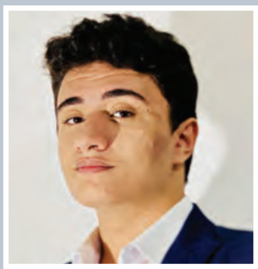
Underwater Communication



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Researchers propose using Reconfigurable Intelligent Surfaces in machine learning-assisted underwater communication, supported by a comprehensive bibliometric analysis.

Who should read this paper?

This study is for anyone interested in the cutting-edge developments of Reconfigurable Intelligent Surfaces (RISs) and their revolutionary applications in machine learning-assisted underwater communications.

Why is it important?

RIS is an emerging technology that uses principles from electromagnetics, signal processing, and antenna theory to control the transmission of electromagnetic waves in wireless communication channels. When merged with machine learning, RISs could revolutionize wireless underwater communication by offering a more efficient, cost-effective, and adaptable solution.

The authors examine potential signalling technologies in a RIS-assisted underwater environment, including the Internet of Underwater Things (IoUWT), various RIS implementation approaches, and hardware architecture. They also investigate machine learning-enabled optimization techniques for RIS-aided networks. Their pioneering systematic bibliometric analysis on RISs gives insight into research trends and citation patterns in the published literature on RISs.

The findings will establish a baseline for evaluating the future path for RIS publications. They raise awareness of the critical areas of research that demand immediate exploration, especially in the application of Artificial Intelligence in RISs and the profound influence of RISs on machine learning-assisted underwater communications.

About the authors

Mohamed Ashraf Ouf earned his B.Sc. in computer engineering from Arab Academy for Science, Technology, and Maritime Transport in July 2023. His passion revolves around integrating cutting-edge technologies to revolutionize industrial standards. With a focus on harnessing the power of AI, he is dedicated to unlocking new possibilities across diverse sectors. Continuously seeking innovative ways to merge ML, he aims to tackle complex challenges and elevate operational efficiency to unprecedented heights.

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A REVIEW OF RECONFIGURABLE INTELLIGENT SURFACES AND THEIR APPLICATION TO MACHINE LEARNING-ASSISTED UNDERWATER COMMUNICATIONS

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ABSTRACT

Underwater communication systems face unique challenges that require advanced research and technologies. Environmental factors such as surface scattering, harsh sea conditions, water currents, and marine life can disrupt the propagation of acoustic signals. Integrating Reconfigurable Intelligent Surfaces (RISs) into underwater communication systems is a promising solution to address these challenges. RISs enhance signal propagation by creating optimal environments through passive beamforming and phase tuning, reducing scattering and absorption. This research proposes integrating RIS technology with machine learning (ML) techniques in underwater communication systems, leveraging recent advancements in both fields. This paper is the first to combine RIS technology with ML techniques in underwater communications while offering a comprehensive bibliometric analysis of RISs.

Keywords: Reconfigurable Intelligent Surfaces (RISs); Bibliometric Analysis; Wireless Communication; Underwater Communications; Machine Learning (ML); Artificial Intelligence (AI); Research Productivity; Internet of Underwater Things (IoUWT); Challenge State Information (CSI); Non-Orthogonal Multiple Access (NOMA); Multiple Input Multiple Output (MIMO)

1. INTRODUCTION

1.1 Motivation

Reconfigurable Intelligent Surfaces (RISs) represent a groundbreaking technology that merges principles from electromagnetics, signal processing, and antenna theory to dynamically manage the transmission of electromagnetic waves in wireless communication channels [1], [2], [3], [4]. RISs consist of an array of passive reflecting elements, each capable of independent tuning to introduce phase shifts to incident signals [5], [6], [7], [8]. These meticulously designed planar structures feature reconfigurable properties enabled by integrated electronic circuits [9]. By programming these circuits, we can control the reflection of incoming incident electromagnetic waves, creating an innovative and adaptable wireless communication environment [10], [11]. The key advantages of RIS technology are:

1. **Energy Efficiency:** RIS elements consume minimal power, enhancing wireless network performance without significantly increasing power consumption [12].
2. **Cost-Effectiveness:** The technology can be implemented using low-cost materials and integrated with existing infrastructures, providing an economical solution for improving wireless communication systems [13], [14], [15].
3. **Spectrum Optimization:** RIS technology optimizes spectrum use by mitigating interference, enhancing the signal-to-noise ratio (SNR), and enabling more efficient utilization of available frequency resources [16].

Overall, RIS technology offers a promising approach to creating more efficient, cost-effective, and adaptable wireless communication networks.

RISs, which are made from cost-effective materials, have lightweight and low-profile designs that make them easy to deploy in modern networks and attach to various surfaces such as building facades, walls, ceilings, and windows [17]. By optimizing the phase shifts of the RISs, the signals transmitted via the reflecting channel link can be added constructively at the intended receiving user or destructively at the interferer, resulting in a higher rate compared to not deploying RISs [9]. Nonetheless, conventional passive RISs can only reflect the incident signal without introducing any gain [18]. Also, the capacity gain achieved by passive RISs is limited because of the *multiplicative fading* effect, which is very significant in communication scenarios with strong line-of-sight (LOS) links between the base station (BS) and the users [14], [19]. To address these issues, active RISs have been suggested. In active RISs, the incident electromagnetic signal is amplified, and its phase shift is favourably adjusted simultaneously. Compared with amplify-and-forward (AF) relays, active RISs operate in full-duplex (FD) mode and rely on low-power reflection amplifiers instead of power-hungry radio frequency chains [20].

RIS technology is recommended for underwater communications because of its ability to create favourable propagation environments using passive beamforming and wave manipulation. However, there are challenges. This technology can effectively address these challenges, such as severe scattering and absorption, high path loss, multipath fading, non-line-of-sight (NLoS) scenarios, harsh sea conditions, and the dynamic nature of the underwater environment, by reducing signal scattering and absorption [21], [22].

Although RIS technology holds great promise for underwater communication deployment, it also faces several obstacles [23]. These obstacles range from the need for physical robustness to withstand harsh underwater conditions to dynamic reconfiguration in response to constantly changing underwater topography. Moreover, integrating RISs with existing underwater communication infrastructure requires careful consideration to ensure compatibility and realize the full benefits of this technology. Nonetheless, RISs remain an effective technology for improving signal propagation characteristics by concentrating signal power in the desired direction, making the communication environment reconfigurable [24]. One of the most effective approaches to reconfiguring RISs in underwater communications is to use different machine-learning techniques [1].

1.2 Literature Review

In the literature, there are several works that explore the use of RISs in communication networks. These works can be categorized into three main groups:

1. **RIS-Assisted Wireless Communication Networks:** In reference [9], the authors discussed the use of an unmanned aerial vehicle (UAV) with an active RIS operating in the terahertz (THz) band. They considered a scenario involving a cellular user and multiple device-to-device (D2D) links. The authors proposed a joint power allocation and active RIS precoding matrix optimization scheme to maximize the uplink sum rate, considering coexisting D2D links. Their simulations demonstrated that their proposed active RIS-aided approach outperformed other schemes, achieving the highest sum rate. In [25], the authors proposed a dynamic RIS sub-array structure to enhance the performance of a THz downlink multiple-input-multiple-output (MIMO) communication system. They introduced a weighted minimum mean square error-RIS local search (WMMSE-LS) scheme with limited RIS phase shift accuracy and an adaptive block coordinate descent (BCD)-aided joint beamforming approach to improve throughput performance for the investigated RIS THz system. In [26], the authors developed an RIS-enhanced uplink user-centric network (UNC), where RISs are used to enhance the signal quality of uplink transmission for users with minimal additional energy consumption. To achieve optimal energy efficiency, the authors jointly performed reflect beamforming at the RISs and uplink power control at users. The numerical results showed that their proposed algorithm could achieve significant gains in energy and spectral efficiency compared to the benchmark algorithm.

2. **RISs and ML-Assisted Wireless Communication Networks:** In reference [27], the authors propose a deep learning (DL)-based rate-splitting multiple access (RSMA) scheme for RIS-aided THz multi-user MIMO systems. Their approach involves a hybrid data-model driven DL-

based RSMA precoding scheme that includes passive precoding at the RISs, as well as analog active precoding and RSMA digital active precoding at the BS. The authors tested their scheme and demonstrated its advantages, showing that the proposed DL-based RSMA scheme enhances the robustness against challenge state information (CSI) imperfections and achieves higher spectral efficiency with lower signalling overhead in RIS-aided THz MIMO systems. In reference [28], the authors provide an overview of RISs and explain the operations and implementations of reinforcement learning (RL) algorithms for optimizing RIS technology parameters. They highlighted the significant performance improvements in communication systems when RL algorithms are implemented for RIS technology in wireless communications.

3. **RISs in Underwater Communications:** Several papers in the literature discuss the use of reconfigurable intelligent surface (RIS) technology in underwater communications [29], [30], [31], [32]. In the first paper [29], the authors used RIS-assisted optical links to minimize the effects of skip zones and enable high-speed, efficient communication. They also proposed an RIS-assisted dual-hop underwater wireless optical communication system and derived mathematical expressions for outage probability and bit error rate for various modulation techniques. The authors validated their results using Monte-Carlo simulations and asymptotic analysis. In the second paper [30], they focused on analyzing the performance of an RIS-assisted underwater optical communication system using a decode-and-forward (DF) relaying protocol. The authors derived mathematical expressions for the total outage probability and average bit error rate (ABER) for various modulation schemes. Their findings highlighted the significant impact of the number of RIS elements, detection techniques, and optical turbulence on the system's performance. In the third paper [31], the authors developed specific hardware to create an acoustic RIS system to address challenges in underwater communications. Their proposed acoustic RIS system demonstrated, through simulations, the ability to function as an underwater infrastructure enabling beamforming capabilities for various devices, such as small robots and low-cost sensors, by efficiently reflecting acoustic waves and significantly increasing communication data rates and distances. In the fourth paper [32], the authors designed three key components of the acoustic RISs to realize the underwater RIS concept, including new acoustic RIS hardware, ultra-wideband beamforming (UWB), and a practical operation protocol. Additionally, the authors developed a practical operation protocol to implement acoustic RIS functionalities in complex underwater environments, and they validated their acoustic RIS design through COMSOL multi-physics simulations and end-to-end Bellhop-based simulations.

