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Programvezető: Dr. Varga Gábor, egyetemi tanár

Témavezető: Dr. Rózsa Noémi Katinka, egyetemi tanár

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PROCESS OPTIMIZATION IN ORTHODONTICS THROUGH STRUCTURED REPORTING AND AUTOMATED CEPHALOMETRIC ANALYSIS

Doctoral thesis

Réka Bagdy-Bálint, DMD

Dental Research Division

Doctoral School, Semmelweis University

Supervisor:
    Noémi Katinka Rózsa DMD, Ph.D
Official reviewers:
    Árpád Joób-Fancsaly DMD, DMS, Ph.D
    Géza Vitályos DMD, Ph.D
Head of the Complex Examination Committee:
    Gera István DMD, Ph.D, CSc.
Members of the Complex Examination Committee:
    Gábor Gerber DMD, Ph.D, CSc.
    Ákos Nagy DMD, Ph.D

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LIST OF ABBREVIATIONS

AI - Artificial Intelligence

AP - Anteroposterior Cephalogram

AR - Augmented Reality

CNN - Convolutional Neural Network

D - Dimension, spatial direction

D.E.M.O. - Digital Health Solutions in Medicine

EDR - Electronic Dental Record

EESZT - Elektronikus Egészségügyi Szolgáltatási Tér (Hungarian Health Data Space / National eHealth Infrastructure of Hungary)

EHR - Electronic Health Records

epSOS - The European Patient Smart Open Services

EU - European Union

GDPR - General Data Protection Regulation

HIS - Hospital Information System

HIT - Hospital Information Technology

HITECH - Health Information Technology for Economic and Clinical Health

ICT - Information and Communication Technologies

IT - Information Technology

ITS - Intelligent Tutoring Systems

KDE - Kernel Density Estimation

L2 - Euclidean distance error

MeSH - Medical Subject Headings

ML - Machine Learning

OP - Orthopantomogram

PA - Posteroanterior Cephalogram

PPT - PowerPoint presentation

SE - Semmelweis University

SQL - Structured Query Language

STL - Stereolithography

TAD - Temporary Anchorage Devices

TD - Training Dataset

VR - Virtual Reality

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XLS - Excel-compatible binary file format

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I. INTRODUCTION

I.1 MOTIVATION FOR THE RESEARCH

When I began my research career at the Semmelweis University (SE) (Budapest, Hungary), I encountered several challenges, particularly in managing orthodontic treatments, which are inherently long-term processes. At the Department of Paediatric Dentistry and Orthodontics, Faculty of Dentistry, Semmelweis University, there was no standardized digital system for patient handovers among postgraduate students. Early in my career, I was entrusted with managing over 140 ongoing patients. Out of all their accompanying records, approximately 15 were complete (including anamnesis, cast analysis, photographic and radiographic records), around 65 were partially filled out or inconsistent, and about 60 were entirely missing. This made reliable long-term follow-up for these patients difficult. For each patient admission, new documentation had to be made, including the acquisition and evaluation of new radiographs. The software used for analysis proved to be relatively slow and not consistently accurate. Furthermore, its unavailability for an entire year meant that cephalometric analyses had to be performed manually, with each one taking approximately 30 minutes per radiograph. These difficulties raised the question of whether AI could be utilized for cephalometric analysis, and how advancements in Information and Communication Technologies (ICT) could be leveraged to improve efficiency and the quality of patient care, research, and education at our clinic. This thesis focuses on AI applications in data-driven healthcare within the field of orthodontics, with particular emphasis on cephalometric analysis, driven by two technological innovations aimed at optimizing diagnostic workflows.

I.2 BACKGROUND AND CONTEXT

Fortunately, the digital era of contemporary medicine facilitates rapid progress in medical diagnostics, therapy, and research. Consequently, technological innovations serve as the driving forces behind the advancements in modern dentistry as well. (1-3) From the perspective of university-level research, teaching, and medical care, Artificial Intelligence (AI), Virtual Reality (VR), and Augmented Reality (AR) play increasingly important roles in tertiary education and research (Figure 1.). (4) These technologies are applied in intelligent tutoring systems (ITS), laboratory and pre-clinical teaching, patient-centred interactive education, and research-driven instruction, all supported by accurate digital data storage. (2-4) There is also a growing body of literature highlighting the significant demand for advanced ICT solutions such as modern data structuring and the implementation of structured query language (SQL) databases. These technologies are increasingly recognized for their potential to enhance university-level research, teaching, and medical care by improving data management, optimizing clinical workflows, and enabling more efficient and effective research processes. This dissertation will explore these advancements in detail and examine their applications in healthcare and science.

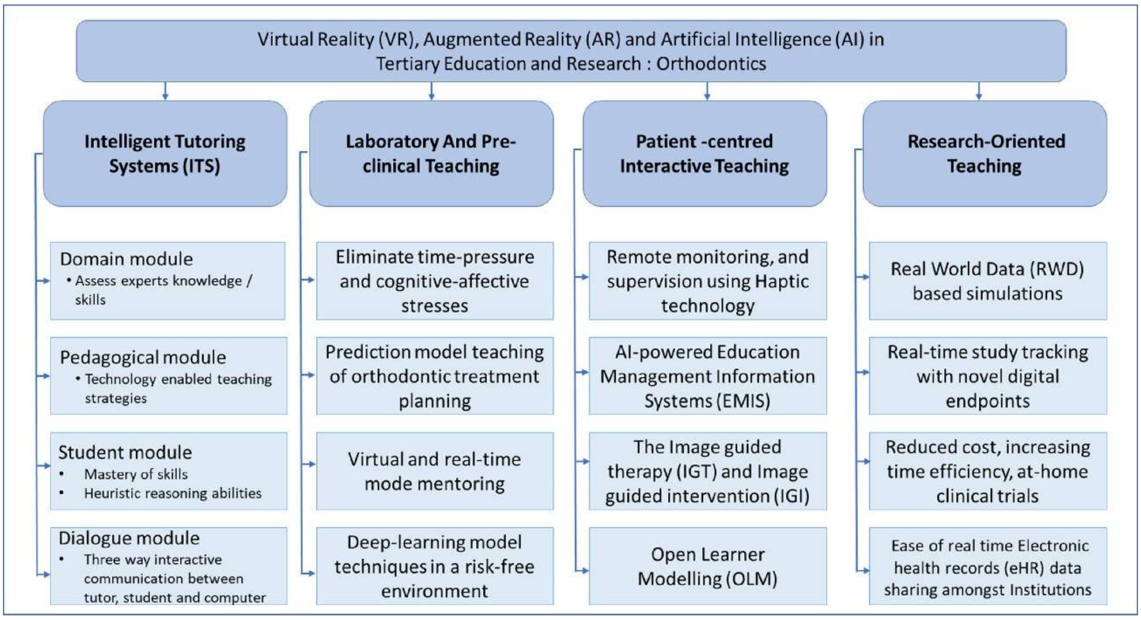

Figure 1. „Interaction of strategic framework, professionalism and patient care delivery in the era of AI, VR, and AR". (4)

As Machine Learning (ML) plays a crucial role across various modern professions, it is to be expected that research in medicine and orthodontics is increasingly focusing on the use of AI tools to optimize diagnostic, therapeutic, and follow-up workflows. (1,5-7) The latest literature on AI applications in orthodontics reports numerous studies showing promising results in early prediction of treatment requirements, evaluating maturational characteristics in growing patients, assessing the need for orthognathic surgery or tooth extraction, determining tooth movements, estimating therapeutic changes and identifying cephalometric landmarks on 2 dimensional (D) or 3D radiographs. (1,6-10) However a literature review identified potential biases, highlighting the need to consider factors such

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as system complexity, costs, setup requirements, and training methods for each AI model. (11) While the integration of AI prediction models into clinical practice has advanced significantly in recent years, data on diagnostically and therapeutically relevant metrics for cephalometric analysis tools are still lacking. (1)

In orthodontics, the 2D evaluation of lateral cephalometric radiographs (Figure 2.) plays a critical role in diagnostic assessment. However, manual evaluations performed by clinicians may introduce substantial error, even when measurements are repeated. Although numerous studies on digital cephalometric analysis exist, fewer have focused on the validity and reliability of 2D landmark detection. (1) While cephalometric analysis requires time-consuming human intervention, the process of tracing specific landmarks is relatively straightforward, as the anatomical structures are predefined. Although concentration is essential for accuracy, the task itself is less cognitively demanding, making it well-suited for automation with minimal human oversight.

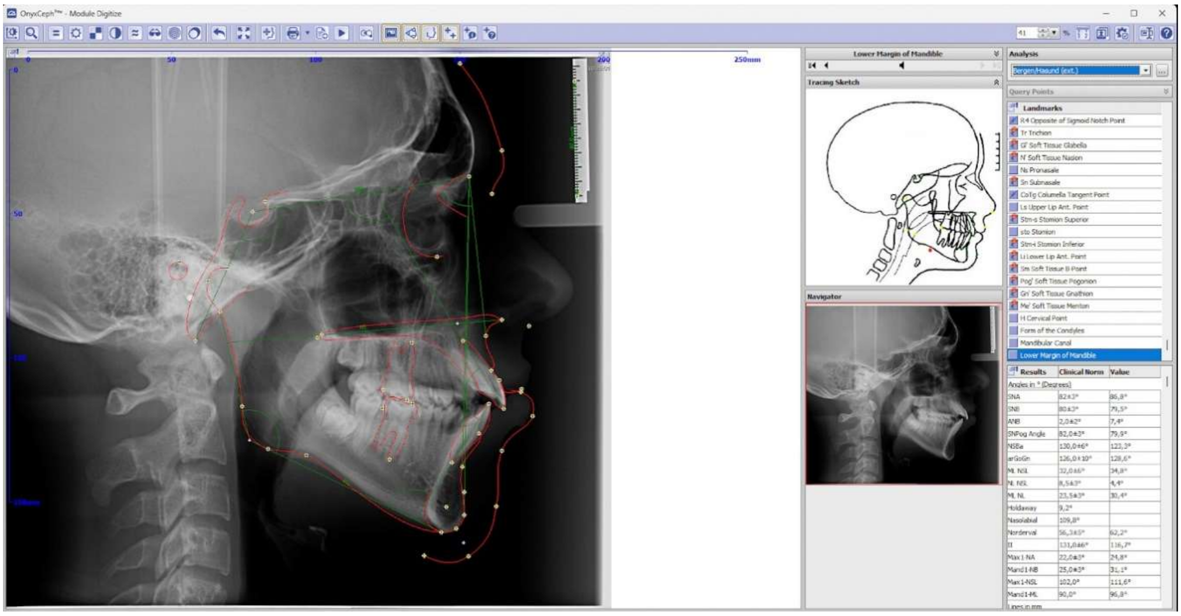

Figure 2. Interface for manual evaluation of digital cephalograms in the OnyxCeph3TM (Chemnitz, Germany) software. (1)

Reviews indicate promising results regarding the effectiveness of AI tools in cephalometric analysis, however, it is important to consider that the outcomes are influenced by factors such as the quality of input data, the number of training cycles, and the characteristics of the algorithms used. Studies have shown that the automation of manual landmark detection, image quality, and sample variability impact performance.

Several studies have demonstrated favourable results using larger sample sizes, whereas others have reported comparable outcomes based on smaller datasets. The mean error in landmark identification typically ranges from 1 mm to 4 mm. (1,8)

Our hypothesis was that AI-based predictions of cephalometric landmarks, when applied to clinically relevant data, would facilitate more accurate angular and proportional measurements, thereby supporting more efficient and reliable orthodontic diagnosis. In this study, our aim was to demonstrate the significance of both the quality and quantity of training datasets (TD) regarding the accuracy and time efficiency of an AI model in clinical applications, utilizing relatively large datasets. However, we hypothesized that after a certain threshold of training data, further increases in dataset size would result in marginal improvements. Among the available software solutions, the model we tested stands out for its comprehensive, criteria-based assessments that directly investigate the physician-AI relationship. To minimize clinician-induced errors in landmark detection accuracy, we aimed to repeat measurements multiple times by two independent experts on separate occasions. (1)

Upon working deeply in this topic, it became apparent that a contradiction exists. While leveraging AI tools across various industries seems promising, and there is a strong emphasis on gathering increasingly large volumes of data in short time, the challenges associated with data storage and management are often overlooked. Is it truly beneficial to accelerate data collection and expand its volume if effective storage and reuse mechanisms do not exist? It may be more appropriate to first establish robust systems for storing and managing the outputs of AI-driven analyses before further refining the tools themselves.

