REVIEW ARTICLE
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Impact of artificial intelligence on breast care pathways and future perspectives

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ABSTRACT

Artificial intelligence (AI) is a sophisticated technology already established in medicine. In mastology, there is robust evidence of the ability of AI software to optimize screening, reduce interval cancer rates, and decrease patient recall rates. In addition, AI provides parameters for predicting surgical complications and oncological therapeutic outcomes. Considering the rise of AI, this article aimed to conduct an integrative review, highlighting its main tools developed in mastology. A search was performed on the United States National Library of Medicine (PubMed) platform, using descriptors associated with AI and breast cancer. Retrospective studies, systematic reviews, and prospective clinical studies published in English in the last ten years were included. The results were organized by thematic areas and summarized in a table and the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) flowchart. Data analysis showed a concentration of information in the area of imaging — with advances in radiomics — and a still incipient, albeit promising, development in areas such as genetics and surgery. The article highlights the need for discussion on the ethical issues surrounding the implementation of AI. The reliability of data collection and manipulation must be guaranteed, and data automation should not imply automation of conduct, since medical responsibility in patient care is perennial.

KEYWORDS: artificial intelligence; breast cancer; mastology.

INTRODUCTION

Artificial intelligence and mastology

The term “artificial intelligence” (AI) was first used in 1955 by John McCarthy, a computer scientist at Dartmouth College[1]. At that time, the idea that computer systems could mimic human cognition seemed utopian. However, its implementation in current clinical practice is already evident and involves the entire patient care continuum[2].

In mastology, AI enables better assessment of lesions, early diagnosis of breast cancer, prediction of treatment success, and evaluation of drug targets[3].

Types of artificial intelligence

Machine learning (ML), deep learning (DL), and convolutional neural network (CNN) are examples of subdivisions within AI and have different technologies in their data processing.

Briefly, ML involves feeding data to a computer, enabling the creation of algorithms. Patterns are detected that predict outcomes, such as risk stratification or personalized survival rates. The more data provided, the greater its ability to optimize results, since ML improves with experience[3]. When clinical data are provided, automated information is generated using a process known as natural language processing (NLP).

DL is a technique within ML that is capable of interconnecting data stored by ML in a manner analogous to the neural networks of the human brain. These techniques are especially relevant in large databases with information that is difficult to quantify. These models can be applied to healthcare system databases such as UK-wide and the DATA-CAN hub, enabling early diagnostic predictions and treatments based on real data[1].

CNNs are a subclass of DL designed to process image data. Alex Krizhevsky, a computer scientist at the University of Toronto, was one of the pioneers in amplifying this technology with the creation of AlexNet, published in 2012, which revolutionized

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image recognition using DL[4]. CNNs are used in image classification, object segmentation, and image exam analysis tasks.

METHODS

An integrative review was conducted with data collection between March 2024 and January 2025. The descriptors "breast cancer and artificial intelligence," "AI breast chemotherapy," "AI breast radiotherapy," "AI mammography," and "AI pathology breast cancer" were used on the PubMed platform.

Inclusion criteria: original articles, comparative clinical studies, meta-analyses, randomized clinical trials, and systematic reviews involving AI tools in breast care. Studies on imaging, radiotherapy, pathological anatomy, genetics, and breast surgery were included. Studies published in the last ten years and written in English were selected.

Exclusion criteria: gray literature, conference abstracts, narrative reviews, case reports, or studies that did not describe the software used or its practical applications in AI.

The articles were identified; their titles and abstracts were read — when available — and selected for full reading. The organization was carried out according to the PRISMA flowchart, and the main results were compiled in a structured table according to the study author, year of publication, number of cases included, AI modality, and main findings (Table 1 and Figure 1)[5-28].

Table 1. Featured software developed in the last six years.

