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Intracranial pressure analysis software: A mapping study and proposal

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ABSTRACT

Introduction Intracranial pressure (ICP) monitoring and analysis are techniques that are, each year, applied to millions of patients with pathologies with million of patients annually. The detection of the so called A and B-waves, and the analysis of subtle changes in C-waves, which are present in ICP waveform, may indicate decreased intracranial compliance, and may improve the clinical outcome. Despite the advances in the field of computerized data analysis, the visual screening of ICP continues to be the means principally employed to detect these waves. To the best of our knowledge, no review study has addressed automated ICP analysis in sufficient detail and a need to research the state of the art of ICP analysis has, therefore, been identified.

Methodology This paper presents a systematic mapping study to provide answers to 7 research questions: publication time, venue and source trends, medical tasks undertaken, research methods used, computational systems developed, validation methodology, tools and systems employed for evaluation and research problems identified. An ICP software prototype is presented and evaluated as a consequence of the results.

Results A total of 23 papers, published between 1990 and 2020, were selected from 6 online databases. After analyzing these papers, the following information was obtained: diagnosis and monitoring medical tasks were addressed to the same extent, and the main research method used was evaluation research. Several computational systems were identified in the papers, the main one being image classification, while the main analysis objective was single pulse analysis. Correlation with expert analysis was the most frequent validation method, and few of the papers stated the use of a published dataset. Few authors referred to the tools used to build or evaluate the proposed solutions. The most frequent research problem was the need for new analysis methods. These results have inspired us to propose a software prototype with which provide an automated solution that integrates ICP analysis and monitoring techniques.

Conclusions The papers in this study were selected and classified with regard to ICP automated analysis methods. Several research gaps were identified, which the authors of this study have employed as a based on which to recommend future work. Furthermore, this study has identified the need for an empirical comparison between methods, which will require the use and development of certain standard metrics. An in-depth analysis conducted by means of systematic literature review is also required. The software prototype evaluation provided positive results, showing that the prototype may be a reliable system for A-wave detection.

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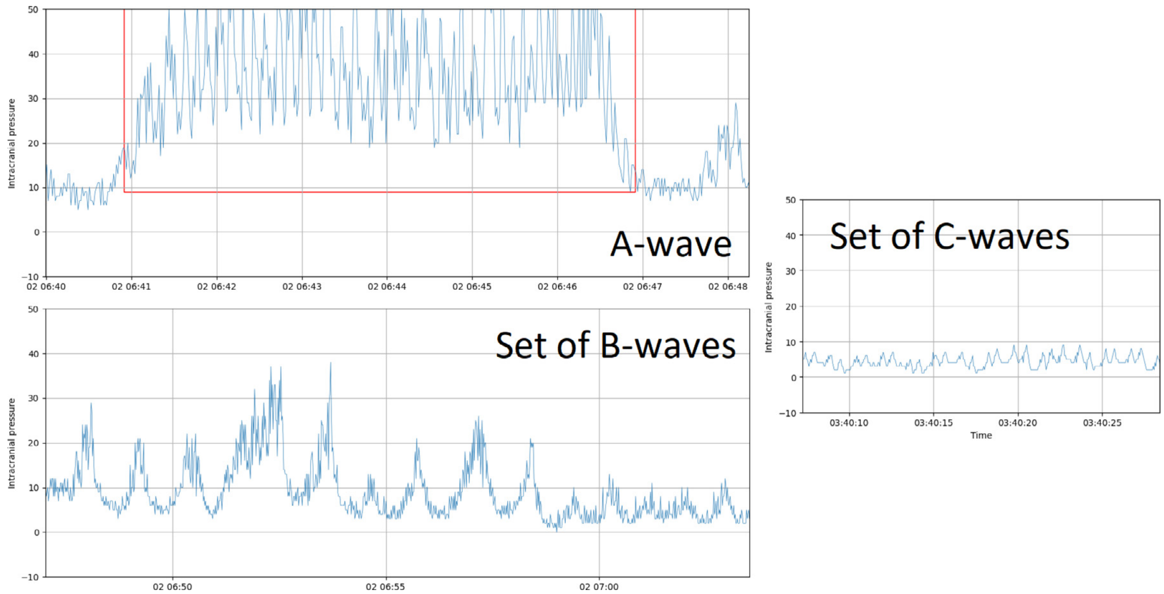

Fig. 1. Example of intracranial pressure waves. Horizontal axis: time. Vertical axis: ICP measured in mmHg.

1. Introduction

Intracranial pressure (ICP) monitoring is a diagnosis technique that is used in the treatment of several neural diseases, such as traumatic brain injury (TBI), subarachnoid hemorrhage, and hydrocephalus [1]. Traumatic brain injuries affect more than 2 million people annually in the United States alone, and this number continues to increase [2]. Recent studies associated favorable outcomes and a significant decrease in mortality after intracranial pressure monitoring has been carried out on intracerebral hemorrage patients [3,4] and traumatic brain injury patients. Moreover, traumatic brain injury is a pathology with a mortality rate of 35% and unfavorable outcomes of 70% [5,6].

Intracranial pressure is the consequence of the interaction between the brain, cerebrospinal fluid (CSF) and cerebral blood. ICP varies according to the patient's position (standing vs. decubitus) and oscillates with systemic blood pressure and respiration. Maneuvers that increase intrathoracic or intra-abdominal pressure, such as coughing, crying, or defecation, increase the pressure of the jugular veins and/or the epidural venous plexus [7]. A rise in this pressure may impede blood flow and produce other disorders [8].

In non-pathological conditions, the factors that control ICP are the following:

1. The volume of CSF production.
2. The resistance of the system to CSF reabsorption.
3. The venous pressure of the intracranial space, represented by the pressure in the superior longitudinal sinus.

According to the Monro-Kellie doctrine, the central nervous system can be divided into three mainly incompressible liquids: blood, parenchyma and cerebrospinal fluid. The total volume of the skull and lumbar sac remains constant over a period of time longer than a cardiac cycle, when given the case, if one of the liquids presents an increment in its volume, it is compensated with the decrease of another [9].

When the intracranial pressure is measured we can, in addition to the absolute value, observe its morphology and see how changes in it can alert us to the failure of self-regulation [10,11]. Known morphologies occur in intracranial pressure waveform, A-waves, B-waves, and C-waves, which are also known as Lundberg waves (Fig. 1), as they were first defined by Nils Lundberg in 1960 [12]:

- A-waves, which Lundberg also denominated as “plateau waves”, present a substantial steep up-slope increase in intracranial pressure values for at least 5 minutes, followed by a steep down-slope decrease to almost normal levels [13–15]. They are usually accompanied by clinical signs of distress on examination.
- B-waves, also known as “slow waves”, which occur between 0.5 and 2 times per minute, are repeated elements, with less increment in intracranial pressure when compared with plateau waves [16]. They can progress to A-waves and are related to variations in physiological or pathological cerebral blood flow.
- C-waves, occur with maximum amplitude of 20 mmHg and a frequency of 4–8 per minute [17,18]. These waves have been documented in healthy individuals and are thought to occur because of interaction between cardiac and respiratory cycles [19].

Fig. 1 shows an example of each one of the Lundberg wave types. Intracranial pressure is measured in millimeters of mercury (mmHg). As each type of wave occurs in a different time range, the time axis is different for each wave example. For instance, A-waves and B-waves can be seen in a 10 minute range, while C-waves can be seen in a 20 second range.

Several imprints can be distinguished through the inspection of an isolated intracranial pressure wave [10]:

- Cardiac waves: originated by the transmission of the beat of the cerebral vessels with a morphology similar to the arterial pulse wave and three imprints: P1 (percussion wave), P2 (Tidal wave) and P3 (dicrot wave). Also known as “single pulses”.
- Respiratory waves: these confer the sinusoidal pattern to the recording.

The detection of A-waves and B-waves, and the analysis of subtle changes in single pulses, may indicate decreased intracranial compliance [20,21]. Despite the advances in the field of computerized data analysis, the visual screening of intracranial pressure wave-forms continues to be the means principally employed to detect slow waves [22]. This method is very inaccurate and may lead to contradictory conclusions [23], signifying that it is necessary to develop ICP monitoring to a greater extent. Furthermore, according to our clinical experience in visual analysis, the results are not only inaccurate but also expensive to obtain. Highly qualified professionals have to dedicate a significant amount of time to the aforementioned method. These practitioners currently perform data extraction by means of overnight monitoring, and the monitoring process is often maintained for more than one day. The results are long waveforms whose visual analysis can take more than 4 hours per patient and data extraction session.

After a thorough search, no systematic reviews or mapping studies addressing this issue were found, signifying that there is a need to study the research background of automated intracranial pressure analysis, and to review the proposed solutions so as to describe the actual trends in the field and identify possible research problems and gaps. Furthermore, this need has been stated recently [1]. This paper, therefore, undertakes a mapping study in order to address this need and propose a preliminary software solution that will deal with the automated analysis of the data monitored.

Thus, this work provides, as main contributions: i) a mapping study that describes the findings of all relevant individual studies in the field of automated intracranial pressure analysis, thus, making the available evidence more accessible to researchers and health-care professionals, and identifies the main gaps and future lines of research of interest in this field; ii) a software prototype that fulfills some of the problems detected in the mapping study, by integrating ICP analysis and monitoring techniques.