Another persistent challenge in healthcare, including specialised fields such as orthodontics, is the continued reliance on labour- and resource-intensive documentation processes. Structured, accessible, and transparent medical data storage remains unresolved in most healthcare providers in Hungary. The limited reusability of clinical data restricts the potential to improve patient care quality, enhance the transparency of treatment pathways, foster research development, and fully leverage the opportunities afforded by data-driven analysis. The use of data lakes, which rely on paper-based or unstructured electronic health records (EHRs), complicates data sharing among clinicians even when they work in close physical proximity. This difficulty limits the inclusion of relevant subjects in research and reduces the availability of case numbers necessary for future studies. Optimizing workflows through the digitalization and structuring of medical records is expected to address these challenges, reduce burnout among healthcare providers, and enable more accurate and faster results, along with deeper insights into diseases. (2-3,12-13)

Although healthcare in Europe lags behind other sectors in the everyday use of ICTs, the European Commission addressed this gap as early as 2004 with the adoption of the e-health action plan, further updating it for 2012-2020. (3,14-16) From the perspective of Western-level healthcare, e-health, developed through the European Patient Smart Open Services (epSOS) project, offers significant social and economic benefits by fostering interoperability and standardized systems. (3,17-18) In addition, Hungary's participation in the epSOS project, the progress demonstrated by the Digital Health Solutions in Medicine (D.E.M.O.) project led by the Institute of Behavioural Sciences at Semmelweis University, reflects notable advancements in e-health. (3,19) The D.E.M.O. project emphasizes the evolving role of healthcare professionals, suggesting they will increasingly act as intermediaries between data and patients, while highlighting that the current digital transition benefits patients more than their physicians. (3,19) This perspective aligns with the growing importance of Information Technology (IT) professionals, or "data scientists," in healthcare. Rethinking innovative documentation systems, organizing medical records, and advancing data utilization are critical steps to support this transformation and enhance healthcare, academic performance and medical education in Hungary. (3,20)

Since I started exploring data science, workflow optimization, and the rational application of AI in Hungarian healthcare, I was confronted with the reality that the field faces numerous unresolved questions and uncertainties requiring clarification. Additionally, there revieled a need for strategic plans to be developed regarding digital healthcare and the use of ICT systems. Today, we can take pride in several innovations at Semmelweis University, including the establishment of the Institute for Clinical Data Management (21) in 2023 and the launch of Europe's unique master's program in healthcare data science. (22) This master's program has been established in recent years within the Faculty of Health and Public Services of Semmelweis University as a methodological centre, supporting the systemic implementation of data-driven and artificial intelligence supported solutions through extensive collaborations with partner institutions and research centres. (22) A notable milestone was the latest agreement between the Faculty of Health and Public Services Management and the National Media and Infocommunications Authority signed in November 2024. This partnership aims to advance data-driven health research, enhance media literacy, and promote digital competencies. This collaboration focuses on integrating ICTs into healthcare, promoting the widespread adoption of digital health services, and exploring the intersections of infocommunications and healthcare to advance modern medical practices in Hungary. (23) Further revolutionary innovation is being developed by the collaboration of the Health Management Training Centre and the Hun-Ren Rényi Alfred Mathematical Research Institute’s AI research group, creating a comprehensive patient pathway and health life-course analysis platform that leverages AI models to predict risks of disease onset, progression, and health deterioration. This platform aims to improve prevention, enable early detection, and support personalized treatments for the entire Hungarian population. (24) Among other factors, this indicates that Hungary is among the leaders in building a data-driven and AI-supported healthcare network in the global innovation landscape. The key question is whether this position can be sustained over time. As clinicians and researchers, we must consider how we can contribute to this progress. Even small improvements in our daily work can greatly support both our university’s academic mission and the rapid development of the national healthcare system of Hungary.

On an international level, interoperable channels are being established through initiatives such as the DIGI4Care project, which forms part of the European Union (EU) Strategy for the Danube Region. DIGI4Care focuses on transforming patient pathways through digital and AI innovations, with an emphasis on the testing and integrating these solutions into healthcare systems. The project also promotes collaboration and knowledge sharing to help bridge the digital gap between EU and non-EU countries within the Danube region. (25)

Focusing on the dental field, the use of electronic databases in dental practices offers numerous advantages, including efficient data retrieval, quality assurance programs, and strategic planning, as outlined in the Dental Provider’s Guide (26) to the Electronic Dental Record (EDR), 2015. With the integration of standardized databases and query tools, dental providers can implement longitudinal quality assurance and improvement programs, enhancing patient care and operational efficiency. (26) In clinical settings, the adoption of EDRs for clinical support in dental practices has shown significant progress. A 2017 study reported that 52% of dental practices had implemented EDRs, indicating integration of electronic reporting in routine dental care. Interestingly, the adoption rate of EDRs in dental offices of the United States was higher in 2012 compared to the adoption rates of EHRs in medical offices during the same period and this trend was not driven by the Health Information Technology for Economic and Clinical Health (HITECH) program. (27) The maintenance of structured databases for dental medical records is becoming increasingly prevalent, contributing to improved patient management and care in both private practices and educational institutions. However, the integration of patient portals by dental practices has remained relatively low, reflecting an area for potential improvement in patient engagement and accessibility. (27-28) The studies by Kalenderian et al., conducted at the Harvard School of Dental Medicine in the United States, aimed to develop and validate a methodology for identifying and classifying adverse events in dentistry using data from electronic dental records. While these efforts indicate a certain level of structured documentation, they do not provide sufficient evidence to confirm the use of an SQL-based database. (29-30)

Despite the advantages of optimized documentation processes, limitations remain. Many electronic dental record (EDR) systems continue to prioritize administrative and clinical documentation over comprehensive patient histories, diagnostic data, and therapeutic details, which restricts their utility for longitudinal research and advanced analytics. For example, while EDRs have improved billing and scheduling efficiency, their capacity to monitor detailed clinical metrics and patient outcomes over time often remains underdeveloped. (31) These findings highlight the growing global demand for structured databases in dental practices and institutions, while also revealing areas for improvement, especially in research capabilities and patient-centred functionalities

II. OBJECTIVES

My ongoing interest in modern, efficient, and time-saving solutions has driven me to focus on improving diagnostic workflows within my profession particularly through the development of AI tools and the optimization of data collection, utilization and storage. While this goal may appear straightforward, the overall landscape is complicated by limited access to advanced technology, inadequate computer training, and challenges posed by the current system and circumstances. To ensure that my work is well-founded and thoroughly prepared, I must start by reviewing the literature and examining the challenges faced by other institutions to understand the existing structures in healthcare. This includes assessing the adaptability of our country's documentation systems and exploring how software can be customized to address both external requirements and local needs. Building on previous studies and established policy guidelines, this study aimed to highlight the increasing demand for modern digital tools, electronic workflows, and efficient data processing within the medical sector. (3)

Furthermore, through surveys of anamnestic and diagnostic trends within our clinic, we emphasize the importance of integrating medical data into a structured retrieval system to improve patient care and research efficiency. My ultimate objective is to develop a custom interface within a structured database, enabling seamless application in daily medical and research practices while supporting future statistical analyses, scientific studies and evidence based clinical practice. (3)

In comparing the temporal duration and data comprehensiveness of the diagnostic steps and evaluations, it is evident that cephalometric analysis ranks first in terms of reporting during the recording process. To facilitate faster and more accurate orthodontic X-ray analysis, I have started working on a project aimed at training an algorithm utilizing a relatively large dataset of 1,600 images, to automate cephalometric landmark detection on lateral cephalometric radiographs. Being sceptical of several AI solutions, we initially conducted a highly comprehensive and representative study before integrating the software's tools into our clinic's daily diagnostic routine. This study aimed to demonstrate the training process of a cascaded Convolutional Neural Network (CNN) for landmark detection on lateral cephalograms of varying quantity, and to assess the speed, reliability, and clinical accuracy of the algorithm for orthodontic diagnosis. Together with IT professionals, our aim was to demonstrate that an AI software becomes progressively better, more reliable, and faster as it is trained with upgraded and expanded datasets. We hypothesized that after a certain threshold of training data, further increases in dataset size would result in diminishing returns. Additional aim of this study was to demonstrate the relevance of both the quality and quantity of testing data in the accuracy and time efficiency of an AI model developed for automated landmark detection on lateral cephalograms, for clinical applications. (1) The ultimate goal of this research is to demonstrate with high-quality data, that the latest AI model can function as an accurate diagnostic tool, providing insights in both spatial and temporal dimensions, while also highlighting its benefits and limitations.

The future aim of this study is to analyse the clinical and scientific impact of an existing structured documentation system, in conjunction with the AI tool for automated cephalometric analysis on clinical efficiency. Additionally, it seeks to provide a framework for further integration of diagnostic tools, along with a direction for its implementation in other healthcare institutions.

Ultimately, I aim to contribute to the establishment of a Dental Data Centre that supports both clinical care and academic advancement across Hungary, for the benefit of my colleagues, my university, and my national healthcare system.

III. METHODS

III.1 LITERATURE REVIEW

A literature search for systematic reviews on the topic of EHR and ICT in healthcare was conducted in the Pubmed/Medline database, by using several Medical Subject Headings (MeSH) terms and free-text keywords, including e-health, documentation, EHR, computerized, and structured. The analysis was restricted to systematic reviews published in the international literature over the past 15 years. With one exception, all seven selected articles were written in English. (2-3)

III.2 IN-HOUSE RESEARCH

In addition, we evaluated the documentation system utilized at our clinic, which is based on unwritten internal protocols and practices. This system includes a paper-based medical record and a supplementary PowerPoint presentation (PPT) for each patient, summarizing their anamnestic data and diagnostic findings from radiographic, cephalometric, dental cast, and photographic analyses. A total of 30 patients' documentation, including both paper-based and PPT records (n=60) were reviewed. Fourteen thematic areas of medical history and diagnostics were analysed, as outlined in Table 1. These areas encompassed essential components of general and dental history, extra- and intraoral clinical examinations, as well as results of the diagnostic findings. Specific data points included general health status, etiological factors, harmful habits, joint dysfunctions, other systemic dysfunctions, radiographic evaluations (orthopantomogram [OP], lateral cephalogram, anteroposterior [AP] and posteroanterior [PA] cephalogram - PA and AP radiographs are hereinafter referred to as AP cephalogram uniformly), photographic analysis, jaw asymmetry, and key metrics from model analysis (Bolton discrepancy, WALA ridge, spacing, and crowding). The proportion of available versus missing data was assessed for each documentation type, and the time required to review each patient's records was recorded. Statistical analyses, including Pearson correlation and two-sample t-tests, were performed to evaluate the results. (2-3)

Table 1. 14 Thematic areas across the documentation of 30 patients were analysed. (3) (OP: orthopantomogram, AP: anteroposterior and posteroanterior)

1.	Anamnesis	8.	AP Cephalogram
2.	Etiology	9.	Joint Function
3.	Photo Analysis	10.	Other Disfunction
4.	Cast Analysis	11.	Bolton Analysis
5.	WALA Ridge	12.	Spacing
6.	OP	13.	Crowding
7.	Lateral Cephalogram	14.	Asymmetry

III.3 DEVELOPMENT OF A CUSTOM STRUCTURED REPORTING PLATFORM

To address the development needs identified in the international literature regarding documentation systems, as well as our validated hypotheses concerning inaccuracies in our reporting practices, I collaborated with IT professionals from the Graid IT Solutions Kft. (31) (Budapest, Hungary) to develop an evaluation template within Graid structured reporting software. This template was designed specifically for the Department of Paediatric Dentistry and Orthodontics (3) at Semmelweis University. The template was designed to allow clinicians to input results from cephalometric, photographic, and model analyses on an interactive platform while simultaneously establishing the clinic's standardized SQL database. I organized the database thematically in line with the sequence of routine diagnostic steps, paying particular attention to the specific needs of the research teams at our clinic. The SQL database was selected for its platform-independent, set-oriented structure and standardized query language capabilities. It allows for efficient data retrieval through keyword queries and facilitates data export in Excel-compatible binary file format (XLS) for further analysis. To ensure broad accessibility, the documentation database was integrated into our hospital information system (HIS), which communicates with the National eHealth Infrastructure of Hungary (Elektronikus Egészségügyi Szolgáltatási Tér , EESZT). Later, with the establishment of the Institute for Clinical Data Management at Semmelweis University (21), I identified the final location for our structured database at the Semmelweis University Biobank Network (33). (2-3) This platform is essentially a robust, eCRF-like application equipped with form and report builders. Importantly, it was designed for practicing clinicians, making all its functions highly medically oriented (including visits, report generation, calculations between visits, etc.). With simple PHP coding, it can be customized even without advanced IT expertise. Additionally, it supports evaluation fields for performing calculations and allows integration of imaging materials.

III.4 TESTING AN AI ALGORITHM TRAINED ON AUTOMATED CEPHALOMETRIC LANDMARK DETECTION

As cephalometric analysis is the most time-consuming and detailed part of orthodontic diagnosis, we collaborated with the IT specialists of Ceph Assistant Ltd. (Budapest, Hungary) (34) to develop a reliable, automated solution. To further enhance the speed and accuracy of orthodontic X-ray analysis, we simultaneously initiated work on training an algorithm to identify cephalometric landmarks on lateral cephalometric radiographs. A highly representative study preceded the incorporation of the Ceph Assistant software into our clinic's routine diagnostics. Among the studies on software solutions for cephalometry discussed in the literature, this research stands out for its comprehensive, criteria-based evaluations, which directly assess the interaction between clinicians and AI across a broad set of cephalometric landmarks and a wide range of radiographic image qualities. (1)

The CNN model developed by Ceph Assistant was trained using a total of 1,600 lateral cephalograms, divided into four different training dataset (TD) quantities (inputs of 400, 800, 1,200, and 1,600 images). After each TD were added, the model was evaluated on a test set containing 78 images of varying quality. We expected the accuracy and time efficiency of the model to improve as the training datasets increased, reflecting this progress in our results. Most studies examine no more than 20 landmarks, frequently excluding difficult-to-detect profile outlines and tangent points, that are nonetheless routinely used by specialists in clinical practice. This selective approach may compromise the statistical accuracy and clinical relevance of the findings. Our study considers 48 cephalometric landmarks (detailed in Table 2.) and compares evaluations of images of varying quality, using models trained on four datasets of different sizes. The evaluation with these landmarks covers dental, dentoalveolar- and alveolar deviations examined, based on the Rickett's and Hasund analysis, and can be used to analyse the entire skull, jaw relationships, dentition and profile. (1)

Table 2. Cephalometric landmarks detected on all digital radiographic images and their abbreviations. (1)

Number	Landmark	Abbreviation
	Calibration point 1	Cal 1
	Calibration point 2	Cal 2
1.	Mesial apex of mandibular 6	1LoMma
2.	Mesial apex of maxillary 6	1UpMma
3.	Downs A-point	A
4.	Articulare	Ar
5.	Downs B-point	B
6.	Basion	Ba
7.	Columella	Co
8.	Condylion	Cond
9.	Center of symphysis	D
10.	Soft tissue glabella	Gl'
11.	Gnathion	Gn
12.	Soft tissue gnathion	Gn'
13.	Infradentale	Id
14.	Mandibular notch point	Im
15.	Lower incisor apex	La
16.	Lower incisor crown tip	Li
17.	Lower lip anterior point	Ll
18.	Upper incisor labial outline	Ls1u
19.	Mesial cusp of maxillary 6	M6lo
20.	Menton	Me
21.	Soft tissue menton	Me'
22.	Nasion	N
23.	Soft tissue nasion	N'
24.	Orbitale	Or
25.	Supra pogonion	PM
26.	Pronasale	Pn

