. Microsoft Azure IoT Hub secured the third rank, demonstrating its competitive performance compared to other platforms.

ThingWorx obtained the fourth rank, indicating its relatively good performance based on the COPRAS method. Particle ranked fifth, positioning its performance in the middle range among the evaluated platforms. Oracle IoT obtained the sixth rank, suggesting its performance was comparatively lower among the platforms. IBM Watson IoT received the seventh rank, indicating its relatively weaker performance in the evaluation. These rankings offer valuable insights for decision-making and platform selection, enabling stakeholders to assess the overall performance and relative positions of the IoT platforms based on the COPRAS method

Conclusion:

With the advancement of Internet of Things (IoT) deployments, they are becoming increasingly automated and complex. Through programming abstractions such as trigger-action rules, end-users can easily create new functionalities by connecting their devices and online services. However, complications arise when multiple rules are activated simultaneously, resulting in intricate system behaviors that are difficult to understand and troubleshoot. Historical incidents have demonstrated that such conditions can be exploited. Presently, the security status of trigger-action IoT deployments is largely unknown, adding to the concerns surrounding their implementation. “The use of Multicriteria Decision Making (MCDM) methods in selecting a specialized IoT platform” is essential due to “the complexity of considering all the features, opportunities, and services offered by IoT platform developers”. Failing to choose the right platform may result in “decreased reliability and safety of the IoT systems”. In the ranking derived from the COPRAS method, Google Cloud IoT emerged as the top-ranked platform, demonstrating its superior performance and highest utility. Amazon AWS IoT Core closely followed in the second rank, showcasing its strong performance and positive attributes. Microsoft Azure IoT Hub secured the third rank, highlighting its competitive performance compared to other platforms. ThingWorx obtained the fourth rank, signifying its relatively good performance based on the COPRAS method. Particle ranked fifth, positioning its performance in the middle range among the evaluated platforms. Oracle IoT obtained the sixth rank, suggesting its performance was comparatively lower among the platforms. IBM Watson IoT received the seventh rank, indicating its relatively weaker performance in the evaluation. These rankings provide valuable insights for decision-making and platform selection, allowing stakeholders to assess the overall performance and relative positions of the IoT platforms based on the COPRAS method.

