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Review Article

Obstacles behind the innovation- a peek into Artificial intelligence in the field of orthodontics – A Literature review

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ABSTRACT

This article explores the potential benefits of Artificial Intelligence (AI) and Machine Learning (ML) in Orthodontics, highlighting their efficiency and accuracy. While AI has influenced various fields, its application in orthodontics is just being explored. With the innovation comes challenges that are associated with AI. This article emphasizes the documented role of AI and its associated barriers in Orthodontics.

Methods: Literature research is performed in data sources like online library journals PubMed and MEDLINE, NIH (National Institute of Health), Science Direct, WILEY online library, and ORAL HEALTH GROUP, among others. Our review was carried out on articles published to date.

Conclusion: The findings in this review highlight the considerable promise of employing AI within orthodontics. However, the emergence of AI also brings forth fresh challenges that must be considered. Striking a balance between innovation and addressing these challenges is crucial for advancing orthodontics.

1. Introduction

Artificial Intelligence (AI) is a crucial field in computer science focused on emulating human intelligence in machines. This enables them to carry out tasks traditionally requiring human cognitive abilities. (Boden, 1996). " Machine Learning (ML) is a component of AI that empowers machines to learn and enhance their performance automatically through experience, without the need for explicit programming." (Mahesh, 2020). (SEE Fig. 1).

The genesis of the AI field dates back to 1956 when a pivotal conference at Dartmouth College in Hanover, New Hampshire, marked its formal establishment, thanks to the visionary John McCarthy, who coined the term "artificial intelligence" (McCarthy et al., 2006).

AI, a diverse field integrating technologies, is crucial in Dentistry, showing immediate relevance with versatile solutions. Evolving AI impacts healthcare, including dentistry, reshaping clinical practices and enhancing education. However, challenges and conflicts arise in orthodontics, requiring resolution before commercializing AI. This review delves into AI's principles, challenges, conflicts, and transformative potential in Orthodontics.

2. Algorithms of AI

Various algorithms (problem-solving instructions) have been proposed to achieve AI. Some of them are:

2.1. Machine learning (ML)

It is a subset of AI that allows machines to learn automatically and improve from experience without being explicitly programmed (Park et al., 2019).

ML can be broadly divided into 4 types:

2.1.1. Supervised machine learning algorithms

In this scenario, external data or instances, which are already labeled and classified, are provided, and machines create algorithms based on this data to derive general patterns and hypotheses for handling future instances (Hwang et al., 2019). SMLA has been applied to diagnose dental deformities on Cephalometric imaging (Banumathi et al., 2011), identifying disease progression (Uddin et al., 2019), dental fear and behavioral management in children (Klingberg et al., 1999).

2.1.2. Unsupervised machine learning algorithms

Data provided is neither labeled nor structured in these machines.

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The system explores the data by itself and can interpret the data sets to describe hidden structures from unclassified data. Bokhari et al. have applied an Unsupervised machine learning algorithm to dental patient records and found dental caries to be the most common problem (Bokhari and Khan, 2016).

2.1.3. Semi-supervised machine learning algorithms

Lies between supervised and unsupervised. A small amount of data is labeled, and the rest is unlabeled. The system can improve its learning abilities.

2.1.4. Reinforcement machine learning algorithms

Reinforced ML uses algorithms where the machine interacts with its environment, leading to actions and discovering errors or rewards. This works on the Trial-and-Error principle. This is used in treatment strategies for septic patients, focusing on offline learning (Killian et al., 2020).

2.2. Neural networks

Artificial Neural Network (ANN) is a technology that simulates the human Nervous system (Kunz et al., 2020), wherein it has several units comparable to human neurons. Like neurons, which are activated by electric signals, these units are activated by data. Several layers of such units process the data, memorize its features, and interpret the new data based on previous learnings. S.K Jung. et al. used this technology to interpret the probability for extraction during orthodontic treatment (Jung et al., 2016), and Li.et.al used it for orthodontic treatment planning (Li et al., 2019).

2.3. Deep learning

This is a complex form of ANN in which a large amount of data is presented to the computer, which analyzes and classifies data based on binary (True/False) questions (Montúfar et al., 2018). This technology involves high-end mathematical calculations to make predictions. Hwang. et al. used deep learning to evaluate cephalometric analysis (Hwang et al., 2021).