Based on the preceding discussions, it is evident that prior research has not explored the potential of deploying machine learning (ML) in RIS-assisted underwater communications.

This presents an exciting opportunity to harness the combined capabilities of ML and RIS technology in underwater communications, an area that is ripe for significant research and technological advancements.

Therefore, the focus is to combine the benefits of ML techniques and RIS technology in underwater communications, which poses significant propagation challenges. The goal is to integrate RIS technology and ML techniques in underwater communications, as previous literature has yet to do so. Initially, we aimed to include a comprehensive bibliometric analysis to integrate ML techniques with RIS technology. Nevertheless, the total number of publications considering RIS and ML techniques was less than 300, which is insufficient for a reliable bibliometric analysis. As a result, this paper will incorporate a detailed systematic bibliometric analysis of RISs; as far as we know, it represents the first comprehensive systematic bibliometric analysis of RISs.

The remainder of this paper is structured as follows: Section 2 introduces possible signalling technologies in RIS-Assisted Underwater Environments. Section 3 provides an overview of the Internet of Underwater Things (IoUWT). In Section 4, the joint power allocation and phase shift optimization are introduced, along with different approaches to deploying RISs underwater and hardware architectures. Section 5 summarizes ML-enabled optimization techniques for RIS-aided networks. In Section 6, a systematic bibliometric analysis provides insights into research directions and citation patterns in the RIS field. Finally, Section 7 includes the conclusion and suggestions for future work.

2. POSSIBLE SIGNALLING TECHNOLOGIES IN RIS-ASSISTED UNDERWATER ENVIRONMENT

In RIS-assisted communication systems, RISs play a crucial role in shaping the electromagnetic signal path between the transmitter (Tx) and receiver (Rx). As shown in Figure 1, the RIS consists of multiple passive reflecting elements that intelligently mould the wireless environment. The Smart controller allows precise control over each RIS element to introduce specific phase shifts, thus steering the beam toward the receiver with amplified signal strength and minimized interference.

In underwater environments, electromagnetic waves struggle to provide a strong signal because of challenges such as scattering and absorption. Therefore, alternative signalling technologies have been suggested to overcome these obstacles. Two suitable signalling technologies in underwater environments are acoustic communication and magnetic induction (or magnetic resonance):

1. **Acoustic Communication.** Transmitting signals underwater relies on acoustic signalling due to the high absorption of electromagnetic waves by water, especially saline water. This absorption significantly reduces the range and quality of electromagnetic signals. In contrast, acoustic waves can travel much longer distances underwater with minimal attenuation, making them more practical for communication in underwater environments. Speakers are used to transmit acoustic signals, which are then received using hydrophones. These signals

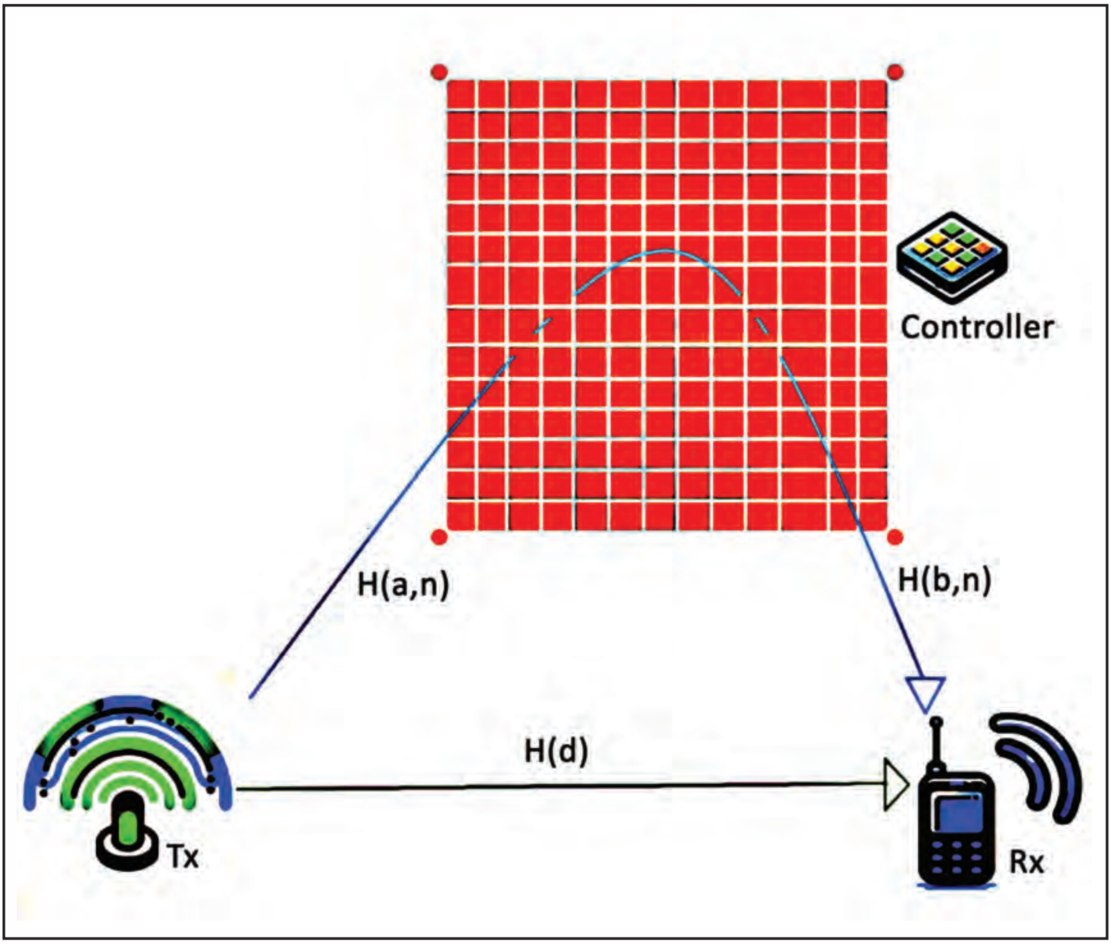

Figure 1: An RIS manipulating the signal propagation between the transmitter (Tx) and the receiver (Rx) to optimize communication performance.

have frequencies ranging from a few Hertz to a few Megahertz (ultrasound). Acoustic signal propagation underwater is affected by scattering at uneven surfaces, water currents, and fish, resulting in severe frequency selectivity and high pass loss due to multipath, leading to a low effective data rate. While conventional RIS technology has been recommended for electromagnetic waves, deploying acoustic waves has also been proposed to address the challenges alluded to earlier [33].
In underwater environments using acoustic signalling, RISs are deployed to overcome the multipath effect, even in line-of-sight (LOS) propagation, owing to frequency selectivity fading. Recent literature has suggested acoustic RIS technology, where uneven surfaces are concealed to eliminate scattering [34], [35], [36], [37].

Underwater communications present unique challenges that differ from those found in land-based environments. Signal transmission becomes more complex because there are many paths it can take, including direct paths, surface reflections, and bottom reflections (as shown in Figure Furthermore, ambient noise from passing vessels and biological noise from marine

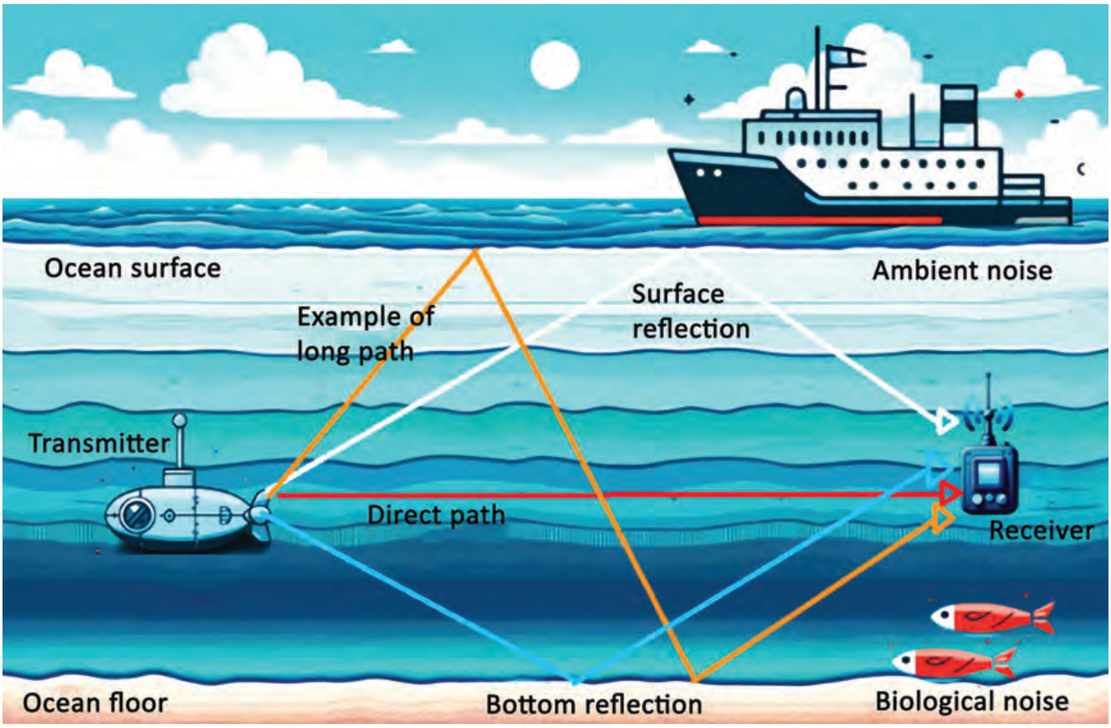

Figure 2: An underwater communication scenario highlighting the signal paths between a transmitter and a receiver, including the challenges of surface and bottom reflections, ambient noise, and biological noise.

life add to the complexity of signal reception. These impediments (when combined) make designing reliable communication systems for underwater applications challenging.