2. Methodology

The research method undertaken in this paper is a systematic mapping study. A systematic mapping study makes it possible to extract an overview from a research field, and classify the information regarding the topic selected. It shares some commonalities with a systematic literature review, but differs as regards the main purpose, which is that of extracting a structure from a research field, and not that of synthesizing evidence, as occurs in systematic literature reviews. The systematic mapping study guidelines proposed by Petersen et al. [24] were followed in this paper. These guidelines were complemented with the systematic literature review guidelines proposed by Kitchenham and Charters [25], which are also recommended by Petersen et al. [24]. Table 12 and Table 13 show the mapping study tasks undertaken, along with the quality evaluation checklist employed during the review conduction process.

2.1. Research questions

The proposed research questions and the motivation for each of them are presented in Table 1.

Table 2
Databases and number of results per search.

Database	Link	Res.
ACM Digital library	https://dl.acm.org/	0
IEEE Xplore	https://ieeexplore.ieee.org/	33
PubMed	https://pubmed.ncbi.nlm.nih.gov/	70
ScienceDirect	https://www.sciencedirect.com/	54
Wiley	https://onlinelibrary.wiley.com/	1
Springer	https://link.springer.com/	235

2.2. Search strategy

The search was carried out by conducting an automated database search as the main method and snowballing as the secondary method. The database search was defined in 4 stages: (1) Selection of the search databases, (2) definition of the search string, (3) definition of the selection criteria and (4) search and selection. Each stage is described in the following sections. Finally, the snowballing method was used to complete the search.

2.2.1. Selection of the search databases

The search was carried out in 6 different databases: IEEE Xplore, ACM Digital Library, PubMed, ScienceDirect, SpringerLink and Wiley Online Library. PubMed was recommended to the authors of this study by researchers with experience in the field, and Petersen et al. [24] recommend the use of at least 4 search databases including IEEE Xplore and ACM Digital Library.

2.2.2. Search strings and databases

The search was carried out in March, 2020. The main source of papers for the review was an automated search, complemented with snowballing technique [26]. The databases and results found are presented in Table 2. The keywords for the search strings were established employing PICO(C) (Population, Intervention, Comparison, Outcomes, Context) [27], expert consultation, studies known by the authors, the IEEE taxonomy [28] and a thesaurus. The search string was tested iteratively in order to improve its precision, and was reviewed so as to enable between all the authors of this study to reach an agreement. The following search string was adapted for each digital database: (“intracranial pressure’)’ AND (“analy*” OR “diagnos*” OR “detection”) AND (“software” OR “program*” OR “computer*”) AND (“wave*”). The majority of the results obtained were published at medical venues, as can be seen in Table 4, which is why computer science domain venues produced fewer results.

2.2.3. Selection criteria

The selection process was carried out according to the following criteria:

Table 1
Research questions and motivations.

ID	Research question	Motivation
RQ1	In which years, venues and sources have the selected papers been published?	To identify time tendencies and the different venues and sources (journals, conferences...)
RQ2	What medical tasks are being addressed in the selected papers?	Identification of the medical tasks used or defined in the context of intracranial pressure.
RQ3	Which research methods were used in the selected papers?	To determine the frequency of research strategies and types of empirical studies adopted for evaluation.
RQ4	What type of computational systems have been developed for pressure wave analysis?	To identify the systems presented in literature for automated or assisted intracranial pressure analysis.
RQ5	What datasets, validation methods and metrics are used most frequently used to evaluate the intracranial pressure wave analysis methods and techniques?	To contrast the evaluation data sources used in the different methods.
RQ6	Which tools are used to build and evaluate intracranial pressure wave analysis systems?	Exhaustive study of analysis system development, to identify potential tools assisting in ICP analysis.
RQ7	Which research problems have been identified?	To identify research gaps and main research fields.

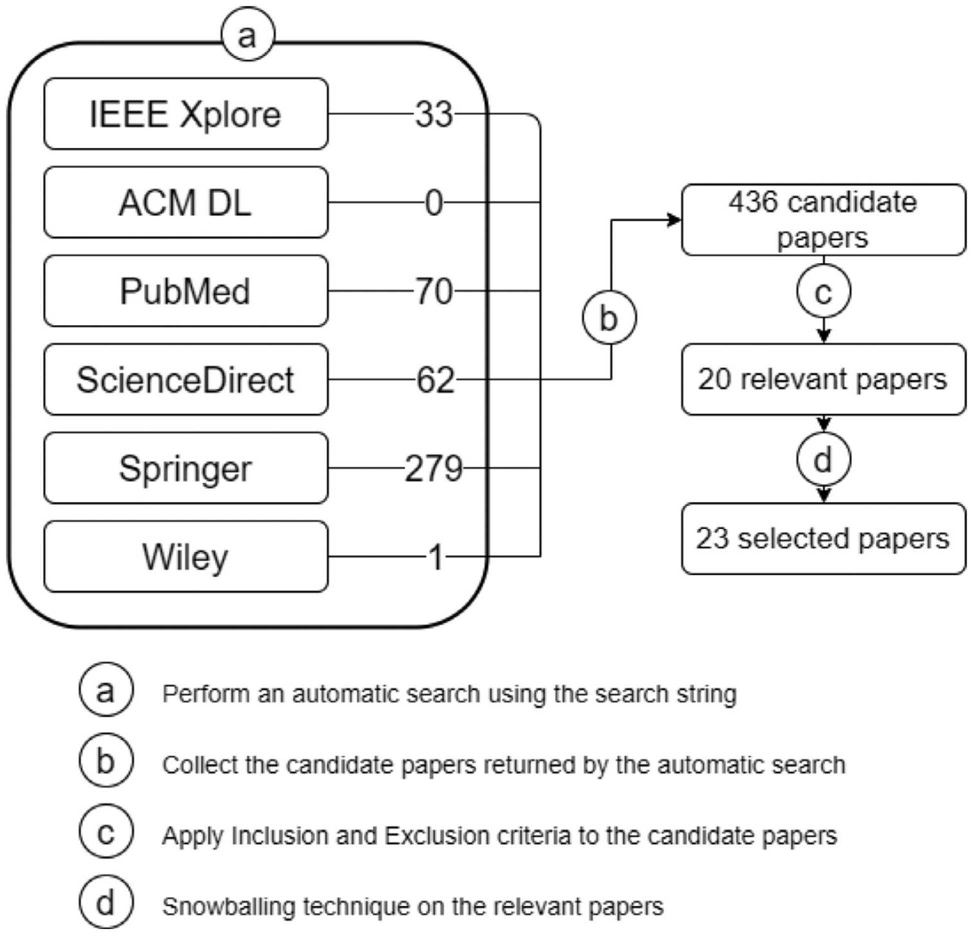

Fig. 2. Search process.

- Inclusion criteria
  - IC1: Papers which mainly focus on the study of intracranial pressure.
  - IC2: Papers that present a formal analysis method for intracranial pressure.
  - IC3: Papers that focus on intracranial pressure waves detection or computer-aided diagnosis.
  - IC4: Papers that present and detail their objectives and research methodology.
- Exclusion criteria
  - EC1: Papers not available in English.
  - EC2: Non peer-reviewed papers.
  - EC3: Gray literature.
  - EC4: Duplicates from other studies.

A paper had to satisfy all the inclusion criteria and none of the exclusion criteria for it to be selected. Both the inclusion and exclusion criteria were discussed by all the authors of this study in order to reach an agreement.

2.2.4. Search conduction and selection

Once all the elements described in the previous sections had been defined and established, the search and selection process was carried out by a single researcher. In those cases in which doubts or different interpretations arose, the other researchers were consulted. For the selection process, the title, abstract and keywords were examined, including a full text examination when necessary. The studies identified in each stage of the selection are shown in Fig. 2. A set of 436 candidate papers were returned by the 6 digital libraries using the search string presented in Section 2.2.2. The authors of this study aimed to identify any papers regarding automated intracranial pressure analysis, reflected in the search string. Duplicate papers were discarded and the results were filtered by the researcher in charge of the selection process, according to the selection criteria. This led to 20 relevant papers. After the selection of a relevant set of papers, snowballing was applied in order to obtain any potentially relevant papers that could have been missed by the automatic search. Briefly, the snowballing technique consists of the review of papers that are cited by a selected paper or papers that cite a selected paper. A total of 3 new papers were then added. This led to the attainment of the final number of 23 selected papers, which were used to address the 7 RQs of this study. The list of selected papers, and the research questions they address can be seen in Table 11, and the complete list of candidate papers, with the reason why they were selected or not, is available on the following link: Selection process.

2.3. Data extraction

The information concerning the research questions was extracted by following the data form created for this purpose. Table 3 presents the form filled out by the researcher in charge of the data extraction in order to accomplish this task. MS Excel was used for this purpose. The extraction form includes topic independent classification (RQ1-RQ3, RQ7), and topic dependent classification (RQ4-RQ6), according to the guidelines proposed by Petersen et al. [24]. Not all the selected papers addressed the seven research questions. The research questions addressed in each of the papers were properly registered.

Table 3
Data extraction form. *Machine learning is a sub-field of computer science which develops algorithms with the capacity of "learning" from the data.