References

1. Varadharajan, Vijay, and Udaya Tupakula. "Security as a service model for cloud environment." IEEE Transactions on network and Service management 11, no. 1 (2014): 60-75.
2. Noor, Talal H., Quan Z. Sheng, Sherali Zeadally, and Jian Yu. "Trust management of services in cloud environments: Obstacles and solutions." ACM Computing Surveys (CSUR) 46, no. 1 (2013): 1-30.
3. Grozev, Nikolay, and Rajkumar Buyya. "Performance modelling and simulation of three-tier applications in cloud and multi-cloud environments." The Computer Journal 58, no. 1 (2015): 1-22.
4. Xu, Baomin, Chunyan Zhao, Enzhao Hu, and Bin Hu. "Job scheduling algorithm based on Berger model in cloud environment." Advances in Engineering Software 42, no. 7 (2011): 419-425.
5. Hussein, Mohamed K., Mohamed H. Mousa, and Mohamed A. Alqarni. "A placement architecture for a container as a service (CaaS) in a cloud environment." Journal of Cloud Computing 8 (2019): 1-15.
6. Kaliski Jr, Burton S., and Wayne Pauley. "Toward risk assessment as a service in cloud environments." In 2nd USENIX Workshop on Hot Topics in Cloud Computing (HotCloud 10). 2010.
7. Stewart, Craig A., Timothy M. Cockerill, Ian Foster, David Hancock, Nirav Merchant, Edwin Skidmore, Daniel Stanzione et al. "Jetstream: a self-provisioned, scalable science and engineering cloud environment." In Proceedings of the 2015 XSEDE Conference: Scientific Advancements Enabled by Enhanced Cyberinfrastructure, pp. 1-8. 2015.
8. Sakr, Sherif, Anna Liu, Daniel M. Batista, and Mohammad Alomari. "A survey of large scale data management approaches in cloud environments." IEEE communications surveys & tutorials 13, no. 3 (2011): 311-336.
9. Dubey, Kalka, Mohit Kumar, and Subhash Chander Sharma. "Modified HEFT algorithm for task scheduling in cloud environment." Procedia Computer Science 125 (2018): 725-732.
10. Ghoshal, Devarshi, Richard Shane Canon, and Lavanya Ramakrishnan. "I/o performance of virtualized cloud environments." In Proceedings of the second international workshop on Data intensive computing in the clouds, pp. 71-80. 2011.
11. Abirami, S. P., and Shalini Ramanathan. "Linear scheduling strategy for resource allocation in cloud environment." International Journal on Cloud Computing: Services and Architecture (IJCCSA) 2, no. 1 (2012): 9-17.
12. Xiong, Pengcheng, Yun Chi, Shenghuo Zhu, Hyun Jin Moon, Calton Pu, and Hakan Hacigümüş. "Intelligent management of virtualized resources for database systems in cloud environment." In 2011 IEEE 27th International Conference on Data Engineering, pp. 87-98. IEEE, 2011.
13. Vignesh, V., K. Sendhil Kumar, and N. Jaisankar. "Resource management and scheduling in cloud environment." International journal of scientific and research publications 3, no. 6 (2013): 1-6.
14. Namasudra, Suyel. "Fast and secure data accessing by using DNA computing for the cloud environment." IEEE Transactions on Services Computing 15, no. 4 (2020): 2289-2300.
15. Lorido-Botran, Tania, Jose Miguel-Alonso, and Jose A. Lozano. "A review of auto-scaling techniques for elastic applications in cloud environments." Journal of grid computing 12 (2014): 559-592.
16. He, Sijin, Li Guo, Moustafa Ghanem, and Yike Guo. "Improving resource utilisation in the cloud environment using multivariate probabilistic models." In 2012 IEEE Fifth International Conference on Cloud Computing, pp. 574-581. IEEE, 2012.
17. Xing, Tianyi, Dijiang Huang, Le Xu, Chun-Jen Chung, and Pankaj Khatkar. "Snortflow: A openflow-based intrusion prevention system in cloud environment." In 2013 second GENI research and educational experiment workshop, pp. 89-92. IEEE, 2013.
18. Kaur, Harleen, M. Afshar Alam, Roshan Jameel, Ashish Kumar Mourya, and Victor Chang. "A proposed solution and future direction for blockchain-based heterogeneous medicare data in cloud environment." Journal of medical systems 42 (2018): 1-11.
19. Toosi, Adel Nadjaran, Rodrigo N. Calheiros, and Rajkumar Buyya. "Interconnected cloud computing environments: Challenges, taxonomy, and survey." ACM Computing Surveys (CSUR) 47, no. 1 (2014): 1-47.
20. Kaur, Harleen, M. Afshar Alam, Roshan Jameel, Ashish Kumar Mourya, and Victor Chang. "A proposed solution and future direction for blockchain-based heterogeneous medicare data in cloud environment." Journal of medical systems 42 (2018): 1-11.
21. Organ, Arzu, and Engin Yalçın. "Performance evaluation of research assistants by COPRAS method." European Scientific Journal 12, no. 10 (2016): 102-109.
22. Kundakcı, Nilsen, and A. Işık. "Integration of MACBETH and COPRAS methods to select air compressor for a textile company." Decision Science Letters 5, no. 3 (2016): 381-394.