Reference	Year	No	Software	AI modality	Study design	Main findings
Rodríguez-Ruiz et al.[5]	2019	240	Transpara® Breast AI	Mammography	Retrospective study	AI system that increased breast cancer detection without increasing reading time
Eisemann et al.[6]	2025	463,094	Safety-Net	Mammography	Retrospective study	AI in mammography cancer screening; time reduction with double reading
Kwon et al.[7]	2024	89,855	Lunit INSIGHT MMG	Mammography	Retrospective study	AI with performance comparable to radiologists in dense breast mammography
Vourtsis[8]	2019	-	ABUS	Ultrasound	Systematic review	ABUS has shown potential for 3D breast assessment
Zhang et al.[9]	2021	-	S-Detect	Ultrasound	Narrative review	S-Detect useful in differentiating benign and malignant masses on ultrasound
Kelly et al.[10]	2010	4,419	AW BU	Mammography	Comparative study	AW BU complemented mammography in dense breasts to increase neoplasia detection
Hejduk P et al.[11]	2022	113	ABUS	Ultrasound	Retrospective study	CNN accurately classified ABUS images according to BI-RADS
Wanderley et al.[12]	2023	555	Koios DS™ Breast	Ultrasound	Retrospective study	High accuracy of AI in the assessment of malignancy risk in breast nodules
Salim et al.[13]	2024	-	AISmartDensity	Mammography	Randomized clinical trial	AI screening using mammography scoring for supplemental MRI in breast cancer screening
Bouchebbah and Slimani[14]	2020	22	3D-ALPA	Nuclear magnetic resonance	Descriptive study	Accuracy of AI in segmentation and reading of breast MRI images
Caballo et al.[15]	2023	251	Radiomics	Nuclear magnetic resonance	Retrospective study	Radiomics predicted complete pathological response to neoadjuvant chemotherapy on MRI
Qu et al.[16]	2020	302	Deep learning model	Magnetic resonance imaging	Retrospective study	AI method evaluating pCR after NAC in breast cancer
Müller-Franzes et al.[17]	2023	9751	GANs	Nuclear magnetic resonance	Retrospective study	Creation of simulated images with AI reducing the need for contrast in NMR
Chung et al.[18]	2023	96	Deep learning model	Nuclear magnetic resonance	Retrospective study	Creation of images with AI-simulated contrast to enable NMR without its use
Wong et al.[19]	2020	60	Limbus Contour build 1.0.22	Radiotherapy	Descriptive study	DL-based autosegmentation comparably to radiotherapy specialists

Continue...

Table 1. Continuation.

Reference	Year	No	Software	AI modality	Study design	Main findings
Nyflot et al.[20]	2019	558 images	Deep learning model	Radiotherapy	Retrospective study	DL identified errors in radiotherapy delivery via gamma image analysis
Shen et al.[21]	2022	312	ImResNet	Ultrasound	Retrospective study	Identification of PIK3CA mutation in breast cancer via ultrasound using AI
Han et al.[22]	2017	82	CSDCNN	Pathology	Descriptive study	CSDCNN model classified breast cancer based on histopathological images
Wu et al.[23]	2023	576	Artificial Intelligence	Pathology	Descriptive study	AI optimized the interpretation of HER2 scores in breast cancer
Retamero et al.[24]	2024		Paige BLN	Pathology	Retrospective study	AI increased accuracy and efficiency in detecting lymph node metastases
Saliba and Alves[25]	2021	93	Laser-level application	Oncoplasty	Retrospective study	The application assisted in preoperative marking in mammoplasty
O'Neill et al.[26]	2020	1012	Machine learning model	Oncoplasty	Retrospective study	ML model predicted flap failure factors in breast reconstruction
Myung et al.[27]	2021	568	Machine learning model	Oncoplasty	Retrospective study	ML predicted donor-related complications in breast reconstruction
Wei et al.[28]	2021	533	Machine learning model	Surgery	Retrospective study	AI model for predicting lymphedema in breast cancer survivors

AI: artificial intelligence; ABUS: automated breast ultrasound; CNN: convolutional neural network; BI-RADS: Breast Imaging Reporting and Data System; pCR: pathological complete response; NAC: neoadjuvant chemotherapy; MRI: magnetic resonance imaging; NMR: nuclear magnetic resonance; GANs: generative adversarial networks; WSI: whole slide image; BLN: breast lymph node; AWBU: automated whole-breast ultrasound; TNBC: triple-negative breast câncer; CSDCNN: deep convolutional neural network; HER2: human epidermal growth factor receptor 2.