Study identifier
Paper title
RQ1: In which years, venues and sources have the selected papers been published?
Publication Year.
Publication Venue [24]: Journal, Conference, Book, Magazine.
Source Name.
RQ2: What medical tasks are being addressed in the selected papers?
Medical task tackled [29]:
- Screening, whose objective is identify an unrecognized disease before the appearance of its signs and symptoms.
- Diagnosis procedure, which is the attempt to identify the nature of a disease.
- Treatments, all the activities that are carried out to remedy the health problem after the disease has been detected.
- Prognosis, which consists of predicting current disease outcomes in terms of morbidity and mortality and the patient's chances of recovery.
- Monitoring, which, in the medical domain, is identified as the observation of a disease and the patient's conditions over time.
- Management, whose objective is the promotion of health and medical services.

RQ3: Which research methods were used in the selected papers?
Research Type [30]:
- Evaluation: paper empirically evaluating a given analysis method.
- Validation: paper investigating an analysis approach in practice, i.e., in a hospital or healthcare unit.
- Solution: paper proposing a new ICP analysis method.
- Philosophical: paper providing a new way in which to build and apply analysis methods.
- Experience report: paper reporting a personnel experience related to the construction or application of analysis methods for ICP.
- Opinion paper: paper that contains the author's opinion of ICP analysis methods.

RQ4: What type of computational systems have been developed for pressure wave analysis?
- Name of the technique of the data analysis undertaken.
- Analysis objective (A-waves, B-waves or single pulses).
- Use of machine learning* (yes, no).

RQ5: Which datasets, validation methods, and metrics are most frequently used to evaluate intracranial pressure wave analysis methods and techniques?
Evaluation methods: Bootstrapping cross-validation, correlation between different methods, correlation with expert analysis, cross-validation, others.
Metrics: Precision, sensitivity, P-value, others.
RQ6: Which tools are used to build and evaluate intracranial pressure wave analysis systems?
Programming language/software framework name.
Developing or testing system.
RQ7: Which research problems have been identified?
Further work lines:
- New analysis methods.
- ICP wave parameters research.
- Empirical validation of existing methods.
- Theoretical research.
- Others.

2.4. Synthesis

The goal of data synthesis is to summarize and categorize the extracted data related to each RQ. The results were reported using charts to facilitate visualization, accompanied by a narrative synthesis, and were then discussed with regard to the research questions. All the data charts were generated using R.

3. Results

3.1. RQ1: In which years, venues and sources have the selected papers been published?

The purpose of this research question is to trace and detail the publication trends over time, and to identify the most frequent venue types and sources. Fig. 3 presents the number of selected papers divided by venue type from 1990 to 2020. The time range was established as being between the year of the oldest selected paper (1990) and early 2020, when this research was conducted. The graph shows very few publications until 2008, with a total of 6 publications before 2008, and a slight increase in the number of publications until 2020, with a total of 17 publications after 2007.

The selected papers were published in the following venue types: 74% (17 papers) of the selected papers were published in journals, 17% (4 papers) were published in conferences, 4% (1 paper) were published as chapters in books, and 4% (1 paper) were published in magazines.

The sources of the selected papers are shown in Table 4. As will be noted, the selected papers have very few trends regarding the

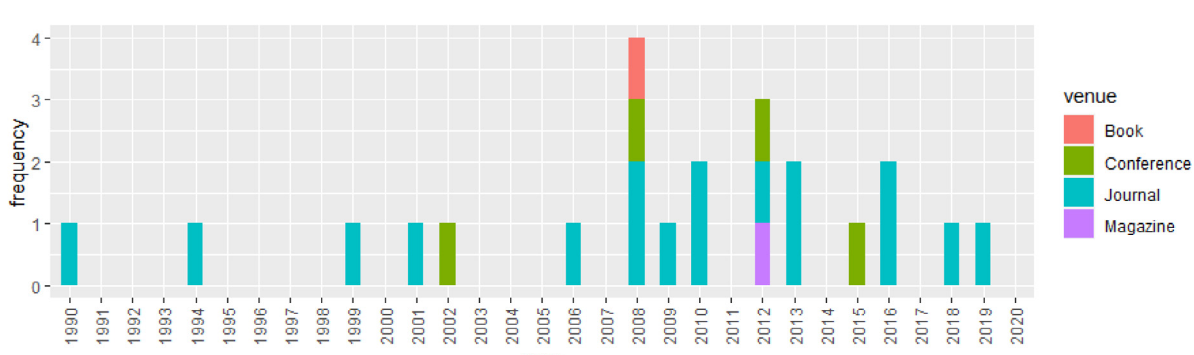

Fig. 3. Years and venues of the selected papers.

Table 4
Sources of the selected papers.

Venue name	# pap.	Papers
Acta neurochirurgica	1	[31]
Acta neurochirurgica, supplement	2	[21,32]
Annual International Conference of the IEEE Engineering in Medicine and Biology Society	2	[33,34]
Artificial Intelligence in Medicine	1	[35]
Biomedical Engineering Online	1	[36]
Computer methods and programs in biomedicine	1	[18]
IEEE Pulse	1	[37]
IEEE Transactions on Biomedical Engineering	4	[38–41]
International Winter Conference on Brain-Computer Interface	1	[42]
Journal of Neourosurgery	1	[22]
Journal of Neuroscience Methods	1	[23]
Journal of the Neurological Sciences	1	[43]
Lecture Notes in Computer Science	1	[44]
Medical Engineering and Physics	2	[45,46]
Medical Informatics	1	[47]
Physiological Measurement	2	[48,49]

Table 5
Selected papers by medical task.

Medical task	# pap.	Papers
Diagnosis	17	[18,21–23,31,33,34,36,39,40,42–44,46–49]
Monitoring	6	[32,35,37,38,41,45]

Table 6
Selected papers by research method.

Research method	# pap.	Papers
Evaluation research	21	[18,21–23,31,33–42,44–49]
Solution proposal	2	[32,43]

publication source, which are “IEEE Transactions on Biomedical Engineering” with 17% (4 papers) of the total papers, and “Acta neurochirurgica, supplement”, “Annual International Conference of the IEEE Engineering in Medicine and Biology Society”, “Medical Engineering and Physics”, and “Physiological Measurement” with 9% (2 papers) of the total papers each.

Upon considering the information regarding the publications per year extracted (Fig. 3), it is evident that intracranial pressure waveform analysis has gained attention since 2008. The usefulness of intracranial pressure analysis methods had still not been proven in the years before 2000, and the field required further development [50]. This along with technical issues such as computational capacity, has led to an increase in the research interest in automated intracranial pressure analysis.

3.2. RQ2: What medical tasks are being addressed in the selected papers?

The purpose of this question is to identify the medical tasks addressed by the authors in the selected papers, using the classification proposed by Esfandiari et al. [29]. As presented in Table 5, the selected papers addressed diagnosis and monitoring as medical tasks, with 52% (12 papers) addressing medical diagnosis, and 48% (11 papers) addressing medical monitoring. As stated by Scalzo et al., intracranial pressure single pulse peak detection methods can be classified as on-line methods if they are designed to work in a real-time execution environment, or off-line methods if they are designed to work after all of the ICP data has been acquired [36]. In order to establish decision rules for the medical task classification, the selected papers were labeled as on-line or off-line, after which each paper labeled as an on-line method was included as a monitoring method, and each paper labeled as an off-line method was included as a diagnosis method. One of the off-line method studies [34] stated that its algorithm was implementable as an on-line method.

While on-line analysis is preferable in terms of pathology detection, it also has higher efficiency requirements as it has to work in real-time. Off-line analysis provides better options for in-depth analysis. The oldest papers selected, therefore, presented diagnosis (off-line) analysis, while the trend over time has moved toward monitoring (on-line) analysis, which is more interesting for researchers.

Although non-invasive techniques have continued to be published over the last few years, invasive intracranial pressure measurement is still the most frequently employed used technique [51] and is especially useful if cerebrospinal fluid drainage is required, which is usually the case. While invasive intracranial pressure measurement is the most precise technique [1], it also leads to a risk of infection and requires surgery. It was for this reason that the only medical tasks addressed in the selected papers were diagnosis, which is the process of recognizing a disease, and monitoring, which is the observation of a disease, a condition, or medical parameters over time. In this context, both diagnosis and monitoring are carried out when a disease is suspected.

3.3. RQ3: Which research methods were used in the selected papers?

This research question was posed in order to categorize the selected papers within the main research methods proposed by Wieringa et al. [30]. As will be seen in Table 6, the research method categories found in the selected papers were Evaluation Research, 91% (21), and Solution Proposal, 9% (2). The categorization of the papers investigated followed the rules proposed by Petersen et al. [24], and, as stated in the aforementioned rules, the main difference between Evaluation Research and Solution Proposal is the presence of empirical evaluation, which should be present in Evaluation Research, and is not present in Solution Proposals.

Most papers have been included in the “Evaluation Research” category, as they propose and evaluate a solution to a research problem. Only papers including solution proposals have been included, as the selection criteria focus on system proposals.

3.4. RQ4: What type of computational systems have been developed for pressure wave analysis?

This question has been addressed from the perspective of the objective of the analysis, the methodology, and the presence of machine learning techniques in the proposals. The selected papers have been mapped onto different categories related to each perspective.

With regard to the analysis objective, 74% of the selected papers (17) analyzed intracranial pressure single pulses, including subpeak

Table 7
Methodology used in the selected papers.

