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Review

A Visual Survey of Tunnel Boring Machine (TBM) Performance in Tunneling Excavation: Mainstream Direction, Brief Review and Future Prospects

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Abstract: This study employs scientometric analysis to investigate the current trajectory of research on tunnel boring machine (TBM) performance and collaborative efforts. Utilizing software tools like Pajek 5.16 and VOSviewer 1.6.18, it scrutinizes literature from 2000 to 2021 sourced from the Web of Science (WOS). The findings illuminate TBM research as an interdisciplinary and intersectoral field attracting increasing national and institutional attention. Notable contributions from China, Iran, the United States, Turkey, and Australia underscore the global significance of TBM research. The recent upsurge in annual publications, primarily driven by Chinese research initiatives, reflects a renewed vigor in TBM exploration. Additionally, the paper presents a succinct evaluation of TBM advantages and drawbacks compared to conventional drill and blast methods, discussing key considerations in excavation methodology selection. Moreover, the study comprehensively reviews TBM performance prediction models, categorizing them into theoretical, empirical, and artificial intelligence-driven approaches. Finally, rooted in metaverse theory, the discourse delves into the immersive learning model and the architecture of a TBM metaverse. In the future, the immersive training and learning model diagram can be employed in scenarios such as employee training and the promotion of safety knowledge. Additionally, the TBM metaverse architecture can simulate, monitor, diagnose, predict, and control the organization, management, and service processes and behaviors of TBMs. This will enhance efficient collaboration across various aspects of the project production cycle. This forward-looking perspective anticipates future trends in TBM technology, emphasizing societal impact and enhancement of economic benefits.

Keywords: TBM performance; tunneling excavation; conventional drilling and blasting; scientometric analysis; visualized review

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1. Introduction

With the continuous advancement of TBM technology, this excavation method has achieved extensive utilization in underground projects worldwide. TBMs are primarily employed for the excavation of hard geomaterials on a full scale. The essential components of a TBM include the cutterhead, the cutterhead carrier (housing the cutterhead drive motor), the frame, and the clamping and drive equipment. Rock excavation is achieved through the rotation of discs and blades on these excavation tools, applying pressure to the rock face [1]. Radial cracks emanate from the cutter ring where the blade interacts with the rock surface, leading to the fragmentation of the rock into coarse fragments along these cracks.

For a project to achieve success and efficiency, it is crucial for TBM performance to effectively address the challenges posed by lithologically and geomechanically heterogeneous rock masses. These heterogeneous environments are frequently encountered in practice, and factors such as variations in lithology, faulting, and folding can significantly impact the quality of the rock mass. This, in turn, can result in supply delays, downtime, and overall progress rate reductions. Consequently, the successful execution of tunneling projects is heavily reliant on the precise prediction of rock behavior.

Researchers actively engage in TBM performance prediction studies to ensure the smooth execution of TBM construction projects. However, predicting TBM performance solely based on theoretical considerations is a formidable challenge due to the complex interaction between the TBM and the rock, as highlighted in previous studies [2,3]. Over the years, the persistent efforts of numerous researchers [4–6] have led to the evolution of predictive models, transitioning from single-factor prediction models to multifactor prediction models. Various empirical models have been introduced to forecast TBM performance, but these models typically rely on specific geographical locations, geological characteristics, and limited data, resulting in imprecise predictions, particularly when applied beyond their intended scope and without sound judgment [7,8]. To address this challenge, certain artificial intelligence models based on real tunnel engineering data are employed to establish mathematical relationships between rock behavior. This approach helps overcome the limitations associated with site-specific models [9,10].

Amid the current diverse research directions in TBM performance, conventional literature reviews face increasing challenges when it comes to identifying trends and gaining insights into the evolving landscape of research in this field [11]. Furthermore, the existing TBM literature lacks a comprehensive visual presentation of research progress and publication trends, which prevents reading from obtaining a clearer understanding of the subject. For newcomers to the field, comprehending prior developments in TBM performance and staying updated on the latest research can be demanding, particularly when reading every paper in detail. To address these challenges and provide a complementary approach to traditional literature reviews, visual survey analysis has gained popularity in various research domains [12–15]. Diverging from conventional literature reviews, visual survey analysis methods create detailed knowledge maps that highlight research trends, developments, and prominent topics within the specified research area [16]. This paper serves to bridge the existing gap in TBM performance research and available models by conducting a visual survey and analysis of pertinent literature obtained from the WOS database spanning from 2000 to the end of 2021. The study delves into various aspects, including the collaboration between countries and institutions in TBM research, the number of publications and citations in this domain, and key works in the field. Additionally, the paper conducts a comparative analysis of the advantages and drawbacks of TBM methods versus drill and blast methods, followed by a summary of TBM performance predictive models. Finally, the paper offers insights into the potential utilization of metaverse techniques for enhancing TBM operations.

The remaining sections of this paper are structured as follows: Section 2 describes the data sources and research tools; Section 3 presents the findings of the visual survey analysis; Section 4 provides a brief review of the benefits and drawbacks of TBM performance predictive models and TBM construction; Section 5 discusses the future prospects of TBMs in relation to metaverse techniques; and Section 6 offers concluding remarks.

2. Materials and Methods

2.1. Data Source

This study utilized the Corevantage data platform of the Web of Science (WOS) to conduct the research. The search was conducted on 15 July 2022, using the subject search terms "TBM performance" and "tunnel boring machine". No restrictions were applied to the source or type of literature, while the language was limited to English. The selected time frame spanned from 2000 to 2021, covering a total of 22 years. By employing this search strategy, a total of 528 documents were retrieved. The downloaded format for the documents was in "full record" text format. Figure 1 displays the results obtained from the visual search conducted within the WOS database. Among the various document types, research articles and conference papers dominated, with 445 and 78 instances, respectively.

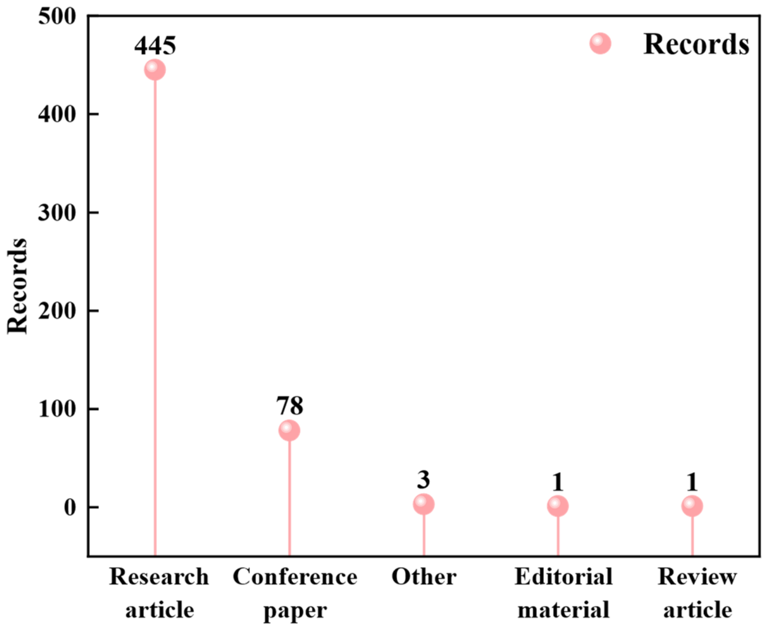

Figure 1. Visual search results of the Web of Science database.

2.2. Research Tool

This study employs scientometric methods to perform a statistical analysis of the gathered literature data. Subsequently, the results are visualized using specialized tools like VOSviewer and Pajek [17–19]. Scientometric analysis entails a quantitative examination of various aspects, including the characteristics of output, research directions, and the authors of the papers. This process is aimed at revealing the overarching dynamics within the research discipline of interest and providing valuable scientific insights to researchers in the field. Visual analysis of the literature complements scientometric analysis by utilizing visualization software to enhance the visual appeal and intuitiveness of the obtained results. Within the scope of this study, the collected literature on TBM performance is analyzed in the following three distinct ways: (1) scientometric analysis of TBM performance literature data, (2) visual analysis of TBM performance research areas, and (3) identification of key literature in TBM performance research.

3. Results

3.1. Mainstream Area Analysis

In the domain dimension, an overlay analysis was conducted to explore the domains that are involved in the literature related to TBM performance. The results reveal that the 528 papers were distributed across 40 different domains. The number of records in each domain reflects the frequency of articles within that domain. Notable domains, based on the number of records, include Engineering (486), Construction Building Technology (290), Mathematics (144), Business Economics (142), Mining Mineral Processing (132), Computer Science Processing (132), Computer Science (199), and Geology (100). This observation underscores that TBM performance research encompasses a wide spectrum of research areas and displays a clear interdisciplinary nature. The study of TBM performance requires the application of mathematical methods, consideration of construction processes, and attention to economic aspects, which elucidates the higher number of articles in the fields of Construction Building Technology, Mathematics, and Business Economics. Additionally, TBM software and hardware frequently rely on computer technology and internet applications, leading to coverage in the domains of Computer Science Processing and Computer Science.