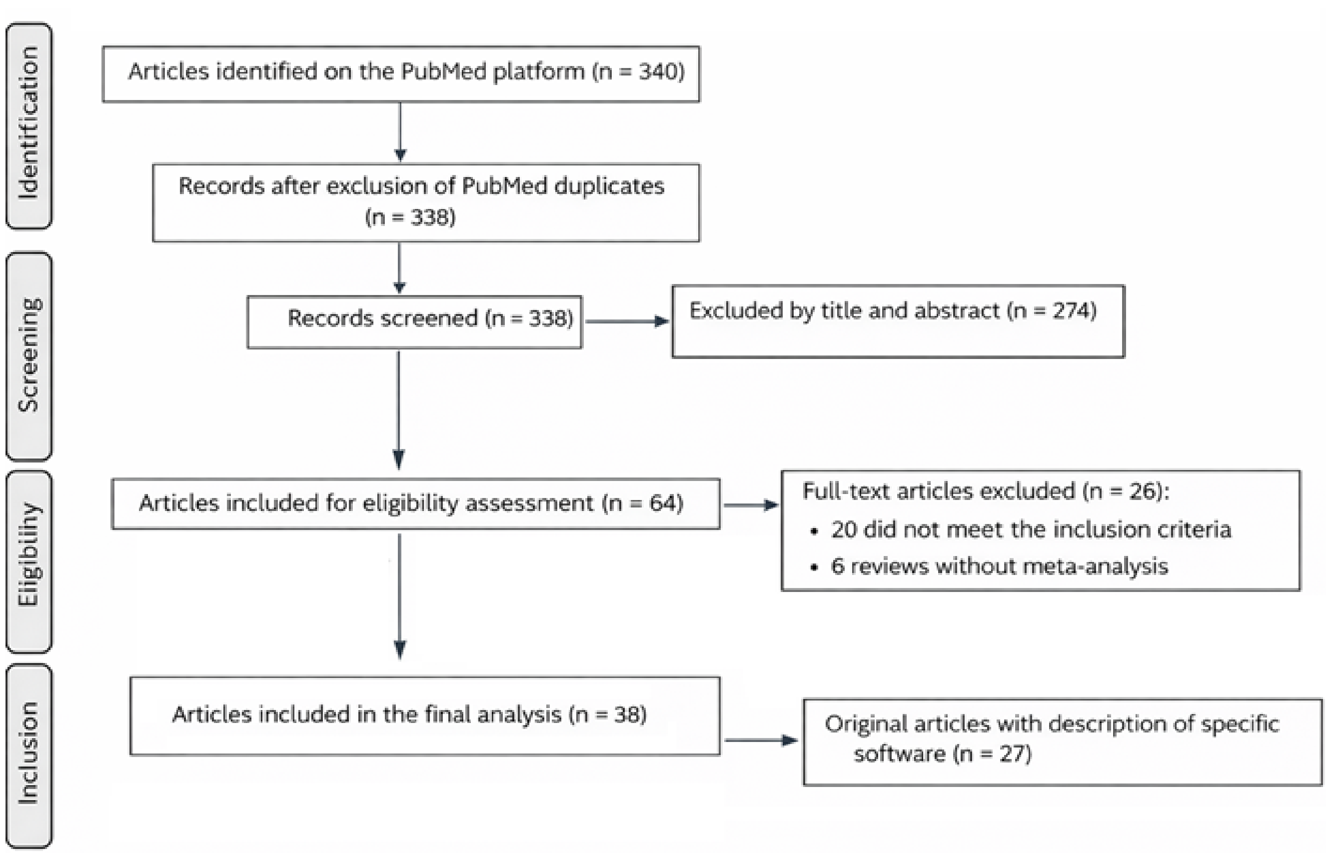

Figure 1. PRISMA Table: Flowchart for article selection.

The results were summarized descriptively according to the areas of AI application: imaging, radiotherapy, genetics, pathological anatomy, and breast surgery.

RESULTS

Imaging

Among the studies included, the area of diagnostic imaging was the most representative. The implementation of AI has expanded exponentially since 2010 with the development of radiomics. This technique involves extracting characteristics from large volumes of images and transforming this visual information into data that can be statistically analyzed to aid in the diagnosis, prognosis, and monitoring of diseases. This technique differs from CNNs in that it provides clear clinical associations[29].

Mammography and tomosynthesis

Mammography remains the cornerstone of screening in mastology because it is the only proven method to reduce breast cancer mortality by 20–30% in Brazil, according to data from the National Cancer Institute (INCA)[30]. This modality was one of the first to be adapted for the use of AI. In 1998, the United States Food and Drug Administration (FDA) approved the implementation of CAD (computer-aided detection), which quickly led to its widespread use. This software detects changes in mammograms and digital breast tomosynthesis — such as peculiarities in textures, shapes, colors, and calcifications — for evaluation by the radiologist that might otherwise not be visible. The method allows for double reading of the images, reducing false negatives by about 5–10%[31].