Paper	Preprocessing methods	Segmentation methods	Feature extraction methods	Feature classification methods
[47]	Fast Fourier Transformation, Low pass filter, Sampling, Window function			
[18]	Fast Fourier Transformation, Sampling, Temporal window			
[43]			Tailor-made methods	
[22]	Sampling		Tailor-made methods	
[32]	Direct spectral estimation			
[45]	Low pass filter		Quadratic polynomial, Time window	
[33]	Fast Fourier Transformation, High Pass Elliptical Filter, Autoregressive Model, Band Pass Filter	Tailor-made methods	Tailor-made methods	
[44]		Second derivative	ECG QRS detection, Tailor-made methods, Hierarchical clustering, Kernel Density Estimation, Second derivative, (MOCAIP)	Classification model, KD-Tree Nearest Neighbour classifer, Support Vector Machine, Extremely Randomized Decision Trees
[46]	Discrete Fourier Transform, Fast Fourier Transformation, Best fitting sinusoid			
[48]	Band pass filter, Low pass filter	Tailor-made methods		
[38]		Tailor-made methods	Hierarchical clustering, ECG QRS detection, Tailor-made methods, Second derivative	
[36]	Gaussian smoothing filter	Tailor-made methods	Hierarchical clustering, Tailor-made methods, ECG QRS detection, Second derivative, Gaussian Model, Gaussian mixture models, Kernel spectral regression, (MOCAIP)	
[23]			(MOCAIP)	Simple regularized linear quadratic classifier, ANOVA analysis, Differential evolution
[34]	Median filter, Low pass filter, Temporal window		Tailor-made methods	Tailor-made methods
[37]		Tailor-made methods	Dynamic Markov model, Gaussian model, Kernel density estimation, nonparametric belief propagation	
[35]			ECG QRS detection, Hierarchical clustering, Second derivative, Hidden Markov model, Bayesian model, nonparametric bayesian method, Pairwise Markov random field, Dynamic Markov model, (MOCAIP), Kernel density estimation, Nonparametric belief propagation	
[40]	Principal component analysis, Power spectral density, FIR low pass filter, Smoothing filter	Tailor-made methods	Tailor-made methods	
[39]			(MOCAIP), Supervised dimensionality reduction algorithm, Spectral regression discriminant analysis, Support vector machine, Kernel spectral regression	
[42]	Low pass filter	Tailor-made methods	Tailor-made methods	
[31]	Tailor-made methods			Artificial neural network
[41]	Low pass filter	Tailor-made methods	Tailor-made methods, Clustering	
[21]			Tailor-made methods	
[49]			(MOCAIP), Hierarchical clustering, Tailor-made methods, Logistic regression model	

analysis; 26% of the selected papers (6) analyzed intracranial pressure B-waves, and 4% of the selected papers (1) analyzed A-waves. One paper [18] analyzed both A-waves and B-waves.

From the methodological perspective, Table 7 shows the methods identified in the selected papers, according to the four general schemes for a computer-aided diagnosis system [52]. Preprocessing methods can have a severe impact on execution time, thus, on-line methods tend to have a light preprocessing step, which is empty in some cases. The majority of the papers selected focus on feature extraction, in order to provide information about ICP waves, with no feature classification step. MOCAIP, a system presented in one of the selected papers [38], has been extended and reused in other papers, and has been included among feature extraction methods. The "Tailor-made methods" category includes all the methodologies used which were specifically designed and implemented for the system that the article is proposing. Each tailor-made method is based on ICP morphology values, therefore, they could also be addressed as "morphology-based algorithms", or as part of said algorithms.

Fig. 4 presents the trend as regards the use of machine learning techniques related to the year of publication.

Several analysis methods regarding A-waves, B-waves and single pulses were found. There is a clear lack of A-wave analysis methods (1 out of 23 papers) and a slight lack of B-wave analysis methods (6 out of 23 papers), while the main focus of the selected papers has been single pulse analysis (17 out of 23).

A-waves always indicate a pathology, and it is very likely that the patient will suffer neurological deterioration [53]. Nonetheless, only 1 paper, published in 1994, addressed this problem.

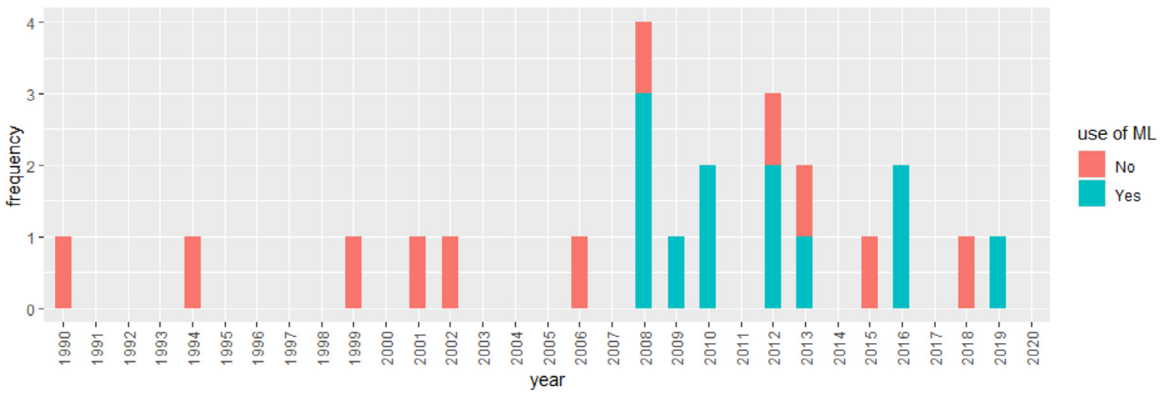

Fig. 4. Machine learning use over the years in the selected papers.

Table 8
Selected papers by validation method.

Validation method	# pap.	Papers
Correlation with expert analysis	10	[21,31,33,38–42,48,49]
Correlation with visual analysis	3	[22,34,45]
Correlation between two different methods	2	[35,46]
Five-fold cross-validation	2	[36,37]
Bootstrapping cross-validation procedure	1	[23]
Subwindow classification accuracy and peak position accuracy	1	[44]
Not provided	4	[18,32,43,47]

B-waves can indicate the presence of several intracranial homeostasis abnormalities, but these may also be present in normal intracranial pressure [53]. Furthermore, there is an agreement that B-waves are an indicative of reduced intracranial compliance [16], and their detection could, therefore, prove useful. However, only 2 of the selected papers addressed this subject between 2006 and 2019.

With regard to pulse present in intracranial pressure, the interest in its analysis has grown to be the principal research objective in this field. These waves are related to heart rate and are, therefore, always present in the intracranial pressure waveform. Moreover, single pulse analysis, and particularly pulse sub-peak configuration, is a potentially relevant indicator of reduced intracranial compliance [54]. These two factors may have led researchers to focus on single pulse morphology analysis.

The analysis techniques identified in this study have a clear trend of rising complexity, from techniques such as the Fast Fourier Transformation, low pass filtering or sampling, to more complex ones such as clustering or regression models. Machine learning techniques have also become common since 2008, as seen in Fig. 4.

Some signal processing on-line systems have not been included in the study, as they do not comply with inclusion criteria IC3 (they do not focus on intracranial pressure wave detection or computer-aided diagnosis). However, they are relevant regarding ICP analysis and should be mentioned. These are: ICM+ [55], a user configurable signal processing engine that allows real-time trending of complex parameters derived from signals from bedside monitoring devices, CNS Monitor [56] and BedMasterEx [57], both online signal monitoring systems.

3.5. RQ5: Which datasets, validation methods, and metrics are more frequently used to evaluate intracranial pressure wave analysis methods and techniques?

This question focuses on the validation trends related to automated intracranial pressure analysis. Table 8 shows the validation methods identified as regards the trends related to the validation strategies in the selected papers.

Only one paper [33] reported using a public dataset. The remaining selected papers reported using data extracted from clinical patients.

A total of 96% (22) of the selected papers used empirical validation as a validation method, and 4% (1) of the selected papers did not present any validation method. In this context, empirical validation is the natural solution, as: (1) the analysis system described in each paper is meant to help practitioners, who are supposed to use the system in a context very similar to that of empirical validation, (2) in most cases, real data was used to develop the solution proposed, and that real data can also be used to validate it (by separating development data from validation data), and (3) some of the authors are also medical practitioners and/or have direct access to intracranial pressure monitoring data. This last factor (3) may also explain why most of the selected papers (22 out of 23) did not present a particular dataset, but rather data collected from clinical patients. Only one paper [33] stated the use of an online public dataset. While this might also be a consequence of (3), the lack of published datasets should not be ignored.

In relation to the validation methods, the authors presented several validation methods, as shown in Table 8. The principal method used was correlation with expert analysis (10 out of 23), plus correlation with visual analysis (3 out of 23), which is, in practice, the same method, but is not explicitly undertaken by an expert.

3.6. RQ6: Which tools are used to build and evaluate intracranial pressure wave analysis systems?

This question was proposed in order to present trends in the intracranial pressure analysis system frameworks. Only 3 papers [18,41,47] presented the computer system used to evaluate the analysis system proposed, and very little information about these systems was provided. With regard to the programming languages used for implementation, these were reported in only one paper [18], in which the algorithm was written in Quickbasic.

