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TG-Dental Output 2 – Artificial intelligence for oral and dental health care: Core education curriculum

ITU-T FG-AI4H Deliverable

TG-Dental Output 2 – Artificial intelligence for oral and dental health care: Core education curriculum

Summary

The core elements of a curriculum for oral and dental artificial intelligence (AI) identified in this document were produced as a collaboration of experts from the International Association for Dental Research (IADR) E-oral Health Network and the ITU/WHO Focus Group on AI for Health.

Objectives: Artificial intelligence (AI) is swiftly entering oral health services and dentistry, while most providers show limited knowledge and skills to appraise dental AI applications. We aimed to define a core curriculum for both undergraduate and postgraduate education, establishing a minimum set of outcomes learners should acquire when taught about oral and dental AI.

Methods: Existing curricula and other documents focusing on literacy of medical professionals around AI were screened and relevant items extracted. Items were scoped and adapted using expert interviews with members of the IADR's e-oral health and education group and the ITU/WHO's Focus Group AI for Health. Learning outcome levels were defined and each item assigned to a level. Items were systematized into domains and a curricular structure defined. The resulting curriculum was consented using an online Delphi process.

Results: Four domains of learning outcomes emerged, with most outcomes being on the "knowledge" level: (1) Basic definitions and terms, the reasoning behind AI and the principle of machine learning, the idea of training, validating and testing models, the definition of reference tests, the contrast between dynamic and static AI, and the problem of AI being a black box and requiring explainability should be known. (2) Use cases, the required types of AI to address them, and the typical set-up of AI software for dental purposes should be taught. (3) Evaluation metrics, their interpretation, the relevant impact of AI on patient or societal health outcomes and associated examples should be considered. (4) Issues around generalizability and representativeness, explainability, autonomy and accountability and the need for governance should be highlighted.

Conclusion: Both educators and learners should consider this core curriculum during planning, conducting and evaluating oral and dental AI education.

Clinical significance: A core curriculum on oral and dental AI may help to increase oral and dental health-care providers' literacy around AI, allowing them to critically appraise AI applications and to use them consciously and on an informed basis.

Keywords

Artificial intelligence, curriculum, deep learning, dental, education, machine learning, teeth.

Note

This is an informative ITU-T publication. Mandatory provisions, such as those found in ITU-T Recommendations, are outside the scope of this publication. This publication should only be referenced bibliographically in ITU-T Recommendations.

Change Log

This document contains Version 1 of the TG-Dental Output 2 on "Artificial intelligence for oral and dental healthcare: Core education curriculum" approved on 24 March 2023 at the ITU-T Focus Group on AI for Health (FG-AI4H) meeting R held in Cambridge, 21-24 March 2023.

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TG-Dental Output 2 – Artificial intelligence for oral and dental health care: Core education curriculum

1 Introduction

With the advent of the data era, data-driven tools have become ubiquitous in our daily lives. An unprecedented explosion of structured and (more so) unstructured data generated by mobile applications, social media or the Internet of Things (IoT) has facilitated the development of numerous technologies to leverage data. In fact, data is increasingly seen as a major resource needed for modern societies to thrive, fulfilling a range of requirements needed to ignite disruption. Also in health care, the digitalization of the care process, from the initial assessment to diagnostics, decision-making and therapy planning, therapy conduct and supportive care, results in the generation of large amounts of data. Semi-structured electronic health record data, speech or imagery data, data from further physical, chemical or biological tests are emerging. Dentistry, dealing with the most prevalent conditions of humankind and being one of the costliest health-care sectors in many health-care systems worldwide [1], [2], observes a similar "data deluge". With the majority of dental patients attending their dentist regularly and long-term, most dental practices or hospitals harbour a treasure trove of data. For each individual patient there exists usually longitudinal multimodal data.

In parallel to this explosion of data, the last decade has witnessed the development of powerful hardware (compute and storage, both on premise and in the cloud) and open-source software tools to leverage large data. Taken together, data, software and compute have made possible what has been strived for since the late 1940s, the development of artificial intelligence (AI). AI is defined as "a type of computer technology which is concerned with making machines work in an intelligent way, similar to the way that the human mind works" [3]. In health care and, specifically, dentistry, AI applications have already entered dental offices, for example via automated analysis of dental imagery like radiographs. The vast majority of AI applications in health care employ the technology of machine learning, where machines learn patterns in data and generalize them for prediction making on other unseen data. In most cases supervised machine learning has been used, where data and data information is provided to the machine. Data information, for example, could relate to a specific diagnosis in an e-health record note or a radiographic finding on an image. Data information can be generated by an active process (often involving medical experts) or can rely on existing data labels, for example from electronic health records. Alternative approaches to supervised learning such as unsupervised, semi-supervised or self-supervised learning, where no, little or indirect (weak) data information is provided are currently less common, but increasingly mixed learning approaches are employed for fully-fledged medical applications.