Number	Landmark	Abbreviation
27.	Porion	Po
28.	Pogonion	PoG
29.	Prosthion	Pr
30.	Pterygoid point	Pt
31.	Sella turcica midpoint	S
32.	Center of sella's entry	Se
33.	Submentale	Sm
34.	Subnasale	Sn
35.	Posterior spine nasal	SnA
36.	Anterior spine nasal	SnP
37.	Stomion inferius	Stm-i
38.	Stomion superius	Stm-s
39.	Tangent 1/Gonion posterior	T1
40.	Tangent 2/Gonion Inferior	T2
41.	Trichion	Tr
42.	Mesial cusp of maxillary 6	U6
43.	Distal contact of maxillary 6	U6d
44.	Upper incisor apex	Ua
45.	Upper Incisor crown tip	Ui
46.	Upper lip anterior point	Ul
47.	Condylion posterior	ppCond
48.	Soft tissue pogonion	sPoG

We measured the accuracy of AI-based landmark detection by statistical analysis of intra- and interexaminer distance errors defined as Euclidean distances (L2), as well as examiner versus model predictions, furthermore by prognosis of consecutive diagnostic failures. L2 distance, defined as the shortest distance between two points in a coordinate system, is widely used in AI radiographic analysis due to its effectiveness in accurately measuring and comparing landmark positions. To minimize clinician-induced errors in landmark detection accuracy, measurements were repeated eight times; twice by two independent experts and four times by AI models with subsequent correction by a senior expert. (1)

Shortly after, we successfully implemented the import of results, extracted by the automated cephalometric program into our structured medical platform within the Biobank. This advancement considerably reduces the time and effort required from our colleagues by enabling the immediate and seamless transfer of complete diagnostic data to the Biobank interface. (1)

III.4.1 Data collection

Regardless of whether the radiographs showed dentures or orthodontic appliances, a total of 1678 2D lateral cephalometric images (2485 × 2232), all uniformly downsampled to a pixel size of 512 × 512, were randomly selected and anonymously downloaded from the OnyxCeph3TM server at Semmelweis University, Department of Paediatric Dentistry and Orthodontics. Altogether, 1600 cephalograms were manually (using mouse-controlled cursor) evaluated by the orthodontists working at the clinic. Each evaluation were completed based on Hasund and Ricketts' analysis in the OnyxCeph3TM software (Figure 2). Before data export each calibration and resolution elements of the recordings were checked and verified by three experienced professionals. The X and Y coordinates of each of the 48 landmarks were separately saved, along with the results of the digital cephalometric evaluations manually performed by clinicians using the software. These datasets were systematically organized, transferred, and subsequently utilized for training the AI model of Ceph Assistant. (1)

78 cephalograms were randomly selected from a total of 1678 images and used as a test dataset. To prove the representativeness of the test dataset, cross-validation was performed on a set of 39 (50 %) and 20 (25 %) elements randomly selected 10000 times from the 78 test samples. We calculated the percentage fluctuation of prediction for comparing AI versus AI-corrected and AI versus gold standard as well, to confirm the role of sample selection data over prediction or any reference. (1)

III.4.2 Training process and technical features of four prediction models with varying training levels

The Convolutional Neural Network (CNN) of Ceph Assistant AI-architecture, utilized in this study is specifically developed for landmark localization on lateral cephalometric images, as a reference AI-based cephalometric solution. The TD consisted of a total of 1600 lateral cephalograms, together with their corresponding preliminary manual evaluations was stored in .xls/.xlsx format. The model underwent training on four distinct datasets, containing 400/800/1200 and 1600 images, respectively. During each training process, the model received cephalometric images as input and the manually recorded location data of the 48 landmarks as output. (1)

III.4.3 Testing at four different levels of the model

During testing, the test dataset was automatically analysed by the AI-model following each training set (TD = 400/800/1200/1600 cephalometric images). Once the test set was processed by the AI-algorithm, the senior examiner manually corrected landmark using mouse-controlled dot tracing. The L2 distance errors were subsequently calculated from the X and Y coordinates generated by the software during the evaluation process. Manual evaluation of the test dataset was performed separately using a test environment of the Ceph Assistant (Figure 3.), configured directly for this experiment. The evaluation was performed by two experts with 4 (medior) and 10 (senior) years of clinical orthodontic experience. The 78 cephalograms included images of 41 female and 37 male patients with an average age of 13.8 years. Both manual and AI evaluations included 48 cephalometric landmarks of skeletal, dental and profile markers (Table 2.). Time for each procedure was automatically recorded by the software. (1)

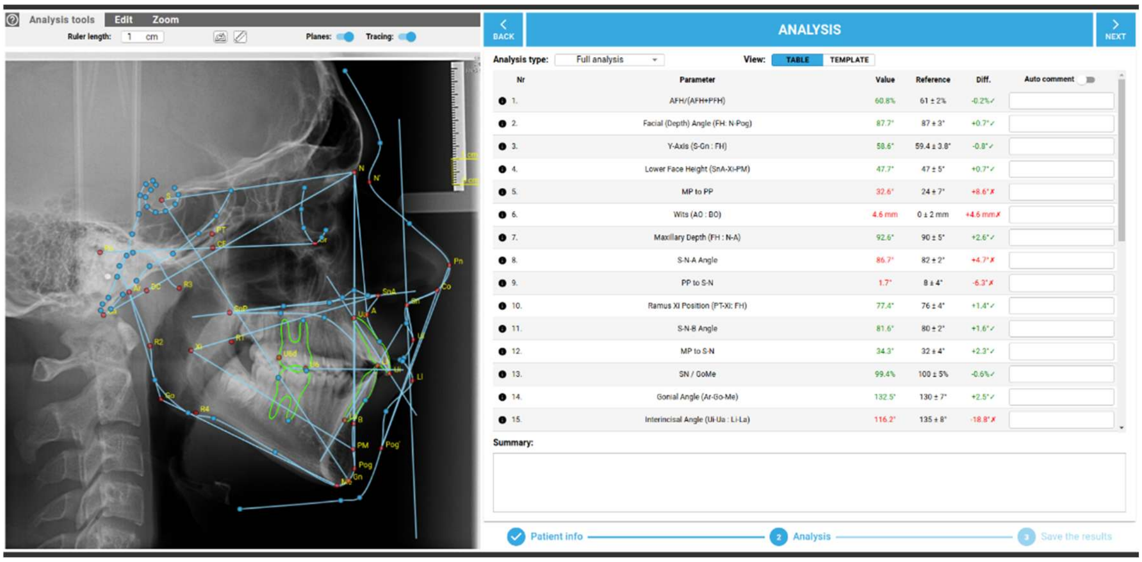

Figure 3. Interface for manual evaluation in the Ceph Assistant software. (1,34)

III.4.4 Statistical analysis

A statistical analysis was performed on time efficiency and accuracy of landmark detection achieved by the different methods. The average of the landmark coordinates, calculated from the corrected landmarks detected by the senior expert on four different occasions, was defined as the gold standard. After measurements were performed ten times (2 “manual”, 4 “AI-corrected”, 4 “AI”), data were compared to the gold standard. Euclidean (L2) distances were considered for distance errors, as L2 performed better than Manhattan (L1) in research where directional information of the coordinates yielded less difference and relevance. (35,36) After recognizing, that the quality of the test images substantially influenced the decision of the experts on landmark positioning and time taken for evaluation, we graded images based on quality. Statistical analysis was further refined to identify differences associated with these variations. This process involved precise calibration to ensure accurate comparisons between different image qualities. As shown in Table 3., nearly one-fourth of the images were classified as either easy (scores 4 and 5) or difficult (scores 1 and 2) to analyse, while more than half (42) of the images received a moderate rating (score 3). (1) Compared to Pearson correlation and t-test statistical methods, the application of Kernel Density Estimation (KDE) proves to be a more advantageous choice when testing AI-based radiographic analysis software, particularly in examining the relationships between the algorithm and the physician. KDE not only provides a continuous representation of the data distribution, but also has the ability to detect and model complex, nonlinear relationships that may not be well captured by traditional linear models, such as Pearson correlation or t-tests. The primary advantage of KDE lies in its ability to smooth out noise and mitigate potential errors arising from consistent deviations, thus reducing the impact of distortions that can occur when relying on conventional statistical methods. By visualizing the density function of the data distribution, KDE serves as a more flexible and robust tool for accurate data analysis, particularly when the data exhibit heterogeneous or complex structures. This approach ensures more reliable and credible results by accurately capturing the true diversity of data distributions, without being excessively influenced by random fluctuations or outlier effects. To illustrate discrepancies in time measurements, we employed a violin plot chart, as it can reveal clustering and distribution roughness, providing additional insight and visual representation. (1,37) Histograms and a box plot diagram were used to compare manual versus AI-corrected, manual versus AI-generated, and AI-generated versus AI-corrected distances following each training dataset. (1)

Table 3. Distortion on evaluability of test images by quality scaling with 1–5 scores. (1)

Number of the X-ray	**Evaluability score of the X-ray**	**Gender**	**Age**
1	3	Female	17
2	5	Male	29
3	3	Female	48
4	3	Female	9
5	3	Female	9
6	3	Male	22
7	3	Male	13
8	5	Female	16
9	3	Male	16
10	1	Male	16
11	3	Female	11
12	2	Male	14
13	3	Female	18
14	3	Female	18
15	3	Female	14

Number of the X-ray	Evaluability score of the X-ray	Gender	Age
16	3	Male	7
17	1	Male	13
18	5	Female	15
19	3	Male	10
20	3	Female	10
21	4	Female	10
22	3	Male	13
23	3	Male	14
24	3	Female	14
25	3	Female	17
26	4	Male	11
27	3	Female	14
28	4	Female	18
29	3	Female	17
30	2	Male	11
31	4	Male	16
32	3	Female	14
33	3	Male	12
34	3	Female	8
35	2	Female	11
36	2	Female	10
37	3	Female	13
38	2	Female	14
39	3	Male	16
40	3	Male	16
41	4	Male	13
42	3	Male	15
43	4	Female	15
44	2	Female	16
45	3	Female	15
46	3	Male	15

Number of the X-ray	Evaluability score of the X-ray	Gender	Age
47	2	Male	16
48	3	Male	13
49	2	Male	15
50	4	Female	8
51	3	Male	10
52	3	Female	10
53	4	Male	16
54	2	Male	15
55	3	Male	12
56	3	Male	12
57	2	Female	15
58	2	Female	12
59	4	Male	17
60	3	Male	7
61	3	Male	14
62	4	Female	16
63	2	Female	10
64	3	Female	14
65	3	Male	12
66	3	Female	13
67	2	Male	15
68	4	Male	9
69	3	Male	10
70	4	Female	16
71	3	Female	14
72	2	Female	24
73	4	Male	9
74	3	Male	13
75	4	Female	17
76	4	Female	14
77	2	Female	13

Number of the X-ray	Evaluability score of the X-ray	Gender	Age
78	5	Female	12

The scaling process in this study follows established methodologies for image analysis;

Scaling explanation:

Score 5: Adequately assessed, high-resolution image (total: 2).

Score 4: Adequately assessed, high-resolution image; however, the presence of orthodontic appliances during image acquisition and other factors may have contributed to visible blurry areas, though these are minimally distracting and did not affect analysis integrity (total: 15).

Score 3: Blurred double lines hinder accurate area evaluation, suggesting potential patient movement during image acquisition, complicating analysis (total: 42).

Score 2: Image quality is sub-optimal, with insufficient detail, making it challenging to accurately identify cranial or profile landmarks (total: 17).

Score 1: Image resolution is inadequate, resulting in poor quality and insufficient detail, thereby making it difficult to accurately identify both cranial and profile landmarks (total: 2). (1)

IV. RESULTS

IV.1 FINDINGS FROM THE SYSTEMATIC REVIEWS

The authors of a Finnish study reviewed 89 papers on EHRs in 2008, highlighting the need for reusable data and standardized terminology. They found that electronic records improve healthcare documentation and suggested early research on integrating AI tools into EHRs. These tools were found to rely on high quality, structured, accurate data, as incomplete data do not support decision-making, research, or policy. (3,38-40)

Kruse et al. summarized 37 publications in a 2018 review, highlighting the limited number of studies focusing on hospital information technology (HIT). Buntin et al. reported that nearly 10% of the studies found negative outcomes regarding HIT applicability, while Goldzweig et al. observed that HIT significantly enhanced healthcare efficiency and productivity. Similarly, 81% of the studies included in Kruse et al.'s review reported positive outcomes, while the remaining 19% may have been influenced by confounding factors. (3,41-44) These findings reflect a broader policy trend: health care providers are increasingly incentivized to adopt HIT as policymakers respond to rising demands for quality and safety, and reimbursement models shift toward value-based purchasing. (45)

According to a review published in 2020, the application of graph-theoretical algorithms for visualizing and processing patient data, points toward a future in which decision-support systems for diagnosis, differential diagnosis, medication, and therapy may be developed. However, there are currently insufficient number of studies to predict the full potential of this area. Most publications emphasize in this survey that clinical documentation not only impacts the quality of patient care, patient safety, and the incidence of medical errors but is increasingly used for quality assurance, financial management and research purposes. (3,46)

Separately, a multicenter retrospective study published in 2022 and earlier work using the QNOTE tool (Burke et al., 2014) demonstrated that structured clinical documentation improves documentation quality—by as much as 20% - compared to traditional narrative reporting. Structured notes were found to be more concise, easier to assess, and more consistent across providers. (3,12,47-50)

A 2021 systematic review presented quantitative and qualitative methods for leveraging patient data from EHRs using advanced deep learning techniques and mathematical code. Among the 49 reports analysed, 37 utilized structured patient data for mathematical encoding. Findings demonstrated that, beyond model development, advanced deep learning techniques enable AI to identify and address issues related to patient data, thereby contributing to the optimization of healthcare processes and advancing research. (3,51)

A systematic review from Denmark and Switzerland assessed the inter-institutional and cross-border collection, sharing, and integration of healthcare data, focusing on factors that hinder or facilitate data harmonization. Based on their findings, Denmark's centralized and Switzerland's distributed governance model emphasizing health data interoperability were identified as the most effective solutions. In Estonia, the implementation of blockchain technology in healthcare aims to revolutionize data management by establishing a secure and reliable patient record system. The review concludes that although technical issues are critical in data harmonization, addressing ethical, legal, social, and cultural challenges should also be considered. For instance, in Iceland, a project to establish a national healthcare database failed due to the underestimation of ethical and legal concerns, which should have been considered equally important. (3,52-56)

When exploring Hungarian literature, a notable 2023 summary stands out, highlighting the significance of personalized medicine within the framework of Hungary's current and proposed medical models. This summary addresses emerging challenges and needs in areas such as medical education, communication and data flow, digital innovation and implementation, as well as legal and economic difficulties. Structured health data collection was identified as a fundamental requirement for a well-coordinated healthcare system, supporting both data accessibility and effective communication. The summary refers to the expanded use of telemedicine and the EESZT during the COVID-19 pandemic. It emphasizes the critical need for structured medical databases to improve the effectiveness and cost-efficiency of personalized medicine in Hungary, however noting that certain specifications, such as molecular oncology or cardiology have already initiated efforts to develop such systems (Semmelweis Onkobank or Semmelweis cardiac CT registry) within their networks. (3,57-58)

Summarizing the key points identified throughout the review process, it becomes evident that while technical challenges play a crucial role in data management, structured and standardized documentation ensures retrievability and supports data reuse for research, therapy monitoring and population assessments. However, this approach restricts the expressiveness of reports by requiring the use of specific, predefined keywords to describe anomalies. Structured documentation is preferred when data reprocessing is necessary, as it allows for precise filtering based on keywords and minimizes inconsistencies arising from the use of synonyms in narrative descriptions. In contrast, traditional narrative documentation is more appropriate when reanalysis of data is unnecessary. (3,59) The review notes, that most studies still focus on differences between paper-based and electronic records, leaving the specific impact of structuring and standardization on EHR quality unclear. Driven by the potential to enhance personalized patient care, healthcare efficiency, cost-effectiveness, research outcomes, and inter-institutional communication, we initiated a project on evaluating and improving the existing documentation systems within our clinic. This process highlighted a critical need, which led to the development of a novel, structured database that is expandable to any specialty and applicable across various healthcare fields. (3,13)

IV.2 INTERNAL RESEARCH ON THE EFFICIENCY OF CLINICAL DOCUMENTATION

After confirming that structured data collection and assessment is a promising technique for improving medical documentation, diagnoses, therapy, and research processes, we conducted a study within our clinic. Our goals were to evaluate internal documentation practices, assess their effectiveness, identify deficiencies, and determine areas requiring development.