3.2. Publication Analysis

Within the specified timeframe, according to the Web of Science citation analysis report, the literature obtained a total citation frequency of 23,199, after the removal of 17,762 self-citations. The cited literature amounted to 12,393, with 11,536 self-citations removed. The average citations per article were 18.28, and the h-index was 68.

The top fifteen countries, as illustrated in Figure 2, contributed a total of 810 articles, representing 90% of the global total. These data provide an overview of the publication trend based on the top fifteen countries. Notably, there is a consistent upward trend in the number of published articles and citation frequency globally from 2000 to 2021. The most substantial increase in the number of published articles and citations occurred primarily after 2009, with the most significant growth observed after 2015. Statistical analysis reveals that the total number of articles published after 2009 is approximately 18 times higher than before 2009. Before 2009, TBM performance research faced significant technical challenges that had not yet been resolved, leading to a smaller number of published articles, citable articles, and corresponding citations. However, with the increasing recognition of the challenges and issues encountered in tunneling, as well as the critical role of TBM performance in selecting tunnel construction methods, construction scheduling, and cost estimation, more countries have explored TBM performance prediction models. It is worth noting that the rapid growth in TBM performance research can also be attributed to close collaboration and cross-fertilization between countries, which will be further elaborated upon in the subsequent discussion.

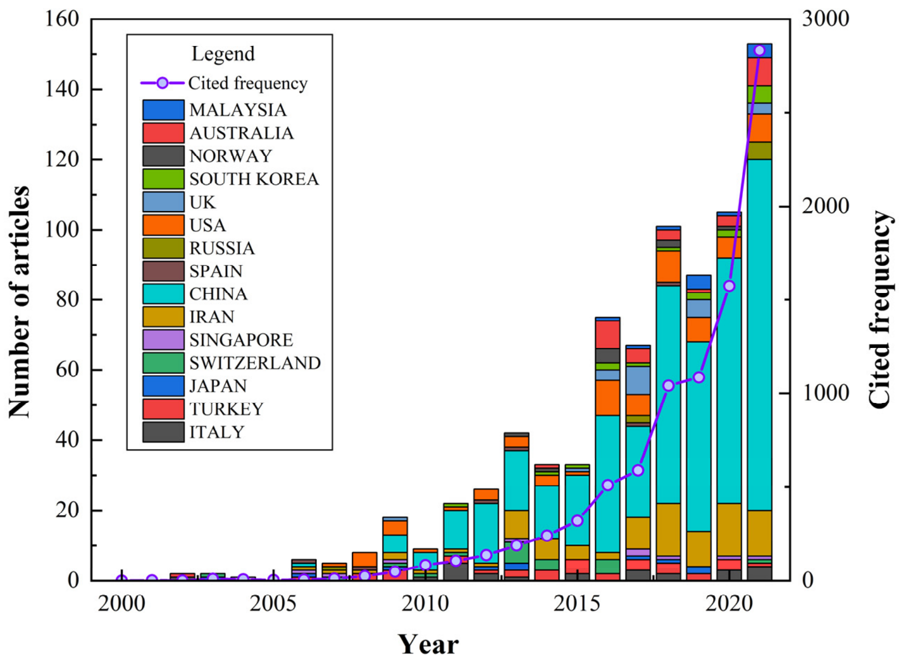

Figure 2. Descriptive statistical distribution of the TBM performance literature.

3.3. Study Countries

The distribution of TBM performance research among countries is illustrated in Figure 3A. Presently, there are 49 countries that have contributed to the TBM performance literature. China takes the lead with 442 articles, constituting 49.11% of the total. Iran secures the second position with 90 articles, representing 10% of the total. The United States follows closely in third place with 67 articles, making up 7.44% of the total. Subsequently, we have Turkey, Australia, Italy, Germany, the UK, Switzerland, South Korea, and Malaysia as contributors in the field. The prominence of a country, its physical and geographical context, and the specific tunneling challenges it faces all play pivotal roles in shaping the development of TBMs and, by extension, TBM performance research. Consequently, TBM performance research has been predominantly concentrated in regions such as Europe, North America, East Asia, and South Asia, where tunneling activities and infrastructure development are extensive.

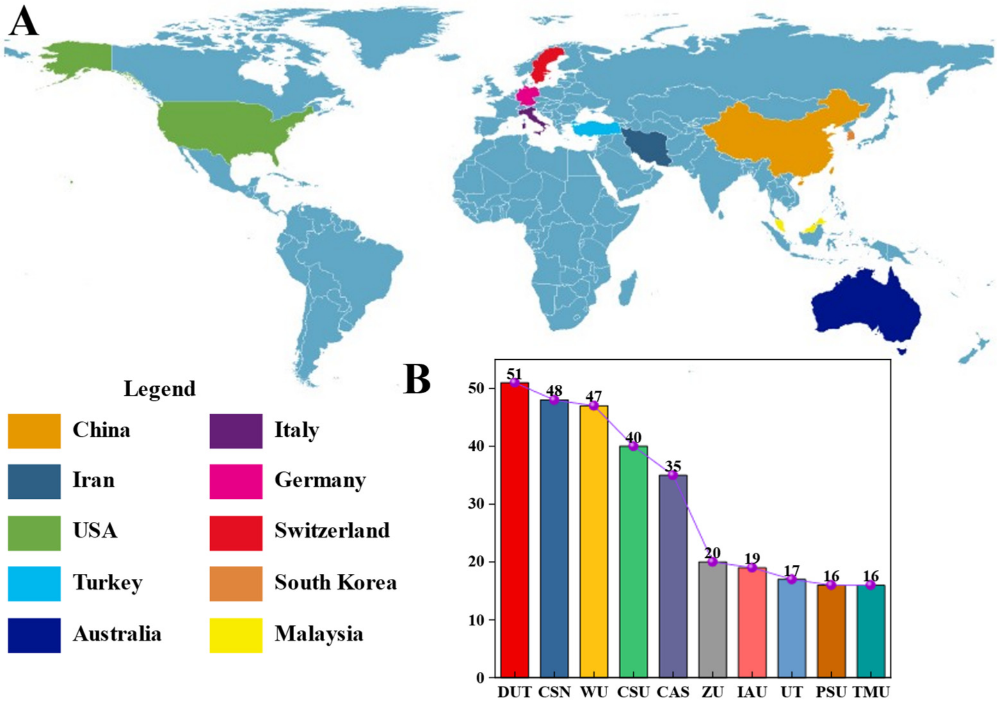

Figure 3. TBM performance literature published by major national and research institutions. (**A**) Leading countries in the world that publish TBM performance literature. (**B**) The research institution that published the most TBM performance literature. (Dalian University of Technology: DUT; Colorado School of Mines: CSM; Wuhan University: WU; Central South University: CSU; Chinese Academy of Sciences: CAS; Zhejiang University: ZU; Islamic Azad University: IAU; University of Tehran: UT; Pennsylvania State University: PSU; Tarbiat Modaris University: TMU).

Close collaboration and cooperation among countries have played a pivotal role in driving the progress of TBMs. During the period spanning from 2000 to 2021, numerous international conferences have been convened, facilitating effective communication and collaboration within the TBM research community. Prominent conferences such as the Conference on Tunnel Boring Machines in Difficult Grounds, TBM Digs, World Tunnel Congress (WTC), the 39th General Assembly of the International Tunnelling and Underground Space Association (ITA), and the 2009 Rapid Excavations and Tunnelling Conference have served as valuable platforms for scholars from diverse countries to exchange ideas and insights. These conferences have had a profound impact on the progression of TBM performance research by promoting cross-border knowledge sharing and fostering international research cooperation.

China has emerged as the leading contributor of articles in the field of TBM performance research from 2000 to 2021, making it a subject of significant analytical interest. During this period, China contributed a total of 442 relevant articles, which garnered a combined citation frequency of 3995, with an average of 14.53 citations per article and an h-index of 34. The number of articles published in China has exhibited an overall upward trajectory, with a notable surge after 2011, accounting for 95.02% of the total publications from China. In contrast, as depicted in Figure 2, the number of publications from countries other than China has gradually plateaued over the past decade. This suggests that there is still substantial potential for further development in the field of TBM performance research, particularly in China. It is worth noting that China's h-index in this domain is relatively low when compared to the global average. This discrepancy can be attributed to the relatively lower citation rate of articles published in China, which is inversely related to the number of articles published. Consequently, there is ample room for China to enhance its influence and impact within the realm of TBM performance research by improving the citation rates and the quality of its publications.