2. **Magnetic Induction (or Magnetic Resonance).** Magnetic induction or magnetic resonance involves creating non-propagating quasi-static magnetic fields using induction coils within resonance circuits rather than traditional EM antennas [38]. Magnetic induction typically operates at low frequencies, ranging from a few kHz to around 13.56 MHz, resulting in a narrow frequency band. Due to the low frequency, the signal wavelength is very large and does not experience reflections or scattering. Consequently, it is not practical to deploy RIS technology alongside magnetic induction [39]. Nonetheless, utilizing magnetic induction waveguides can achieve a similar effect through the passive relaying of magnetic fields [40]. When passive magnetic induction coils align in a wave, they induce secondary magnetic fields without consuming power. This phenomenon is analogous to pseudo-reflections. By adjusting the impedance of the resonance circuit of each magnetic conduction relay, these pseudo-reflections become both tunable and reconfigurable. Therefore, passive magnetic induction relays represent a unique case of magnetic RISs, where each device functions as a single reflective element [21].

3. INTERNET OF UNDERWATER THINGS (IoUWT)

3.1 Overview of IoUWT

The Internet of Underwater Things is a

concept that aims to create large-scale wireless networks connecting devices below the water's surface, like the Internet of Things (IoT) above the surface [41]. The IoUWT involves various underwater devices such as submarines, autonomous underwater vehicles (AUVs), sensors, and ships [42]. The main goal is to ensure that these devices have reliable connectivity in the challenging underwater environment, which differs significantly from terrestrial networks attributable to their impact on signal propagation and path loss. This is particularly evident in the underwater environment's conductivity, which varies based on salinity, temperature, and pressure, significantly affecting the absorption of electromagnetic fields, and causing high path loss. This limits data rates to below 8 kbit/s for distances greater than 10 metres in seawater. It is also important to note that the conductivity in freshwater is 0.01 S/m and can reach 4-5 S/m in seawater.

3.2 Challenges in IoUWT

Underwater communications primarily use acoustic waves because they are less susceptible to absorption compared to electromagnetic and other signalling techniques [43]. Acoustic communication transmits through pressure variations in the water, allowing signals to travel tens of kilometres in open water. However, this communication method faces challenges such as interference from marine life, signal scattering, and reflections caused by the heterogeneity of the underwater environment, including varying water currents with different pressures and temperatures. These factors lead to multipath propagation, frequency-selective, and time-variant channel responses [44]. Although some alternative communication methods (utilizing very low signal frequencies through magnetic induction or optical communications) have been proposed, they have not yet been implemented due to similar path loss issues [41].

3.3 Application of IoUWT

There are various deployment scenarios for IoUWT, such as monitoring maritime animals, observing seismic activities to predict natural disasters like tsunamis, and communicating with underwater vehicles [43]. Some networks also incorporate floating buoys that gather data from submerged sensors. The primary challenge in all these scenarios is dealing with the time-variant multipath channels when using acoustic waves for communication. IoUWT is an area of significant research interest and has seen substantial advancements in recent years [45].

4. APPROACHES FOR RIS DEPLOYMENT UNDERWATER AND HARDWARE ARCHITECTURE

In this section, we introduce the various methods for deploying RISs underwater and discuss the hardware architecture for RIS-assisted networks in underwater communications.

4.1 Approaches for Deploying RISs Underwater

For deploying RISs in the underwater medium, particularly within the context of IoUWT, the approaches that have been considered are:

- ***Stationary Deployment.*** The simplicity and minimal design challenges of this method make it particularly beneficial for integrating into IoUWT [46]. One of its key advantages is that the static geometrical configuration ideally leads to relatively stable communication channels. On the contrary, this stability is generally only applicable for short distances. For longer distances, especially over 100 metres, the rapidly changing channels in the underwater medium present significant challenges [47].

- ***Autonomous Underwater Vehicles (AUVs).*** AUVs are expected to support the distributed nodes of the IoUWT by moving from one node to another like traditional mobile relaying [48]. Their key role is to improve connectivity and recharge node batteries, and they are also well-suited for carrying RISs, contributing to the smart underwater environment. This type of mobility can be adjusted to enhance signal propagation using the RIS's phase shifting capabilities, in addition to the vehicles' mobility [21]. The trajectory of the AUVs in this context is of particular interest, and one challenge related to their mobility scenarios is channel prediction. Unlike stationary deployment, the system configuration's geometry is not fixed but changing, making communication channels time-varying. However, the relatively slow motion of the AUVs results in a long motion-related coherence time, meaning that the motion is not critical for the RIS-equipped AUVs. On the other hand, the AUVs' surfaces are likely designed to reduce friction in water, which could otherwise be a primary issue for vehicle control. Therefore, RISs should cover only relatively small areas to minimize this effect while maintaining control over the smart environment [46].
- ***Floating RISs.*** The floating deployment is a strategic option for RISs that hold great promise. In this approach, the RISs are tethered to the seabed with cables, allowing them to be positioned at an optimal depth between underwater sensors and the surface. This method limits the maximum distance between the RISs and their anchor position on the ocean floor. By using this strategy, control over the position of the RISs is maintained, and it also helps stabilize the communication channels by maintaining a certain level of geometrical configuration [21].

N.B.: These different deployment methods limit the adaptability of RISs for underwater communication challenges, aiming to maximize communication effectiveness within underwater constraints.

4.2 Hardware Architecture for RIS-Assisted Networks in Underwater Communications

In underwater communications, the hardware architecture for RISs is designed for autonomous operation. RISs extend beyond simply reflecting signals to include advanced features such as wireless sensors and actuators [23].

The proposed architecture is a modified version of traditional wireless sensor node structures. Each RIS node integrates the RIS as a front-end and can also have conventional antennas for extra functions like active relaying and signal buffering [49]. Traditional antennas and RISs work in parallel and have the same connections to other hardware components. To address energy limitations underwater, a power unit with a battery power all components, including the tunable reflective elements of the RISs. Energy harvesting modules, supporting the idea of self-sustainable RISs, capture signals not reflected by the RISs [50]. This approach, which involves simultaneous signal reflection and energy harvesting clusters, aligns with potential advances in simultaneous wireless information and power transfer (SWIPT) technology [51].

A processing unit, consisting of a processor and memory storage, manages phase shifts in the RISs. It operates as a transmitter or receiver through a dedicated transceiver, allowing communication with other RISs [52]. For improved signal processing capabilities, the processing unit can link to external processors and memory blocks from neighbouring RIS patches.

This architecture aims to reduce the computational complexity per Reconfigurable Intelligent Surface (RIS) while allowing for functional extensions. It ensures that the nodes of the RIS in underwater environments can not only reflect signals but also have advanced functionalities and efficient power management systems.

5. ML-ENABLED OPTIMIZATION TECHNIQUES FOR RIS-AIDED NETWORKS

Machine learning (ML), when used with RIS technology, can significantly enhance network performance in RIS-aided networks. By using various ML-based optimization techniques, such as dynamic spectrum allocation and interference mitigation, we can optimize predictive resource management to improve overall network capacity. In this context, we will explore several ML techniques that can be used within RIS, including supervised learning, unsupervised learning, reinforcement learning, federated learning, graph learning, transfer learning, and hierarchical learning.

- ***Supervised Learning.*** In Supervised Learning algorithms, the model learns to map input data to the correct output labels using a labelled dataset. A technique described in [53] aims to maximize the power received in an RIS-enabled network. In a scenario involving multiple users and a multiple-input single-output (MISO) system, the downlink is examined, and a deep neural network (DNN) is utilized to learn the mapping between the users' locations and the RIS reflecting elements. The goal is to enhance the signal quality at each predicted user position in indoor environments. The proposed DNN architecture consists of five layers, with each output layer employing a nonlinear function. In another study [54], a communication link between two nodes is supported by multiple RISs. Low-complexity supervised learning algorithms are used to configure the phase shifts of the RISs. A multi-layer perceptron neural network is proposed, which can be trained with positioning values or instantaneous channel coefficients. The study explores centralized and individual training of the RISs and their coordination and computational requirements. Simulation results in the paper demonstrate the advantages of using individual neural networks at the RISs to improve the link budget performance.

- ***Unsupervised Learning.*** Unsupervised Learning involves identifying patterns or structures in data without using explicit labels. Unsupervised learning techniques work with unlabelled input data to discover connections between data points and form clusters [55]. In a paper referenced as [56], the authors introduced a low-complexity unsupervised learning scheme, named a learning-phase-neural network, to maximize spectral efficiency in RIS-aided MIMO networks. Their simulation results demonstrate that the proposed scheme significantly improves network performance in terms of spectral efficiency while reducing system complexity. Also, in reference [57], the authors proposed an unsupervised learning-based joint active and passive beamforming design for RIS-aided wireless networks. Their proposal involved a deep learning-based algorithm for joint active and passive beamforming design. They trained a two-stage neural network offline without supervision and implemented it online for real-time prediction. Their simulation results showed that their proposed scheme significantly reduces computational complexity compared with existing methods in the literature.
- ***Reinforcement Learning.*** Reinforcement Learning (RL) teaches a model to make sequences of decisions by rewarding desired actions and punishing undesired ones. It includes model-free algorithms such as Q-learning and deep Q-learning (DQN) and model-based algorithms like dynamic programming [58]. In a study referenced as [59], an RIS-assisted cellular network, supported by an RIS reflector powered via energy harvesting technologies, was considered, and the energy efficiency optimization problem was investigated. The study proposed a deep reinforcement learning algorithm to optimize the BS transmit power allocation and RIS phase shift configuration by deploying a neural network. The simulation results indicated significant improvements in energy efficiency when the number of RIS elements increased from 9 to 25. Besides, in reference [60], UAVs were integrated with RISs to passively communicate information sampled by Internet of Things Devices (IoTDs) to the BS. The study aimed to minimize the expected sum age-of-information (AoI) by optimizing the altitude of the UAV, the phase shifts of the RIS elements, and the communication schedule. The authors developed a proximal policy optimization algorithm, a deep reinforcement learning approach, to solve the optimization problem. Their numerical results demonstrated the superiority of the authors' suggested scheme over all other counterparts presented in the literature.
- ***Federated Learning.*** Federated Learning (FL) is an approach to training machine learning models across multiple decentralized devices or servers without directly sharing the data. In a wireless FL system described in reference [61], many edge devices synergize to train a shared model. This process is coordinated by a centralized base station (BS) using over-the-air computation. The authors used an RIS to adjust the wireless environment and

focused on minimizing the gap between the model's performance and its optimal state. They also addressed differential privacy and transmit power constraints. To achieve these goals, they jointly optimized the transmit power of the devices, the phase shifts of the RIS, and the artificial noise, using a two-step alternating minimization framework. Their research demonstrated that the proposed scheme outperformed the benchmarks regarding accuracy and privacy. Reference [62] introduces a framework for balancing the accuracy and integrity of over-the-air FL, utilizing an RIS to optimize multi-antenna devices and the BS. The system aimed to minimize the distortion of the aggregated model by optimizing the transmit beamformers of the devices, the receive beamformers of the BS, and the phase shifts of the RIS. The research considered both perfect and imperfect channel state information (CSI). Simulations confirmed that the proposed scheme achieved a robust design of the beamformers and RIS configuration, even around imperfect CSI. Furthermore, experimental results indicated that the framework achieved accuracy close to the ideal FL.