In our study, we analysed the paper-based and PPT documentation of 30 patients (n=60) across 14 key questions, aiming to retrieve a total of 840 desired answers. We measured the number of answers (out of the total 420) found in each documentation format, as well as the ratio of answers present versus absent. Responses were provided for only 35% of the total patient history and diagnostic questions in the paper-based documentation and 34% in the PPT format. In numerous instances, neither format, nor their combined use offered sufficient information, severely restricting the number of cases that could be included in retrospective studies. We found no significant correlation between the document type and the amount of recorded information, with a total of 290 responses recorded, of which 50.3% were on paper-based and 49.7% in PowerPoint format (Table 4.). Table 4. presents the findings, with significant differences marked in red (indicating a higher number of responses) and green (indicating a lower number of responses), while white indicates less significant variations. (3)

Table 4. The documentation of 30 patients, including both paper-based records and PPTs (n=60), was analysed across 14 thematic areas. (3) (OP: orthopantomogram, AP: anteroposterior and posteroanterior, values in bold indicate the most outstanding results)

N=60	Anamnesis	**Etiology**	Photo Analysis	Cast Analysis	Wala Ridge	**OP**	Lateral Cephalogram	AP Cephalogram	Joint Function	**Other Disfunction**	Bolton Analysis	**Spacing**	Crowding	Asymmetry
paper	19	**20**	**6**	17	17	**5**	11	2	8	**12**	9	**8**	7	5
PPT	18	**2**	**19**	9	9	**20**	20	4	4	**0**	6	**18**	15	11

The null hypothesis of the p-chi-square test states that there is no association between the responses to specific questions and the type of documentation (paper-based and PPT-based). However the statistical test result, with a p-value of less than 0.05, indicates a significant relationship between the documentation type and the number of responses to the individual questions. According to Figure 4., a significant difference was found in the frequency of information for individual patient history and diagnostic responses. Paper-based documentation provided more responses for patient history and clinical examinations, while PowerPoint-based documentation yielded more responses for photo and radiographic image analyses. (3) This may be attributed to the pre-printed templates used for paper-based patient forms, while PPT templates are blank, which facilitates the digital storage and interpretation of imaging data.

The digital PPT documentation proved to be more effective in managing imaging data, however, the imaging diagram in Figure 5. illustrates that information was frequently missing in both the paper-based and PPT formats.

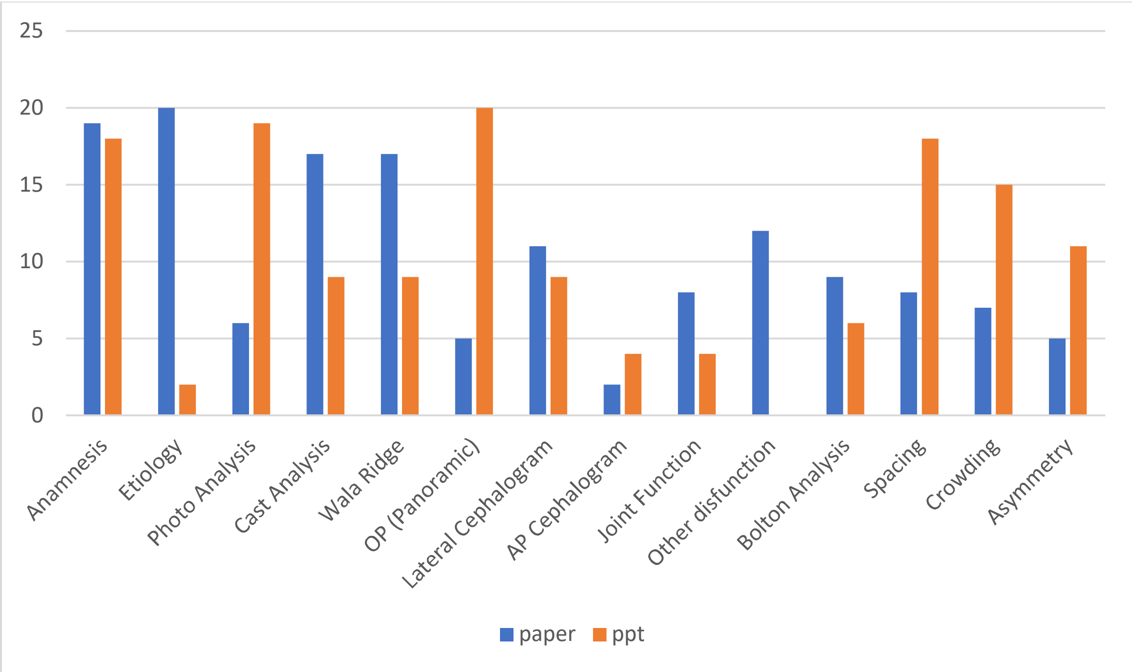

Figure 4. The distribution diagram of 14 question areas according to the method of documentation (paper-based or PPT format) for 30 patients. (3)

This is particularly remarkable, as OP and lateral cephalograms should be routinely performed and evaluated for every orthodontic patient. (3)

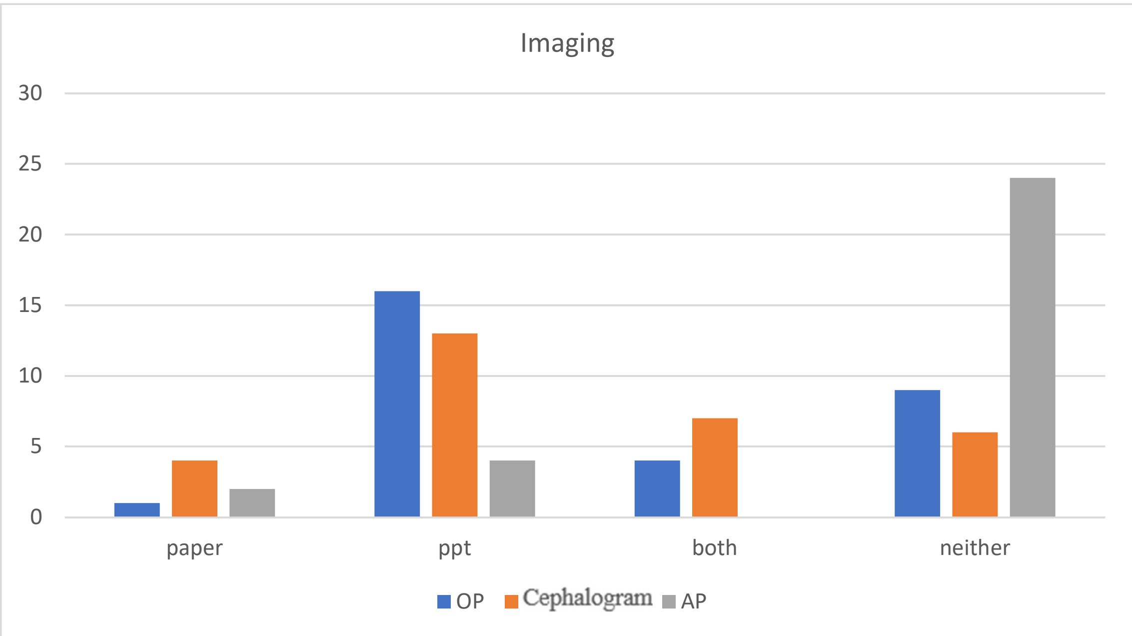

Figure 5. Inclusion of imaging results in the patient's complete documentation record (OP: orthopantomogram, AP: anteroposterior and posteroanterior cephalogram). (3)

We measured the time taken to find the desired answers to the questions in the two different documentation formats. A paired two-sample t-test was conducted to compare the retrieval times for answers between paper-based and PPT-based documentation. The t-value was 0.2099, with a p-value of 0.836 for a two-tailed test, indicating no significant difference in retrieval times between the two formats. The F-value was 0.2643, with a significance of 0.9978, further supporting the conclusion of no significant difference. Based on the descriptive statistics, it can be concluded that the average retrieval times for answers do not differ significantly between the two formats. However, PPT documentation showed a consistent retrieval time, whereas paper-based records had a more unpredictable distribution. In 40% of cases, retrieval from paper records was faster than the shortest PPT retrieval time, but in 15% of cases, it was slower than the longest PPT retrieval time. Overall, retrieval was faster in PPTs for 60% of cases and in paper records for 40% (Figure 6., 7.). Considering the large sample sizes required for high-quality research, both methods are time-intensive compared to the seconds or minutes required to search in structured databases. (3)

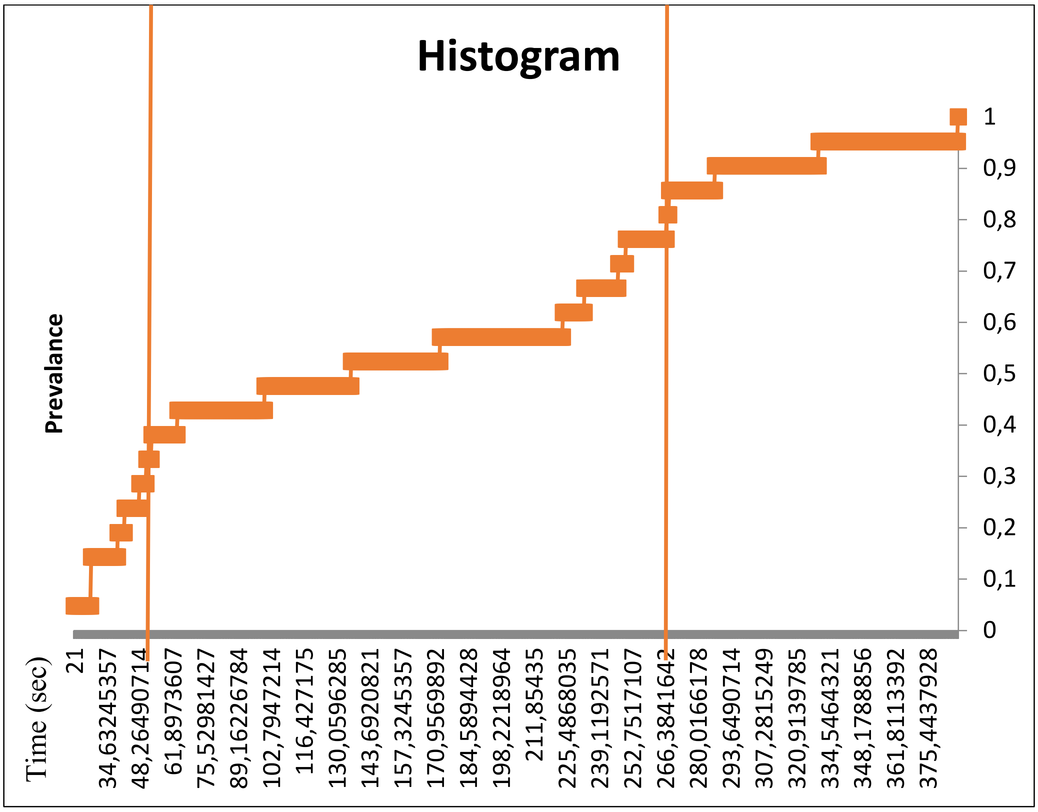

Figure 6. Paper-based retrieval time diagram (the vertical boundary lines indicate the range of the PPT retrieval time). (3)