There is a clear lack of technical information in the selected papers regarding software development. Automated intracranial pressure analysis combines the research fields of computer science and

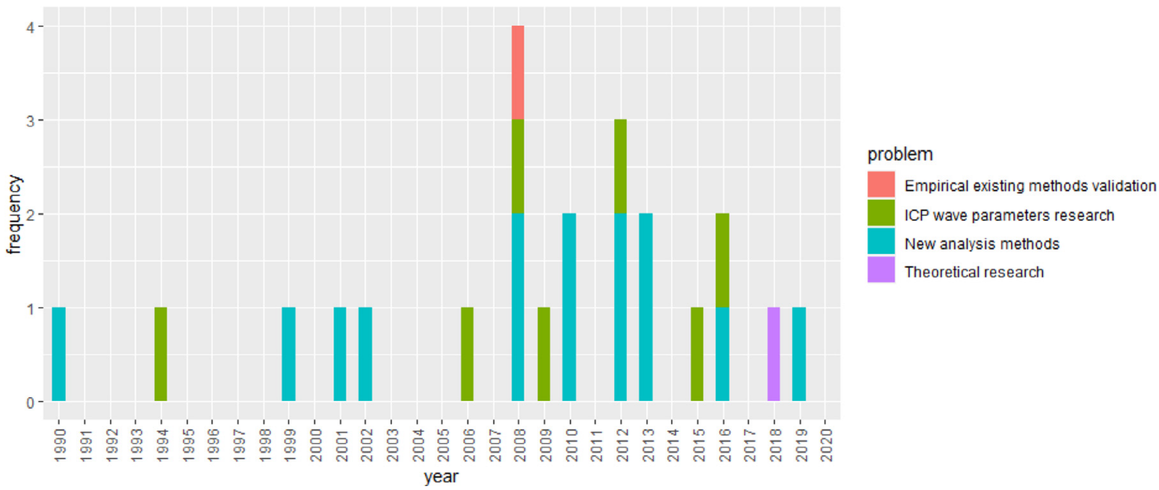

Fig. 5. Problems identified by the selected papers.

neurology. However, the papers show far more details about neurology than computer science. Some examples of this are Glasgow Outcome Score [41], neuromonitors [34], and ICP sensors [45]. All of them have to do with the neurology perspective of the methodology. These topics are relevant in the context of the methodology presented in those papers, but they do not address the systems used to build or evaluate the analysis systems proposed.

3.7. RQ7: Which research problems have been identified?

This question tackles research problem trends. Moreover, the most and the least frequently problems addressed, and some research gaps are identified. Fig. 5 shows the main research problems identified by the selected papers. The majority of the selected papers (61%, 14 out of 23) addressed the need for new analysis methods, followed by the need for research into intracranial pressure parameters (30%, 7 out of 23). The need for the validation of existing empirical methods and theoretical research related to intracranial pressure was also identified (4%, 1 out of 23 each one). The results show an increase in the interest in new analysis methods and pressure wave parameters research that is below the previously mentioned 2008 threshold.

Analysis capability improvements make it possible to evaluate new metrics. Moreover, their capacity to extract useful information for the patients' medical outcomes can be validated. This has been stated by some of the selected papers that address intracranial pressure parameter research [31,38,48]. New analysis methods are appearing as a result of the increasingly complex techniques used, thus making it possible to perform more in-depth studies.

Only one selected paper addressed the need to validate the existing methods. A research gap was, therefore, detected, given the increasing number of new analysis methods. The empirical validations presented in most of the selected papers cannot be easily related to each other, as no standard metrics for validation have been proposed. Since new analysis methods continue to be developed, and their complexity continues increasing, the definition and homogenization of adequate metrics for comparison are necessary.

4. Intracranial pressure wave analyzer prototype

4.1. Motivation

The mapping study conducted in this paper identified several methods for intracranial pressure analysis systems. Only one of these papers [18] addressed A-wave identification, signifying that the research on A-wave automatic identification has not, to the best of our knowledge, been developed in any great depth. Furthermore, the last and only paper that addressed this problem was published in 1994, at which time the technological context was much more limited than it is currently. This solution, therefore, further develops a research field that has undergone very little development, and provides a new approach that takes better advantage of the computing power now available.

These results have enabled us to propose a software prototype (Fig. 6) with which to illustrate an automated solution that integrates ICP analysis and monitored data. The purpose of this software is to act as a first step in the task of integrating the analysis and monitoring of intracranial pressure techniques into a complete solution. The prototype enables data visualization, and helps the user detect A-waves with specific graphic suggestions, provided in a visual representation of the ICP waveform. This prototype would, according to the computer-aided biomedical system classification, be classified as computer-aided detection (CAD detection) [58,59].

4.2. Development

Algorithm 1 has been implemented as a simple solution to the A-wave identification problem. This algorithm has been developed to work when the ICP readings are completed. However, as can be seen in the pseudo-code presented below, it is highly compatible with on-line analysis.

The prototype was developed using Python and by employing the Kivy graphical library. The system used to build and evaluate the prototype was a Personal Computer (CPU: Intel Core i7-7700K, RAM: 16GB, SO: Windows 10x64, GPU: AMD RX 5700 XT, SSD: 500GB).

4.3. Evaluation

The prototype was tested by employing the following process: 1) The patients' ICP was measured through the use of *ICP Express* registered by *Codman*, which registers one ICP value every 0.025 seconds; 2) the signal was digitalized using a connected instrument called *Power Lab*, registered by *AD Instruments*; 3) the file, in proprietary format, was opened in *Lab Chart* by employing *AD Instruments*, from which it was exported to a plain text format, and finally 4) the file was imported to the software prototype, which directly provided the analysis results.

The dataset used in the process of developing the prototype is composed of 6 ICP registers appertaining to 6 different patients whose ICP was measured from 3 to 9 complete days. The dataset was then divided into two parts, one of which was used for the

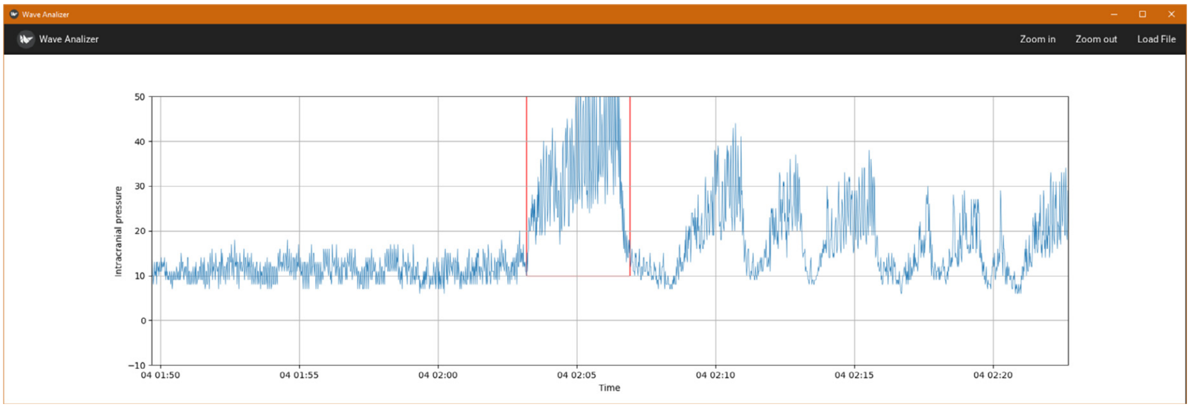

Fig. 6. Prototype graphic user interface developed.

```
INITIALIZE PRESSURE VALUES[NUMBER OF ELEMENTS] TO THE PRESSURE READINGS;
WINDOW SIZE ← MINIMUM A WAVE DURATION / MEASURE FREQUENCY;
INITIALIZE WINDOW[WINDOW SIZE] TO EMPTY BOOLEAN ARRAY;
MIN A WAVE TRUE ELEMENTS ← WINDOW SIZE * (1 - TOLERANCE);
CONDITION COUNTER ← 0;
i ← 0;
while i < window size do
    window[i] ← pressure values ≥ MINIMUM A WAVE PRESSURE VALUE;
    if window[i] then
        condition counter ← condition counter + 1;
    end
    i ← i + 1;
end
while i < number of elements do
    old value ← window[i];
    window[i % window size] ← pressure values[i] ≥ MINIMUM A WAVE PRESSURE VALUE;
    if not old value and window[i] then
        condition counter ← condition counter + 1;
    else
        if old value and not window[i] then
            condition counter ← condition counter - 1;
        end
    end
    if detection AND condition counter < min a wave true elements then
        stop detection;
    else
        if no detection AND condition counter ≥ min a wave true elements then
            start detection;
        end
    end
    i ← i + 1;
end
```

Algorithm 1: Core detection algorithm.

development of the prototype (5 registers), and the other of which was used in the testing process (1 register). A total of 91,673,296 ICP registry values were processed.

We evaluate the effectiveness of the proposed solution by comparing the analysis results provided by the prototype with the analysis results provided by the neurosurgeon expert who is collaborating in this study, using the register included in the testing dataset. The expert analysis detected the appearance of 7 different A-waves appearances in the register, which were used to calculate the following evaluation metrics:

Table 9
Confusion matrix. Actual values correspond to the expert analysis carried out, while predicted values correspond to the detections made by the prototype. * The true negatives cell is measured in terms of percentage, as there is an almost infinite number of possible detections, taking into account that time is not a discrete variable.

		Actual values	
		Positive	Negative
Predicted values	Positive	7	0
	Negative	0	100% *

Table 10
Technology Acceptance Model (TAM) questions and scores. All items were measured on a 7-point Likert scale, where 1 = strongly disagree, 2 = moderately disagree, 3 = somewhat disagree, 4 = neutral (neither disagree nor agree), 5 = somewhat agree, 6 = moderately agree, and 7 = strongly agree.