- ***Graph Learning.*** The field of Graph Learning involves using machine learning techniques on graph data. Some of these techniques include graph attention networks (GAN), graph neural networks (GNN), and graph convolution networks (GCN). In a study referenced as [63], the authors addressed the joint optimization problem involving user scheduling, RIS configuration, and base station (BS) beamforming in an RIS-assisted downlink network with limited pilot overhead. The authors found that GNN, characterized by permutation invariance and equivalent properties, was an effective approach for scheduling users and optimizing RIS phase shifts, thus enhancing system performance in terms of throughput while ensuring fairness among users. The proposed scheme first optimizes the user schedule and then the RIS phase shifts using a second GNN. Subsequently, the BS beamformers are designed based on the overall effective channel. The results presented by the authors indicated that their approach utilizes received pilots more efficiently than conventional channel estimation-based approaches. In another study referenced as [64], a smart RIS-THz-MIMO-NOMA framework was proposed to reconfigure hybrid beams effectively through the cooperation between access points (APs) and the RIS. The authors employed a decentralized partially observable Markov decision process (Dec-POMDP) to optimize the network's energy efficiency while meeting diverse user performance requirements. The authors jointly optimized the RIS element selection and power allocation strategy and coordinated discrete phase-shift control. They proposed a multi-agent deep reinforcement learning (MADRL) algorithm to solve the non-convex and strongly coupled optimization problem. Their numerical results demonstrated that their proposed algorithm outperforms traditional MADRL algorithms.
- ***Transfer Learning.*** Transfer Learning allows knowledge gained in one problem domain to be applied to a different but related domain. In the context of RISs, transfer learning can be beneficial when

there are limited labelled datasets for specific conditions. It can be used to expedite the training of machine learning algorithms in RIS-assisted wireless networks, where fast decision-making is crucial. However, low sampling efficiency may impede the deployment of machine learning in RIS-assisted wireless communication networks [58]. In a study [65], transfer learning was used to jointly optimize resource allocation for network slicing. The authors proposed a deep transfer reinforcement learning (DTRL) scheme for joint radio and cache resource allocation for 5G RAN slicing. Their proposed algorithms were compared with bonus deep Q-learning, model-based priority proportional fairness, and time-to-live (PPF-TTL) algorithms, and their scheme achieved lower delay and higher throughput. In another study [66], the authors addressed interference mitigation in a 5G millimeter-wave (mm Wave) communication network by using beamforming and NOMA techniques to improve the network's aggregate rate. They considered jointly optimizing the user-cell association and the number of beams to maximize the aggregate network capacity. Three machine learning-based approaches were deployed: Q-learning, transfer Q-learning (TQL), and Best SINR association with density-based spatial clustering of applications with noise (BSDC) algorithms. The authors compared the performance of these approaches under mobility and stationary scenarios. Moreover, transfer learning can be used in machine learning-enabled RIS wireless networks to achieve prompt phase-shift responses and faster convergence [58].

- ***Hierarchical Learning.*** Hierarchical Learning is a powerful approach in reinforcement learning that enhances exploration efficiency by breaking down long-term tasks into multiple sub-tasks [67]. This method allows for more manageable and focused learning processes, leading to better performance and faster convergence. In a comprehensive survey, the authors of [68] discussed various approaches to hierarchical reinforcement learning. They identified several critical open problems that could inspire future research directions in this field. These open problems highlight the potential for further advancements and innovations in hierarchical reinforcement learning, motivating researchers to explore new methodologies and applications.

6. SYSTEMATIC BIBLIOMETRIC ANALYSIS

The integration of Reconfigurable Intelligent Surface (RIS) technology and machine learning (ML) techniques in underwater communications is an emerging area with limited existing literature. With fewer than 300 publications addressing RISs and ML techniques simultaneously, conducting a comprehensive bibliometric analysis on this specific intersection is challenging.

As a result, this section will present a systematic bibliometric analysis focusing solely on RISs. To our knowledge, it is the first comprehensive systematic bibliometric analysis in the field of RIS. This analysis aims to provide valuable insights into research trends, key contributors, and significant developments within the RIS domain, laying the groundwork for future studies and innovations.

Table 1: Main information about data on RIS publications.

Description	Results
Timespan	2019-2024
Sources (Journals, Books, *etc.*)	625
Documents (TP)	4537
Total Citation (TC)	54012
Annual Growth Rate %	169.59
Document Average Age	1.48
Average citations per doc	11.9
References	72185
Keywords Plus (ID)	10223
Author's Keywords (DE)	6243
Authors	5023
Authors of single-authored docs	67
Single-authored docs	85
Co-Authors per Doc	4.43
International co-authorships %	41.92
Article	2609
Book chapter	30
Conference paper	1802
Conference review	38
Review	58

6.1 Research Methodology

We used the Scopus database to examine the publishing trends and patterns in the global literature on RISs. The Scopus database is known for indexing and abstracting scholarly publications and provides extensive bibliometric data through a straightforward extraction method, making it well-suited for comprehensive analyses [69].

To extract relevant data, we designed a comprehensive search strategy that focused on specific aspects such as titles, author keywords, and abstracts using the advanced search feature of the Scopus database with the following search query: TITLE-ABS-KEY ("Reconfigurable Intelligent Surface*" OR "Reconfigurable Intelligent Surface (RIS)").

The initial search yielded 4,632 publications. After refining the search by limiting it to English language documents and specific document types (articles, conference papers, reviews, conference reviews, and book chapters), as well as excluding irrelevant documents, the final dataset consisted of 4,537 publications. This data was downloaded in CSV and Research Information System formats for further analysis and visualization.

For data analysis, we utilized Microsoft Excel, VOSviewer [70], and Biblioshiny [71]. Additionally, to ensure the accuracy and consistency of the data and information, we standardized discrepancies in organization names, author details, source titles, and countries. The accuracy of the data was verified by replicating the process with two other members of the research group.

6.2 Results and Discussions

In the field of data analysis, various terms are used to quantify research output and impact. TP stands for total publications, TC stands for total citations, and TC/TP represents the average citation per publication. Table 1 provides valuable information about RIS publications from 2019 to 2024. A bibliometric study of RISs reveals that there were 4,537 publications and 54,012 citations from 625 diverse sources during this period. The data indicates an annual growth rate of 169.59% and an average age of 1.48 years for the publications. On average, each paper received 11.90 citations and had 72,185 references.

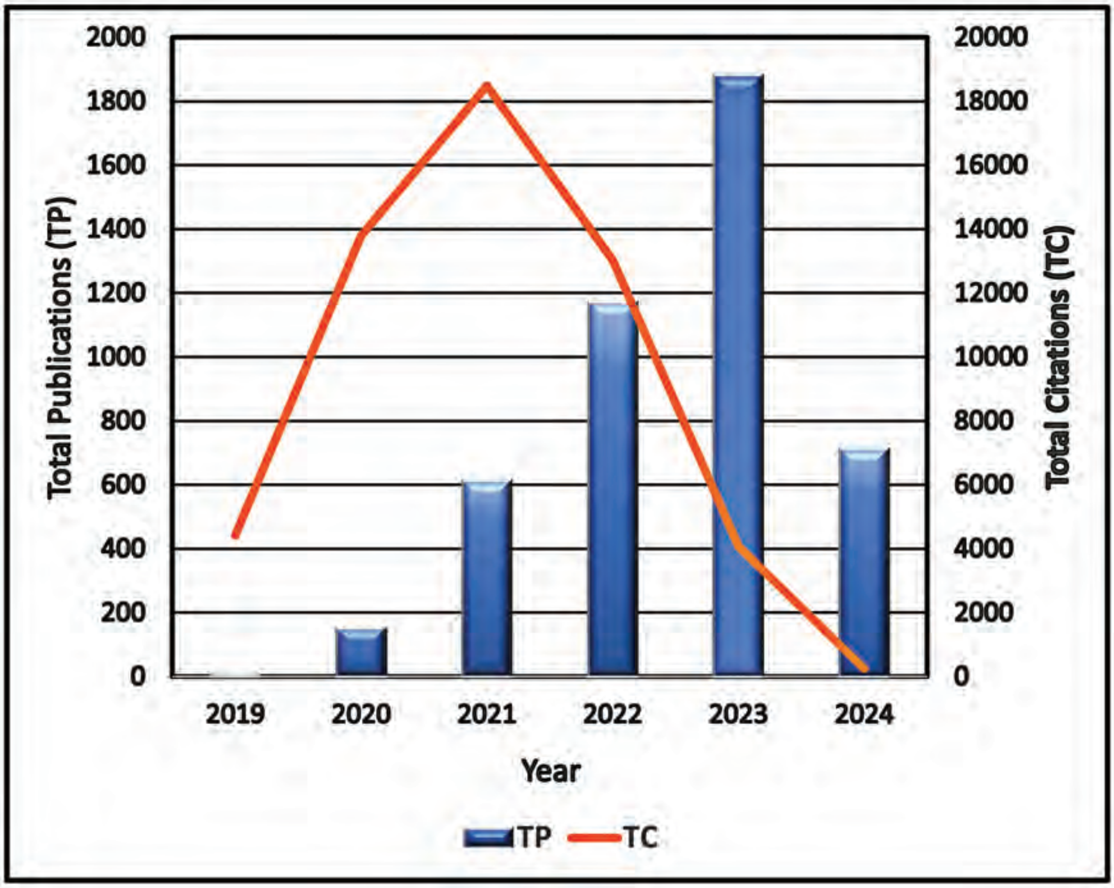

Figure 3: Yearly citation and citation trends.