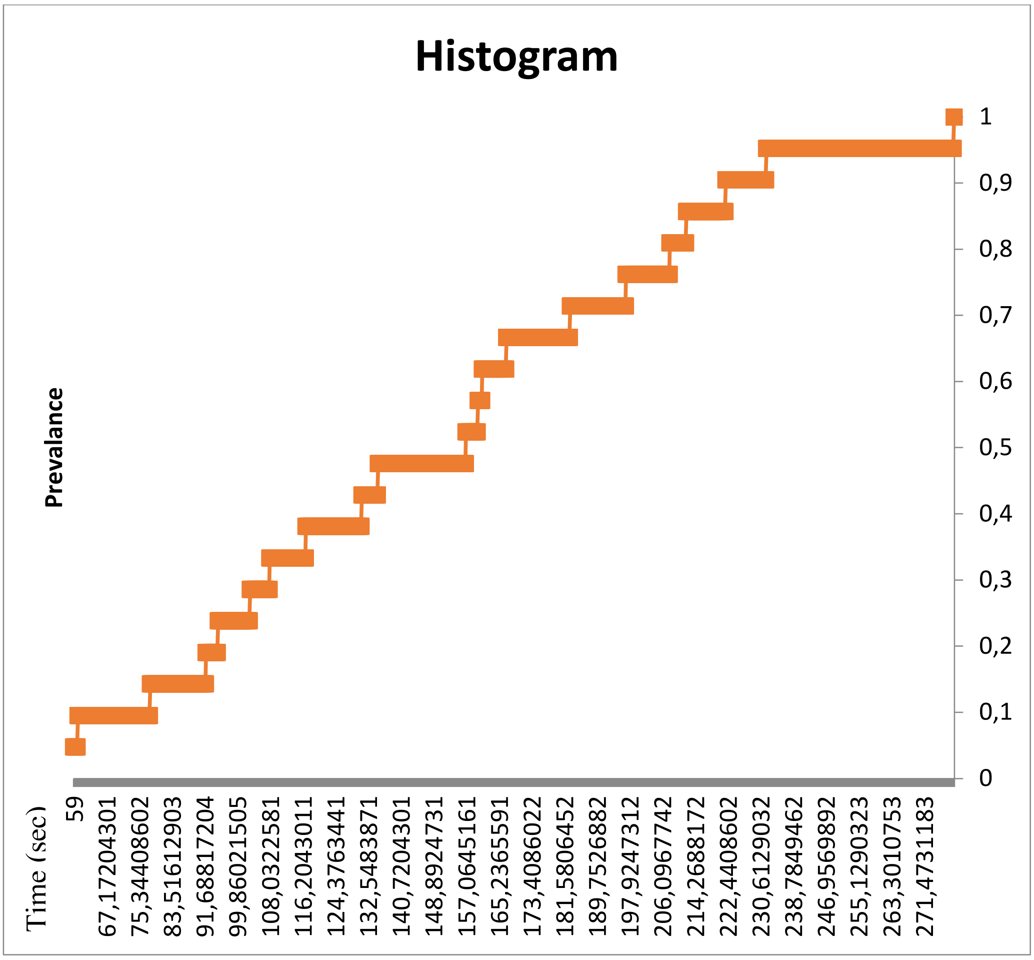

Figure 7. PPT retrieval time diagram. (3)

In summary, the previous methods of searching for only 14 answers (out of approximately 130) in non-structured patient diagnostic data points, such as distances, angles, and ratios - either manually on paper or digitally in PPT format - were often incomplete and not fully retrievable. Despite the dual availability of the data, both the paper-based text and the non-standardized digital formats proved unsuitable for structured data analysis. This confirmed our hypothesis that digitizing and structuring the evaluation template used at the Department of Paediatric Dentistry and Orthodontics, Semmelweis University would improve documentation efficiency. These findings motivated the development of a custom structured template for orthodontic evaluation, integrated into a well-structured SQL database.

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IV.3 DEVELOPMENT OF AN OWN STRUCTURED REPORTING SYSTEM

With the assistance of IT specialists of the Graid IT Solution Kft., we constructed a comprehensive, structured orthodontic template that spans from detailed patient history, through complex diagnostics to a long-term medical follow-up documentation platform, designed specifically for research and clinical care purposes. (Figure 8.)

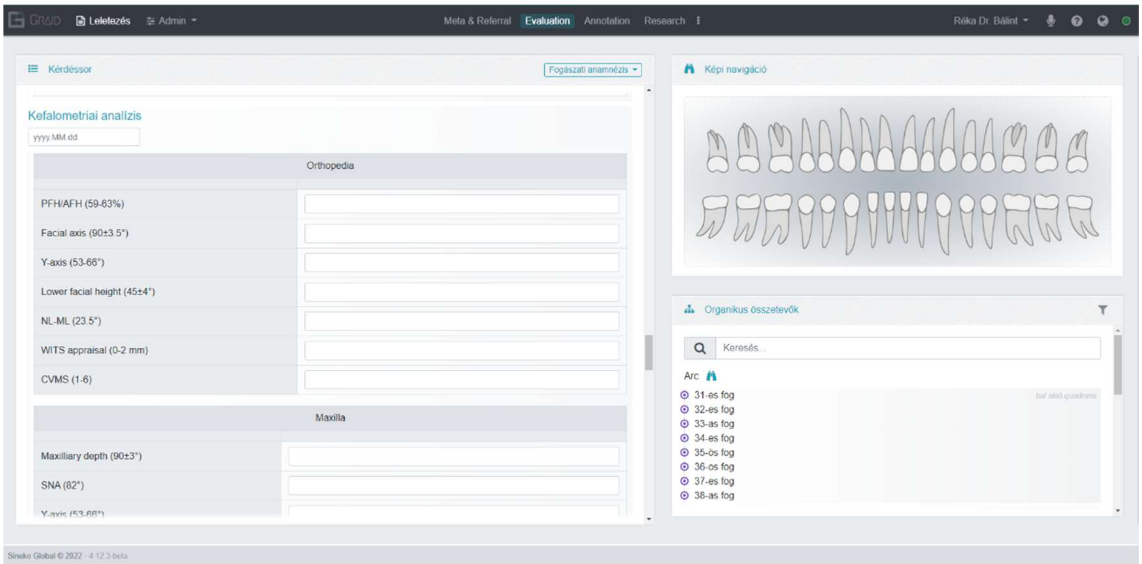


Figure 8. Interface of a structered database in the Graid Software built and formulated for orthodontic medical recording (1,31)

The template was designed to facilitate standard diagnostic procedures, while simultaneously recording routine orthodontic measurements and calculations. I structured the database thematically, aligning it with the sequence of diagnostic steps and tailoring it to meet the specific needs of our clinic's research teams. This includes support for teams focusing on general diseases, cleft care, maxillofacial surgery, TAD and other specialized fields.

In the patient history section of the template, the clinician systematically goes through general medical, dental, and orthodontic history questions, with responses structured in a yes/no format. Based on the responses, additional questions are generated (e.g., regarding diseases, types of allergies, dental or maxillofacial traumas, bad habits, hobbies, or lifestyle inquiries) (Figure 9.), leading to the next section including extra- and intraoral

DOI:10.14753/SE.2025.3245

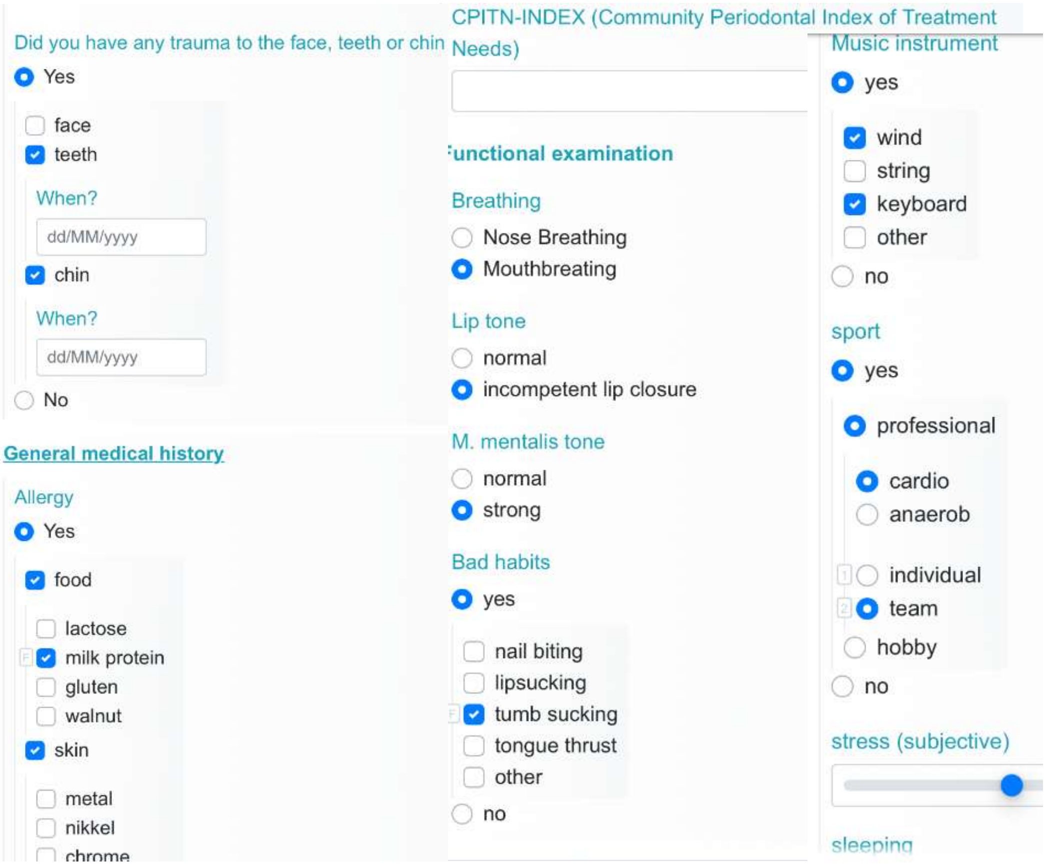


Figure 9. Questions regarding allergies, bad habits, hobbies, or well-being inquiries.

clinical examination, and functional analysis forms. The orthodontic structured form was subsequently expanded with additional sections customized to specific research requirements, such as surveys on diabetes, twin comparisons, or miniscrew applications (Figures 10 and 11).

Following this systematic approach, results from diagnostic processes, such as photo, x-ray and dental cast analysis, relevant to orthodontic evaluations are collected for each patient. Using the data provided by these diagnostic steps, the software automatically calculates certain values, such as WALA ridge or Bolton discrepancy, based on specific formulas. Additionally, the photo analysis section offers the option for a detailed macro- and micro-aesthetic evaluation, along with profile and full-face analysis. For cephalometric analysis, dental, profile, and skeletal indicators have been organized by vertical and sagittal dimensions for the maxilla, mandible, and craniofacial skeleton. As cephalometric analysis is the most time-consuming part of data collection, I have initiated efforts to automate both the analysis itself and its seamless integration into the database. The training process and testing experiment on clinical relevance of the Ceph Assistant software will be discussed in further detail.

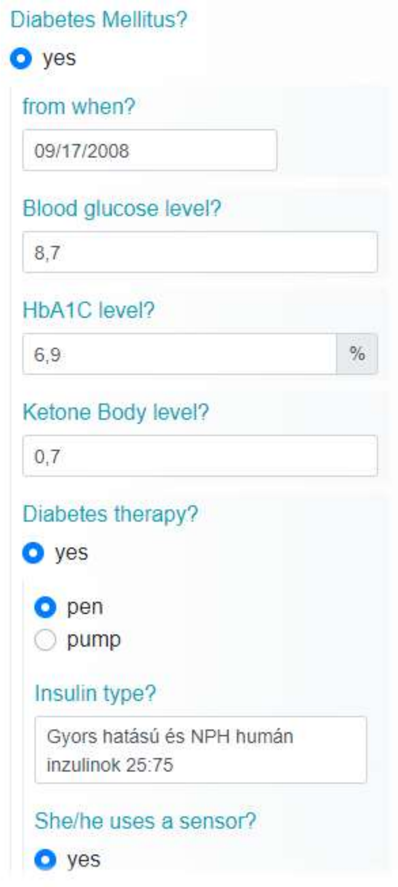


Figure 10. Questions related to studies of the diabetes research team.

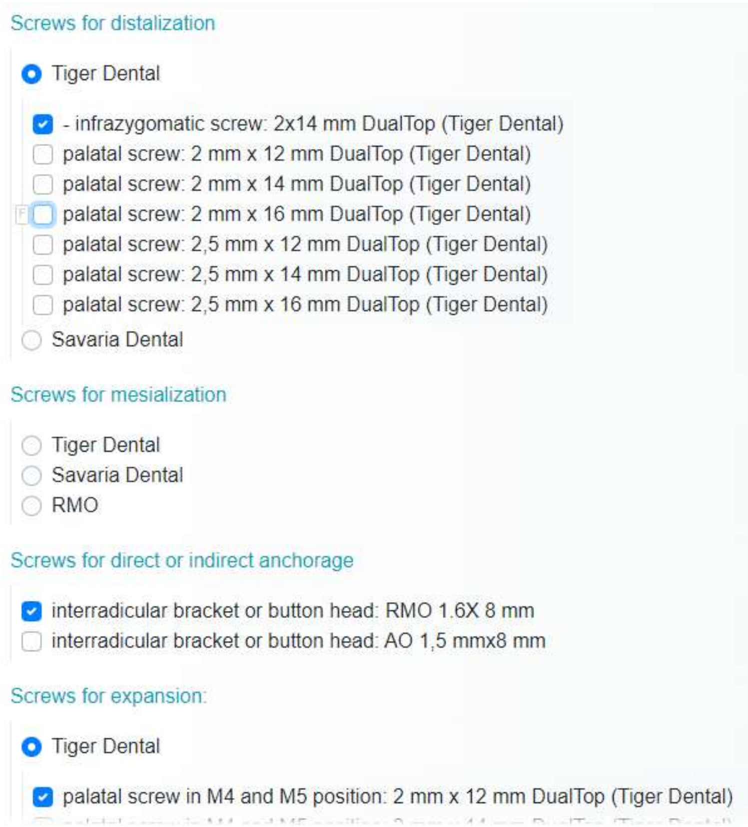


Figure 11. Questions related to studies of the miniscrew research team.

The problem list and planned therapy can be recorded point by point, allowing the selection of various orthodontic interventions or types of specific appliances. For instance, miniscrews of different sizes and surface designs from various manufacturers, thereby supporting clinical research utilizing TADs. Notably, a non-AI-based decision support system was also incorporated in this planning block, offering therapeutic recommendations based on empirical data rather than serving as a rigid protocol.