Question	Score
Field independent questions.	
Assuming I have access to the system, I intend to use it.	7
Using the system improves my performance in my job.	6
Using the system enhances my effectiveness in my job.	6
My interaction with the system is clear and understandable.	5
I find the system to be easy to use.	6
My use of the system is voluntary.	7
Usage of the system is relevant in my job.	6
Field dependent questions.	
The system is useful for automatic A-wave detection.	6
The system's precision is sufficiently high to be reliable.	6
Using the system saves time in ICP diagnosis.	7

Table 9 shows the confusion matrix associated with the metrics (precision and recall) extracted:

$$\text{Precision} = \frac{\text{True positives}}{\text{True positives} + \text{False positives}} = \frac{7}{7+0} = 1 = 100\% \quad (1)$$

$$\text{Recall} = \frac{\text{True positives}}{\text{True positives} + \text{False negatives}} = \frac{7}{7+0} = 1 = 100\% \quad (2)$$

True positives correspond to the Positive - Positive cell in Table 9. *False positives* correspond to the Positive predicted value - Negative actual value cell in Table 9. *False negatives* correspond to the Negative predicted value - Positive actual value cell in Table 9.

Table 10 shows the Technology Acceptance Model [60] applied in order to evaluate the usefulness of the prototype. The questions have been divided into two different categories: field independent questions, directly extracted from TAM, and field dependent questions, specifically designed to evaluate the prototype in its own context. The questions were given a score of between 1 (strongly disagree) and 7 (strongly agree) by an expert neurosurgeon after using the prototype.

The lowest score (5 out of 7) in Table 10, corresponding to the question "My interaction with the system is clear and understandable", was explained after a brief interview with the user (the expert neurosurgeon). The user stated that the information related to a detection, which is currently provided only graphically, needs to be provided explicitly in order to support verification of the detection. This functionality is not provided, as the system is in its first version, and had been designed to be a prototype and a proof of concept. However, it is included in the planning for future versions. The metrics extracted and the Technology Acceptance Model developed show that the prototype may be a reliable analysis system for A-wave detection, and a solid first step toward a system that is capable of extracting information regarding any type of wave.

5. Conclusions and further work

In this paper, a systematic mapping study was carried out and a software prototype for automatic intracranial pressure analysis was presented and evaluated. Papers regarding automated intracranial pressure analysis methods have been selected, classified, and analyzed. A set of 23 papers were identified in six digital libraries: ACM Digital Library, IEEE Xplore, PubMed, ScienceDirect, Wiley and Springer. The papers selected were published between 1990 and 2019, and were analyzed by addressing 7 research questions. The main findings of this study are:

- **RQ1:** Research interest in the field of automated intracranial pressure analysis has undergone an increase over time, and future contributions may be published in several sources, with a slight trend as regards IEEE Transactions on Biomedical Engineering.
- **RQ2:** The most frequent medical task used in the selected papers is diagnosis, followed by monitoring. The latter has become more frequent in recent years.
- **RQ3:** The research methodologies conducted in the selected studies were evaluation research and solution proposals, with evaluation research being the main methodology.
- **RQ4:** All of the papers selected developed a computational system for automated intracranial pressure analysis. The systems have been classified according to their objective, techniques employed, and the use of machine learning. With regard to the objective, the solutions most frequently identified were those concerning single pulse analysis. A and B-wave focused analysis solutions were also identified, although much less frequently. With regard to the techniques employed, the complexity over time has undergone an increase, and several techniques were identified. Most techniques were included as feature extraction methods. The field has experienced a great increase in the use of machine learning techniques over time. Furthermore, since 2008, most papers have included a machine learning technique in the solutions they provide.
- **RQ5:** Very little information was found regarding the datasets used in the selected papers, and the most frequent strategy adopted was that of private local datasets. The principal validation method was correlation with expert analysis.
- **RQ6:** The majority of the selected papers did not report the technical framework used to develop and test the solution proposed.
- **RQ7:** Researchers are most interested in intracranial pressure parameters and analysis methods.

The present study has identified several gaps and future work lines that could be addressed:

- Research into A and B-wave detection systems, as only 7 out of the 23 selected papers were related to that topic.
- The development of multiple wave analysis methods, since the papers selected analyzed only one Lundberg wave type per system.
- The publication and development of public intracranial pressure datasets. Only one selected paper reported the use of a published dataset.
- The development of standard metrics with which to measure new proposals. The definition of standard metrics, together with an in-depth analysis of this field by means of a systematic literature review, would be necessary to enable the correct comparison between existing methods, which is a research gap identified by this study and a future line of work.
- The use of empirical studies to compare the different techniques employed in intracranial pressure analysis.
- The further development of the prototype proposed to integrate different analysis techniques and scopes.
- Continuation of this study with an in-depth analysis of the literature through a systematic literature review.
- Application of parallel research fields to the prototype such as non-invasive data acquisition or feature extraction of other medical signals to improve ICP analysis (i.e. cardiac pulse).
- The development of precise unambiguous Lundberg waves definitions. The review identified a lack of consensus regarding Lundberg waves definitions, moreover, the definitions given are very ambiguous and susceptible to interpretations. For this reason, Lundberg waves are difficult to interpret in an automatic system, and the development of precise, unambiguous definitions is a promising future work line.
- Deployment of a centralized web service to provide researchers a tool for uploading and downloading ICP labeled data. This would help with the construction of a public online ICP dataset which has also been identified as a research gap.

A systematic literature review has been identified as an interesting future line of research. Among other reasons, the comparison between the systems present in the literature requires both the development of standard metrics together with the further study of the field, which can be provided by this methodology, and the disambiguation of waves' definitions could also be benefited by this kind of study.

With regard to the software prototype solution provided, the positive results given by the evaluation (Table 10) suggest that the software covers an actual need, and it was proven to be a useful aid in the diagnosis of ICP. Further development of the functionality of the solution is a relevant research line, particularly with the addition of B-wave detection and single pulse analysis, and this will be undertaken as future work.

Declaration of Competing Interest

We confirm that the authors in this study have no conflicts of interest to report.

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Appendix A. Selected papers

Table 11
Questions addressed by the selected papers. (RQ5 has 3 sub-questions: D: dataset, V: validation method, M: metrics). (RQ6 has 2 sub-questions: L: programming language, S: development or test system).

Ref.	RQ1	RQ2	RQ3	RQ4	RQ5			RQ6		RQ7
					D	V	M	L	S	
[47]	✓	✓	✓	✓	✓	✓	✗	✗	✓	✓
[18]	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓
[43]	✓	✓	✓	✓	✓	✓	✗	✗	✗	✓
[22]	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓
[32]	✓	✓	✓	✓	✓	✗	✗	✗	✗	✓
[45]	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓
[33]	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓
[46]	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓
[44]	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓
[48]	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓
[38]	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓
[36]	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓
[23]	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓
[35]	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓
[37]	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓
[34]	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓
[39]	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓
[40]	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓
[42]	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓
[41]	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓
[31]	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓
[21]	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓
[49]	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓

Appendix B. Mapping study tasks

Table 12
Mapping study tasks conducted in accordance with the guidelines of Petersen et al. [24].

Phase	Activities	Applied
Need for map	Motivate the need and relevance	✓
	Define objectives and questions	✓
	Consult with target audience to define questions	✓
Study ident.	**Choosing search strategy**	
	Snowballing	✓
	Manual	•
	Conduct database search	✓
	Develop the search	
	PICO(C)	✓
	Consult librarians or experts	✓
	Iteratively try finding more relevant papers	✓
	Keywords from known papers	✓
	Use standards, encyclopedias, and thesaurus	✓
	Evaluate the search	
	Test-set of known papers	•
	Expert evaluates result	•
	Search web-pages of key authors	•
	Test-retest	•
	Inclusion and Exclusion	
	Identify objective criteria for decision	✓
	Add additional reviewer, resolve disagreements between them when needed	•
	Decision rules	•
Data extraction and classification	**Extraction process**	
	Identify objective criteria for decision	✓
	Obscuring information that could bias	•
	Add additional reviewer, resolve disagreements between them when needed	•
	Test-retest	•
	Classification scheme	
	Research type	✓
	Research method	✓
	Venue type	✓
Validity discussion	Validity discussion/limitations provided	✓

Appendix C. Systematic literature review evaluation checklist

Table 13
Systematic literature review evaluation checklist proposed by Ali et al. [61]. √: the answer to the evaluation question is yes, and the information related to it is at least available from the corresponding author upon request. - : the evaluation question cannot be answered because the subject that the question addresses was not included in the review. •: the answer to the evaluation question is no, or the information which the question requires is not available.