The field of RISs includes a variety of keywords, with 10,223 keywords and 6,243 author keywords identified. Collaboration in RIS research is evident, with 5,023 contributing authors, including 123 who have authored only one paper. On average, there are 4.43 authors per publication, and international co-authorships account for 41.92% of collaborations. The analysis also shows the types of research conducted; out of 4,537 publications, articles were the most usual form (2,609 publications), followed by conference papers (1,802), reviews (58), conference reviews (38), and book chapters (30).

6.3 Yearly Publishing and Citation Trends in RIS Literature

Figure 3 provides a detailed overview of the research productivity and citation trends for Reconfigurable Intelligent Surfaces (RISs) from 2019 to 2024. The analysis shows that RIS is a relatively new field of study, with the first research paper being published in 2019 (TP = 5) and receiving 4,425 citations, resulting in the highest average citation per article at 885, TC/TP. There has been an exponential increase in publication growth over the years, with a significant surge in 2020, which saw 153 publications and a certain number of citations. In 2023, there was the highest number of research papers, with 1,882 publications and 4,065 citations, followed by 1,172 publications and a certain number of citations in 2022, 613 publications and a certain number of citations in 2021,

Table 2: Top ten most relevant sources in RISs. (JIF = journal index factor)

Rank	Element	TP	TC	TC/TP	PY Start	h-index	JIF	Country	Publisher
1	IEEE Transactions on Vehicular Technology	291	3596	12.36	2020	32	6.8	USA	IEEE
2	IEEE Transactions on Wireless Communications	285	8329	29.22	2019	38	10.4	USA	IEEE
3	IEEE Wireless Communications Letters	275	4099	14.91	2020	34	6.3	USA	IEEE
4	IEEE Communications Letters	224	3248	14.50	2020	29	4.1	USA	IEEE
5	IEEE Transactions on Communications	211	5050	23.93	2020	36	NA	USA	IEEE
6	Proceedings - IEEE Global Communications Conference	202	688	3.41	2019	11	NA	USA	IEEE
7	IEEE Internet of Things Journal	132	1174	8.89	2021	15	10.6	USA	IEEE
8	IEEE Vehicular Technology Conference	132	371	2.81	2020	9	NA	USA	IEEE
9	IEEE International Conference on Communications	124	869	7.01	2020	14	NA	USA	IEEE
10	IEEE Access	115	4177	36.32	2019	24	3.9	USA	IEEE

and 712 publications and 125 citations in 2024. The year 2021 recorded the highest total citations with a certain number, followed by 2020 with a certain number, 2022 with a certain number, 2019 with 4,425, and 2023 with 4,065; the year with the oldest data had the highest average number of citations per article, while the most recent year experienced a decline in the average number of citations per article. The decrease in citations can be attributed to the additional two to three years needed to attain significance and impact. The year 2024 had the lowest number of publications and citation impact, likely because the data were acquired on May 8, 2024, before the year was complete.

The significant increase in RIS research publications and citations from 2019 to 2024 underscores the rapid growth and growing significance of the field. The collaborative aspect of the research, along with the high impact of early publications, highlights the dynamic and evolving nature of RIS studies. As the field continues to develop, the findings from this analysis will provide a crucial foundation for future research and advancements in RIS technology.

6.4 Top Relevant Sources of RIS-related Research

Table 2 is an exhaustive overview of the primary sources in RISs. From 2019 to 2024, 625 sources (journals and books) have produced 4,537 publications. The top ten leading sources have contributed approximately 30% of these papers. Among them, IEEE Transactions on Vehicular Technology (JIF = 6.8) has published 291 papers with 3,596 citations, followed by IEEE Transactions on Wireless Communications (JIF = 10.4) with 285 papers and 8,329 citations. Other prominent sources include IEEE Wireless Communications Letters, IEEE Communications Letters, and IEEE Transactions on Communications. Notably, all the top ten sources are from the USA and published by IEEE. Besides, the table reveals

Table 3: Top ten most prolific authors in RISs.

Rank	Author	Affiliations	Country	TP	TC	TC/TP
1	Pan C	Southeast University	China	109	3444	31.60
2	Liu Y	Queen Mary University of London	UK	98	3195	32.60
3	Jin S	Southeast University	China	95	1825	19.21
4	Yuen, C	Nanyang Technological University	Singapore	89	6076	68.27
5	Alexandropoulos, G.C	National and Kapodistrian University of Athens	Greece	88	4815	54.72
6	Huang C	Zhejiang University	China	83	4748	57.20
7	Di Renzo, M	Laboratoire des Signaux et Systèmes	France	76	6968	91.68
8	Han, Z	University of Houston	USA	70	2457	35.10
9	Wu, Q	Shanghai Jiao Tong University	China	68	660	9.71
10	Hanzo, L	University of Southampton	UK	64	2617	40.89

other journals with significant h-index values, PY Start, journal impact factors, publisher, and country of publication. This overview can help researchers identify key publication platforms in RISs and concentrate on influential outlets for sharing their research.

6.5 Top Prolific Authors on RIS Literature

Table 3 presents a comprehensive review of the top ten authors who have made significant contributions to the field of RISs between 2019 and 2024.

The leading author in the top ten list is Pan C from Southeast University, China, with 109 publications and 3,444 citations. Next is Liu Y from Queen Mary University of London, the UK, with 98 publications and 3,195 citations. Followed closely is Jin S from Southeast University, China, with 95 publications and 1,825 citations. Yuen C from Nanyang Technological University, Singapore, is the fourth most productive author with 89 publications and 6,076 citations, closely followed by Alexandropoulos, G.C from National and Kapodistrian University of Athens, Greece, with 88 publications and 4,815 citations. Hanzo, L from the University of Southampton, the UK, has 64 publications and 2,617 citations, making him the least productive on the list. Also, Di Renzo, M, of Laboratoire des Signaux et Systèmes, France, received the highest citation count with 6,968 TC for 76 publications, followed by Yuen, C from Nanyang Technological University, Singapore, with 6,076 citations. Notably, Di Renzo, M from Laboratoire des Signaux et Systèmes and Yuen, C from Nanyang Technological University also have impressive citation impacts of 91.68 and 68.27, respectively.

Most of the top ten productive authors conduct their research in China (4), the UK (2), and one each from Singapore, Greece, France, and the USA, respectively. This assessment facilitates the identification of leading authors who have contributed to the field, their affiliations, and their impact on literature. As a result, it helps scholars comprehend the prominent persons and institutions affecting the subject of discussion in RIS literature.

6.6 Top Productive Organizations on RIS Literature

Table 4 provides an overview of the top ten most productive organizations in the field of RIS during 2019-2024. The leading

Table 4: Top ten most prolific organizations in RISs.

Rank	Organization	Country	TP	TC	TC/TP
1	Southeast University	China	406	6706	16.52
2	University of Electronic Science and Technology of China	China	215	4979	23.16
3	Queen Mary University of London	UK	199	6596	33.15
4	Beijing University of Posts and Telecommunications	China	182	2675	14.70
5	CNRS Centre National de la Recherche Scientifique	France	154	9911	64.36
6	Université Paris-Saclay	France	152	12849	84.53
7	Nanjing University of Post and Telecommunications	China	147	678	4.61
8	Centrale Supélec - Paris-Saclay	France	146	13084	89.62
9	Xidian University	China	141	1154	8.18
10	Laboratoire des Signaux et Systèmes	France	125	9402	75.22

organization was Southeast University in China, with 406 publications, 6,706 citations, and an average of 16.52 citations per publication. Following was the University of Electronic Science and Technology of China with 215 publications and 4,979 citations, Queen Mary University of London with 199 publications and 6,596 citations, and Beijing University of Posts and Telecommunications with 182 publications and 2,675 citations.

Laboratoire des Signaux et Systèmes in France had the lowest number of publications on the list (125) but the highest number of citations at 9,402. Centrale Supélec-Paris-Saclay received the highest number of citations with 13,084 and a TC/TP ratio of 89.62.

Other organizations (e.g., Université Paris-Saclay and Laboratoire des Signaux et Systèmes) had high total citation numbers, demonstrating their significant impact in the field of RIS. The analysis also indicates that the top ten organizations are predominantly from China (5), followed by France (4) and the UK (1), suggesting that organizations from China and France are leading in RIS literature. This comprehensive analysis provides valuable insights into the importance and global distribution of institutions in RIS literature, aiding scholars in understanding research trends and the contributions of different universities.

6.7 Top Productive Countries on RISs

Please note the following information: Figure 4 shows the countries with the highest number of publications in RISs from 2019 to 2024. China had the most publications with 2,301, along with 30,258 citations, followed by the United Kingdom with 703 publications and 14,206 citations, the United States with 524 publications and 8,841 citations, Canada with 315 publications and 4,210 citations, and South Korea with 300 publications and 3,140 citations. Other significant countries include India, France, Singapore, Australia, Greece, Germany, Taiwan, Italy, Sweden, Saudi Arabia, Turkey, and Finland, each with over 100 publications. On the other hand, Indonesia, the Netherlands, Vietnam, and Zimbabwe had the fewest publications, each with five. China, Cyprus, Germany, the United Kingdom, and South Africa had the highest number of citations of 30,258, 29,341, 14,625, 14,206, and 10,306, respectively. The average citation per publication (i.e., TC/TP) varies across the countries. Cyprus, Chile, South Africa, Indonesia, and the USA have the highest