As per the assessments made by funding organizations, China has made significant strides in the realm of TBM performance research, even though it entered this field relatively late. Table 1 presents a comprehensive overview of the top 20 global funders, where a remarkable eight out of the top ten funders hail from China. These prominent contributors include the National Natural Science Foundation of China, responsible for 155 articles, the National Basic Research Program of China with 78 articles to its credit, the Fundamental Research Funds for The Central Universities, which has sponsored 20 articles, and the National Key Research and Development Program of China, having supported 18 articles. Additionally, the National High Technology Research and Development Program of China and the China Postdoctoral Science Foundation have both played a significant role with 10 and 8 articles, respectively, followed by the National Key Research and Development Program of China with another 8 articles, and the China Scholarship Council with 7 articles. Completing this list are two international funding bodies, namely the German Research Foundation and the Scientific and Technical Research Council of Turkey, each having supported seven articles. This array of funders underscores China's strong commitment to advancing TBM performance research on the global stage. The growth of TBM performance research in China can be attributed to the favorable research environment and substantial financial support that the nation has provided in this field.

Table 1. Top 20 global foundation funding agencies.

No.	Fund Institutions	Region	Articles
1	National Natural Science Foundation of China	China	155
2	National Basic Research Program of China	China	78
3	Fundamental Research Funds for The Central Universities	China	20
4	National Key Research and Development Program of China	China	18
5	National High Technology Research and Development Program of China	China	10
6	China Postdoctoral Science Foundation	China	8
7	National Key Research and Development Program of China	China	8
8	China Scholarship Council	China	7
9	German Research Foundation	German	7
10	The Scientific and Technical Research Council of Turkey	Turkey	7
11	China Postdoctoral Science Foundation Program	China	6
12	Key Research and Development Program of Shandong Province	China	5
13	National Funded Program for Graduate Students Studying Abroad of China Scholarship Council	China	5
14	Malaysian University of Technology	Malaysia	5
15	Natural Science Foundation of Hunan Province	China	4
16	Natural Science Foundation of Liaoning Key Fund	China	4
17	European Commission	European	3
18	Hunan Provincial Innovation Foundation for Postgraduate	China	3
19	Innovation Driven Project of Central South University	China	3
20	Interdisciplinary Development Program of Shandong University	China	3

3.4. Research Institutions

Conducting a co-occurrence analysis of research institutions offers valuable insights into the core research strengths within a particular field and enables a scientific evaluation of the academic impact of these institutions [20–22]. In Figure 3B, we present the top ten research institutions globally in terms of the number of articles published, shedding light on their pivotal role in the field of TBM performance research.

Leading the pack is Dalian University of Technology, holding the prestigious first place with an impressive 51 publications. Following closely is the Colorado School of Mines, securing second place with 48 articles to their name. Other notable institutions, each contributing significantly with at least 15 publications, encompass Wuhan University (47 articles), Central South University (40 articles), Chinese Academy of Sciences (35 articles), Zhejiang University (20 articles), Islamic Azad University (19 articles), University of Tehran (17 articles), Pennsylvania State University (16 articles), and Tarbiat Modaris University (16 articles). Notably, all of these research institutes are affiliated with higher education institutions, predominantly hailing from China, the United States, and Iran.

Furthermore, it is worth highlighting that 710 additional research institutions are actively engaged in TBM performance studies; however, their individual contributions consist of fewer than 15 articles. This extensive list underscores the global interest and engagement in TBM performance research across various institutions worldwide.

Regarding institutional affiliation, it is noteworthy that five out of the top ten publishers are Chinese institutions. This indicates that TBM performance research has garnered significant attention and focus within China. In terms of publication volume, Chinese institutions collectively contribute a substantial 62.46% of the world's top 10 publications. Over the past two decades, Chinese research institutions have made noteworthy and substantial contributions to the advancement of TBM performance research, solidifying their pivotal role in shaping the field.

3.5. Research Hotspots

The research literature on TBM performance underwent a comprehensive terminology analysis. The findings of this analysis are visually represented in Figure 4, while the distribution of the primary keywords is detailed in Table 2. Keywords, in research, play a pivotal role as they encapsulate the fundamental arguments and themes of a paper. Analyzing the keywords in the relevant literature of a specific field serves as a valuable tool for identifying research trends and focal points [23].

Table 2. Hot keywords in TBM performance studies.

No.	Keyword	Frequency	Relevance	No.	Keyword	Frequency	Relevance
1	Prediction	152	0.3335	11	Accuracy	71	0.442
2	Test	126	0.4792	12	Estimation	71	0.6167
3	Efficiency	110	0.4838	13	Technique	68	0.4818
4	Disc cutter	100	0.9397	14	Simulation	66	1.1793
5	Force	99	0.6139	15	Database	62	1.0776
6	Cutter	93	0.6988	16	Interaction	61	0.5368
7	Index	88	0.4663	17	Coefficient	59	0.7648
8	Penetration rate	88	0.6442	18	Ground	58	0.9006
9	Algorithm	83	0.5215	19	Uniaxial compressive strength	57	1.1401
10	Prediction model	74	0.3399	20	Mechanism	56	1.4459

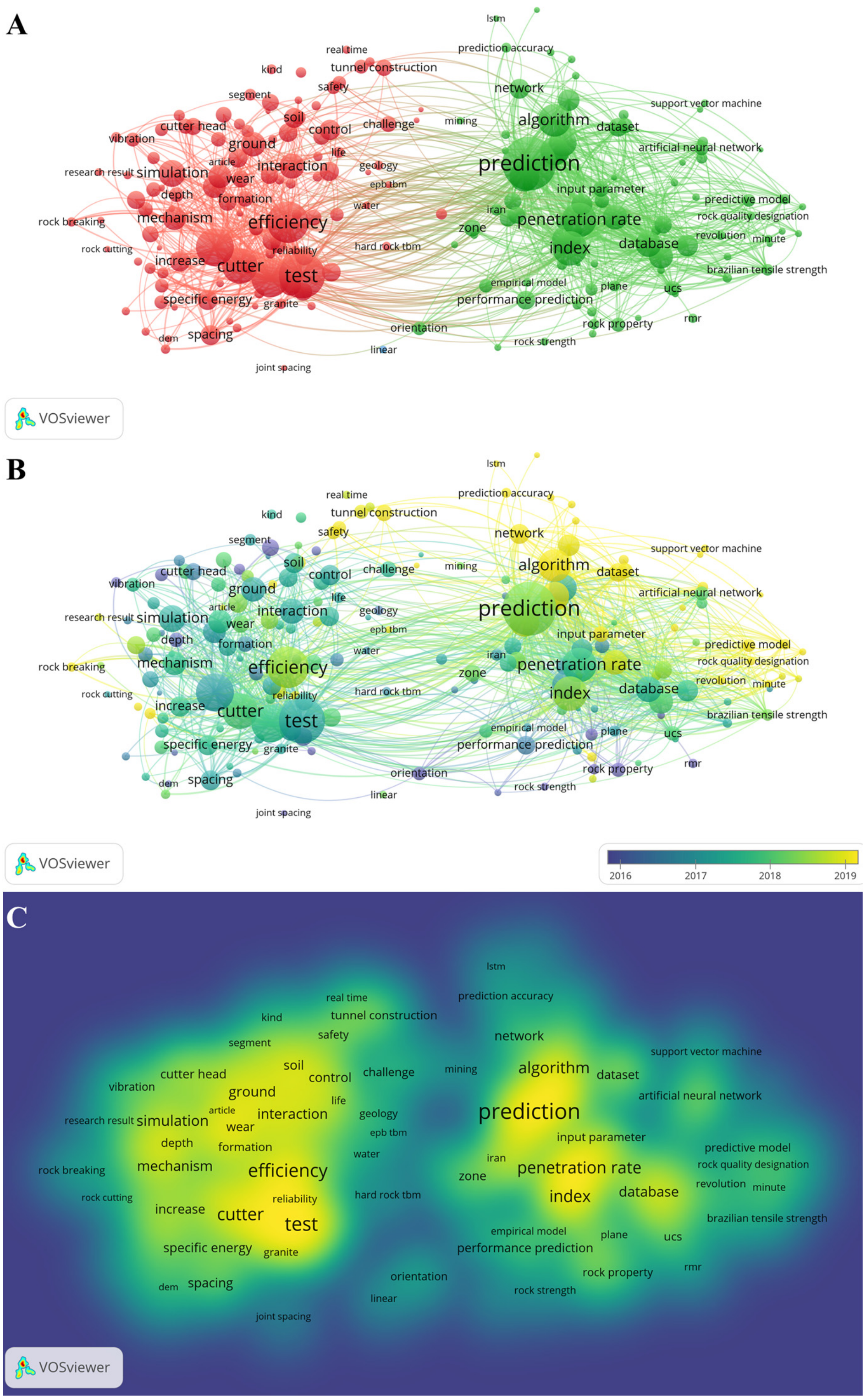

Figure 4. Hot topic analysis. (**A**) Keyword network visualization. (**B**) Keyword overlay visualization. (**C**) Keyword density visualization.

The process of extracting these keywords was carried out using VOSviewer, with a predefined threshold of 15 occurrences (i.e., keywords that appeared at least 15 times), involving the consolidation of keywords with similar meanings and the removal of keywords not directly relevant to the current study. Through these operations, a total of 197 pertinent keywords were identified, forming a network of 9610 interconnected relationships.