2.4. Natural language processing (NLP)

The system analyzes and understands human text and speech. Chatbots use this technology (Alsharhan et al., 2023).

2.5. Rule-Based expert systems (RBES)

The system uses a specific set of rules derived from Human experts to make a deduction. RBES can help a doctor diagnose a disease accurately based on symptoms (Hambali and Adewole, 2015).

3. Searching methods

Systematic reviews, with or without *meta*-analyses, published in English from 2001 to the present, including studies performed in humans on the application of AI in health care and dentistry and the challenges that must be considered.

Letters to the editor, subjective opinions, book chapters, case reports, congress abstracts, and studies with animals were excluded.

4. Applications of Artificial intelligence in orthodontics

Orthodontics, a branch of dentistry, is evolving with technology. Malocclusion treatment, traditionally tedious, now has quick alternatives. As the world embraces Neuralink and SpaceX, Dentistry must keep up. AI and ML can redefine Orthodontics, bringing positive changes. Various aspects of Orthodontics can leverage AI, including:

4.1. Orthodontic images and scans

Whether intraoral or extraoral, images play a vital role in dental diagnosis and treatment planning. AI techniques enhance the quality and resolution of dental images. Modern 3D scanners like iTero and Lava Chairside Oral Scanner use AI to illustrate intricate details. Intraoral scanners and cameras, replacing conventional impressions, contribute to digital dentistry advancements.

In recent days, AI has been used to capture images of oral cavities using the Mobile Mouth Screening Anywhere (MeMoSA)app for remote interpretation by specialists. One such scanner is the Dental Monitoring Scan Box, which is very cost-efficient and can be used for virtual visits by

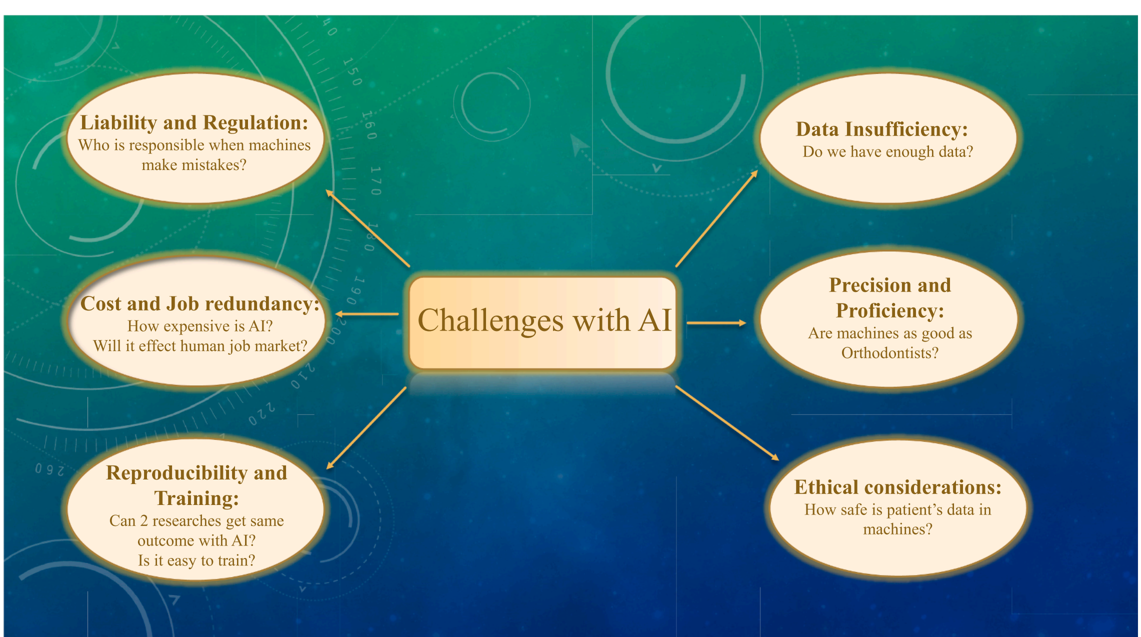

Fig. 1. Challenges with AI in Orthodontics.

the patient, leading to fewer clinical visits. Dental monitoring Golive, a new remote monitoring device, uses AI and can be used to monitor Invisalign patients to decrease office visits (Caruso et al., 2021). This at-home dental monitoring was very efficient during Covid19 pandemic.