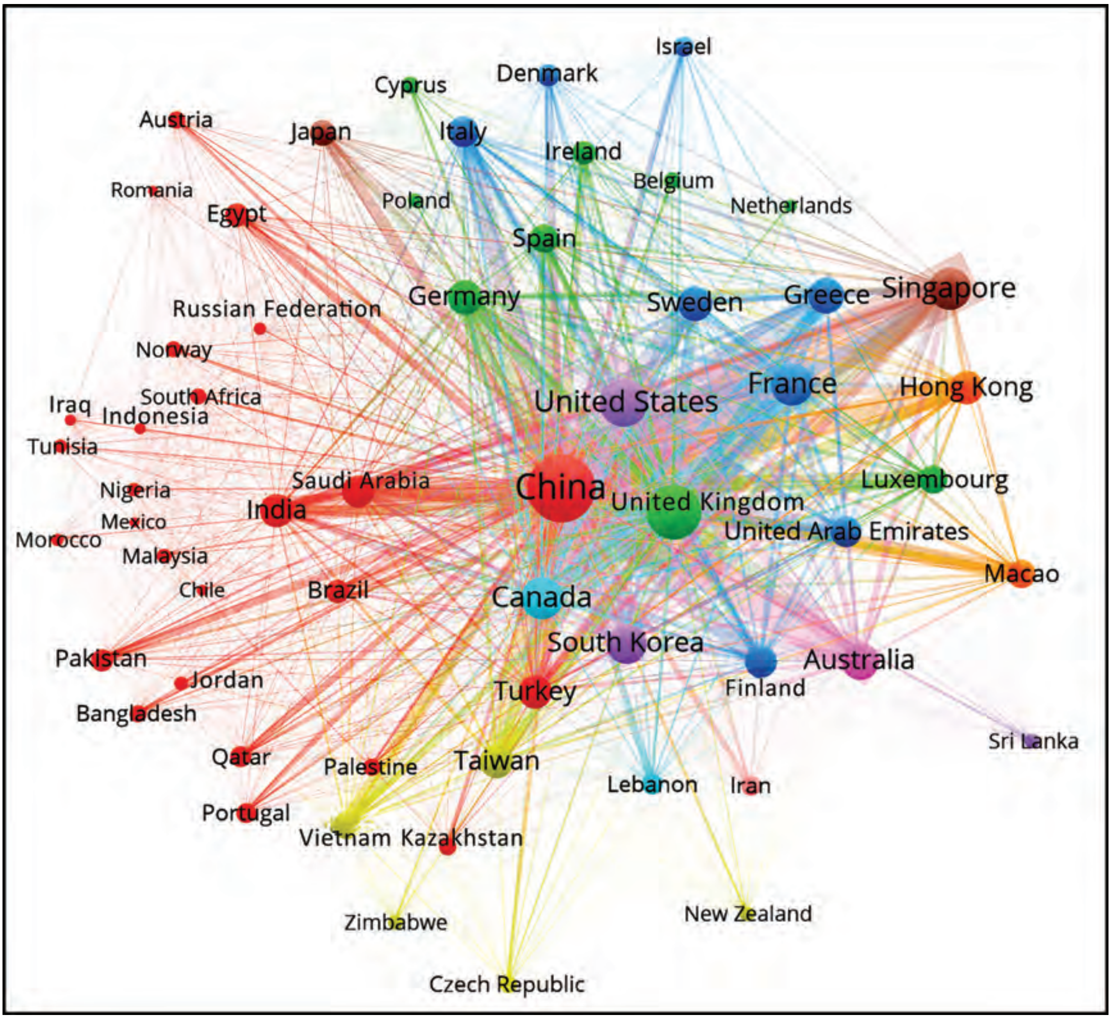

Figure 4: Productive country on RIS publications.

averages of 1,630.06, 722.00, 515.30, 205.20, and 205.16, respectively.

This analysis provides valuable insights into the global distribution of research efforts, allowing scholars to understand the geographical contributions to the subject. It also helps identify the leading nations in RIS literature.

6.8 Authorship Pattern in RIS Publications

In Figure 5, we can see the classification of authorship patterns in RIS publications. The analysis shows 18 diverse types of authorship, resulting in 4,537 publications. These ranged from single publications to as many as 22 for a single author. The fourth authorship pattern contributed to the highest number of research papers, totalling 986 publications and 9,844 citations, followed by the fifth with 945 publications and 13,135 citations. Three authorship patterns held the third position with 815 publications and 6,805 citations, while the sixth authorship pattern contributed 682 publications and 8,834 citations.

Meanwhile, the authorship patterns of the 16th and 21st had the lowest number of publications, with only one publication

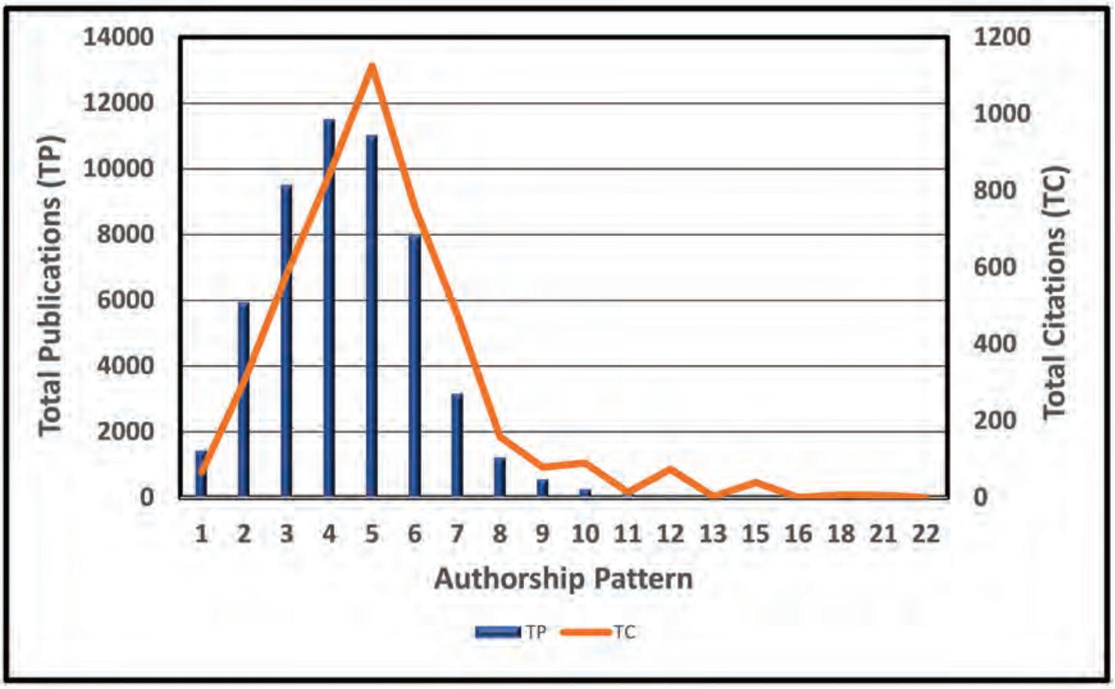

Figure 5: Authorship pattern in RIS publications.

each. Furthermore, patterns 15, 12, 21, 10, and 18 had the highest average citations per publication, with 229.00, 216.50, 71.00, 45.43, and 39.50, respectively. The analysis suggests that 99% of researchers in the field are highly interested in collaborative work rather than pursuing solo research (TP = 123).

6.9 Mapping Author Keyword Co-occurrence in RIS Literature

Figure 6 portrays the results from a comprehensive evaluation of the most used author keywords in the field of RISs. VOSviewer, a bibliometric software, was used to create the illustration. The investigation focused on keywords that co-occurred at least 15 times out of 6,177 instances. In total, 88 keywords met this threshold and were included in the analysis. These top 88 keywords were selected based on their overall link strength and were categorized into 12 clusters or themes, each represented by a distinct colour. Each bubble size reflects the frequency of keyword usage, and the connections between the bubbles show the number of research publications featuring these keywords.

The analysis revealed the top five most frequently used keywords by RIS researchers to be “Reconfigurable Intelligent Surface,” “Wireless Communication,” “Non-Orthogonal Multiple Access,” “Energy Efficiency,” and “Unmanned Aerial Vehicle.” The figure illustrates 12 distinct clusters of keywords, each corresponding to a specific research area:

- ***Cluster 1.*** This cluster is the largest and consists of 24 keywords. The primary topics covered in this cluster include Wireless Communication, Non Orthogonal Multiple Access, Physical Layer Security, Internet of Things, Simultaneous Wireless Information and Power Transfer, Active Reconfigurable Intelligent Surface, Simultaneously Transmitting and

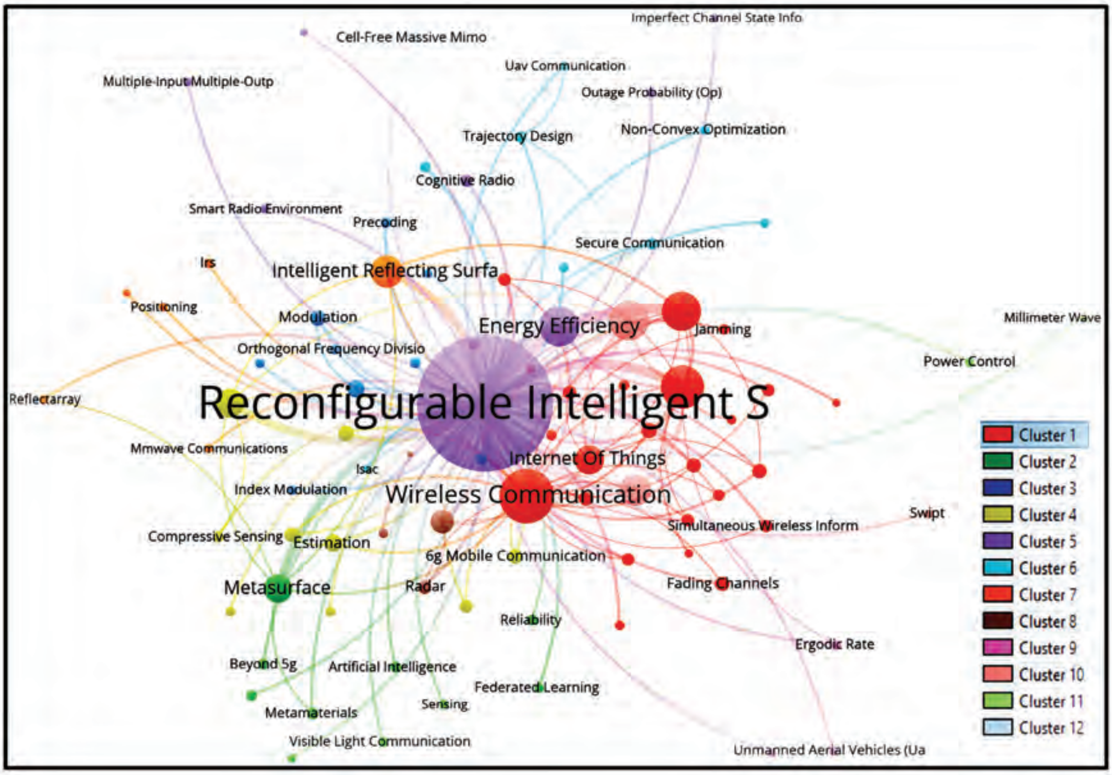

Figure 6: Mapping co-occurrence and author keywords.