CAD systems have continuously revised designs and databases to increase their accuracy. With the advent of DL, more modern models reduce patient recall rates by 10–20%[31] and are capable of providing interactive diagnostic support. In addition, they reduce image reading time, as they can calculate scores for the likelihood of malignancy of lesions found in images[5].

The relevance of AI systems became clear in the PRAIM study published in January 2025 with 461,818 participants in a German screening program. Patients aged 50-69 who underwent mammography between July 2021 and February 2023 were selected. A total of 119 radiologists who were not breast specialists were selected to evaluate the exams. The results of 201,079 patients underwent single reading, and 260,739 were selected for the double reading method using AI software. Double reading increased breast cancer detection from 5.7 to 6.7/1.000 exams and reduced exam interpretation time by 43%[6].

In addition, AI-based CAD systems allow for risk assessment and stratification according to breast density[7].

In a literature review, Schopf et al. analyzed 16 retrospective studies presenting AI models that, based on mammographic findings, establish breast cancer risk assessment[32]. These tools may be more objective ways of calculating risk in the clinical setting and signal the need for more frequent and/or complementary screening. Most software was compared with established risk stratification models, such as Tyrer-Cuzick, Gail Index, and Breast Cancer Surveillance Consortium (BCSC), but did not show improvements in overall risk assessment[32].

Ultrasound

Breast ultrasound is a complementary imaging modality to mammography in screening. It is also a method for evaluating dense breasts when breast magnetic resonance imaging (MRI) is not available[33]. Although it is cost-effective and well tolerated by patients, its operator-dependent nature has motivated the creation of software that reduces disparities related to the professionals' skills and expertise[8].

Automated ultrasound methods began to be described in 2009 in an attempt to overcome the limitations of interobserver variability and the technical difficulties imposed by large or dense breasts. At that time, the combination of the new technology with mammography doubled the detection rate of neoplasia, signaling its potential[8]. Like DL, automated breast ultrasound (ABUS) has become established in daily practice and is currently used as a routine tool, with several software programs available, such as Koios DS Breast[34] and S-Detect[9].

A major challenge in adapting to the automated method is the increase in the time required to perform the exam, since updated 3D models provide serial slices and a high volume of information for interpretation by the radiologist[10]. A CNN model was trained to identify images and classify them according to the Breast Imaging Reporting and Data System (BI-RADS®) classification system to optimize the information reported[11]. In order to taught the model to identify breast structures and classify potential lesions, 645 images were selected from the automated system. An accuracy of 95% was achieved in the trained system.

Similarly, a group from the A.C. Camargo Cancer Center evaluated the accuracy of automated ultrasound systems using the Koios DS Breast software. Data analysis of 555 images resulted in sensitivity of 99.1% and specificity of 34%, comparable to those from the five breast radiologists recruited for the comparative study[12].

Magnetic resonance imaging

Nuclear magnetic resonance (NMR) imaging allows for the morphofunctional evaluation of the breast. Its fundamental role in mastology, under study since the 1970s[35], ranges from high-risk screening to breast cancer treatment planning.

One of the biggest obstacles to accessing NMR, for example, is its high cost. In this regard, an AI-based score — AISmartDensity — was developed to select among mammographic screening, which patients would be indicated for complementary examination with NMR[13]. This was the prospective ScreenTrustMRI Trial study, and in its evaluation, among the 559 patients allocated to the intervention with normal mammograms, 36 additional invasive carcinomas were diagnosed once they were selected for complementary examination.

The foundations of DL are also applied to MRI to assist in the categorization of breast lesions. In 2021, the *3D Automatic Levels Propagation Approach (3D-ALPA)* software was developed — an image reconstruction technique for breast nodules that increases its quality and accuracy when measuring volume from 2D images analyzed by previously used models[14].

In addition to optimizing screening, the prediction of complete pathological response (pCR) after neoadjuvant treatment (NAC) is a growing field of research in studies based on 4D radiomics models in NMR[15].

