# PRISMA 2020 Checklist

| Section and Topic | Item # | Checklist item | Location where item is reported |
|---|---|---|---|
| **TITLE** | | | |
| Title | 1 | Physics-Informed Neural Network (PINN) Evolution and Beyond: A Systematic Literature Review and Bibliometric Analysis | Page: 1 |
| **ABSTRACT** | | | |
| Abstract | 2 | This research aims to study and assess state-of-the-art physics-informed neural networks (PINNs) from different researchers' perspectives. The PRISMA framework was used for a systematic literature review, and 120 research articles from the computational sciences and engineering domain were specifically classified through a well-defined keyword search in Scopus and Web of Science databases. Through bibliometric analyses, we have identified journal sources with the most publications, authors with high citations, and countries with many publications on PINNs. Some newly improved techniques developed to enhance PINN performance and reduce high training costs and slowness, among other limitations, have been highlighted. Different approaches have been introduced to overcome the limitations of PINNs. In this review, we categorized the newly proposed PINN methods into Extended PINNs, Hybrid PINNs, and Minimized Loss techniques. Various potential future research directions are outlined based on the limitations of the proposed solutions. | Page: 1 |
| **INTRODUCTION** | | | |
| Rationale | 3 | PINNs are receiving more attention for solving a variety of differential equations with applications in weather modeling, healthcare, manufacturing, and other fields [5–7]. However, PINNs are not suitable for several real-time applications because of their high training costs. Although various proposals have been made to enhance the training effectiveness of PINNs, only some have considered the effects of initialization [8–10]. Another obstacle to the application of PINNs to a wide range of real-world problems is their poor scalability [5]. However, PINNs are not suitable for several real-time applications because of their high training costs. Although various proposals have been made to enhance the training effectiveness of PINNs, only some have considered the effects of initialization [8–10]. Another obstacle to the application of PINNs to a wide range of real-world problems is their poor scalability [5].<br><br>According to Raissi et al. [1], Schiassi et al. [21], and Zhang et al. [22], the key drawback of conventional PINNs is that even the DE limitations are still not mathematically solved, hence they need be learned concurrently with the DE solutions within the domain. As a result, we cope with competing goals during PINN training: learning the concealed DE solutions well in domains while also learning the hidden DE solutions on the boundary [21,23,24]. This results in imbalanced gradients during network training using gradient-based approaches, causing PINNs to fail to learn the basic DE solutions accurately [21,25]. According to Dwivedi et al. [26], despite the numerous benefits that PINNs provide, they have three major drawbacks. The first is their slowness [26,27] when applied to real problems; PINNs use up gradient descent optimization and are quite slow when compared to other numerical approaches. For highly deep networks, PINNs are vulnerable to vanishing gradient problems [6,26,28]. There is also the possibility that a solution will become stuck at a minimal point. Finally, the PINN's learning process is fine-tuned by hand. We cannot ascertain exactly how much data or even which framework is sufficient for a particular set of sample instances [1,29–31].<br><br>We have found that, there is no any review paper that critically review Physics-Informed Neural Networks studies. For that reason, we team up and work on that. We have also intend to optimize PINNs in near future by combining it with either graph or advanced recurrent neural network like LSTM or GRU.<br><br>As part of our contribution to the literature, we intend to implement a new model that combines PINNs with either a graph neural network or a recurrent neural network using a time series dataset. | Section 1: Page: 1 First paragraph<br><br>Section 1: Page: 2 Second paragraph<br><br>Section 6 Page: 18 Last paragraph |
| Objectives | 4 | The goal of this research is to find physics-informed neural network adaptations for solving various problems from the literature and to highlight newly improved PINN methodologies that have been proposed using different techniques. The main objectives of the study were to evaluate the current state of the art in this field of research using numerous bibliometric analyses, identify the full spectrum of eligibility requirements studied in the literature through information synthesis, create a collection of general information about how far research on PINNs has changed over | Section 1 Page 2 |