Reflecting Reconfigurable Intelligent Surface (STAR-RIS), Fading Channels, Quality of Service, Wireless Networks, Manifold Optimization, Receivers, Sum-Rate Maximization, Hardware, Interference Cancellation, Mutual Coupling, Protocols, Backscatter, Fractional Programming, Backscatter Communication, Communication System Security, Jamming, MISO Communication, and Full-Duplex (FD).

- ***Cluster 2.*** The primary focus of this cluster includes Metasurfaces, Beyond 5G, Federated Learning, Intelligent Reflecting Surfaces, Metamaterials, Artificial Intelligence, Reliability, Smart Radio Environments, Sensing, and Visible Light Communication.
- ***Cluster 3.*** The significant topics in this cluster include Modulation, Symbols, Index Modulation, Precoding, Reflection Coefficient, Index Modulation (IM), Orthogonal Frequency Division Multiplexing (OFDM), Cell-Free Network, and Wideband.
- ***Cluster 4.*** The main topics in this cluster include Millimeter Wave, Estimation, Compressive Sensing, Training, Location Awareness, 6G Mobile Communication, Beam.
- ***Cluster 5.*** The main topics in this cluster include Reconfigurable Intelligent Surfaces, Energy Efficiency, Cognitive Radio, Convex Optimization, Outage Probability (OP), Smart Radio Environment, Imperfect Channel State Information (CSI), Multiple-Input Multiple-Output, Training, Antenna Arrays, and Terahertz Communication.
- ***Cluster 6.*** The main topics in this cluster include Successive Convex Approximation, Non-Convex Optimization, Phase Shift

Optimization, Trajectory Design, Physical-Layer Security, Secure Communication, ISAC, and UAV Communication.

- ***Cluster 7.*** The main topics in this cluster include Intelligent Reflecting Surface (IRS), Positioning, Reflectarray, mmWave Communications, and Compressed Sensing.
- ***Cluster 8.*** Topics in this cluster are Integrated Sensing and Communication, Radar, Robust Beamforming, Relay, and Active RISs.
- ***Cluster 9.*** Includes topics like Ergodic Rate, Coverage Probability, and UAVs.
- ***Cluster 10.*** Covers Unmanned Aerial Vehicle (UAV), Deep Reinforcement Learning, and SWIPT.
- ***Cluster 11.*** Focuses on mmWave and Power Control.
- ***Cluster 12.*** Addresses Cell-free Massive MIMO.

Figure 6 provides a comprehensive summary of the main ideas and research topics in RISs, making it a significant source of information. It demonstrates that RISs are a rapidly expanding domain with numerous practical applications.

6.10 Most Cited Papers on RISs

Table 5 provides an in-depth analysis of the top ten most highly cited research papers on Reconfigurable Intelligent Surfaces (RISs) published between 2019 and 2024. These papers have made significant contributions and gained substantial recognition in the academic community. The papers received varying citations, with the highest being 2,158 and the lowest being 458. Notably, three of the publications received over 1,000 citations.

Among the top ten papers, four were published in “IEEE Transactions on Wireless Communications,” two in “IEEE J Sel Areas Commun,” and one each in “IEEE Open J Commun Soc,” “IEEE Access,” “IEEE Trans Commun,” and “IEEE Commun Surv Tutor.”

The most cited paper is “Reconfigurable Intelligent Surfaces for Energy Efficiency in Wireless Communication” by Huang C (2019), published in “IEEE Transactions on Wireless Communications,” with 2,158 citations [72]. It is followed by “Wireless Communications through Reconfigurable Intelligent Surfaces” by Basar E (2019), published in “IEEE Access,” with 1,834 citations [73]. “Smart Radio Environments Empowered by Reconfigurable Intelligent Surfaces: How it Works, State of Research, and the Road Ahead” by Di Renzo M (2020) has 1,452 citations [74]. The fourth most cited paper is “Wireless Communications with Reconfigurable Intelligent Surface: Path Loss Modeling and Experimental Measurement” by Tang W (2021) with 736 citations [75], and “Multicell MIMO Communications Relying on Intelligent Reflecting Surfaces” by Pan C (2020) ranks fifth with 616 citations [76].

The least cited paper in the top ten list is “Reconfigurable Intelligent Surfaces vs. Relaying: Differences, Similarities, and Performance Comparison” by Di Renzo M (2020) with 458 citations [77].

This study aims to highlight impactful research in the field of RISs to help researchers gain a deeper understanding of important topics.

Table 5: Top ten most cited research papers on RISs.

Rank	Title	Paper	TC	TC/Year	Normalized TC
1	Reconfigurable Intelligent Surfaces for Energy Efficiency in Wireless Communication	Huang C, 2019, IEEE Trans Wireless Communication	2158	359.67	2.44
2	Wireless Communications Through Reconfigurable Intelligent Surfaces	Basar E, 2019, IEEE Access	1834	305.67	2.07
3	Smart Radio Environments Empowered by Reconfigurable Intelligent Surfaces: How It Works, State of Research, and the Road Ahead	Di Renzo M, 2020, IEEE J Sel Areas Communication	1452	290.4	16.12
4	Wireless Communications with Reconfigurable Intelligent Surface: Path Loss Modeling and Experimental Measurement	Tang W, 2021, IEEE Trans Wireless Communication	736	184	24.41
5	Multicell Mimo Communications Relying on Intelligent Reflecting Surfaces	Pan C, 2020, IEEE Trans Wireless Communication	616	123.2	6.84
6	Reconfigurable Intelligent Surfaces: Principles and Opportunities	Liu Y, 2021, IEEE Communication Surv. Tutor	596	149	19.77
7	Weighted Sum-Rate Maximization for Reconfigurable Intelligent Surface Aided Wireless Networks	Guo H, 2020, IEEE Trans Wireless Communication	538	107.6	5.97
8	Reconfigurable Intelligent Surface Assisted Multiuser Miso Systems Exploiting Deep Reinforcement Learning	Huang C, 2020 IEEE J Sel Areas Communication	504	100.8	5.59
9	Reconfigurable Intelligent Surface-Based Index Modulation: A New Beyond Mimo Paradigm for 6G	Basar E, 2020, IEEE Trans Communication	489	97.8	5.43
10	Reconfigurable Intelligent Surfaces Vs. Relaying: Differences, Similarities, and Performance Comparison	Di Renzo M, 2020, IEEE Open Journal Communication Soc.	458	91.6	5.08

6.11 Analysis of Trend Topics in RISs

Figure 7 depicts the results from a detailed analysis of trends in RIS research. It shows the frequency and distribution of different themes in RIS research over time. The most frequently occurring themes include reconfigurable (n = 3,545), Reconfigurable Intelligent Surface (n = 2,552), interlocking signals (n = 939), beamforming (n = 859), wireless communications (n = 856), signal-to-noise ratio (n = 706), 5G mobile communication systems (n = 306), and wireless networks (n = 265). Other significant topics common in RIS research are performance, outage probability, reflecting elements, optimization problems, propagation environment, closed-form expression, modulation, task analysis, and job analysis.

The analysis reveals the emerging research themes in RISs during 2021, which include interlocking signals, reflecting elements,

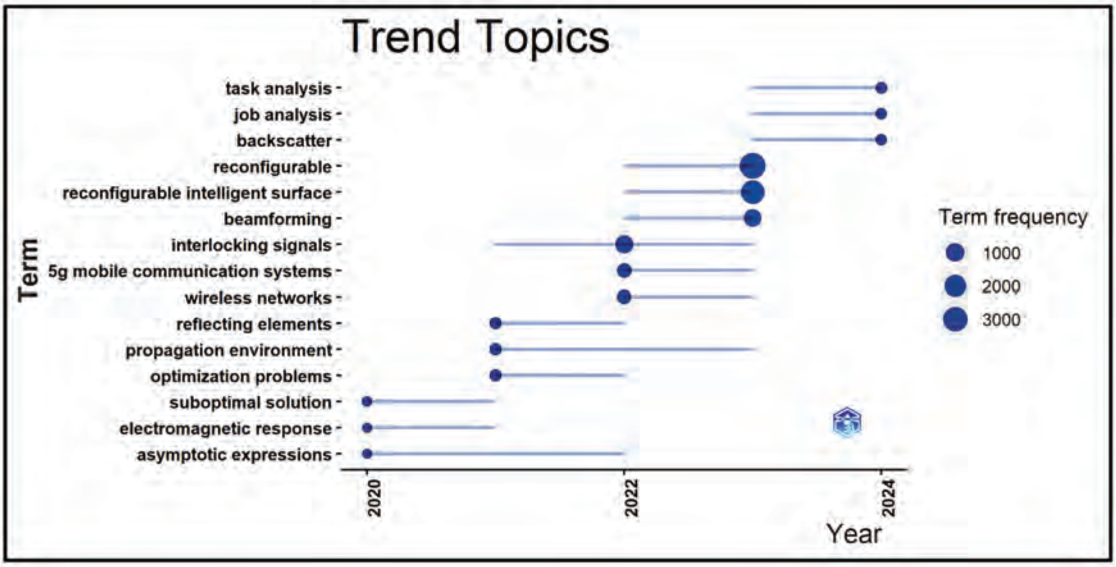

Figure 7: Analysis of trend topics in RISs.

optimization problems, propagation environment, closed-form expression, and modulation. In 2022, the emerging research themes are Reconfigurable Intelligent Surface, beamforming, wireless communications, signal-to-noise ratio, 5G mobile communication systems, wireless networks, performance, and outage probability. The emerging trends in recent years (2023 and 2024) include task analysis, job analysis, and backscatter.

This thorough review highlights the dynamic nature of RIS research, with themes changing over time to address new opportunities and challenges in the field.

6.12 Factorial Analysis-MCA Method

Factorial analysis is a method used to examine the dimensions and clusters of a conceptual structure map derived from Multiple Correspondence Analysis (MCA). It provides valuable insight into the primary patterns of data variation, the impact of specific variables, and the interconnections among categorical variables. In Figure 8, two distinct clusters are visually represented with varying colour shades. Each cluster is linked to a set of keywords that symbolize a specific theme.