With the aid of AI, NMR images can be segmented using semi-automatic methods, and then, according to the identified patterns, image characteristics are extracted. Combining DL, with the addition of clinical information, with multiparametric MRI assessment enabled high predictive accuracy of pCR[36]. Qu et al. developed a DL model based on 302 cases of locally advanced breast cancer and achieved an area under the curve (AUC) of 0.98, demonstrating superior performance to traditional MRI analysis[16].

Other AI algorithms are being developed both to reduce the use of contrast agents[17] and to simulate their presence artificially[18], benefiting patients with contraindications to their use or who would have to be exposed to contrast agents in serial forms — as is substantially the case in breast cancer treatment.

Radiotherapy

AI in radiotherapy (RT) has developed alongside imaging methods, enabling the delivery of individualized treatments and automating complex tasks. With computed tomography (CT), MRI, and positron emission tomography (PET), for example, the anatomical assessment of the tumor and adjacent organs at risk is now performed in 3D with accurate representations to guide treatment. In addition, Kawamura et al.[37] pointed out, in a literature review, how AI is present in the planning, delivery, and evaluation of RT.

In the planning phase, AI is capable of compiling databases of thousands of atlases, reducing the time spent on segmentation of the tumor area and adjacent organs at risk. These software programs allow the reduction in the time spent on anatomical analysis and decrease variability among examiners in the planning and delivery of accurate RT volumes, sparing adjacent healthy organs[19]. At this point, the quality of intensity-modulated radiation therapy (IMRT) delivery can be monitored using DL — verifying proper positioning through gamma images based on previous databases[20].

Moving on to the irradiation phase, programs such as U-Net and CycleGAN allow for proper patient positioning and use MRI and CT data to generate virtual images of tumors and organs. However, there is a limitation to the dose calculation performed by AI, since volume conversions are restricted in certain areas due to image artifacts[19].

It is important to note that, in the approach to breast cancer, data are still limited in relation to predictive models and RT outcomes, requiring additional data and international collaboration to improve technologies[38].

Genetics

Since the early 2000s, with the completion of the Human Genome Project, the initiative to individualize the treatment of breast cancer patients has been the basis for the creation of the concept of Precision Oncology[39]. In the field of genetics, the analysis of both single-gene sequencing and next-generation sequencing enables patient stratification and accurate clinical and surgical planning[40]. The high cost of tests, poor global laboratory infrastructure, and difficulty interpreting data are some of the factors that prevent adequate access to this resource.

In the included studies, AI was explored as a tool to support genomic evaluation. Several CNN models are being studied to perform multimodal integration of information and to predict the possibility of tumor genetic alterations. Shao et al. conducted a review of the main emerging models for predicting genetic mutations using imaging or histopathology[41]. The initial basis for all these models involved the manual provision of complete data from patients who already had known genetic and molecular profiles. From these data, automated information was extracted using DL and radiomics.

These elements form patterns that undergo external validation of their performance in terms of sensitivity, specificity, accuracy, and characteristic AUC. In general, models involving imaging achieved satisfactory performance, with an AUC of 0.62–0.89[41], and models based on digital pathology achieved an AUC of 0.68–0.92, according to the study analyzed.

Studies involving genetics and breast cancer initially focused on the evaluation of histological subtypes using imaging methods and radiomic properties. Currently, CNN models focus on other mutations with recently discovered therapeutic impact. Shen et al. proposed the creation of a CNN from the analysis of breast lesions by ultrasound to identify mutations in the PIK3CA gene (phosphatidylinositol-4,5-bisphosphate 3-kinase)[21]. Based on the analysis and development of the CNN, the model named ImResNet presented an AUC of 0.77, signaling an important result, since the presence of the mutation has a therapeutic target approved by the FDA and Brazilian Health Regulatory System (ANVISA)[42].

Pathological anatomy

Pathological anatomy plays a central role in the diagnosis of malignant tumors. Its evaluation involves a series of steps that require precision and accuracy. Traditional pathology is based on the direct observation of tissue samples through microscopes. With the advent of digitization, it has become possible to capture high-resolution microscopic images and store them digitally as slides (whole slide images – WSIs)[43].

Digital adaptation is essential, since one of the limitations of pathology is the low scalability of the work, which requires long hours of repetitive tasks that can impact accuracy[44]. In this sense, with AI tools, the efficiency of specialists can be improved. New data are also generated by DL, which can detect previously unnoticeable patterns in digitized slides.