The promises of AI for medicine and dentistry are high; a deeper, more reliable and accurate understanding of our patients' health and conditions may allow a more targeted prediction-based assignment of therapies. Care may become more precise and personalized, at higher effectiveness and safety. Moreover, AI may allow us to provide services at a greater scale and efficiency, by a more diversified workforce, helping to address global workforce shortages and increasing accessibility. Notably the expectations into AI technologies have been high before, the history of AI is characterized by excitement and disappointment alike [4].

Current AI technologies in medicine and dentistry have not yet fulfilled all promises made: In many instances AI is trained on small, non-representative datasets, introducing bias, and limiting the generalizability of the emanating application. Research on medical and dental AI focuses on accuracy metrics instead of demonstrating true usefulness and clinical benefit to patients, providers or the health-care system. As a result, there is a strong case for caution and governance. At present, a wide range of principles and standards have been developed or are under development, also for AI in the dental domain. AI products will need to be appraised against the strict criteria of evidence-based care, similar to other medical products, and against such standard and norms [5].

One major element of governance and oversight, however, cannot necessarily be realized by standards, norms or external governance: Possibly the most important instance to check for the evidence behind a dental application, its usefulness and applicability for daily care is dental health-care provision, i.e., dentists and other dental professionals. Notably, admission to dental schools and the studies of dentistry, dental therapy or dental hygiene do not focus on what we call data literacy [6]. Biostatistics or bioinformatics and further "data sciences" are only a very minor aspect covered by current dental curricula, if at all. For example, ADEE provides guidelines for dental education based on defined areas of competence with expected learning outcomes, with AI not being considered specifically at present [7]. Having knowledge and understanding of AI could support competence building towards future evidence-based practice and professional education, as outlined in the ADEE guidelines. Given the dynamics in the field of medical and dental AI, it cannot even be expected that existing curricula have incorporated these aspects in sufficient breadth and depth. Hence, the aim of the present study was to develop a core curriculum for dentists and other oral health-care professionals, providing them with the minimum knowledge (and, to some degree, other learning outcomes) of dental AI.

2 Methodology

The development of the curriculum followed a stepwise process. First, existing curricula and other documents focusing on literacy of medical professionals around AI were screened and relevant items extracted. Items were scoped and adapted using expert interviews with members of the International Association of Dental Research's (IADR) e-oral health group (https://www.e-oralhealth.org), the ITU/WHO's Focus Group AI for Health (FG AI4) and the Association of Dental Education in Europe (ADEE). Second, learning outcome levels were defined and each item assigned to a level. Third, items were systematized into domains and a curricular structure defined. The resulting curriculum was then voted on using an online Delphi process.

2.1 Scoping and derivation of items

To derive items for the curriculum, two authors (FS, JK) assessed existing documents on the literacy of medical professionals on AI. Most documents stemmed from radiology [8] to [12], some from pathology [13], [14], traumatology [15] or medical physics [16]. We further conducted interviews with members of the IADR's e-oral health network, the ADEE and the FG AI4H, specifically Topic Group Dental Diagnostics and Digital Dentistry (TG-Dental) to identify possible additional items. Both authors synthesized and structured a list of items which was discussed and revised among the groups using electronic communication.

2.2 Definition of learning outcome levels

For each item, a learning outcome level was assigned using the Recommendation of the European Parliament and of the Council on the Establishment of the European Qualifications Framework for Lifelong Learning [17]. Learning outcomes, i.e., "key realizations or tasks a learner achieved", were defined in three levels; knowledge ("the outcome of the assimilation of information through learning"; also known as "what the learner knows and understands"), skills ("the ability to apply knowledge and use know-how to complete tasks and solve problems", also known as "what the learner is able to do"), and competence ("the proven ability to use knowledge, skills and personal, social and/or methodological abilities, in work or study situations and in professional and personal development", also known as "what the learner is ready to do") [17].

2.3 Delphi process

Members of the described groups were contacted and invited to participate in an online Delphi process where they anonymously voted on the items and levels and could suggest additional ones. The group leaders were further asked to support snowballing sampling, inviting further interested parties or individuals. Overall, we contacted around 90 individuals (given that not all groups used individual email addresses, we cannot ascertain the exact number), 28 of which participated. The overall consensus group represented dental educators, clinical and technical researchers, editors and reviewers, and researchers.