These relationships can be effectively categorized into the following three overarching themes: “mining”, “TBM performance prediction”, and “testing”, as visually represented in Figure 4A. The cumulative strength of these keyword connections amounts to 29,040, indicating a notably strong interrelation among these keywords. Broadly speaking, the examination of test studies encompassed the majority of the keywords, signaling a heightened level of research activity within this domain. This prevalence can be ascribed to the inherent nature of most TBM performance prediction models, which tend to be theoretical and intricately empirical. The inclusion of keywords such as “behavior”, “cutter head”, “cutter wear”, “deformation”, “disc cutter”, “dynamic model”, “joint”, “hard rock”, “mechanics”, “numeric simulation”, “test result”, and others underscores the exploration by researchers into rock and machine parameters. These investigations often take place in laboratory settings and play a pivotal role in the development of the aforementioned prediction models. This reflects the meticulous examination of factors that exert an influence on TBM performance, further enriching the field’s knowledge base.

The temporal progression of keywords is visually presented in Figure 4B, with color bars ranging from purple to yellow. In this color scheme, purple denotes the earlier appearance of a keyword, while yellow signifies more recent occurrences. Examining this temporal evolution, we observe that keywords such as “cutter head”, “depth”, “orientation”, “rock”, “property”, and “joint spacing” emerge in the earlier stages, highlighting the predominant focus of early studies on understanding rock mechanisms and related factors. In the medium term, we notice an increased prominence of words like “prediction”, “efficiency”, “index”, “tensile strength”, “UCS”, and “wear”. This shift reflects a transition in researchers’ perspective from fundamental theoretical aspects towards performance indicators. Moreover, the recent appearance of terms such as “algorithm”, “dataset”, “input parameters”, “support vector machine”, “predictive model”, and “accuracy” signifies a notable integration of machine learning techniques in the realm of TBM research. This points to a contemporary emphasis on leveraging advanced computational methods for improved analysis and prediction. Additionally, the emergence of keywords like “safety” and “rock damage” indicates the sustained global concern for safety issues within the field, reaffirming the ongoing importance of addressing safety considerations and minimizing rock-related damages in TBM operations.

The visualization of keyword density, as depicted in Figure 4C, follows a network-based approach. In this visualization, each point is assigned a color corresponding to the density of the associated term, in line with the methodology by Van and Waltman [17]. The color spectrum spans from blue to green to yellow, with the shading indicating the frequency and importance of a given keyword. Points closer to yellow represent keywords with a high frequency and significant weighting, while those closer to blue denote keywords with lower occurrence and impact. The pronounced presence and weighting of terms like “prediction”, “test”, “efficiency”, “disc cutter”, “force”, “cutter”, “index”, “penetration rate”, “algorithm”, “prediction model”, “accuracy”, “estimation”, “technique”, “simulation”, and “database” underscore their central role in the current research hotspots within the realm of TBM performance research. Furthermore, these keywords exhibit strong relevance to those outlined in Table 2, offering additional confirmation of their significance in shaping the field and underlining their relevance in contemporary TBM research.

3.6. Citation Frequency Analysis

The frequency of citations can serve as an indicator of a paper’s academic influence to some extent. To identify highly cited papers, the citation frequency distribution of 528 papers was analyzed [24,25]. The analysis revealed that 73 papers, accounting for 13.83% of the sample size, had a citation frequency of 0 in the field of TBM performance research. Furthermore, a significant portion of papers exhibited low citation frequencies, while only a few papers garnered high citations.

Table 3 displays the top ten papers in terms of citation frequency. The most frequently cited paper is “Disc cutting tests in Colorado red granite: Implications for TBM performance prediction" by Gertsch et al. [26], published in the *International Journal of Rock Mechanics and Mining Science* in 2007. Gertsch et al. [26] conducted laboratory disc cutting experiments using a 432 mm diameter disc cutter and granite. During these experiments, they measured indicators such as single disc spacing, normal, rolling, and side forces, and subsequently calculated other cutting parameters. The second most cited paper is "Development of hybrid intelligent models for predicting TBM penetration rate in hard rock condition" by Armaghani et al. [27], published in the *Journal of Tunnel and Underground Space Technology* in 2017. This paper focuses on the development of an intelligent predictive model specifically for water transfer tunnel projects in Malaysia. Additionally, numerical simulations have garnered considerable interest in the TBM performance literature. Relevant highly cited articles in this domain include those by Gong et al. [28], Gong et al. [29], and Grima et al. [30].

Table 3. The top ten papers in terms of citation frequency.

No.	First Author	Time	Title	Journal	Cited Frequency
1	Gertsch, R	2007	Disc cutting tests in Colorado red granite: Implications for TBM performance prediction	INTERNATIONAL JOURNAL OF ROCK MECHANICS AND MINING SCIENCES	268
2	Armaghani, Danial Jahed	2017	Development of hybrid intelligent models for predicting TBM penetration rate in hard rock condition	TUNNELLING AND UNDERGROUND SPACE TECHNOLOGY	218
3	Gong, QM	2006	Numerical modelling of the effects of joint spacing on rock fragmentation by TBM cutters	TUNNELLING AND UNDERGROUND SPACE TECHNOLOGY	218
4	Gong, QM	2005	Numerical modeling of the effects of joint orientation on rock fragmentation by TBM cutters	TUNNELLING AND UNDERGROUND SPACE TECHNOLOGY	216
5	Gong, QM	2009	Development of a rock mass characteristics model for TBM penetration rate prediction	INTERNATIONAL JOURNAL OF ROCK MECHANICS AND MINING SCIENCES	208
6	Yagiz, Saffet	2008	Utilizing rock mass properties for predicting TBM performance in hard rock condition	TUNNELLING AND UNDERGROUND SPACE TECHNOLOGY	200
7	Yagiz, Saffet	2009	Application of two non-linear prediction tools to the estimation of tunnel boring machine performance	ENGINEERING APPLICATIONS OF ARTIFICIAL INTELLIGENCE	182
8	Hassanpour, J.	2011	A new hard rock TBM performance prediction model for project planning	TUNNELLING AND UNDERGROUND SPACE TECHNOLOGY	181
9	Zhao, J.	2007	Tunnelling through a frequently changing and mixed ground: A case history in Singapore	TUNNELLING AND UNDERGROUND SPACE TECHNOLOGY	169
10	Grima, MA	2000	Modeling tunnel boring machine performance by neuro-fuzzy methods	TUNNELLING AND UNDERGROUND SPACE TECHNOLOGY	159

3.7. Key Literature Analysis

The highly cited research literature represents the foundational knowledge base in TBM performance research. In this study, we have identified and analyzed the top ten highly cited articles, which serve as key references in TBM performance research (Table 4). These key documents have all been cited more than 49 times, with some exceeding 80 citations, indicating their significance. Notably, the top five highly cited articles focus on the application of machine learning algorithms to TBM performance studies. Machine learning algorithms have gained popularity in recent years as a promising avenue within artificial intelligence techniques [31]. This trend also signifies the growing adoption of artificial intelligence in the TBM field. Researchers are utilizing machine learning methods to optimize parameters and proactively predict machine performance in complex environments, aiming to minimize project costs. It represents a new and challenging endeavor.

Table 4. Key references in TBM performance studies.

No.	First Author	Time	Title	Journal	Cited Frequency
1	Armaghani, Danial Jahed;Mohamad, Edy Tonnizam	2017	Development of hybrid intelligent models for predicting TBM penetration rate in hard rock condition	TUNNELLING AND UNDERGROUND SPACE TECHNOLOGY	218
2	Armaghani, Danial Jahed	2019	Application of several optimization techniques for estimating TBM advance rate in granitic rocks	JOURNAL OF ROCK MECHANICS AND GEOTECHNICAL ENGINEERING	107
3	Xu, Hai;Zhou, Jian	2019	Supervised Machine Learning Techniques to the Prediction of Tunnel Boring Machine Penetration Rate	APPLIED SCIENCES-BASEL	98
4	Zhou, Jian; Qiu, Yingui; Zhu, Shuangli	2021	Optimization of support vector machine through the use of metaheuristic algorithms in forecasting TBM advance rate	ENGINEERING APPLICATIONS OF ARTIFICIAL INTELLIGENCE	86
5	Koopialipoor, Mohammadreza;Nikouei, Sayed Sepehr	2019	Predicting tunnel boring machine performance through a new model based on the group method of data handling	BULLETIN OF ENGINEERING GEOLOGY AND THE ENVIRONMENT	84
6	Koopialipoor, Mohammadreza	2020	Development of a new hybrid ANN for solving a geotechnical problem related to tunnel boring machine performance	ENGINEERING WITH COMPUTERS	80
7	Zhou, J	2021	Predicting TBM penetration rate in hard rock condition: A comparative study among six XGB-based metaheuristic techniques	GEOSCIENCE FRONTIERS	71
8	Liu, Bolong;Yang, Haiqing	2020	Effect of Water Content on Argillization of Mudstone During the Tunnelling process	ROCK MECHANICS AND ROCK ENGINEERING	57
9	Zhou, Jian; Qiu, Yingui; Zhu, Shuangli	2021	Estimation of the TBM advance rate under hard rock conditions using XGBoost and Bayesian optimization	UNDERGROUND SPACE	51
10	Elbaz, Khalid; Shen, Shuilong	2020	Prediction of Disc Cutter Life During Shield Tunneling with AI via the Incorporation of a Genetic Algorithm into a GMDH-Type Neural Network	ENGINEERING	49

4. Understanding of TBM Performance

4.1. Selection of Excavation Methods

Rock collapse during deep rock excavation can be influenced by the release of strain energy in the surrounding rocks. Several factors can trigger the release of strain energy in tunnels, with the choice of excavation method being of particular significance. Presently, there are two primary methods for tunnel excavation, the TBM method and the drill and blast method. Each of these methods has distinct impacts on the surrounding rock, leading to varying types of damage and necessitating unique reinforcement measures. The advantages and disadvantages of these excavation methods are summarized in Table 5.