23. Addressing Supply Chain Administration Challenges in the Construction Industry: A TOPSIS-Based Evaluation Approach by Vijay Kumar Adari, REST Publisher, 2023. ISBN: 978-81-948459-4-2.
24. Zagorskas, Jurgis, Marija Burinskienė, Edmundas Zavadskas, and Zenonas Turskis. "Urbanistic assessment of city compactness on the basis of GIS applying the COPRAS method." Ekologija 53 (2007). Zagorskas, Jurgis, Marija Burinskienė, Edmundas Zavadskas, and Zenonas Turskis. "Urbanistic assessment of city compactness on the basis of GIS applying the COPRAS method." Ekologija 53 (2007).
25. Kustiyahningsih, Yeni, and Ismy Qorry Aini. "Integration of FAHP and COPRAS method for new student admission decision making." In 2020 Third International Conference on Vocational Education and Electrical Engineering (ICVEE), pp. 1-6. IEEE, 2020.
26. Özbek, Aşir, and Emel Erol. "Ranking of factoring companies in accordance with ARAS and COPRAS methods." International Journal of Academic Research in Accounting, Finance and Management Sciences 7, no. 2 (2017): 105-116.
27. Keshavarz Ghorabaee, Mehdi, Maghsoud Amiri, Jamshid Salehi Sadaghiani, and Golnoosh Hassani Goodarzi. "Multiple criteria group decision-making for supplier selection based on COPRAS method with interval type-2 fuzzy sets." The International Journal of Advanced Manufacturing Technology 75 (2014): 1115-1130.
28. Zheng, Yuanhang, Zeshui Xu, Yue He, and Huchang Liao. "Severity assessment of chronic obstructive pulmonary disease based on hesitant fuzzy linguistic COPRAS method." Applied Soft Computing 69 (2018): 60-71.
29. VimalaSaravanan, Chinnasami Sivaji, Sathiyaraj Chinnasamy, and Chandrasekar Raja. "Using the COPRAS Methodology Cancer with a solution." Computer Science, Engineering and Technology 1, no. 1 (2023): 36-45.
30. Esbouei, Saber Khalili, and Abdolhamid Safaei Ghadikolaei. "Applying FAHP and COPRAS methods for evaluating financial performance." International Journal of Managment, IT and Engineering 3, no. 11 (2013): 10-22.
31. Ayrim, Yelda, Kumru Didem Atalay, and Gülin Feryal Can. "A new stochastic MCDM approach based on COPRAS." International Journal of Information Technology & Decision Making 17, no. 03 (2018): 857-882.
32. Roy, Jagannath, Haresh Kumar Sharma, Samarjit Kar, Edmundas Kazimieras Zavadskas, and Jonas Saparauskas. "An extended COPRAS model for multi-criteria decision-making problems and its application in web-based hotel evaluation and selection." Economic research-Ekonomska istraživanja 32, no. 1 (2019): 219-253.
33. Dorfeshan, Yahya, and S. Meysam Mousavi. "A group TOPSIS-COPRAS methodology with Pythagorean fuzzy sets considering weights of experts for project critical path problem." Journal of intelligent & fuzzy systems 36, no. 2 (2019): 1375-1387.
34. Bitarafan, Mahdi, S. Hashemkhani Zolfani, Sh Lale Arefi, and Edmundas Kazimieras Zavadskas. "Evaluating the construction methods of cold-formed steel structures in reconstructing the areas damaged in natural crises, using the methods AHP and COPRAS-G." Archives of civil and mechanical engineering 12 (2012): 360-367.
35. Hashemkhani Zolfani, Sarfaraz, Nahid Rezaeiniya, Edmundas Kazimieras Zavadskas, and Zenonas Turskis. "Forest roads locating based on AHP and COPRAS-G methods: an empirical study based on Iran." (2011).
36. Bitarafan, Mahdi, S. Hashemkhani Zolfani, Sh Lale Arefi, and Edmundas Kazimieras Zavadskas. "Evaluating the construction methods of cold-formed steel structures in reconstructing the areas damaged in natural crises, using the methods AHP and COPRAS-G." Archives of civil and mechanical engineering 12 (2012): 360-367.
37. Rajareega, S., and J. Vimala. "Operations on complex intuitionistic fuzzy soft lattice ordered group and CIFS-COPRAS method for equipment selection process." Journal of Intelligent & Fuzzy Systems 41, no. 5 (2021): 5709-5718.
38. Adali, Esra Aytac, and Ayġegül Tuş Işık. "Air conditioner selection problem with COPRAS and ARAS methods." Manas Sosyal Araştırmalar Dergisi 5, no. 2 (2016): 124-138.
39. Beena, Mary John, and C. Sudha Kartha. "Fabrication and characterization of dye sensitized polymer films for holographic applications." PhD diss., Department of Physics, 2008.
40. Amudha, M., M. Ramachandran, Chinnasami Sivaji, M. Gowri, and R. Gayathri. "Evaluation of COPRAS MCDM method with fuzzy approach." Data analytics and artificial intelligence 1, no. 1 (2021): 15-23.