The final item list, together with explanations of each item, was sent to all participants. A one-staged e-Delphi survey was undertaken in July to August 2022. Reporting follows the Guidance on Conducting and Reporting Delphi Studies (CREDES) (18). Further details are provided in Appendix I. Participants had a wide breadth of expertise and experience in both AI, dentistry, e-oral health and medicine, and dental education and also covered a wide geographic range. Some of the experts were familiar to the organizers.

Before the Delphi, participants were given written information about the study. We did not inquire further demographic details. There was the option to not answer single questions (opt-out) and to suggest additional or revised items at the end of the survey.

The Delphi asked for an agreement to each item on a scale of 1-10 (do not at all agree to agree fully). Maximum two stages of the Delphi were planned. Each round was planned to be closed after a four-week period. Two reminders via electronic means were planned for each round. Panellists were allowed to comment on each item. The survey was conducted via a customized online platform; and survey data was analysed descriptively. The following consensus rules applied: (1) agreement to an item was defined by marking grades 7-10 on the described scale from 1-10; (2) a minimum of 70% of all participants needed to agree to an item for this to be consensually accepted. Items which did not meet these criteria after the planned two rounds were dropped. As we achieved stable agreement on all items in the first round, with all items being agreed upon, no second round was needed and hence dropped.

2.4 Checklist pilot

The final curriculum was piloted by two FS and JK in lectures at Charité – Universitaetsmedizin Berlin, assessing if the scope and breadth are fitting. Feedback from dental students was received. No changes were required after this piloting.

3 Results

Overall, four main curricular domains were defined:

1) What AI is and how it works for most medical applications;
2) where AI occurs in the oral and dental health-care sector and what applications are or will likely be available;
3) how to evaluate medical and dental AI; and
4) what further aspects dentists and oral health-care providers should know or assess.

For each domain, a number of items, mainly on the knowledge learning outcome level, were defined. The subsequent subclauses provide the domains and items along with the level of agreement (respondents agreeing with an item, i.e., voting 7 or more on the scale 1-10; median and $25^{th}/75^{th}$ percentiles).

1) What AI is and how it works for most medical applications

The following items were defined in this domain; in brackets the learning outcome level is provided:

1.1 Definitions and terms (knowledge)

In this first item, learners should be provided with definitions and a basic terminology around AI. Terms like artificial intelligence, machine learning, deep learning, as well as software as or in a medical device (SaMD/SiMD) should be explained.
Agreement: 28/28; Median ($25^{th}/75^{th}$ percentiles): 10 (10/10)

1.2 The reasoning behind AI (knowledge)

The idea of AI as a learning system to analyse existing data, understand patterns in it and to make predictions from new data should be explained.
Agreement: 26/28; Median ($25^{th}/75^{th}$ percentiles): 10 (9/10)

1.3 Machine learning (knowledge)

The concept of machine learning should be explained; the idea of back-propagation during training and of inference should be described. Supervised, semi-supervised, self-supervised and unsupervised machine learning as alternative concepts requiring different data preparation should be briefly defined.
Agreement: 26/28; Median ($25^{th}/75^{th}$ percentiles): 10 (8/10)

1.4 Training, validation and testing (knowledge)

The steps for developing and testing an AI should be described. Partitioning of datasets into training, validation and testing should be explained together with the reasoning behind such partition.
Agreement: 27/28; Median ($25^{th}/75^{th}$ percentiles): 10 (9/10)

1.5 Reference tests (knowledge)

Supervised machine learning requires a reference test (annotation, label). The difficulty in assigning medical and dental labels should be highlighted together with the fact that for many AI tasks in the field, multiple labels will be needed. Strategies to deal with this multitude of labels should be briefly explained.
Agreement: 26/28; Median ($25^{th}/75^{th}$ percentiles): 10 (9/10)

1.6 Dynamic versus static AI (knowledge)

The concepts of dynamic and static AI should be defined. Chances but also challenges around dynamic AI (constantly expanding datasets for training if acquiring them from the clinical routine, difficulties of establishing defined reference tests in this approach and regulating dynamic AI) should be described.
Agreement: 22/26; Median ($25^{th}/75^{th}$ percentiles): 8 (7/10)