Table 5. Comparison of different excavation methods.

Comparison	Drill and Blast Method	Tunnel Boring Machine
Advantages	• Flexible geometry. Geometries to suit any project requirement. • Short equipment delivery times. Adaptation to different geological conditions. • Extensive background checks are not required. • Low investment in the project. No need to prepare significant amounts of money. • Low power consumption.	• The section is fixed and mainly circular. Generally good stability and low disturbance of the surrounding rock. • Low frictional head loss. Suitable for water-bearing tunnel excavations. • There is no risk of explosion. • Rock support is timely. • Fast boring speed. Good for excavating long tunnels. • Low environmental disturbance. No environmental hazards (blast vibrations, flying rocks, etc.). • A safe working environment. • The working cycle is simple and easy to operate.
Disadvantages	• More unstable due to possible blast-induced fractures. • Low energy utilization. Large frictional head loss. • There are safety hazards associated with the storage and transportation of explosives. • Some areas of the underground work could not be supported. • Low advance rate. • Secondary hazards caused by blasting. • Toxic gases can be produced. • The work process is complex, and the preparation time is long.	• The section shape is restricted. • Circular cross-sections do not meet the shape requirements of road tunnels. • Custom equipment takes a long time. • Poor adaptation to geological conditions. • A detailed pre-survey is required. • The project is a great investment and affects cash flow operations. • High energy consumption, especially electricity.

In recent years, numerous scholars have conducted extensive research on the extent of surrounding rock damage resulting from different excavation methods. For instance, Kelsall et al. [32] investigated the thickness of the damage zone through the utilization of seismic refraction techniques during tunnel excavations in sandstone formations employing both TBM and drill and blast methods. Their test findings demonstrated that the damage zone had a thickness of 0.3 m for the TBM method, whereas it ranged from 0.6 to 1.3 m for the drill and blast method. In 2013, Ji et al. [33] and colleagues carried out a comprehensive study involving electron microscope scanning tests, acoustic emission tests, and relaxation depth tests on Jinping marble under diverse excavation conditions. Their observations revealed that under TBM excavation conditions, the predominant damage mechanism was characterized by shear forces, leading to significant deformation in the rocks near the point of peak load. Bilgin et al. [34] conducted an experimental analysis, which led them to the conclusion that the uniaxial compressive strength of the rock is closely associated with the efficiency of TBM excavation. In general, the drill and blast method, while more complex to coordinate and characterized by an extended construction period, offers a higher degree of adaptability to various geological conditions. Conversely, the TBM method is distinguished by its streamlined procedures, quicker construction pace, and enhanced safety measures. Nevertheless, it exhibits less adaptability to diverse geological conditions and demands the use of costly equipment, as highlighted by Zhou et al. [35]. Therefore, in the excavation design phase of a tunnel project, the process of selecting the appropriate construction method necessitates a thorough comparison of technical and economic indicators, all while taking into account the crucial evaluation parameters presented in Table 6. This meticulous approach is implemented to minimize potential project risks.

Table 6. Important evaluation parameters for the selection of excavation methods.

Parameters to Be Considered When Choosing an Excavation Method	
Project design factors	Costs budget
Ultimate purpose	Overbreak and tunnel profile quality
Excellent working environment	Surrounding rock conditions
Boring speed	Construction time and tunnel layout
Flexibility and acceptable risk	Project contract conditions
Geological situation	Protected buildings

TBMs have benefited from more than five decades of extensive research and development, resulting in the establishment of highly efficient construction technology and a wide array of product types. Owing to their remarkable speed and enhanced safety features, TBMs have garnered widespread adoption in tunnel excavation projects for railways, highways, and water conservancy, making them the preferred choice in numerous countries. The shift from traditional drill and blast technology to TBM technology has been primarily motivated by the pursuit of safer and more efficient construction practices. This transition has shaped the trajectory of TBM tunnelling technology, and its future will continue to be guided by these fundamental principles. As a result, future TBM technology is anticipated to surpass the current generation of TBMs in terms of functionality, cost-effectiveness, automation, and flexibility of use, ultimately leading to substantial economic and social benefits.

4.2. Current Developments in Performance Prediction

Precisely forecasting the performance of TBMs within specific geological contexts holds immense significance in the decision-making process for choosing tunnelling methods, establishing construction schedules, and estimating project costs. This is primarily due to the fact that TBMs are notably sensitive to geological variables and necessitate substantial initial investments. During the feasibility stage, it is imperative for the project owner to employ a predictive model for economic evaluation and method selection. As the construction phase commences, the project owner can continue to utilize this prediction model to assess the contractor's progress, while the contractor, in turn, depends on the model to make estimates for bid prices. Furthermore, the builder can conduct a comparative analysis between the predicted progress and the actual construction progress, thereby facilitating the identification of any potential issues. Nonetheless, the construction speed is subject to the influence of multiple factors (as depicted in Figure 5), and the intricate interplay and relationships among these factors make it a complex task to comprehensively establish the correlation between TBM performance and each specific factor from a purely theoretical standpoint. As stated by Robbins [36], "No task is more challenging than evaluating rock characteristics and applying them to predict TBM performance". Nelson [37] further notes that "the current lack of a standardized method within the geotechnical engineering sector for the quantitative assessment of the influence of rock variations on TBM construction performance".

TBM performance prediction encompasses the estimation of various parameters, including the penetration rate (PR), advance rate (AR), utilization (U), and cutter wear (H). In the initial stages, early prediction models primarily concentrated on PR alone. However, in subsequent developments, multi-factor models were introduced, enabling a comprehensive prediction of all facets of TBM performance. Since the 1970s, numerous researchers have developed various types of TBM performance prediction models, evolving from simple to complex. As depicted in Figure 6, these models can be categorized into three main types, theoretical models, empirical models, and artificial intelligence models. Table 7 illustrates the advantages and disadvantages associated with each of these models.