An additional documentation form was created for patients undergoing dysgnathic and other maxillofacial surgeries. This form enables precise recording of interdisciplinary procedures (preoperative orthodontics, surgery planning, surgery, postoperative care and orthodontics) carried out in collaboration with the Department of Oro-Maxillofacial

Surgery and Stomatology at Semmelweis University. Among other fields of medicine and dentistry, in dysgnathic surgery, traditional manual surgical templates and acrylic splints have been replaced by stereolithography (STL) files generated by 3D digital software, enabling precise recording of movements in all three spatial dimensions with degree or millimetre level accuracy. This new technique generates extensive data that was previously incomplete or unknown. Now, this information is systematically stored in a structured format, making it accessible and organized rather than being dispersed across unstructured patient records. (3)

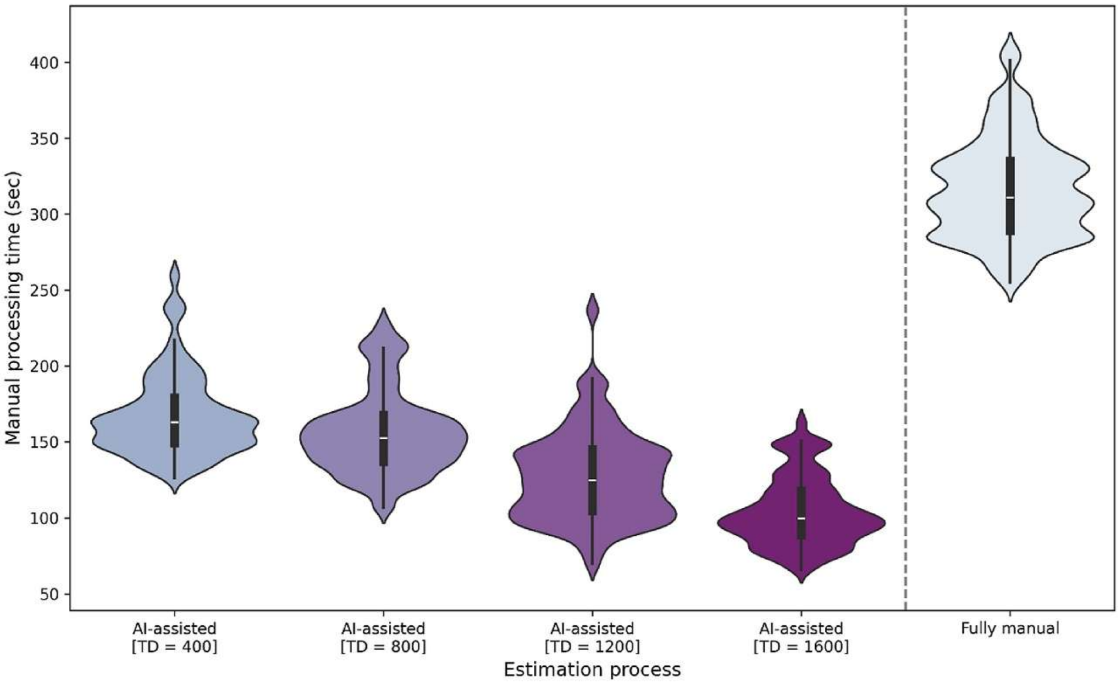
The template now supports the systematic collection of anamnestic, full diagnostic, and therapeutic data for each patient, encompassing approximately 130 parameters, including distances, angles, and ratios, measured in millimetres, degrees, and percentages respectively. These data are recorded in standardized tabular, listed, or graphical formats, ensuring consistency in terminology. This advancement facilitates the long-term processing of a substantially larger patient dataset for scientific research, offering a marked improvement over traditional paper-based and PowerPoint documentation methods while representing a significant milestone in the management of interdisciplinary patient care and scientific research. This large volume of data also aids the easy preservation and future utilization of information for both short- and long-term postoperative assessments, including those examining recidivism or relapse. Evaluation results can be easily queried anytime in XLS file format, and the user-friendly software solution enables users to customize templates according to their medical specialties and specific research needs, effectively addressing emerging issues and demands. After 3.5 years of working on this topic since 2020, developments at the Institute for Clinical Data Management (21) at Semmelweis University provided the opportunity to add my innovative solution into the newly established Semmelweis University Biobank (33). With the successful transfer to the new platform, it is now freely accessible to Semmelweis University colleagues while keeping the previously detailed user-friendly features intact. (2-3)

IV.4 ACCURACY OF AUTOMATED ANALYSIS IN CEPHALOMETRY

As previously mentioned, our team successfully integrated a tool to import the results of cephalometric analyses performed by the Ceph Assistant AI software into our structured database. To ensure the algorithm, trained on 1,600 cephalometric images, is fast, precise, and provides clinically relevant data, we conducted a comprehensive study to model and test its training phases. This allowed us to thoroughly evaluate the algorithm's performance and confirm its clinical applicability before implementing it in routine practice. Cross-validation results, with similar fluctuation values for semi-rotation (3.07%, 3.095%) and quarter rotation (5.15%, 5.29%), confirm the representativeness of our test dataset for clinical cases. (1)

IV.4.1 Time spent on evaluation

A comparative analysis was conducted to evaluate the time-efficiency of manual cephalometric analysis performed by two experts versus automatic evaluation by the Ceph Assistant model, and model prediction with subsequent corrections by a senior examiner. On average, manual evaluations required 315 seconds more per sample compared to the model's predictions, which took only 0.43 seconds. The first four violin plots in Figure 12. demonstrate a significant reduction in the mean correction time (104–167 seconds) as the AI algorithm was progressively upgraded with additional training datasets. (1)

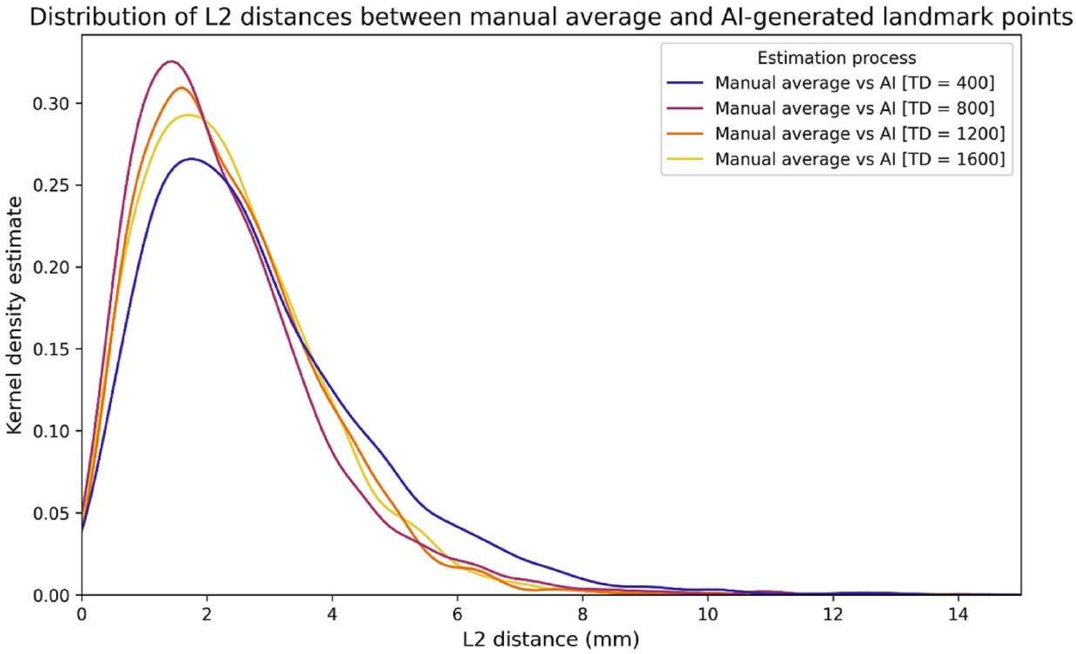


Estimation process	Mean	Std	Min	50%	Max
Fully manual	315.91	32.51	254.71	310.99	407.14
AI-assisted [TD=400]	167.02	26.79	126.08	162.97	259.37
AI-assisted [TD=800]	156.17	27.20	106.77	152.33	227.80
AI-assisted [TD=1200]	127.36	29.35	69.92	124.47	236.57
AI-assisted [TD=1600]	104.12	22.50	65.70	99.79	162.70

Figure 12. Violin plot diagram on time spent by the two examiners on manual analysis (fully manual) and the time spent by the Ceph Assistant model by progressing amounts of training data (TD), on automatic evaluation followed by correction by the senior examiner (AI-assisted). (1)

IV.4.2 L2 Distance errors in cephalometric landmark detection methods

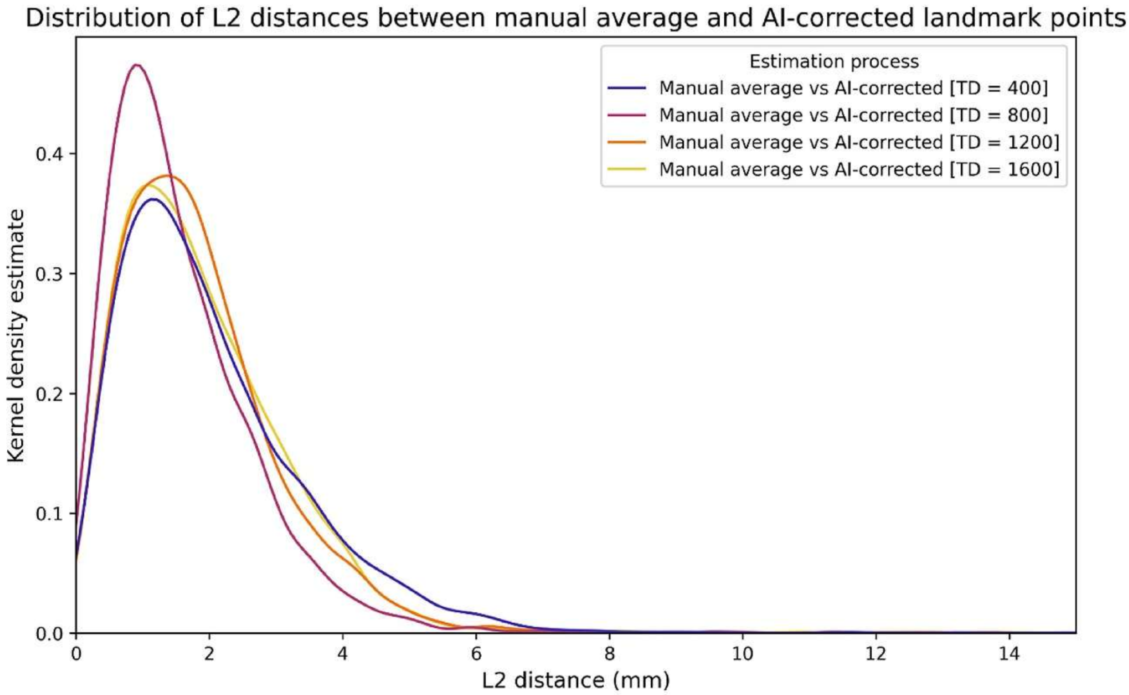
We analysed the X and Y coordinates of each predicted cephalometric landmark within a 2D coordinate system on digital X-ray images, following the algorithm's training processes across all four dataset sizes. We examined the relevance of these predictions to the average of manual corrections of the senior examiner, defined as the gold standard. Initially, the AI-generated results were compared to the gold standard for cephalometric landmark identification, serving as a benchmark for accuracy and reliability. (1) (Figure 13.)



	L2 distance (mm) - manual average vs AI [TD = 400]	L2 distance (mm) - manual average vs AI [TD = 800]	L2 distance (mm) - manual average vs AI [TD = 1200]	L2 distance (mm) - manual average vs AI [TD = 1600]
Mean	2.879313	2.471535	2.429815	2.461958
Std	2.308865	5.207250	1.984417	1.979575
Min	0.035398	0.047131	0.020167	0.027528
50%	2.437301	1.940383	2.122975	2.172452
Max	43.711752	180.110467	46.589230	43.521466

Figure 13. L2 distances between the coordinates of averaged manually corrected landmarks and AI-generated landmarks analysed across varying amounts of training data (TD). (1)

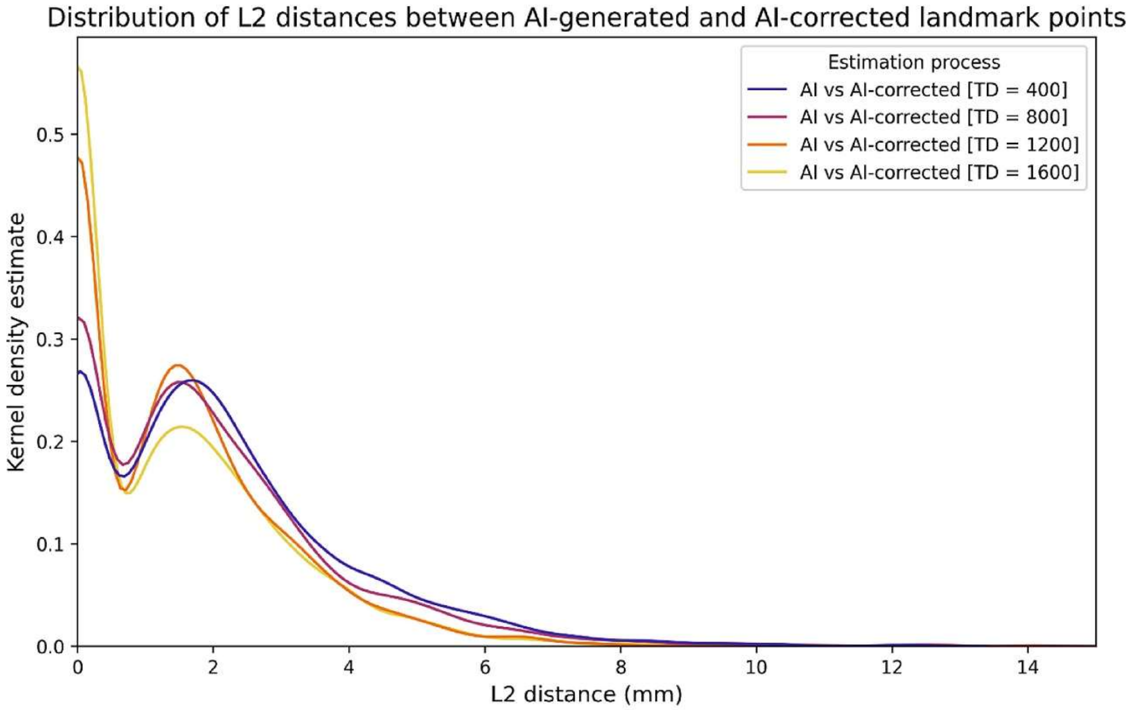
Mean L2 distances between AI predictions and the averaged gold standard ranged from 2.4 to 2.9 mm (median: 1.9–2.4 mm) across the training levels, indicating that with the increasing number of training samples (up to TD = 1200) the accuracy of the model substantially improved. When considering AI-assisted manual corrections, the mean L2 distance further reduced to 1.75–2.1 mm (median: 1.3–1.7 mm), with performance stabilizing after a training dataset size of 800 images. (Figure 14.) The increase in standard deviation observed after the second measurement may be attributed to potential variations in examiner decision-making under different circumstances. (1)