4.2. Cephalometric analysis and segmentation

Cephalometric analysis plays a crucial role in the diagnosis and treatment planning of orthodontic and orthognathic procedures. Cephalometric analysis is carried out in two ways: manual, which has been in use since the beginning, and Computer-aided, which is gaining popularity due to its convenient use and time efficiency. Arik et al. pioneered deep CNNs in fully automated quantitative cephalometry. Their framework, detecting anatomical landmarks and evaluating pathologies, showed enhanced accuracy in landmark detection (1 % to 2 % improvement within a 2 mm range compared to benchmarks) and robust anatomical type classifications (average accuracy around 76 % for the dataset) (Arık et al., 2017). Hwang and Park et al. evaluated YOLOv3 and SSD deep-learning algorithms for cephalometric landmark identification. Comparing YOLOv3′s results with human identification, the average difference in detecting 80 landmarks was 1.46 mm, with a small margin of error of 2.97 mm (Park et al., 2019) (Hwang et al., 2020).

Kunz and colleagues developed an AI X-ray analysis system, comparing its accuracy to human experts. The AI system showed close measurements, with differences less than 0.37 degrees for angles, less than 0.20 mm for lengths, and less than 0.25 % for proportional facial height measurements. (Kunz et al., 2020). Montufar et al. introduced an algorithm for annotating cephalometric landmarks on CBCT volumes. The method involves an initial 2D landmark search followed by a 3D annotation. The results demonstrated significant time savings with this algorithm. (Montúfar et al., 2018). Gupta et al. compared the accuracy of cephalometric landmarks between three human experts and a knowledge-based AI algorithm. The AI algorithm showed 64.67 %, 82.67 %, and 90.33 % accuracy within error ranges of 2 mm, 3 mm, and 4 mm for manual markings. (Gupta et al., 2015).".

Tanikawa et al. employed an automated system to recognize anatomic landmarks and surrounding structures in lateral cephalograms. The system achieved a mean success rate of 88 % (range 77 %-100 %) in identifying specified landmark positions, matching the success rate of human experts. (Tanikawa et al., 2009). Banumati et al. applied a different type of ML algorithm named Support vector to identify the cephalometric landmarks, claiming it to be 98 % accurate (Banumathi et al., 2011).

The average time an orthodontist spends on the cephalometric analysis is 21 min. AI and ML can be used to reduce time and increase human efficiency. Although various algorithms and systems have been proposed, human expertise still holds its ground in cephalometry.

4.3. Predict skeletal bone age and growth patterns

Skeletal age is considered one of the crucial factors during treatment planning, especially among growing patients. Several age-old methods, like changes in voice and height, menarche, chronological age, and bone age, are utilized to predict growth patterns. The gold standard for assessing bone age is hand-wrist radiographs. Lamparski reported that similar accuracy can be attained by reading cervical vertebrae stages, which can also prevent radiation exposure (Cericato et al., 2015). Kök et al. aimed to determine cervical vertebrae stages (CVS) using seven AI classifiers for growth periods. The study found that ANN exhibited greater stability than human experts in identifying cervical vertebrae stages (Kök et al., 2019).

Spampinato employed deep learning to assess bone age in 1391 hand-wrist radiographs of children up to 18 years. The study found an average discrepancy of about 0.8 years between manual and automatic evaluations.(Spampinato et al., 2017). A recent study used cephalometric variables with support vector machines to classify patients' craniofacial growth as normal or abnormal. The results demonstrated a 99.8 % accuracy in correctly classifying abnormal growth patterns (Lakkshmanan et al., 2013).

4.4. Treatment planning - extraction demands and tooth movement planning

Treatment planning aims to design a strategy to address the problem by a wise and judicious clinician using his/her best judgment while maximizing benefits and minimizing the cost and risks. One dilemma during treatment planning is whether to go for extraction, and often there is a substantial difference between orthodontists' decisions. Artificial intelligence algorithms have been used in this aspect to solve the dilemma. Xie et al. studied 200 patients, receiving expert advice for extraction in 120 and non-extraction in 80. They applied an algorithm on 180 patients to predict extraction demands, achieving 80 % accuracy among 11–15-year-old patients, with 20 patients as controls. (Xie et al., 2010).