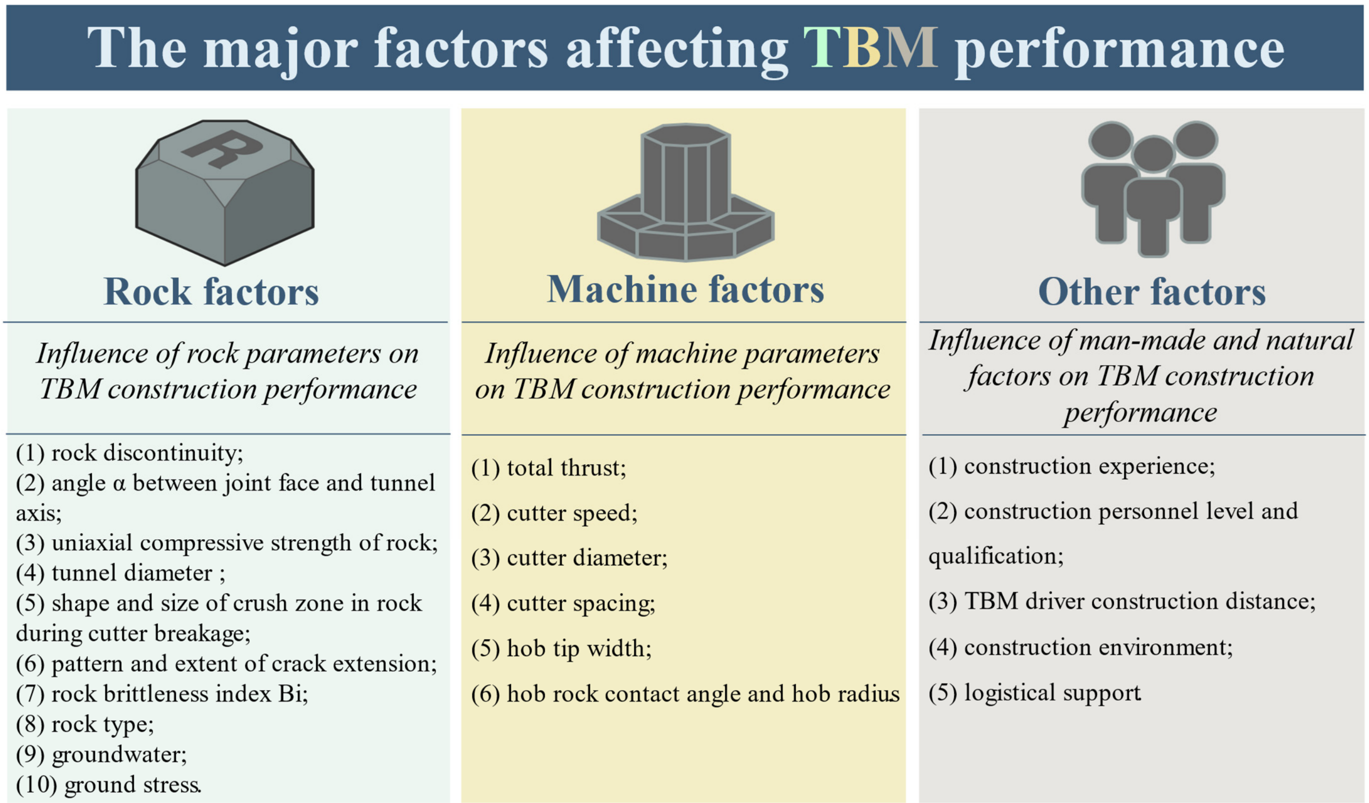

Figure 5. The main factors affecting the performance of TBMs.

Table 7. Comparison of different TBM performance prediction models. [38].

Comparison	Drill and Blast Method	Tunnel Boring Machine
Theoretical	• Flexible with cutter geometry and machine specification. • Can be used in trade off between thrust and torque and optimization. • Can be used for cutterhead design and improvements. • Can explain the actual working condition of the discs and related forces.	• Unable to easily account for rock mass parameters. • Lack of accounting for joints. • Can be off by a good margin in jointed rock. • Inability to account for required field adjustments.
Empirical	• Proven based on observed field performance of the TBMs in the field. • Accounts for TBM as the whole system. • Many of field adjustments (i.e. average cutter conditions) are implied. • Ability to account for rock joints and rock mass properties.	• Lower accuracy when used in cases when input parameters are beyond what was in the original field performance database. • Unable to account for variations in cutter and cutterhead geometry, i.e. cutter tip width, diameter, spacing, gage arrangement. • Extremely sensitive to rock joint properties.
Artificial intelligence	• Highly complex and non-linear problems can be solved. • Introduction of optimization algorithms to improve prediction accuracy. • Performance can be predicted using multiple input parameters.	• Low learning rate. • Tends to fall into local minima. • Subject to the "no free lunch" theorem, there is a lot of experimentation with different algorithms.

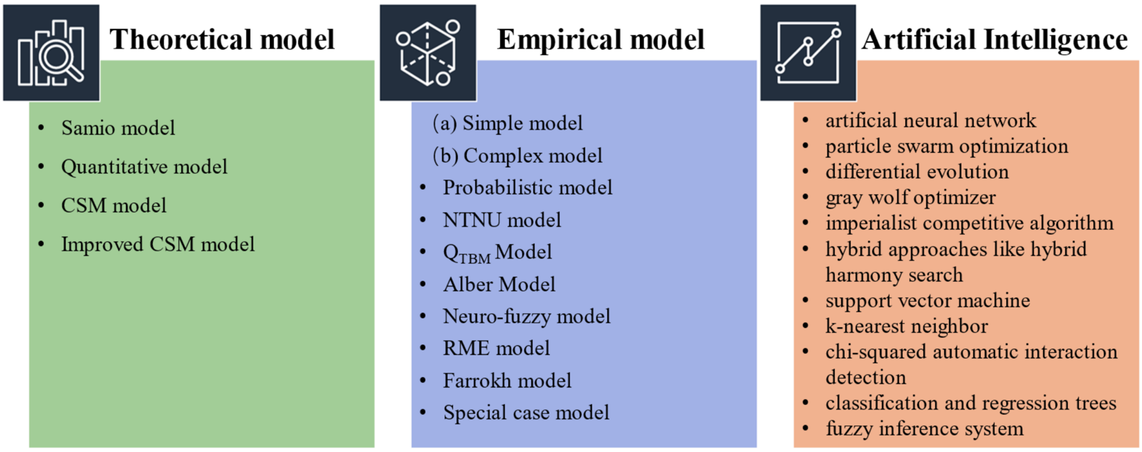

Figure 6. Classification of TBM performance prediction models.

4.2.1. Theoretical Model

Theoretical models in TBM performance prediction are based on the analysis of cutter breaking mechanisms and cutting forces acting on a single cutter. Indentation tests or indoor full-scale cutting tests are conducted to derive the cutter force balance equation. One well-known theoretical model is the CSM model, developed by the Colorado School of Mines [9]. Although the CSM model is primarily theoretical, the equation for calculating the baseline pressure in the crush zone is obtained through multiple regression analysis. The model was developed based on data from indoor full-scale linear cut tests. However, the predictions of TBM performance using the CSM model tend to be conservative due to discrepancies between the rock samples used in the indoor tests and the actual rock conditions encountered during TBM field excavations. Moreover, the model disregards the influence of rock discontinuities, such as joints, on TBM construction performance. Researchers have recognized this limitation and made improvements accordingly. Yagiz [39] developed an enhanced PR prediction model based on TBM construction performance data and geological information from the Queens Tunnel in New York. The model incorporates additional indicators characterizing rock fragmentation and brittleness into the original CSM model. Building upon this work, Ramezanzadeh [40] developed a new model for predicting length per revolution, considering data from 11 TBM tunnels with a total length exceeding 60 km and taking into account the influence of rock parameters on TBM construction performance. This model significantly improves prediction accuracy. Indoor full-scale linear cut tests provide the closest approximation to the field conditions in which TBMs break rocks. Sanio [10] developed formulas to predict cutter breaking performance in laminated and flaky rocks based on simple theoretical analysis and tests, assuming that the primary cutter breaking mechanism is tensile damage. The Sanio model accounts for the effects of rock anisotropy and discontinuities on cutter breaking performance. However, it relies only on point load strengths in different directions to predict the degree of penetration per revolution, resulting in limited accuracy. Additionally, Boyd [41] utilized quantitative analysis to predict PR. The Boyd model addressed issues related to inconsistent magnitudes in regression analysis and fuzzy neural network modeling. However, it lacks detailed specific energy values for each rock type, and the machine efficiency factor must be carefully considered.

4.2.2. Empirical Model

Empirical formulas have proven to be valuable tools during the feasibility, design, and construction stages of a project, as they are more practical and easier for construction personnel to understand compared to theoretical analyses. In geotechnical engineering, empirical formulas based on statistics are widely used to predict target variables. Empirical models can be broadly categorized into two main groups, simple and complex models. Simple empirical models typically consider only one or two rock mechanical parameters, such as uniaxial tensile strength, compressive strength, or hardness of the rock, for simplicity and convenience. For instance, Tarkoy [42] estimated the total rock hardness using Schmidt hammer bounce hardness and Tabor abrasion hardness and examined the relationship between PR and total hardness for limestones, shales, and sandstones with a total hardness ranging from 2 to 242. Graham [43] developed a calculation formula by considering the cutter feed per revolution as a function of the single cutter thrust and the uniaxial compressive strength of the rock. Farmer and Glossop [7] proposed a prediction model based on eight examples of TBM tunnel construction performance data and geological information, which uses the average single cutter thrust and the rock tensile strength to calculate the cutter feed per revolution. Cassinelli [44] studied the relationship between rock structure scoring (RSR) systems and TBM performance, while Innaurato et al. [8] enhanced the model proposed by Cassinelli [44] based on five TBM tunnel construction performance data sets and geological information, using 112 sets of valid data obtained from a 19 km tunnel. The upgraded model considered the effect of uniaxial compressive strength of the rock in the PR prediction model. Nelson et al. [5] developed a TBM feed per revolution prediction model based on four sedimentary rock TBM tunnelling performance data sets and geological information, and they found that PR was not only related to rock type, but also to the single cutter thrust. They therefore proposed a correlation formula between total rock hardness and in situ penetration index. Based on construction performance data and geological information from two TBM tunnels in Australia, Bamford [45] showed that PR could be well predicted using Schmidt hammer bounce hardness, total TBM thrust, NCB indentation hardness, and shear angle. However, these simple models are now mostly obsolete due to their low predictive accuracy.

Empirical models developed at a later stage have created a large database of TBM performance by collecting numerous rock and machine parameters and using advanced techniques such as multiple regression analysis, fuzzy mathematics, and neural networks to develop complex empirical models. Well-known examples include the NTNU model [4], probabilistic model [5], Alber model [6], neuro-fuzzy model [30], Farrokh model [46], and special case model [47–49]. Furthermore, some researchers have attempted to develop new rock excavatability grading systems by linking TBM performance to rock excavatability grading systems, based on the concept of rock quality grading. Examples of such systems include the QTBM model [50] and the RME model [51,52].