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| | | time, and identify newly introduced PINN approaches while highlighting some topics for future research. We tried to categorize state-of-the-art PINN techniques into three groups.<br><br>In this literature review, we aimed to answer the following question: *What techniques have been introduced to optimize the performance of physics-informed neural networks?* Although PINNs are utilized to solve problems in practically all the domains of human endeavor, throughout this review, we focused on computational sciences and engineering. | Fourth Paragraph<br><br>Page 2<br><br>Fourth Paragraph |
| **METHODS** | | | |
| Eligibility criteria | 5 | For reviewing current research, this paper used the PRISMA 2020 framework. The scoping approach was utilized to retrieve the most relevant papers on Physics Informed Neural Network. This method aided in the control of the critical lesson's mandatory components and the classification of potential search terms.<br>The keyword "Physics Informed Neural Network" was solely used in each database search for relevant literature. Predefined inclusion and exclusion criteria and quality requirements were used to refine the data search. Each filter verified that the quality requirement was met. | Section 3:<br><br>Page 7<br>Second paragraph |
| Information sources | 6 | To identify relevant scientific papers and articles, search multiple databases. Several keyword searches were carried out to find relevant published publications from the most reputable and reliable research resources. Scopus and Web of Science were used, with the Web of Science core collection, Derwent Innovations Index, MEDLINE, KCI-Korean Journal Database, and SCIELO Citation Index.<br>The Search in Scopus, and web of Science databases was conducted on 25th May and 5th June 2022 respectively. | Section 3:<br>First paragraph<br>Page 7 |
| Search strategy | 7 | The keyword “Physics Informed Neural Network” was solely used in each database search for the relevant literature. Predefined inclusion and exclusion criteria and quality requirements were used to refine the data search. Each filter verified that the quality requirement was met, and the next section discusses the inclusion and exclusion criteria.<br><br>Because our search query was put in a double quote, we employed deterministic information retrieval to look for suitable papers, as we described earlier. The literature searches in all the databases listed above retrieved articles from 2019 to 2022. Initially, 530 items were found; however, this was largely made up of a variety of materials, such as research articles, reviews, editorials, and book chapters, among others.<br><br>Many researchers use PINNs to solve problems in different areas of human endeavor. We have limited our research to computational sciences and engineering and focused on research articles, review papers, and book chapters in our literature search. A total of 288 documents were chosen, as illustrated in Figure 2. Articles from computational sciences and engineering were chosen as the following sequence. This included computer science, engineering, mathematics, and physics. Non-English documents were also excluded. The PRISMA checklist can be found in supplementary materials. | Section 3:<br>Page 7<br>Second paragraph<br><br>Section 3:<br>Page 8<br>First and second paragraphs |
| Selection process | 8 | This review looks at final published journal articles, reviews, and conference papers to find the best results and capture an excellent overview of previous data. Abstracts and conclusions were separated to keep the archive to a minimum. In addition, cited references in the evaluated articles were considered. As stated earlier, the two metafile records were combined. The duplicate records were eliminated to improve the findings. Irrelevant data were also excluded. | Section 3.1<br>Page 9<br>First paragraph |
| Data collection | 9 | After selecting the documents, a two-step approach was used to confirm the quality of the analysis performed on the published papers. The relevant metadata were initially imported into Microsoft Excel to conduct a descriptive study of physics-informed neural network literature, which | Section 3.2 |

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| process | | included identification of articles relating to the evolution and improvement of PINNs in computational sciences and engineering, among others. | Page 9<br>Second paragraph |
| Data items | 10 | Content analysis was performed in the second stage to classify and analyze recent research across different disciplines and highlight potential challenges and limitations which could represent opportunities for future research. | Section 3.2<br>Page 9<br>Third paragraph |
| Study risk of bias assessment | 11 | No risk of bias assessment study was conducted as part of this study. | |
| Reporting bias assessment | 12 | No bias assessment study was conducted as part of this study. | |
| Certainty assessment | 13 | The core databases we used for this study are highly regarded worldwide. | |
| **RESULTS** | | | |
| Study selection | 14 | Figure 3: PRISMA flow diagram | Section 3:<br>Page:9 |
| Study characteristics | 15 | Quantitative Study Characteristics<br><br>Table 1: Quantitative Study Characteristics | Section 3.3<br><br>Page:10 |
| Risk of bias in studies | 16 | No risk of bias assessments was conducted as part of this study. | |
| **DISCUSSION** | | | |
| Discussion | 17a | One of the main contributions of our study was finding a solution to the limitations of PINNs as mentioned by some authors. Our study also highlights several issues for future research. To focus on the research question, we evaluated the work of numerous authors who have worked on improving the performance of PINNs and found solutions to many of the limitations previously mentioned by different authors.<br><br>Although PINN architecture is built based on feedforward neural networks, due to the shortcomings of PINNs many authors have tried to extend PINNs by using different approaches, such as conservative PINNs (cPINNs), nonlocal PINNs (nPINNs), etc. In contrast, others have tried to combine it with other neural network techniques, expecting better performance and more precise results. This includes CNNs, RNNs, etc. Consequently, other authors have tried to boost performance by reducing loss to a minimal level. We tried to group newly proposed techniques into three categories: Extended PINNs, Hybrid PINNs, and Minimized Loss techniques. | Section 4.1<br><br>Page: 14<br><br>First and second paragraphs |
| | 17b | We previously pointed out various limitations of PINNs that were highlighted by different authors and later discussed the newly proposed techniques used to solve most of the mentioned problems. We have also outlined the limitations of the newly proposed PINN methods. The focus of our future research will be more on the limitations of the newly proposed techniques. Since they have addressed most of the PINN limitations, the limitations of some selected articles are discussed because of their significance | Section 5<br>Page: 17<br>First paragraph |
| **OTHER INFORMATION** | | | |

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| Registration and protocol | 18 | This review has not been registered with any pre-defined protocol. | |
| Support | 19 | This work is funded by Universiti Brunei Darussalam, Brunei under Grant ref: UBD/RSCH/1.11/FICBF(b)/2020/004. | 19 |
| Competing interests | 20 | The authors declare no conflict of interests. | 19 |
| Availability of data, code and other materials | 21 | The data collected for this study are extracted, and downloaded from Scopus and Web of Science websites. | 19 |

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