Step	Checklist	At least accessible upon request
Choosing search strategy	[E1] Is the choice of search strategy (automated-search, manual-search, snowballing, contacting key authors or a combination) clearly described?	√
	[E2] Is the search strategy appropriate for the given topic (search approach and justification)?	√
	[E3] Is an appropriate combination of search strategies used to improve coverage?	√
Identifying known-set	[E4] Are the papers in the known-set reported?	•
	[E5] Is the approach used to identify the known-set likely to identify a good set?	-
Search-string construction	[E6] Are the keywords aligned/derived from the research questions?	√
	[E7] Are the keywords and their sources described?	√
	[E8] Is the choice of keywords appropriate for the topic i.e. likely to ensure coverage?	√
	[E9] Is the general search string reported?	√
	[E10] Is the search string (the terms used and their combination using operators like Boolean operations) appropriate?	√
	[E11] Is the time span of search documented?	√
	[E12] Is the chosen time span for search appropriate for the topic?	√
	[E13] Is the chosen level of search (e.g. title, metadata or full-text) documented?	√
	[E14] Is the chosen search level (title, metadata and/or full-text) appropriate for the topic?	√
	[E15] Is the level of recall acceptable and appropriate for the topic (reflecting on how important is completeness)?	-
Source selection	[E16] Are the databases described that were used in the search?	√
	[E17] Were an appropriate number of databases (both publisher and indexing databases) used?	√
	[E18] In case of manual-search as a supplementary strategy, are the names and years of the selected venues reported?	-
	[E19] Are the selected sources (e.g., databases, venues) appropriate for the topic?	√
	[E20] If gray literature is used, is it reported?	-
	[E21] Were the measures undertaken to reduce publication bias sufficient?	√
SLR protocol validation	[E22] Was the protocol validated by an independent reviewer?	√
Conducting search	[E23] Are the database specific search strings reported?	√
	[E24] Are the additional filters used in the search reported?	√
	[E25] Are the additional filters used in the search appropriate?	√
	[E26] Are the deviations from the general search string documented?	√
	[E27] Are the deviations from the general search string acceptable?	√
	[E28] Are the database specific search hits documented?	√
	[E29] Are database specific search results made available online?	•

References

[1] M. Harary, R.G. Dolmans, W.B. Gormley, Intracranial pressure monitoring-review and avenues for development, Sensors (Switzerland) 18 (2) (2018) 3–7, doi:10.3390/s18020465.
[2] D. Bradshaw, Traumatic Brain Injury Task Force, Technical Report, 2008. https://www.hsdl.org/?view&did=482727
[3] J. Ren, X. Wu, J. Huang, X. Cao, Q. Yuan, D. Zhang, Z. Du, P. Zhong, J. Hu, Intracranial pressure monitoring-Aided management associated with favorable outcomes in patients with hypertension-Related spontaneous intracerebral hemorrhage, Transl Stroke Res (2020), doi:10.1007/s12975-020-00798-w.
[4] X.-r. Che, Y.-j. Wang, H.-y. Zheng, Prognostic value of intracranial pressure monitoring for the management of hypertensive intracerebral hemorrhage following minimally invasive surgery, World J Emerg Med 11 (3) (2020) 169, doi:10.5847/wjem.j.1920-8642.2020.03.007.
[5] F. Al Saiegh, L. Philipp, N. Mouchtouris, N. Chalouhi, O. Khanna, S.O. Shah, J. Jallo, Comparison of outcomes of severe traumatic brain injury in 36,929 patients treated with or without intracranial pressure monitoring in a mature trauma system, World Neurosurg 136 (2020) e535–e541, doi:10.1016/j.wneu.2020.01.070.
[6] Z. Li, F. Xu, Y. Li, R. Wang, Z. Zhang, Y. Qu, Assessment of intracranial pressure monitoring in patients with moderate traumatic brain injury: a retrospective cohort study, Clin Neurol Neurosurg 189 (October 2019) (2020) 105538, doi:10.1016/j.clineuro.2019.105538.
[7] N. Carney, A.M. Totten, C. O'Reilly, J.S. Ullman, G.W. Hawryluk, M.J. Bell, S.L. Bratton, R. Chesnut, O.A. Harris, N. Kissoon, A.M. Rubiano, L. Shutter, R.C. Tasker, M.S. Vavilala, J. Wilberger, D.W. Wright, J. Ghajar, Guidelines for the management of severe traumatic brain injury, fourth edition, Neurosurgery 80 (1) (2017) 6–15, doi:10.1227/NEU.0000000000001432.
[8] M. Czosnyka, J.D. Pickard, Monitoring and interpretation of intracranial pressure, Journal of Neurology, Neurosurgery and Psychiatry 75 (6) (2004) 813–821, doi:10.1136/jnnp.2003.033126.
[9] D.J. Kim, Z. Czosnyka, M. Kasprowicz, P. Smieleweski, O. Baledent, A.M. Guerguerian, J.D. Pickard, M. Czosnyka, Continuous monitoring of the monro-Kellie doctrine: is it possible? J. Neurotrauma 29 (7) (2012) 1354–1363, doi:10.1089/neu.2011.2018.
[10] M. Balestreri, M. Czosnyka, L.A. Steiner, E. Schmidt, P. Smielewski, B. Matta, J.D. Pickard, Intracranial hypertension: what additional information can be derived from ICP waveform after head injury? Acta Neurochir (Wien) 146 (2) (2004) 131–141, doi:10.1007/s00701-003-0187-y.
[11] M. Czosnyka, P.J. Hutchinson, M. Balestreri, M. Hiler, P. Smielewski, J.D. Pickard, Monitoring and Interpretation of Intracranial Pressure after Head Injury, in: Brain Edema XIII, Springer-Verlag, 2006, pp. 114–118, doi:10.1007/3-211-30714-1_26.
[12] N. Lundberg, Continuous recording and control of ventricular fluid pressure in neurosurgical practice., Acta Psychiatr Scand Suppl 36 (149) (1960) 1–193.
[13] E.F. Wijdicks, Lundberg and his waves, Neurocrit Care 31 (3) (2019) 546–549, doi:10.1007/s12028-019-00689-5.
[14] N. Lundberg, H. Troupp, H. Lorin, Continuous recording of the ventricular-fluid pressure in patients with severe acute traumatic brain injury. a preliminary report., J. Neurosurg. 22 (6) (1965) 581–590, doi:10.3171/jns.1965.22.6.0581.
[15] I. Martinez-Tejada, A. Arum, J.E. Wilhjelm, M. Juhler, M. Andresen, B waves: a systematic review of terminology, characteristics, and analysis methods, Fluids Barriers CNS 16 (1) (2019) 1–15, doi:10.1186/s12987-019-0153-6.
[16] A. Spiegelberg, M. Preuß, V. Kurtcuoglu, B-Waves revisited, Interdiscip. Neurosurg. Adv. Tech. Case Manage. 6 (2016) 13–17, doi:10.1016/j.inat.2016.03.004.
[17] R. Hamilton, P. Xu, S. Asgari, M. Kasprowicz, P. Vespa, M. Bergsneider, X. Hu, Forecasting intracranial pressure elevation using pulse waveform morphology, Proceedings of the 31st Annual International Conference of the IEEE Engineering in Medicine and Biology Society: Engineering the Future of Biomedicine, EMBC 2009 (2009) 4331–4334, doi:10.1109/IEMBS.2009.5332749.