4.2.3. Artificial Intelligence Model

There are still studies that rely on conventional statistical and linear methods to forecast TBM performance [53,54]. However, these methods have been criticized for their limitations in resolving complex and non-linear issues. Grima et al. [30] argue that statistical models may not adequately describe non-linear and complex systems, while Xu et al. [55] highlight the deterioration of their performance when outliers and extreme values are present in the data. Farrokh et al. [46] suggest that multi-parameter models, compared to simple models, make better use of available project data and are easier to implement. Consequently, it can be argued that artificial intelligence computational models are the most suitable choice for predicting TBM performance.

Artificial intelligence (AI) models offer substantial benefits in tackling the intricate, multi-parameter challenges characteristic of TBM operations. These advantages can be categorized into two principal aspects, as outlined below:

- Data processing and analysis. AI models, particularly machine learning algorithms, excel in handling large datasets generated during TBM operations. These datasets encompass numerous parameters such as geological conditions, machine performance metrics, and environmental factors. AI models can efficiently process these data to provide real-time insights, which is crucial for making informed decisions and adjusting operational strategies dynamically.

- Predictive modeling and optimization. AI-driven predictive models can forecast the performance of TBMs under varying conditions, enabling operators to optimize machine settings for different segments of a tunnel project. By simulating various scenarios, AI models help in identifying the most efficient operational parameters, which can lead to significant cost savings and improved project timelines. Moreover, optimization algorithms can continuously adjust TBM parameters in real-time, ensuring optimal performance throughout the tunneling process.

Typically, due to the numerous factors influencing TBM performance and the complex interrelationships among these factors, the introduction of AI models to handle these intricate relationships is imperative. Artificial intelligence techniques, such as artificial neural networks (ANNs), imperialist competitive algorithms (ICAs), support vector machines (SVMs), particle swarm optimization (PSO), and adaptive neuro-fuzzy inference systems (ANFISs) (see Figure 6), have been widely applied to solve various geotechnical engineering problems, including TBM performance prediction [56–69]. Currently, many researchers have achieved promising results by utilizing AI technology to predict multiple parameters related to TBM performance after collecting them. Simoes and Kim [70] employ rule-based and parameter-based fuzzy inference systems (FISs) to predict TBM U using data from three different TBM projects. Mahdevari et al. [71] further utilize the SVM technique on the dataset obtained by Yagiz [49]. Mahdevari et al. [71] propose optimization algorithms to enhance SVMs and utilize these hybrid models to evaluate TBM PR. Benardos and Kaliampakos [72] suggest an ANN model for predicting tunnel boring rates using data from Athens metro tunnels. Grima [30] and colleagues introduce the ANFIS, which demonstrates significantly higher PR prediction accuracy compared to statistical methods. Yagiz et al. [53] employ ANNs to forecast TBM PR using data from the Queens Water Tunnel in the United States.

In recent times, researchers have been developing sophisticated artificial intelligence models aimed at enhancing the predictive capabilities of TBM performance. To overcome the low learning rate and the issue of getting stuck in local minima, Yagiz and Karahan [73] introduce several optimization methods, including hybrid harmony search, differential evolution (DE), and grey wolf optimizer (GWO), to estimate TBM PR. The hybrid harmony search technique is found to yield significantly better results compared to other proposed PR prediction methods. Armaghani et al. [74] develop two hybrid models, PSO-ANN and ICA-ANN, to predict TBM PR and TBM AR. The aforementioned models employ optimization algorithms to dynamically adjust multiple hyperparameters, guided by metaheuristic principles. Empirical evidence indicates that this approach markedly enhances the efficiency and effectiveness of multiparameter predictive models by facilitating continuous optimization.

In summary, when selecting a multiparameter prediction method for TBM, it is essential to strike a balance between the accessibility of input parameters, the complexity of the model, and the accuracy of the predicted results [55]. Critical factors influencing TBM construction performance must be carefully considered. Furthermore, most researchers base their studies on performance data obtained from TBM construction sites and geological information to investigate the impacts of various rock and machine parameters on TBM construction performance. While these data can accurately reflect the outcomes of rock–machine interactions, achieving precise TBM performance prediction with a limited number of construction instances is challenging due to the intricate nature of rock–machine interaction processes. For generalizability purposes, it is imperative to gather a substantial amount of TBM construction site data to accurately predict TBM performance.

5. Future Perspectives

In the post-epidemic era, the importance of digital technology has been further highlighted and is once again experiencing rapid growth. The emergence of digital technology has brought about a profound transformation in every aspect of human work and life. Consequently, a group of technology companies and scientists have envisioned the future of human society, with the concept of the metaverse taking center stage. The metaverse, initially conceptualized by renowned American science fiction author Stephenson [75] in 1992 in his novel "*Snow Crash*", focuses on creating a virtual digital world that mirrors the real physical world.

The evolution from Second Life, the virtual world introduced by Linden Lab in the US, to the more recent concept of digital twin represents various stages in the development of the metaverse. This journey spans from digital cities to smart cities and ultimately to digital twin cities. Presently, the metaverse holds a strong commercial dimension, and significant investments have generated excitement surrounding conceptual ideas that are rapidly becoming realities. However, the metaverse has evolved through the integration of advanced science and technology, with its potential harnessed for constructing virtual worlds envisioned for future human societies.

As a prominent buzzword within the internet industry, the metaverse has also garnered attention within scientific research. In recent years, alongside advancements in artificial intelligence and VR/AR/MR/XR reality technologies, the metaverse has transitioned from being a "dream" to a "reality", emerging as a focal point in current internet research. It provides valuable theories, methods, and technologies for the construction and development of future TBMs. Given this context, this paper focuses on two perspectives, i.e., the future application of metaverse technology in the TBM field, particularly in immersive training and learning concepts, as well as the integration of TBM and the metaverse system.

5.1. Immersive Training and Learning

Immersive learning refers to the process by which individuals engage in an immersive learning experience within a physical or virtual interactive learning environment. The creation of such an environment plays a crucial role in facilitating the immersive learning experience and typically involves simulation, cognition, and association [76]. Additionally, the design of immersive learning emphasizes the principles of realism, achievement, and presence [77]. As the metaverse emerges as a new stage in the development of immersive technology, it integrates various technologies such as 5G, VR/AR/MR/XR, big data, blockchain, artificial intelligence, and digital twin. This integration empowers the high-quality development of immersive learning and, to some extent, resolves challenges related to immersion, presence, interactivity, and responsiveness. Furthermore, the metaverse provides a robust network for 5G and AR, supporting a virtual–real overlay experience and offering a more effective avenue for immersive learning to unfold.

Drawing upon metaverse theory, we have devised a model diagram for immersive training learning (refer to Figure 7), which can be employed in future scenarios such as staff training (e.g., TBM driver operation training and on-site accident hazard demonstration) and the promotion of safety knowledge. The combination of 5G and AR overcomes the technical barriers associated with AR. The 5G + AR foundation layer (red layer) encompasses low latency, precise positioning, and high quality, providing fundamental technical support for immersive learning while enhancing the overall immersive learning experience. The 5G + AR transformational layer (yellow layer) incorporates mobile ubiquity, sensory internet, multimodal interaction, and personalized learning analytics with 5G technology, bringing about further advancements in the development of immersive learning. Guided by metaverse theory, immersive learning driven by 5G and AR is characterized by realism, presence, interactivity, and adaptability, forming the characteristic layer (blue layer) of immersive learning. At the elemental level (pink layer), immersive learning involves learners, 5G and AR technologies, mobile learning media, immersive learning environments, and enriched learning resources.

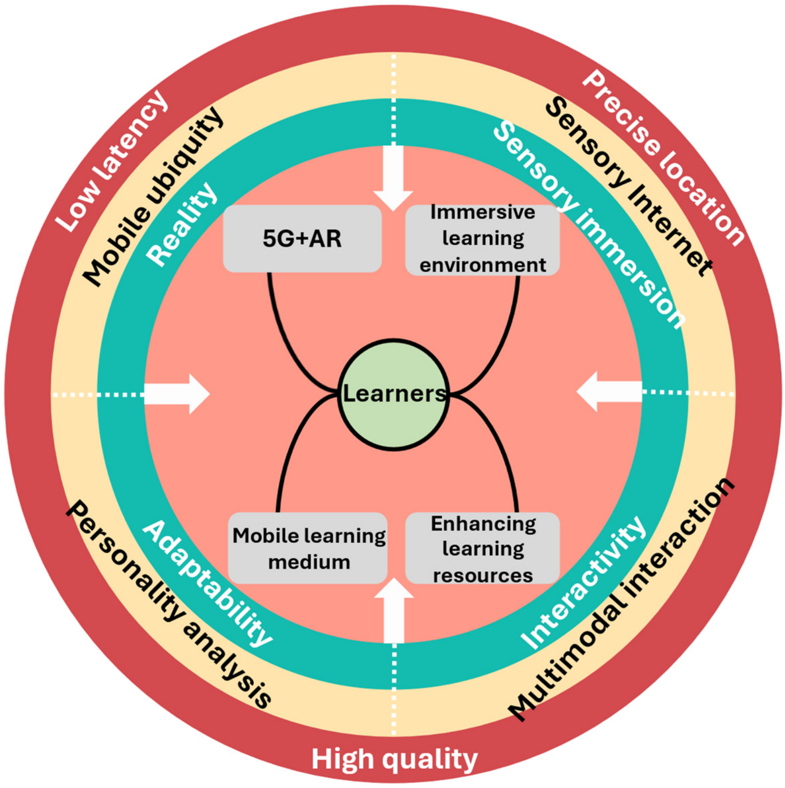

Figure 7. Concept map of immersive training and learning based on the metaverse.