	L2 distance (mm) - manual average vs AI-corrected [TD = 400]	L2 distance (mm) - manual average vs AI-corrected [TD = 800]	L2 distance (mm) - manual average vs AI-corrected [TD = 1200]	L2 distance (mm) - manual average vs AI-corrected [TD = 1600]
Mean	2.097893	1.749552	1.911131	1.956179
Std	2.010346	5.116856	1.821007	1.839027
Min	0.028381	0.015061	0.014115	0.003157
50%	1.713629	1.314164	1.648657	1.652046
Max	45.160761	180.110467	46.589230	44.682014

Figure 14. L2 distances between the coordinates of the averaged corrected landmarks and AI-corrected landmarks analysed across varying amounts of training data (TD). (1)

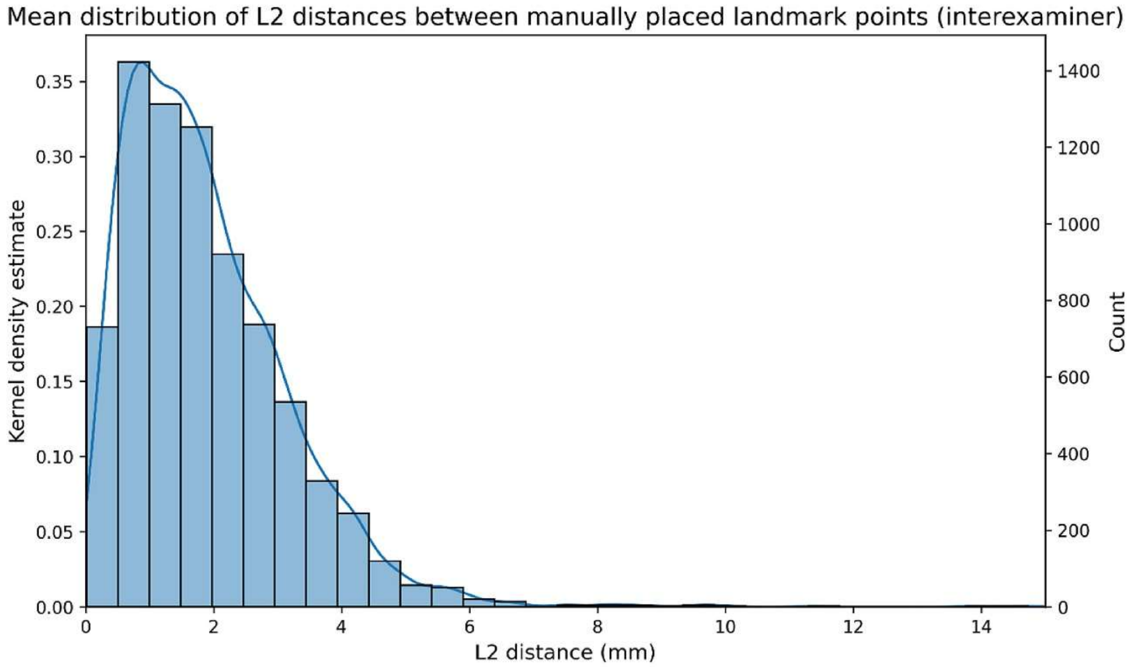
Substantial agreement was observed between the AI-generated and AI-corrected landmarks (Figure 15.), with mean L2 distances ranging from 1.4 to 2.0 mm (median: 1.05–1.8 mm), depending on the model's training level. These findings highlight the impact of AI on examiner decisions during manual dot tracing. To reduce errors associated with the subjective bias of a single examiner, an independent manual evaluation was performed by a second examiner. (1)



	L2 distance (mm) - AI vs AI-corrected [TD = 400]	L2 distance (mm) - AI vs AI-corrected [TD = 800]	L2 distance (mm) - AI vs AI-corrected [TD = 1200]	L2 distance (mm) - AI vs AI-corrected [TD = 1600]
Mean	2.043443	1.849874	1.471819	1.360498
Std	1.832346	1.812247	1.562619	1.585845
Min	0.000000	0.000000	0.000000	0.000000
50%	1.760528	1.553095	1.275366	1.048708
Max	12.350838	14.096345	14.222291	16.992686

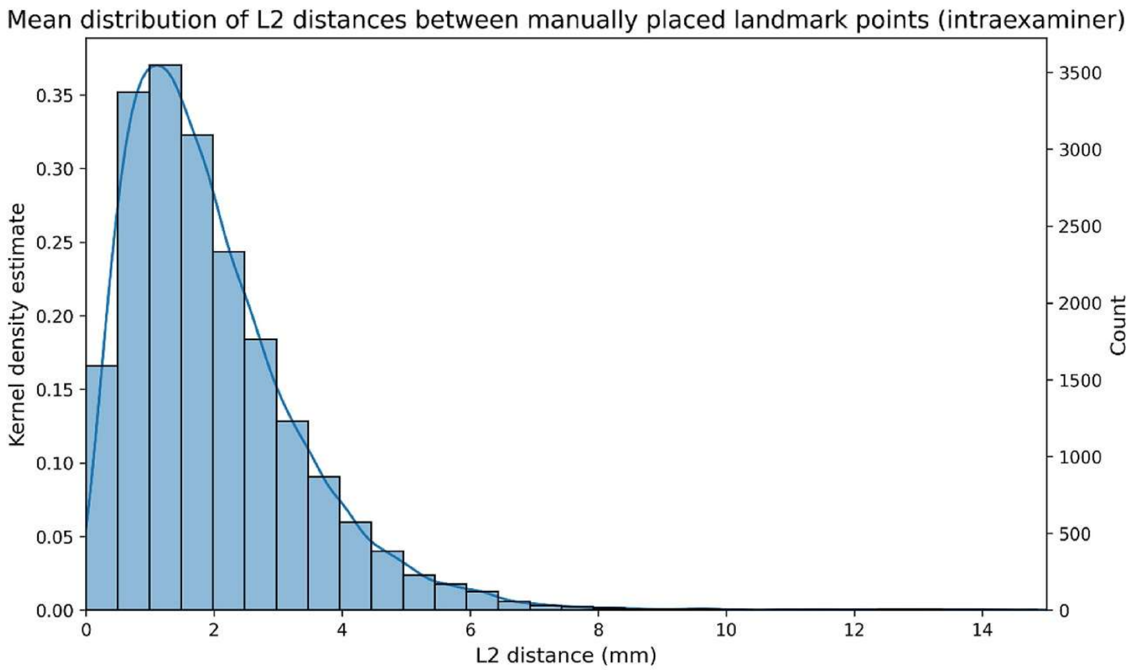
Figure 15. L2 distances between the coordinates of the AI-generated and AI-corrected landmarks analysed across varying amounts of training data (TD). (1)

Measurements of the senior and medior examiners have been compared, as well as between the landmarks identified by the senior examiner and those AI-corrected after TD = 1600. The mean L2 distance between the two examiners, representing inter-examiner error, was 2.0 mm (median: 1.7 mm) (Figure 16.), while the mean intra-examiner variability was 2.1 mm (median: 1.7 mm) (Figure 17.). (1)



	L2 distance (mm) - medior examiner vs mean senior examiner
Mean	2.016651
Std	2.441885
Min	0.013897
50%	1.656302
Max	52.888285

Figure 16. L2 distances between the coordinates of the landmarks detected manually by the senior and medior examiners. (1)



	L2 distance (mm) - mean senior examiner (all predictions) vs manual average
Mean	2.101694
Std	3.262422
Min	0.003157
50%	1.679889
Max	180.110467

Figure 17. L2 distances between the coordinates of the landmarks detected manually by the senior examiner and the averaged manually corrected coordinates. (1)

Additionally, the findings demonstrate that initial AI predictions assist clinician decision-making, as illustrated by the box plot in Figure 18. In this analysis, L2 errors were further evaluated based on the model's training level and the complexity of the images (Table 3.). The box plot displayed here shows the L2 distances after correction across all four models, categorized by radiograph quality. It is clearly visible that even in the case of poor image quality, the evaluation can be performed within a 2 mm margin of error when using the most complex algorithm trained on 1600 images. This deviation is smaller than the differences measured between two specialists or between repeated analyses by the same specialist. In the case of high-quality images, the L2 distance was reduced to approximately 1 mm. (1)

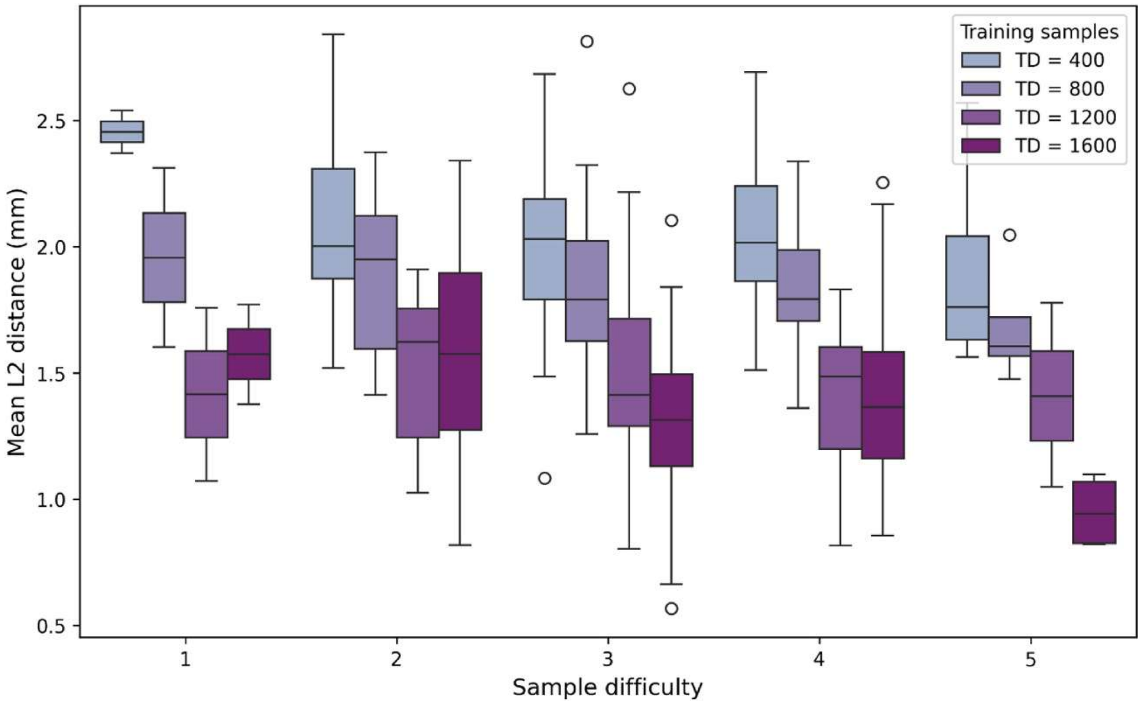


Figure 18. Box plot diagram illustrating mean L2 distances between AI-generated and AI-corrected landmarks across different amounts of training data (TD) and varying image quality levels. (1)

The L2 distance errors of the best models are presented in Table 5. and Table 6. The main distinction between these tables is that Table 5. compares model predictions to the gold standard, defined as the average of four corrected evaluations by the senior examiner, whereas Table 6. reports L2 landmark errors relative to a single correction performed using the latest version of the model's tool. Although the model performs well compared to the average, the senior examiner shows larger displacements when correcting the predictions than would be required according to the gold standard. This indicates that the actual corrections are smaller than the average but may also reflect a potential bias introduced by AI assistance, where the expert's adjustments could be influenced by the AI's predictions. Nonetheless, the placement of both fully manual and AI-assisted landmarks is considered practically acceptable. (1)

Table 5. L2 distances between the average of manually corrected model predictions and model predictions after TD = 1600 detailed for each landmark. (1)

Empty Cell	**Landmark**	**Mean L2 distance (mm)**	**Offset of centers 2D (mm)**	**Offset of centers X (mm)**	**Offset of centers Y (mm)**
	Cal 1	1.637076	0.232855	0.186644	−0.139232
	Cal 2	1.949541	1.029317	0.701492	−0.753261
1	1LoMma	2.461322	0.592650	−0.343009	0.483300
2	1UpMma	2.464983	1.293880	−1.198248	−0.488188
3	A	2.025425	0.763167	0.401496	0.649018
4	Ar	2.060797	1.300355	−0.527451	1.188579
5	B	2.277940	0.861359	0.654628	0.559823
6	Ba	3.498204	2.640550	−1.940610	1.790680
7	Co	2.398892	0.162771	−0.143024	−0.077709
8	**Cond**	**4.031917**	**3.818257**	**3.667022**	**1.063972**
9	D	2.085304	0.680178	−0.614878	0.290805
10	Gl'	2.611720	0.737790	0.138505	0.724672
11	Gn	1.975846	0.435858	−0.207106	0.383510
12	Gn'	2.765901	0.995890	−0.990889	0.099674
13	Id	2.125472	0.570400	0.548000	0.158278
14	Im	3.423167	1.628828	−1.093928	1.206815
15	La	2.399474	1.149321	−0.476898	1.045709
16	Li	2.402736	0.277522	−0.201019	−0.191338
17	Ll	3.064468	1.378565	−0.598300	1.241966
18	Ls1u	2.251858	0.891643	0.102737	−0.885705
19	M6lo	2.493383	1.512762	−1.502171	0.178688
20	Me	2.658894	1.915190	−1.895412	−0.274531
21	Me'	3.249505	2.061361	−2.061004	−0.038344
22	N	1.914186	0.518923	−0.513608	−0.074084
23	N'	2.987097	2.182778	0.270411	−2.165964
24	Or	2.523092	1.193867	−0.569866	1.049081
25	PM	3.278403	1.349037	−0.327414	−1.308702
26	Pn	1.986226	0.270457	0.218972	0.158739
27	Po	2.353079	1.561155	1.072080	−1.134834
28	PoG	1.961738	0.168991	−0.133283	−0.103892

Empty Cell	**Landmark**	**Mean L2 distance (mm)**	**Offset of centers 2D (mm)**	**Offset of centers X (mm)**	**Offset of centers Y (mm)**
29	Pr	1.916989	0.574963	−0.241903	−0.521599
30	Pt	2.213844	0.713175	−0.602327	−0.381865
31	S	1.441243	0.757301	0.674090	−0.345119
32	**Se**	**1.100986**	**0.246422**	**0.152383**	**0.193657**
33	Sm	2.629311	0.842133	0.144136	0.829707
34	Sn	2.268836	0.401509	−0.016119	0.401185
35	SnA	2.260503	0.862765	−0.428025	−0.749105
36	SnP	3.781222	3.401066	−3.319714	−0.739422
37	Stm-i	2.344474	0.736194	0.383469	0.628437
38	Stm-s	2.427442	0.440965	0.342679	−0.277527
39	T1	2.117115	0.371426	0.362880	0.079218
40	T2	3.278450	2.705884	1.354193	2.342642
41	Tr	2.221228	0.636668	−0.449369	−0.451015
42	U6	2.282803	1.167137	−0.850259	−0.799543
43	U6d	3.252854	1.752945	−1.748208	−0.128778
44	Ua	2.062791	0.459479	−0.352060	0.295253
45	Ui	2.201745	0.434141	−0.431062	−0.051614
46	Ul	2.716757	0.864670	−0.263708	−0.823476
47	ppCond	2.767480	2.301227	0.445095	−2.257773
48	sPoG	2.494168	0.809869	−0.179820	−0.789654

Values in bold indicate the most outstanding results.