1.7 Black box and explainability (knowledge)

Lastly, the fact that most AI applications are black boxes should be highlighted. The difficulties in making their reasoning explainable should be underlined and strategies to provide explainability should be briefly explored.
Agreement: 23/28; Median ($25^{th}/75^{th}$ percentiles): 9 (7/10)

2) Where AI occurs in the oral and dental health-care sector and what applications are or will likely be available

The following items were defined in this domain; in brackets the learning outcome level is provided:

2.1 Use cases (knowledge)

The breadth of use cases for AI in the oral and dental domain should be explained. The ITU/WHO Focus Group AI for Health has defined a range of use cases in different disciplines

in the field (https://www.itu.int/en/ITU-T/focusgroups/ai4h/Pages/tg.aspx).
Agreement: 26/28; Median ($25^{th}/75^{th}$ percentiles): 10 (10/10)

2.2 Different types of AI for each use case (knowledge)

It should be highlighted that for different use cases, different approaches of AI (and specifically machine learning) are required. Examples for image analysis are classification, detection and segmentation models. Displaying these different machine learning approaches should be linked to the need for different reference tests (see point 1.5) but also evaluation approaches (see below).
Agreement: 23/28; Median ($25^{th}/75^{th}$ percentiles): 9 (7/10)

2.3 Typical set-up of AI software for dental purposes (knowledge)

A brief overview about how typical AI software in the domain works. This overview should include an explanation of the front end, the back end, the fact that (often) different machine learning models are employed for different subtasks, and that inference will usually run in the cloud (and not on premises) together with the reasoning behind that.
Agreement: 25/28; Median ($25^{th}/75^{th}$ percentiles): 10 (8/10)

3) How to evaluate medical and dental AI

The following items were defined in this domain; in brackets the learning outcome level is provided:

3.1 Metrics (knowledge)

Define a minimum set of metrics (accuracy, sensitivity/recall, specificity, positive predictive value/precision, negative predictive value, area under the curve, F1-score/Dice score, intersection over union, AFROC, among others) used for assessing an AI's performance.
Agreement: 26/28; Median ($25^{th}/75^{th}$ percentiles): 10 (9/10)

3.2 Interpretation (skills)

Highlight that depending on the AI task, the evaluation will be performed on different levels, i.e., patient, tooth, surface or (for images) pixel levels. Describe that to gauge clinical usefulness, these accuracy metrics may not be similarly useful. Discuss that, for example, interpretation of pixel level performances is clinically not easy. Also highlight that given the imbalance in many datasets, especially accuracy as a performance metric is not always useful; high accuracies do not necessarily indicate usefulness. Highlight the difference between prediction and causation.
Agreement: 27/28; Median ($25^{th}/75^{th}$ percentiles): 10 (8/10)

3.3 Impact on patient or societal health outcomes (knowledge)

Recognize the impact that AI applications have at the level of patient outcome measures (e.g., cost per QALY saved) or at the societal level (e.g., benefit-cost or cost-effectiveness analysis from a societal point of view).
Agreement: 27/28; Median ($25^{th}/75^{th}$ percentiles): 10 (9/10)

3.4 Examples (knowledge)

Provide exemplary metrics of current AI applications.
Agreement: 26/28; Median ($25^{th}/75^{th}$ percentiles): 10 (7/10)

4) What further aspects dentists and oral health-care providers should know or assess

The following items were defined in this domain; in brackets the learning outcome level is provided:

4.1 Generalizability and representativeness (knowledge)

Discuss that the selection of the sample for training determines the generalizability of an AI, and that evaluation on different test sets is needed to accurately gauge generalizability. Explain sources of selection bias and impaired generalizability, e.g., data generation device or strategy, sample/population characteristics etc. Expand on the fact that sampling bias may also reflect societal bias; describe a principle of fairness and give examples for bias. Agreement: 25/28; Median (25th/75th percentiles): 10 (8/10)

4.2 Explainability (knowledge)

Take up the argument of many AI applications being black boxes. Describe what explainability means, explain that different systems have different levels of explainability (complexity and output of AI).
Agreement: 23/28; Median (25th/75th percentiles): 10 (8/10)

4.3 Autonomy, accountability (knowledge)

Highlight that current medical and dental AI is supportive in its character; responsibility for using it and for deducing decisions from this support remains with the user. Explain the principles of human oversight and autonomy; consider referring to the WHO ethical AI framework.
Agreement: 26/28; Median (25th/75th percentiles): 10 (8/10)

4.4 Governance (knowledge)

Describe approaches taken in different areas of the world to regulate medical AI (MDR, FDA). Highlight that many medical and dental AI products are medical products and need to be approved by regulatory bodies accordingly. Explain the concept of risk-based regulation. Agreement: 25/28; Median (25th/75th percentiles): 10 (8/10)

4 Discussion

Artificial intelligence (AI) is rapidly entering oral health services and dentistry, and dental professionals are central to ensuring a high quality of any used AI application. To do so, they need basic knowledge and the skills to appraise dental AI. The study that led to the guidelines in this document aimed to define a core curriculum for undergraduate and postgraduate education, establishing a minimum set of learning outcomes which individual institutions could use to tailor, adapt or cross-check their teaching programmes against.