With the ongoing development and maturation of the metaverse and its applications, immersive learning can be redefined, and metaverse-based immersive learning is poised to become a new industry in the "Internet+" era. As two pivotal technologies within the metaverse, 5G and AR synergistically enhance connectivity and expand the possibilities for user engagement, thereby creating numerous opportunities for immersive learning.

5.2. TBM Metaverse Architecture

The TBM metaverse represents the ultimate goal and focal point of integrating TBM and metaverse theory. Its essence lies in achieving the perception, mapping, simulation, decision-making, and control of TBM through pervasive three-dimensional perception of the TBM's physical world. This includes accurate mapping of its state, digital identification of the entire domain, real-time information analysis, collaborative data calculation, service simulation, precise decision implementation, and the cultivation of self-wisdom. These functionalities address a range of dynamic, complex, multifaceted, and uncertain problems in organization, management, and services. Building upon this foundation, the collaborative configuration and information interaction between TBM data, information, knowledge, resources, and all related physical entities (such as tunnels, rock formations, network equipment, office facilities, etc.) will be comprehensively enhanced [78]. This aims to improve the closed-loop empowerment system of TBM's physical entity resources and data resources, gradually establishing a TBM metaverse network ecosystem characterized by virtual–real integration, real-time mapping, and collaborative interaction.

While the application of the metaverse primarily remains within the domain of games and entertainment, it has rapidly extended its reach into various fields such as smart education, smart healthcare, smart manufacturing, culture and art, finance and trade, content production, advertising and media, military simulation, and interactive social networking. This expansion is driven by demand upgrades and technological evolution [79]. The integration of TBM and metaverse theory benefits from this development and serves as an important reference for research. Accordingly, the architecture of the TBM metaverse is designed and constructed based on the following four aspects of integration: integration structure, integration elements, integration technology, and integration capabilities (refer to Figure 8). In terms of integration structure, the TBM metaverse, as a vital component of the metaverse, inherits a corresponding technical structure comprising the following seven layers: the infrastructure layer, human–computer interaction layer, decentralized layer, "human–computer–object environment" spatial computing layer, content production layer, knowledge management and service discovery layer, and immersive experience layer [80]. Regarding integration elements, all elements involved in the operation of the TBM and its metaverse need to be modeled. This encompasses different models, elements, rules, logic, attributes, and knowledge of the cloud universe space, among others. These models simulate the TBM management and service processes within the metaverse. The integration technology of the TBM metaverse primarily encompasses the following four aspects: multi-dimensional interaction technology, high-speed communication technology, efficient computing power, and intelligent core algorithms. These technological innovations converge to simulate, monitor, diagnose, predict, and control TBM organization, management, and service processes and behaviors. They also establish the data foundation for quality tracing and service model innovation throughout the knowledge production process, fundamentally driving efficient synergy across all aspects of the project production cycle and fostering organizational, management, and service innovation. The integration capabilities include the following: virtual–real mapping and integration capabilities; accurate mapping and representation capabilities; visual modeling and visual presentation capabilities; multi-source heterogeneous data association and integration capabilities; spatial–temporal analysis and collaborative computing capabilities; simulation and projection of future operation and development capabilities; virtual–real integration and collaborative interaction capabilities; and self-optimizing wisdom growth capabilities. Understanding the core capabilities that a metaverse can bring to a TBM is essential within the context of current information technology developments and user knowledge service needs, as it provides insights into the type of "metaverse" that a TBM requires [81,82].

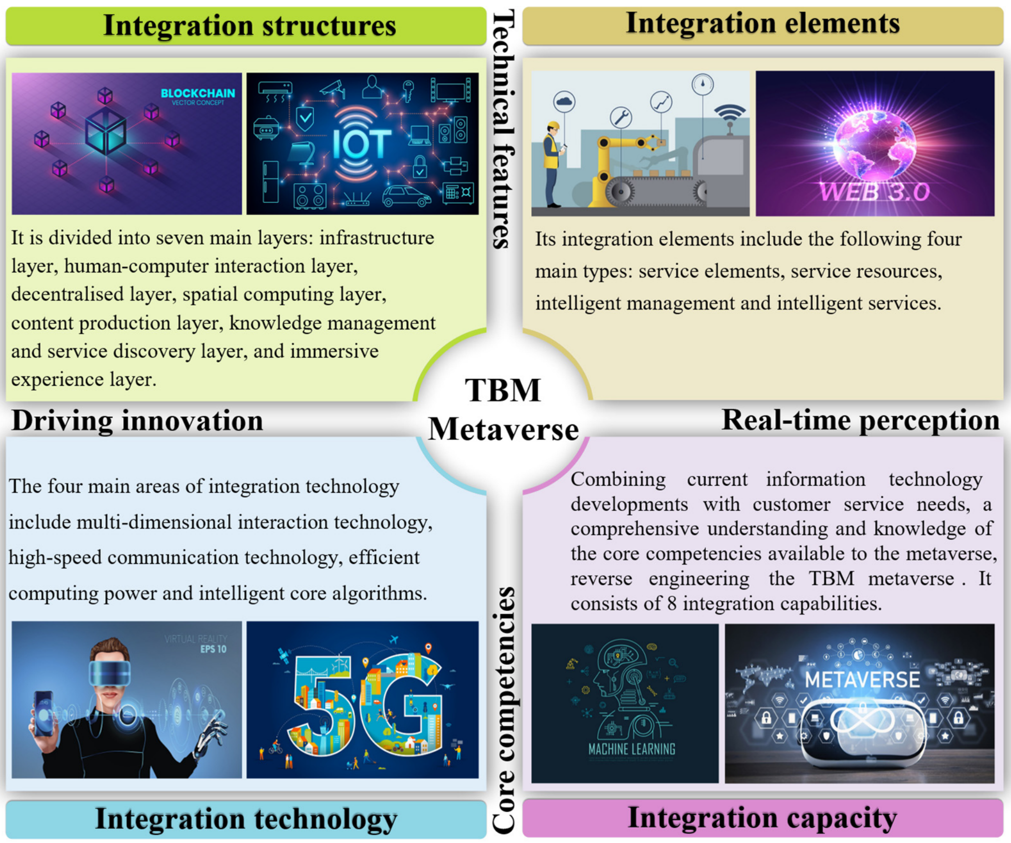

Figure 8. The architecture of the TBM metaverse.

6. Conclusions

This research marks the inaugural attempt to conduct a scientometric analysis of TBM performance. The analysis encompasses 528 English-language articles indexed in the WOS from 2000 to 2021. With the goal of creating a comprehensive knowledge map of the TBM research field, this study endeavors to portray the current landscape of TBM performance research and to provide researchers with valuable insights into the most recent developments in the field.

- This study illuminates the noteworthy contributions made by various nations and institutions to TBM performance research, with a focus on leading contributors such as China, Iran, the United States, and Turkey. The analysis underscores the global scope of TBM research initiatives and emphasizes the necessity of tackling a wide array of tunnelling challenges on a global scale.
- The examination of 40 distinct domains and significant focal points in the study of TBM performance reveals its interdisciplinary character.
- By scrutinizing highly cited articles and essential references, this research offers nuanced insights into pivotal research directions and significant findings.
- Through a comparative analysis of the merits and drawbacks associated with drill and blast methods as opposed to TBM methods, this research provides valuable guidance for stakeholders in the selection of excavation techniques for tunneling projects. It emphasizes the significance of weighing technical and economic indicators to mitigate project risks and optimize efficiency.
- The study further accentuates the potential ramifications of metaverse technology on the future of TBMs, particularly focusing on immersive training and learning concepts and the conceptualization of a TBM metaverse architecture. This integration unveils thrilling prospects for innovation in tunnelling technology and training methodologies.

In summary, this study enriches our comprehension of TBM performance research, offering valuable insights into prevailing trends, emerging topics, and prospective directions within the field. Its discoveries serve as a guiding framework for researchers and practitioners to propel tunnelling technology forward and effectively tackle the challenges inherent in modern infrastructure development.

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