Jung and Kim used a similar AI algorithm and reported a success rate of 93 % for extraction in treatment planning and 84 % for non-extraction cases (Jung and Kim, 2016). Li. et al. used the ANN algorithm for the same and reported an "accuracy of 94.0 %, with an area under the curve (AUC) of 0.982, a sensitivity of 94.6 %, and a specificity of 93.8 %" (Li et al., 2019). Choi et al. created and assessed a 2-layer AI model for surgery and extraction demands in 316 patients. The model achieved a 96 % success rate in diagnosing surgery/non-surgery decisions and 91 % for detailed surgery type and extraction decisions. (Choi et al., 2019).

4.5. Facial attractiveness analysis: Dental simulation

Facial attractiveness or facial profile evaluation is subjective when it comes to orthodontic treatment outcomes but plays a crucial role in motivating a patient. It depends on factors like age, sex, and soft tissue characteristics. Orthodontics and orthognathic surgeries have been extensively used to improve facial attractiveness and correct irregularities. Patcas et al. employed AI to illustrate the impact of orthognathic treatment on age appearance and facial attractiveness. The computer, trained for facial attractiveness, analyzed pre- and post-treatment photos of 146 orthognathic surgery patients. Results indicated a change in facial attractiveness after surgery, with most patients appearing nearly 1 year younger. (Patcas et al., 2019).

Yu. et al. conducted an AI-based analysis of facial attractiveness in patients with Class I, II, and III malocclusions. This was compared with 69 Chinese expert orthodontists' facial attractiveness decisions, and the average coincidence rate was 71.8 %. (Yu et al., 2014).

4.6. Cleft-related studies

Cleft lip and palate (CLP) are some of the most common congenital anomalies seen globally. Children with CLP often require multidisciplinary treatment approaches, including long-term treatment with orthodontists. Many AI alternatives are currently being studied, which might be used in the early detection and treatment of CLP, thereby reducing the overall time for orthodontic treatment. Shafi. et al. collected data from 1000 pregnant women in the form of a questionnaire, and an AI-based algorithm predicted the chances of cleft lip/palate in the babies before birth and was 92.6 % accurate (Shafi et al., 2020).

Omar. Z.A. et al. explored the contributing factors of pre-graft orthodontic treatment in patients with CLP patients using an AI algorithm (Omar et al., 2018). They found the four contributing factors in the order of 1. The affected cleft palate (either soft or hard palate) 2. Ethnicity. 3. Referral age, and 4. Age at the time of treatment to be responsible for CLP.

5. Challenges with AI

AI has proven to be profoundly beneficial across various domains of scientific inquiry, yet many challenges encumber its practical implementation. Several impediments that may manifest during the implementation of AI in the field of dentistry, particularly in the realm of orthodontics, include:

5.1. Data insufficiency

Dental health care datasets, particularly those about orthodontics, tend to exhibit relatively limited scale, as evidenced by numerous research studies. Whether these smaller datasets can yield AI-based results that generalize to a broader population is a subject of ongoing debate (Schwendicke et al., 2021). AI needs the model data, and selection bias must be considered when selecting a dataset. For example, when the data is university or college-based, it might have selection bias as the patients visiting the university hospitals are overtly ill. Similarly, when the data is collected from countries without public insurance, the data set represents the particularly affluent population (Gianfrancesco et al., 2018). AI needs the model data, and selection bias must be considered when selecting a dataset. (Schwendicke (2020)).

5.2. Precision and proficiency

While AI has found application in treatment planning, cephalometric analysis, and various other domains, a pertinent question is whether it is commensurate with human expertise. According to Strunga et al., several studies show that AI algorithms are not as accurate in treating a complex case as an experienced orthodontist (Strunga et al., 2023). While AI offers logical treatment options, it may lack flexibility for unforeseen circumstances, patient preferences, and diverse factors like ethnicity or religion. Human intervention becomes critical in addressing these aspects. AI-driven communication often lacks deliberate intention, posing a notable hindrance in doctor-patient communication. (Ayad et al., 2023). Several studies have demonstrated that patients prefer diagnostic decisions made by clinicians over those made by machines (Promberger and Baron, 2006, Ongena et al., 2020).