Han et al. validated an automated model for multiclass histological classification of breast tumors — deep convolutional neural network (CSDCNN). The goal was to reduce the pathologist's analysis time and diagnostic errors that may occur due to fatigue[22]. The model was trained and run on a large database of 7,909 patients, with an accuracy of 93.2%.

Another key point in the management of patients with breast carcinoma is immunohistochemical evaluation due to its prognostic and treatment value. Interobserver variability in the evaluation of estrogen receptor, progesterone receptor, and receptor tyrosine kinase 2 erb-B2 (ERBB2) human epidermal growth factor receptor 2 (HER2) protein expression can be reduced with data automation. This information is particularly important due to the growing number of therapeutic targets for HER2-low and HER2-ultralow entities[23]. The classification, however, does not replace the pathologist's final evaluation, which is necessary to identify limitations inherent to the system, such as false-positive areas.

The AI algorithm was trained using more than 32,000 WSIs of sentinel lymph nodes. The images were read twice — with and without AI assistance. The result was a reduction in the reading time of the digitized slides and an increase in sensitivity from 74.5 to 93.5%.

It is important to note that AI does not replace the pathologist, who plays a key role in identifying and mitigating algorithmic bias in diagnosis. The lack of standardized data sets and the need for independent validation are barriers to the widespread adoption of these technologies.

Breast surgery

The great challenge for breast specialists is to adapt the surgical treatment of breast cancer to a satisfactory aesthetic result. The so-called oncoplastic surgery, which combines tumor removal with plastic surgery techniques, is gradually gaining ground in Brazil[45].

Soh et al. evaluated 14 AI models implemented in breast surgery. Studies conducted to predict aesthetic results and complications such as lymphedema and pain were included[46]. Saliba and Alves presented the *Laser Level* model to assist in pre-surgical markings and proper positioning of the nipple-areola complex[25]. In addition, models for predicting flap implantation failure in breast reconstruction were also studied, as well as for the adequate identification of risk factors that make patients more susceptible to postoperative complications[26,27].

Other ML tools also have applications in the daily routine of breast surgeons, such as questionnaires that predict the development of persistent postoperative pain[47] and the detection of developing lymphedema[28]. More data are still needed to generate large-scale evidence and reliable recommendations, as most of these software tools are still in the study phase.

DISCUSSION

AI is already a reality in healthcare. In breast surgery, it is widely used in all segments, as presented. However, its clinical application in breast cancer care poses challenges beyond the technical area.

The first challenge is to make AI recommendations reliable and transparent — both for patients and medical staff. This is because, with each improvement, many of its mechanisms, although accurate, become poorly explainable and difficult to describe and even to interpret, as is the case with the use of CNNs.

Another challenge is to minimize selection biases when storing data. AI needs to be constantly fed with accurate data that adequately represent the population, as well as ethnic and racial specificities. If sampling is impaired, the scope of conclusions may be limited to specific subpopulations.

There is currently a trend toward rapid AI implementation, driven by the widely publicized promise on social media of transforming healthcare and generating investment opportunities. This creates a scenario of exaggerated optimism; however, a careful process is needed to make systems more transparent and to regulate the protection of the data provided.

CONCLUSIONS

AI in mastology continues to improve, mainly with advances in DL. In practice, however, its implementation is limited both by cost and by its still incipient clinical applicability. Thus, AI remains restricted to image reading assistance software, such as CAD and ABUS. The other advances mentioned are only available in academic research centers.

There are still challenges to be overcome to ensure wider use of AI. The need for high data volumes for some software and the high investment required are examples of practical obstacles. In addition, there is a dependence on the transmission of accurate data to establish robust algorithms. In conclusion, it is necessary to be aware of the technologies that are emerging in medical practice, but also to adopt measures to enable the accessibility and reliability of these tools.

AUTHORS' CONTRIBUTIONS

VAS: Conceptualization, Investigation, Methodology, Project administration, Supervision, Validation, Visualization, Writing – original article, Writing – review & editing. RCSF: Conceptualization, Investigation, Writing – review & editing. ADS: Formal analysis, Writing – review & editing. WJAJ: Methodology, Project administration, Supervision. GOBG: Data curation, Formal analysis, Investigation, Writing – original draft. BBF: Data curation, Formal analysis, Investigation, Writing – original draft. JLCJ: Data curation, Formal analysis, Investigation, Writing – original draft. JTCA: Conceptualization, Data curation, Formal analysis, Investigation, Visualization, Supervision, Writing – review & editing.

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