[18] J.J. Lemaire, J.Y. Boire, J. Chazal, B. Irthum, A computer software for frequential analysis of slow intracranial pressure waves., Comput Methods Programs Biomed 42 (1) (1994) 1–14, doi:10.1016/0169-2607(94)90133-3.
[19] J. Perez-Barcena, J.A. Llompart-Pou, K.H. O'Phelan, Intracranial pressure monitoring and management of intracranial hypertension, Crit Care Clin 30 (4) (2014) 735–750, doi:10.1016/j.ccc.2014.06.005.
[20] X. Hu, T. Glenn, F. Scalzo, M. Bergsneider, C. Sarkiss, N. Martin, P. Vespa, Intracranial pressure pulse morphological features improved detection of decreased cerebral blood flow, Physiol Meas 31 (5) (2010) 679–695, doi:10.1088/0967-3334/31/5/006.
[21] A. Spiegelberg, M. Krause, J. Meixensberger, B. Seifert, V. Kurtcuoglu, Significant association of slow vasogenic ICP waves with normal pressure hydrocephalus diagnosis, Acta Neurochirurgica, Supplementum 126 (2018) 243–246, doi:10.1007/978-3-319-65798-1_49.
[22] A. Eklund, A. Ågren-Wilsson, N. Andersson, A.T. Bergenheim, L.O. Koskinen, J. Malm, Two computerized methods used to analyze intracranial pressure b waves: comparison with traditional visual interpretation, J. Neurosurg. 94 (3) (2001) 392–396, doi:10.3171/jns.2001.94.3.0392.
[23] M. Kasprowicz, S. Asgari, M. Bergsneider, M. Czosnyka, R. Hamilton, X. Hu, Pattern recognition of overnight intracranial pressure slow waves using morphological features of intracranial pressure pulse, J. Neurosci. Methods 190 (2) (2010) 310–318, doi:10.1016/j.jneumeth.2010.05.015.
[24] K. Petersen, S. Vakkalanka, L. Kuzniarz, Guidelines for conducting systematic mapping studies in software engineering: an update, Inf Softw Technol 64 (2015) 1–18, doi:10.1016/j.infsof.2015.03.007.
[25] B. Kitchenham, S. Charters, Issue: EBSE 2007-001., Technical report 2 (3) (2007).
[26] S. Jalali, C. Wohlin, Systematic literature studies, in: Proceedings of the ACM-IEEE international symposium on Empirical software engineering and measurement - ESEM '12, ACM Press, New York, New York, USA, 2012, p. 29, doi:10.1145/2372251.2372257.
[27] M. Petticrew, H. Roberts, Systematic reviews in the social sciences, Blackwell Publishing Ltd, Oxford, UK, 2006, doi:10.1002/9780470754887.
[28] IEEE 2017 taxonomy, 2019, (https://www.ieee.org/content/dam/ieee-org/ieee/web/org/pubs/taxonomy_v101.pdf). Accessed: 2019-11-07.
[29] N. Esfandiari, M.R. Babavalian, A.M.E. Moghadam, V.K. Tabar, Knowledge discovery in medicine: current issue and future trend, Expert Syst Appl 41 (9) (2014) 4434–4463, doi:10.1016/j.eswa.2014.01.011.
[30] R. Wieringa, N. Maiden, N. Mead, C. Rolland, Requirements engineering paper classification and evaluation criteria: a proposal and a discussion, Requirements Engineering 11 (1) (2006) 102–107, doi:10.1007/s00766-005-0021-6.
[31] C.G. Nucci, P. De Bonis, A. Mangiola, P. Santini, M. Sciandrone, A. Risi, C. Anile, Intracranial pressure wave morphological classification: automated analysis and clinical validation., Acta Neurochir (Wien) 158 (3) (2016) 581–8;discussion 588, doi:10.1007/s00701-015-2672-5.
[32] M. Walter, M. Kiefer, S. Leonhardt, W.I. Steudel, R. Isermann, Online analysis of intracranial pressure waves., Acta Neurochir. Suppl. 81 (81) (2002) 161–162, doi:10.1007/978-3-7091-6738-0_41.
[33] Z.T. Beattie, Algorithm for automatic beat detection of cardiovascular pressure signals, in: Proceedings of the 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS'08 - "Personalized Healthcare through Technology", 2008, pp. 2594–2597, doi:10.1109/iembs.2008.4649731.
[34] I.M. Elixmann, J. Hansinger, C. Goffin, S. Antes, K. Radermacher, S. Leonhardt, Single pulse analysis of intracranial pressure for a hydrocephalus implant, in: Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, IEEE, 2012, pp. 3939–3942, doi:10.1109/EMBC.2012.6346828.
[35] F. Scalzo, S. Asgari, S. Kim, M. Bergsneider, X. Hu, Bayesian tracking of intracranial pressure signal morphology, Artif Intell Med 54 (2) (2012) 115–123, doi:10.1016/j.artmed.2011.08.007.
[36] F. Scalzo, S. Asgari, S. Kim, M. Bergsneider, X. Hu, Robust peak recognition in intracranial pressure signals, Biomed Eng Online 9 (2010), doi:10.1186/1475-925X-9-61.
[37] F. Scalzo, M. Bergsneider, P.M. Vespa, N.A. Martin, X. Hu, Intracranial pressure signal morphology: real-time tracking, IEEE Pulse 3 (2) (2012) 49–52, doi:10.1109/MPUL.2011.2181024.
[38] X. Hu, P. Xu, F. Scalzo, P. Vespa, M. Bergsneider, Morphological clustering and analysis of continuous intracranial pressure, IEEE Trans. Biomed. Eng. 56 (3) (2009) 696–705, doi:10.1109/TBME.2008.2008636.
[39] F. Scalzo, D. Liebeskind, X. Hu, Reducing false intracranial pressure alarms using morphological waveform features, IEEE Trans. Biomed. Eng. 60 (1) (2013) 235–239.
[40] A. Calisto, M. Galeano, S. Serrano, A. Calisto, B. Azzerboni, A new approach for investigating intracranial pressure signal: filtering and morphological features extraction from continuous recording, IEEE Trans. Biomed. Eng. 60 (3) (2013) 830–837, doi:10.1109/TBME.2012.2191550.
[41] H.J. Lee, E.J. Jeong, H. Kim, M. Czosnyka, D.J. Kim, Morphological feature extraction from a continuous intracranial pressure pulse via a peak clustering algorithm, IEEE Trans. Biomed. Eng. 63 (10) (2016) 2169–2176, doi:10.1109/TBME.2015.2512278.
[42] E.J. Jeong, H. Kim, X. Ke Yang, H.J. Lee, D.H. Park, Y.T. Kim, D.J. Kim, Morphological landmark detection in arterial blood pressure and intracranial pressure: Preliminary procedures for intracranial pressure waveform analysis, in: 3rd International Winter Conference on Brain-Computer Interface, BCI 2015, IEEE, 2015, pp. 11–13, doi:10.1109/IWW-BCI.2015.7073049.
[43] M.H. Morgalla, F. Stumm, G. Hesse, A computer-based method for continuous single pulse analysis of intracranial pressure waves, J. Neurol. Sci. 168 (2) (1999) 90–95, doi:10.1016/S0022-510X(99)00137-9.
[44] F. Scalzo, P. Xu, M. Bergsneider, X. Hu, Random Subwindows for Robust Peak Recognition in Intracranial Pressure Signals, in: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), volume 5358 LNCS, 2008, pp. 370–380, doi:10.1007/978-3-540-89639-5_36.
[45] P.K. Eide, A new method for processing of continuous intracranial pressure signals, Medical Engineering & Physics 28 (6) (2006) 579–587, doi:10.1016/j.medengphy.2005.09.008.
[46] S. Holm, P.K. Eide, The frequency domain versus time domain methods for processing of intracranial pressure (ICP) signals, Medical Engineering & Physics 30 (2) (2008) 164–170, doi:10.1016/j.medengphy.2007.03.003.
[47] K. Hara, S. Nakatani, K. Ozaki, T. Ikeda, H. Mogami, Detection of the b waves in the oscillation of intracranial pressure by fast fourier transform., Med Inform (Lond) 15 (2) (1990) 125–131, doi:10.3109/14639239008997664.
[48] X. Hu, P. Xu, D.J. Lee, P. Vespa, K. Baldwin, M. Bergsneider, An algorithm for extracting intracranial pressure latency relative to electrocardiogram r wave, Physiol Meas 29 (4) (2008) 459–471, doi:10.1088/0967-3334/29/4/004.
[49] M. Megjhani, A. Alkhachroum, K. Terilli, J. Ford, C. Rubinos, J. Kromm, B.K. Wallace, E.S. Connolly, D. Roh, S. Agarwal, J. Claassen, R. Padmanabhan, X. Hu, S. Park, An active learning framework for enhancing identification of non-artifactual intracranial pressure waveforms, Physiol Meas 40 (1) (2019), doi:10.1088/1361-6579/aaf979.
[50] C.J. Kirkness, P.H. Mitchell, R.L. Burr, K.S. March, D.W. Newell, Intracranial pressure waveform analysis: clinical and research implications., 200010.1097/01376517-200010000-00007
[51] A. Sonig, F. Jumah, B. Raju, N.V. Patel, G. Gupta, A. Nanda, The historical evolution of intracranial pressure monitoring, World Neurosurg (March) (2020) 1–7, doi:10.1016/j.wneu.2020.03.028.
[52] N. AlHinai, Introduction to Biomedical Signal Processing and Artificial Intelligence, in: Biomedical Signal Processing and Artificial Intelligence in Healthcare, Elsevier, 2020, pp. 1–28, doi:10.1016/B978-0-12-818946-7.00001-9.
[53] A. Hall, R. O'Kane, The best marker for guiding the clinical management of patients with raised intracranial pressure-the RAP index or the mean pulse amplitude? Acta Neurochir (Wien) 158 (10) (2016) 1997–2009, doi:10.1007/s00701-016-2932-z.
[54] A. Kazimierska, M. Kasprowicz, M. Czosnyka, M.M. Placek, O. Baledent, P. Smielewski, Z. Czosnyka, Compliance of the cerebrospinal space: comparison of three methods, Acta Neurochir (Wien) (2021), doi:10.1007/s00701-021-04834-y.
[55] P. Smielewski, A. Lavinio, I. Timofeev, D. Radolovich, I. Perkes, J.D. Pickard, M. Czosnyka, ICM+, A flexible platform for investigations of cerebrospinal dynamics in clinical practice., Acta Neurochir. Suppl. 102 (2008) 145–151, doi:10.1007/978-3-211-85578-2_30.
[56] Cns monitor, 2021, (https://www.moberg.com/products/cns-monitor). Accessed: 2021-06-02.
[57] Bedmasterex, 2021, (https://www.bedmaster.net/en/products/bedmasterex). Accessed: 2021-06-02.
[58] M. Kallergi, Evaluation of Computer Aided Detection and Diagnosis Algorithms for Medical Imaging, in: L. Costaridou (Ed.), Medical Image Analysis Methods (The Electrical Engineering and Applied Signal Processing Series), CRC Press, 2005, pp. 433–472.
[59] A.N. Papadopoulos, M.E. Plissiti, D.I. Fotiadis, Medical-image Processing and Analysis for Cad Systems, in: L. Costaridou (Ed.), Medical Image Analysis Methods (The Electrical Engineering and Applied Signal Processing Series), CRC Press, 2005, pp. 51–86.
[60] V. Venkatesh, F.D. Davis, Theoretical extension of the technology acceptance model: four longitudinal field studies, Manage Sci 46 (2) (2000) 186–204, doi:10.1287/mnsc.46.2.186.11926.
[61] N.B. Ali, M. Usman, Reliability of search in systematic reviews: towards a quality assessment framework for the automated-search strategy, Inf Softw Technol 99 (May 2017) (2018) 133–147, doi:10.1016/j.infsof.2018.02.002.