Cluster 1 includes keywords such as Reconfigurable Intelligent Surface, Interlocking Signals, Beamforming, Wireless Communications, Signal-to-Noise Ratio, MIMO Systems, Optimizations, Energy Efficiency, Antennas, Channel State Information, Millimeter Waves, Array Signal Processing, Channel Estimation, Array Processing, Iterative Methods, Deep Learning, Fading Channels, X5G Mobile Communication Systems, Spectrum Efficiency, Internet of Things, Wireless Networks, Unmanned Aerial Vehicles (UAV), Network Layers, Quality-of-Service, Bit Error Rate, Optimization, Reinforcement Learning, Performance, Millimeter-wave Communications, Outage Probability, Physical Layer Security, Communications Systems, Monte Carlo

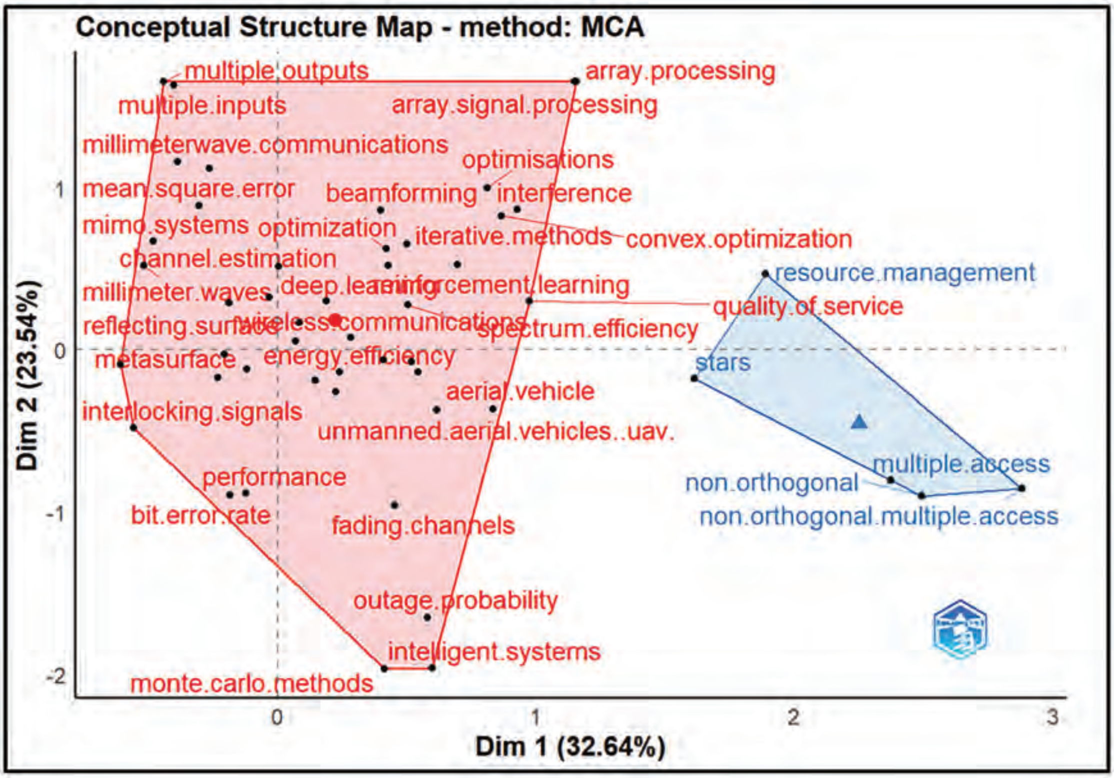

Figure 8: Factorial analysis.

Methods, Aerial Vehicle, Metasurface, Mobile Telecommunication Systems, Signal Receivers, Interference, Multiple Inputs, Mean Square Error, Multiple Outputs, Intelligent Systems, Convex Optimization, and Reflecting Surface. This cluster highlights the multifaceted nature of RIS technology and its potential to revolutionize wireless communications through various optimization and enhancement techniques.

Cluster 2 is a comprehensive collection of topics encompassing Multiple Access, Non-Orthogonal Multiple Access, Stars, and Resource Management. This cluster signifies a central theme associated with advanced multiple-access techniques, potentially referring to the implementation of multiple access-schemes in 5G and resource management strategies within the field of RISs.

6.13 Country Collaboration in Publishing RIS Literature

The data illustrated in Figure 9 underscores the extensive international collaboration in RIS research. It shows that Chinese authors had the most frequent collaborations with other countries among the top ten on the list. The highest number of research collaborations was observed between China and the United Kingdom, resulting in 427 publications. Next are the collaborations between China and the USA (197 publications), China and Singapore (177 publications), China and Australia (145 publications), and China and Canada (114 publications). On the other hand, the USA and Korea had the lowest level of collaboration, with only 54 publications. Noteworthy collaborations also existed between the UK and the USA, China and France, China and Korea, and China and Hong Kong. The map

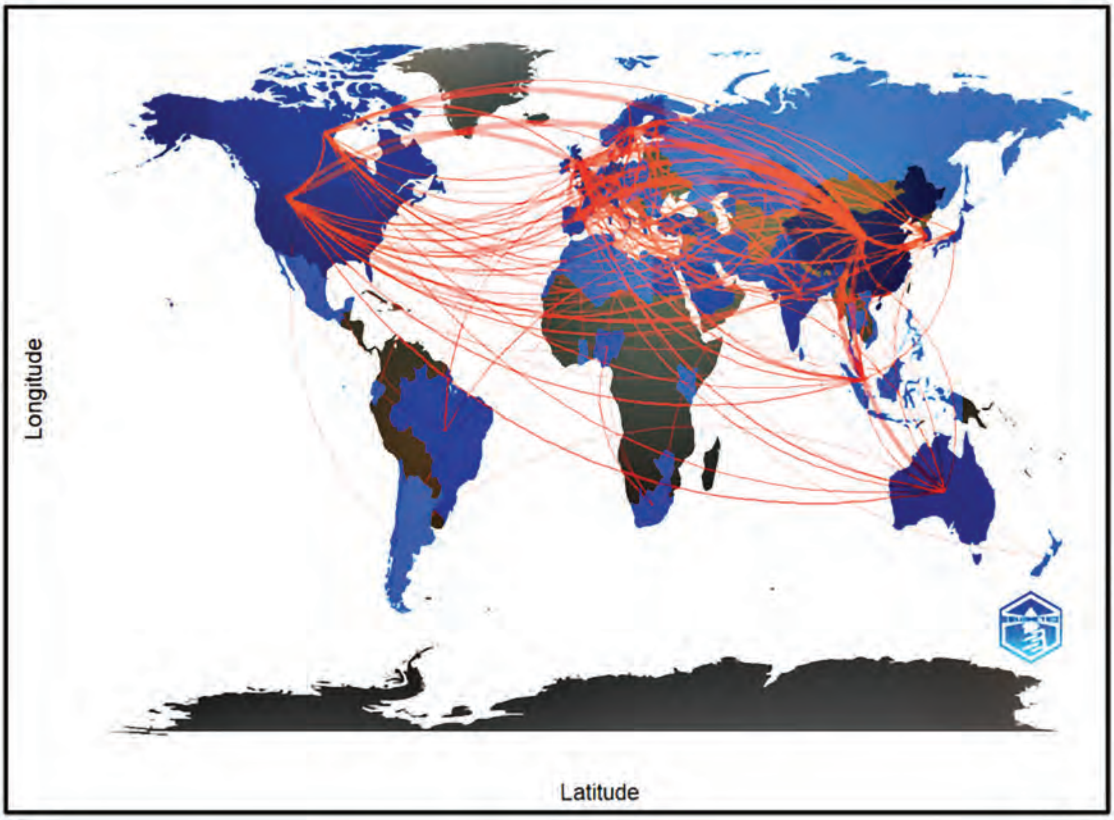

Figure 9: Country collaboration map.

depicts the global nature of RIS research and knowledge exchange across diverse cultures. This international network of collaborations highlights the mutual interest and expertise in RIS across different countries.

The visual representation of these connections provides valuable insights into how various nations contribute to and benefit from RIS research, fostering a rich exchange of knowledge and innovation.

7. CONCLUDING REMARKS

In our research, we focused on RISs and ML-assisted underwater communications. We discussed potential signalling technologies in an RIS-assisted underwater environment, including IoUWT, various RIS implementation approaches, and hardware architecture. Furthermore, we explored ML-enabled optimization strategies for RIS-aided networks. Our systematic bibliometric analysis provided an in-depth look at research trends and citation patterns in the RIS field. This analysis revealed 4,537 publications indexed in the Scopus database over six years between 2019 and 2024, highlighting that RISs is a relatively new research topic. It also highlighted leading figures in the field, trustworthy sources for research dissemination, publication and citation trends, prolific authors, organizations, countries, authorship patterns, key concepts and contributions, highly cited articles, and level of country collaboration.

The analysis of research publications on RISs revealed a remarkable surge in the number of papers over the years, with an astounding annual growth rate of 169.59%. The year 2023 stood out with the highest number of research papers (1,882 publications) and citations (4,065). Additionally, the study unveiled the top three sources favoured by scholars and highlighted the three most prolific authors in the field. Notably, a strong trend toward collaborative authorship emerged, with the fourth authorship pattern contributing the highest count of research papers (986 publications) and citations (9,844), signifying an overwhelming preference for collaborative work (99%) over solo research (1%). It is worth emphasizing that our study is a pioneering effort to conduct a comprehensive bibliometric analysis of the published literature on RISs.

Therefore, our research will establish a baseline for evaluating the future path for RIS publications. The findings of this study will not only pave the way for future research into the many aspects of this subject but also provide valuable insights to guide further studies, inspiring new research directions and methodologies. This study is significant because it relies on high-quality literature indexed by the Scopus database. While our findings already enhance the understanding of research patterns in this domain, including additional bibliographic databases like Web of Science, PubMed, Dimensions, and Google Scholar could impact and supplement our research findings. Scholars, practitioners, and policy-makers interested in RISs will find the analysis presented in this paper beneficial. Our research also highlights areas of study that will require attention in the future, including the application of Artificial Intelligence in RISs and the influence of RISs on machine learning-assisted underwater communications.

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