5.3. Ethical considerations

With the advent of AI and its successful integration into health care, it is imperative to balance addressing ethical challenges and fostering innovation. Gerke et al. highlighted four ethical issues that must be addressed while using AI in dentistry: "1. Informed consent to use data, 2. Safety and transparency, 3. Algorithmic fairness and biases, and 4. Data privacy (Gerke et al., 2020)." AI enhances human expertise without replacing the role of making diagnoses and treatment plans. Explaining its complex workings to patients and obtaining consent can be challenging. Ethical protection of patients' private data is crucial in data commercialization (Roganović et al., 2023). Machines operate autonomously, utilizing existing data to process and derive conclusions for new data sets, making the algorithm used and the resulting outcome opaque. According to the same study, female dentists considered ethical issues more crucial than male dentists (Roganović et al., 2023). Resolving ethical issues will build trust in machines and dentists. A study found that one-third of participants were concerned that integrating AI in dentistry might challenge the trust-based relationship between dentists and patients. (Ayad et al., 2023).

5.4. Liability and regulation

As machines acclimate to novel circumstances, their capacity to produce intended results may become uncertain. There is no law on liability if a legal injustice is caused due to AI (Martins, 2021). One study suggested that organizations should contemplate the issue of accountability in case AI fails to perform as desired (Dhopte and Bagde, 2023). Dentists and orthodontists should understand AI system limits, maintain meticulous record-keeping, and communicate transparently with patients about AI in their treatment. Data breaches are a significant concern, and maintaining the secrecy of medical records is imperative to prevent healthcare data from being sold. (Khan et al., 2023).

5.5. Cost and Job redundancy

The deployment and maintenance of AI can often be associated with huge financial investments, rendering them potentially inaccessible to a broad spectrum of patients and health care practitioners (Strunga et al., 2023) According to a survey by Ayad et al., where patients perspective on AI was established, about one-third of the patients participating in the survey were bothered by a potential surge in treatment cost (Ayad et al., 2023). Nonetheless, several studies have indicated the cost-effectiveness of AI compared to human dentistry, given its potential to save both time and human resources. Nevertheless, its effectiveness across various applications remains a subject of ongoing exploration (Schwendicke et al., 2021). Historically, concerns about AI in healthcare rendering jobs redundant have fueled skepticism and antagonism toward AI-driven initiatives. Job displacement remains a primary concern. (Khan et al., 2023). Cynicism about AI, though understandable, hinders its broader adoption in healthcare. Increased public disclosure on AI in healthcare is imperative to address and rectify perspectives held by both patients and medical practitioners (Cruciger et al., 2016, Díaz et al., 2019).

5.6. Reproducibility and Training

Each doctor has a unique perspective in the healthcare debate. Similarly, replicating the exact outcome of an algorithm becomes challenging if the model is tailored by two different researchers. This reproducibility challenge is attributed to deficiencies in algorithmic and metric knowledge and misunderstandings between researchers (Liu et al., 2021). Avoidable human errors can impact reproducibility. Training dentists, students, healthcare workers, and patients is crucial to universal AI acceptance. Proper AI use reduces dentists' liability and ensures ethical considerations are met.

6. Conclusion

Artificial intelligence and machine learning have expanded in medicine and dentistry. With the latest technologies to diagnose and treat various malocclusions, AI has also invaded the stream of orthodontics. This review presents various areas of orthodontics that can be improved using AI and ML. Though various innovative technologies have been proposed, we need to closely monitor the challenges we might encounter while applying these technologies. Many areas of orthodontics can be explored via AI and ML. We might see a surge in the use of AI soon, which will decrease human effort, save time, and improve the overall quality of care for the patients, but will researchers be able to combat the obstacles and come up with practical solutions that must be seen?

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Bushra Butul: Conceptualization, Writing – original draft, Writing – review & editing, Resources. **Lina Sharab:** Writing – review & editing, Validation, Supervision, Resources.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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