Notably, this approach was only limitedly systematically; the search for existing curricula and other documents focusing on literacy of medical professionals around AI was likely not fully comprehensive. However, a saturation was noted. Moreover, we aimed for inclusiveness and broad representation when inviting bodies and individuals to participate; eventually, 28 individuals spanning from educators to clinicians to researchers were included and voted in the anonymous online Delphi.

As a result, four domains of learning outcomes emerged, with the overall list of items being expected to cover 30 to 45 minute learning sessions. Individual institutions may expand as needed or distribute specific items along other formats (i.e., there is no need to provide all content *en bloc*). Notably, most outcomes were on the "knowledge" level, mainly because in the minimum time available (the new educational content on AI competes with other growing learning fields, e.g., in microbiology, restorative dentistry or implantology) more practical exercises (like hands-on using AI software) are unlikely to be realized. Again, individual institutions may want to expand the scope and level of learning outcomes of AI, and generally this curriculum is likely to be adapted and expanded with the role of AI growing in the future.

In conclusion, both educators and learners should consider this core curriculum during planning, conducting and evaluating oral and dental AI education. It is expected that the adoption of this core curriculum to increase oral and dental health-care providers' literacy of AI, allowing them to critically appraise AI applications and to use them consciously and on an informed basis. Bodies such as the International Association of Dental Research's (IADR) e-oral health group, the ITU/WHO's Focus Group AI for Health (FG-AI4) and the Association of Dental Education in Europe (ADEE) are called to further this work and produce guidelines on granular curricular content and learning outcomes in relation to AI and relevant teaching.

Appendix I

Further details on the Delphi process used

I.1 Rationale for the choice of the Delphi technique

1. Justification: We employed an online Delphi, allowing for transparent, anonymous voting. The technique is accepted by the community. By combining the open-ended initial conception and discussion of the items with a Delphi, a systematic and comprehensive consensus process was possible.

I.2 Planning and design

2. Planning and process. The consensus rules (see below) were set by the authors and communicated via electronic communication before starting the Delphi process. The Delphi asked for an agreement to each item on a scale of 1-10 (do not at all agree to agree fully).

A maximum of two stages of the Delphi were planned. Each round was to be closed after a 4-week period. Two reminders were sent for each round. Panellists were allowed to comment on each item. The survey was conducted via a customized online platform; and survey data was analysed descriptively.

3. Definition of consensus. The following consensus rules applied: (1) Agreement to an item was defined by marking grades 7-10 on a scale from 1-10. (2) A minimum of 70% of all participants needed to agree to an item for this to be consensually accepted. Items which did not meet these criteria after the planned two rounds were to be dropped.

I.3 Study conduct

4. Informational input: The material provided to the panel is described in the main text. Its attainment has been described above.

5. Prevention of bias: A systematic and comprehensive approach under participation of a wide range of experts and two acknowledged international bodies was chosen.

6. Interpretation and processing of results: There was, as discussed, stable agreement to all items after the first round.

7. External validation: Some external validation was sought as the authors have utilized the checklist in recent teaching activities.

I.4 Reporting

8. Purpose and rationale: These have been provided.

9. Expert panel: Three acknowledged international bodies invited a comprehensive sample of experts; participation was further open to other interested parties and individuals.

10. Description of the methods: Preparatory steps, conception and authoring of the document, iteration of the checklist and survey rounds have been described.

11. Procedure: The Delphi steps have been described.

12. Definition and attainment of consensus: The following consensus rules applied: (1) Agreement to an item was defined by marking grades 7-10 on a scale from 1-10. (2) A minimum of 70% of all participants needed to agree to an item for this to be consensually accepted.

13. Results: The results are reported in the main text.

14. Discussion of limitations: A limited group of people have been invited and came to this consensus, which is a limitation.

15. Adequacy of conclusions: The conclusions reflect the outcomes of the Delphi.

16. Publication and dissemination: The checklist is published in an international journal for dissemination.

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