Table 6. L2 distances between model predictions after TD = 1600 and manually corrected model predictions after TD = 1600 detailed for each landmark. (1)

Empty Cell	**Landmark**	**Mean L2 distance (mm)**	**Offset of centers 2D (mm)**	**Offset of centers X (mm)**	**Offset of centers Y (mm)**
	Cal 1	0.643981	0.388422	0.384959	−0.051754
	Cal 2	1.236142	1.150663	0.899862	−0.717129
1	1LoMma	2.088942	0.731733	0.065373	0.728807
2	1UpMma	1.780922	0.962528	−0.806648	−0.525146
3	A	0.976627	0.483491	0.299513	0.379546
4	Ar	2.129158	1.561206	−0.423932	1.502546

Empty Cell	**Landmark**	**Mean L2 distance (mm)**	**Offset of centers 2D (mm)**	**Offset of centers X (mm)**	**Offset of centers Y (mm)**
5	B	1.280191	0.848967	0.792764	0.303761
6	**Ba**	**3.410516**	**2.855413**	**−1.792093**	**2.223013**
7	Co	0.387927	0.192925	0.161667	−0.105281
8	Cond	2.922712	2.663729	2.656214	0.199946
9	D	0.462214	0.371593	−0.245463	0.278979
10	Gl'	2.061247	1.395480	0.174731	1.384497
11	Gn	0.560286	0.366428	0.132685	0.341561
12	Gn'	0.731179	0.342332	−0.332368	0.081989
13	Id	1.274109	0.771261	0.764531	0.101660
14	Im	2.939248	1.598290	−0.378901	1.552728
15	La	1.135205	0.917862	−0.213480	0.892691
16	Li	1.555915	0.068109	−0.019415	−0.065283
17	Ll	2.131087	1.321900	−0.435440	1.248124
18	Ls1u	0.840191	0.609058	0.200682	−0.575047
19	M6lo	1.660013	0.942936	−0.890973	0.308700
20	Me	1.422967	1.346214	−1.346151	0.013062
21	Me'	1.287331	1.087110	−1.081382	0.111444
22	N	0.959346	0.356402	−0.308718	−0.178088
23	N'	0.780227	0.679803	−0.108791	−0.671042
24	Or	1.458742	0.975813	−0.348082	0.911619
25	PM	1.051151	0.876947	0.565909	−0.669912
26	Pn	0.413855	0.238079	0.234168	−0.042974
27	Po	1.871023	1.625108	0.684366	−1.473980
28	PoG	0.310770	0.095398	0.086747	−0.039696
29	Pr	0.853830	0.389805	−0.016424	−0.389459
30	Pt	1.779997	0.548484	−0.542283	0.082244
31	S	0.843171	0.659604	0.647199	−0.127323
32	**Se**	**0.224547**	**0.026718**	**−0.007611**	**0.025611**
33	Sm	1.767907	0.954243	0.228237	0.926546
34	Sn	0.876506	0.445288	0.313968	0.315762
35	SnA	1.712885	0.765973	−0.270384	−0.716664
36	SnP	2.817688	2.599645	−2.529856	−0.598315

Empty Cell	**Landmark**	**Mean L2 distance (mm)**	**Offset of centers 2D (mm)**	**Offset of centers X (mm)**	**Offset of centers Y (mm)**
37	Stm-i	0.596301	0.336120	0.037379	0.334035
38	Stm-s	0.544540	0.130432	0.084280	−0.099546
39	T1	1.369595	0.212281	0.211934	0.012134
40	T2	2.321326	1.976671	0.464824	1.921241
41	Tr	0.377330	0.073026	0.040836	0.060541
42	U6	1.407054	0.915504	−0.784272	−0.472297
43	U6d	1.645479	0.923445	−0.759399	0.525418
44	Ua	1.140231	0.643875	−0.631138	−0.127439
45	Ui	1.133775	0.076869	0.018179	0.074689
46	Ul	1.276720	0.878373	0.027640	−0.877938
47	ppCond	2.602839	2.383307	0.052730	−2.382724
48	sPoG	0.969945	0.469860	0.033531	−0.468662

Values in bold indicate the most outstanding results.

When L2 errors were analysed for the AI-corrected landmarks after TD = 1600, the highest distances were observed at Condylon (4.0 mm), while the lowest was at the centre of Sella's entry (1.1 mm) (Table 5.). In comparison, when L2 errors between AI-corrected and model-predicted landmarks after TD = 1600 were evaluated, the highest errors were noted at Basion (3.4 mm), and the lowest at the centre of Sella's entry (0.2 mm) (Table 6.). (1)

IV.4.3 Errors in clinically relevant diagnostic measurements

In orthodontics, relevant diagnostic and treatment data, such as angles and proportions, generally rely on at least three landmarks. Therefore, L2 errors in X and Y coordinates alone offer limited clinical relevance. To better understand the clinical impact of L2 discrepancies, we calculated how these errors affected specific orthodontic reference angles and proportions. For key angles determined by three landmarks, the mean angular difference between the model’s predictions after TD = 1600 and the manually measured values ranged from 0.17° to 1.09° (Table 7.). (1)

Table 7. Angular differences between the model predictions after TD = 1600 and the manual average for angles determined by three cephalometric landmarks. (1)

Reference	Method	Mean reference angle (deg)	Mean predicted angle (deg)	Mean angular difference (deg)
SNA angle	Manual average and AI 1600	−82.087991	−80.997427	**1.090385**
SNB angle	Manual average and AI 1600	−77.652970	−76.731267	**0.922000**
ANB angle	Manual average and AI 1600	4.435581	4.267428	**−0.168466**
SNPog angle	Manual average and AI 1600	−78.659431	−78.349143	**0.310633**

Similarly, the angular differences for angles determined by four cephalometric landmarks ranged from 0.05° to 1.86° (Table 8.). (1)

Table 8. Angular differences between the model predictions after TD = 1600 and the manual average for angles determined by four cephalometric landmarks. (1)

Reference	Method	Mean reference angle (deg)	Mean predicted angle (deg)	Mean angular difference (deg)
Facial angle	Manual average and AI 1600	90.729613	92.592710	1.861190
Gonion angle	Manual average and AI 1600	120.646687	119.763093	−0.886658
Interincisal angle	Manual average and AI 1600	128.086133	126.961123	−1.117114
IMPA angle	Manual average and AI 1600	98.796140	98.769588	−0.053833

Furthermore, a discrepancy was observed in the proportion of lower and upper facial heights, calculated using three landmarks (N, SnA, Me). Analysis of 78 cephalograms revealed that the predicted ratio deviated by 3.14% from the gold standard after TD = 1600. In this case, as observed previously as well, the model predicted better results (0,8%) compared to the gold standard after training with TD = 1200. This supports our hypothesis that beyond a certain training cycle, the model we investigated performs equally well (Table 9.). (1)

Table 9. Rational differences between the model predictions after each TD and the manual average for proportions determined by three cephalometric landmarks (N, SnA, Me). (1)

Ratio	Reference	Method	Mean Reference Ratio (%)	Mean Method Ratio (%)	Piecewise Ratio of Ratios (%)
Upper-lower facial height index	ceph57_Mean_Corr	ceph57_400_AI	0.792934	0.837030	1.059675
Upper-lower facial height index	ceph57_Mean_Corr	ceph57_800_AI	0.792934	0.819494	1.037539
Upper-lower facial height index	ceph57_Mean_Corr	ceph57_1200_AI	0.792934	0.797356	1.008395
Upper-lower facial height index	ceph57_Mean_Corr	ceph57_1600_AI	0.792934	0.815168	1.031477

V. DISCUSSION

This study aimed to explore the growing demand for modern digital tools, streamlined electronic workflows, AI assisted tools and efficient data processing within the medical sector. This study was based on an internal evaluation of our routine medical recording practices. We aimed to assess the efficiency and accuracy of our current methods, while also identifying the limitations and potential weaknesses inherent in our recording processes. The ultimate goal of this work was to develop a customized interface within a structured reporting database, ensuring its seamless integration into daily medical and research practices while supporting future statistical analyses and scientific investigations. Furthermore, I sought to optimize the recording processes by incorporating time-efficient and accurate diagnostic AI tools, particularly in cephalometry, which had been previously tested for clinical accuracy. While every study has its limitations that may affect the results, efforts have been made to minimize potential errors and inaccuracies in both the internal research and the testing of the algorithm trained for automated cephalometric analysis.

According to the reviewed literature, electronic information systems support healthcare documentation (by maintaining electronic health records) and provide essential data for research, education, patient care, and quality assurance. Moreover, the advancement of electronic health records carries both health policy and economic significance and is expected to drive global transformations within the healthcare sector. Although research primarily focuses on the difference between paper and electronic data, recent studies providing evidence that structured and standardized data management impacts the quality of medical record, enabling data reuse when necessary and facilitating healthcare professionals' documentation activities. (3)

One of the distinctive strengths of our clinic within the specialty is the interdisciplinary collaboration among multiple physicians in developing treatment plans, whether based on a unified or diverse conceptual and methodological approach. This cooperative framework may facilitate the generation of extensive, comparable datasets, substantially enhancing the efficacy of both our research activities and patient care practices. However, the reuse of this high-value data is limited due to the absence of structured, accessible, and transparent data management systems. In the current unstructured and difficult-to-search datasets - often referred to as a "data lakes" - even with strong communication channels and close collaboration among physicians do not ensure the inclusion of all relevant subjects in studies and the optimal utilization of the benefits offered by the large patient database. Findings from our internal study indicate that the type of documentation significantly influences response rates, with notable variations in the accessibility of individual responses to common anamnesis and diagnostic questions. However, in most cases, the existing recording system proves insufficient for supporting patient care or high-quality research. Despite the availability of multiple data entry methods, our findings highlight that the lack of transparency and retrievability often results in physicians losing track of critical information. Consequently, a complete set of medical history and diagnostic data is rarely available for any given patient, even with considerable effort dedicated to data collection. For instance, conducting a retrospective study on 100 patients would require the individual review of their records, PPT documentation, or other unstructured databases within certain HIS systems. This process is not only highly time-consuming but also largely inefficient, as a significant portion of data is lost during storage. At our clinic, most patients are monitored during their active growth phase; a period characterized by ongoing anatomical, morphological, and biological changes that we aim to influence. Reusing data from multi-year treatments and later stages can provide valuable insights, particularly regarding the effectiveness of treatment methods and devices, thereby validating our initial assumptions over time. (3)

In summary, structured data utilization may enhance the value of our services in patient care, education, research, and economics, while standardization drives unified process optimization across our dental institute. This solution is easily adoptable by healthcare professionals, facilitates seamless integration into daily practice, promotes collaboration between institutions and authorities, and lays the groundwork for interdisciplinary therapies, research, and interoperable channels within and beyond national borders. (3)

Based on these findings and the growing demand for data reusability in Hungary, development teams of IT specialists and healthcare professionals have been motivated to optimize processes. In response, we developed a structured database to efficiently manage large volumes of patient data. Our efforts to optimize the workflow of our outdated documentation system aim to improve patient care quality and potentially enhance both the quantity and quality of our scientific publications in the long term, while also focusing on transforming the initial administrative burden on healthcare workers into substantial long-term benefits. (2,3,13,47)

Our template in the new SQL database supports our colleagues' daily diagnostic routines (photo, X-ray, and model analysis). The template is flexible, enabling expansion, edits, and updates to include additional information or meet specific needs. If necessary, we can create new templates based on the patient history and diagnostic principles of any medical field. (2-3)

The opportunity to integrate our reporting system into the university's newly established Biobank (33) at the Institute for Clinical Data Management (21), inaugurated shortly after our work was completed, underscores the critical need for such tools and highlights the rapid advancements in Hungary’s clinical data management and biobanking methodologies. This is further evidenced by the successful integration of result tables from the AI-based lateral cephalometric analysis software, Ceph Assistant into our reporting template. This milestone led to the development of a unique, structured orthodontic reporting tool with a concept, structure and level of complexity that, to our knowledge, has not been reported in international studies or made publicly accessible in routine clinical practice. This platform will become even more distinctive and unparalleled globally once we can integrate the results of the automated photo analysis (Figure 19.) from the latest version of Ceph Assistant into our structured reporting interface. These statements reflect the completion of ongoing developments rather than future intentions.

To ensure the reliability of the integrated model, high-quality training and evaluation have been achieved through standardized protocols, diverse samples, and thorough statistical analyses, supporting the development of a robust AI model. We found that with the application of a well-trained AI algorithm the precision of orthodontic cephalometric analysis showed less variability between models than the variability observed among human experts. AI predictions enhanced the accuracy and efficiency of landmark identification, particularly as the automatic prediction model advanced.

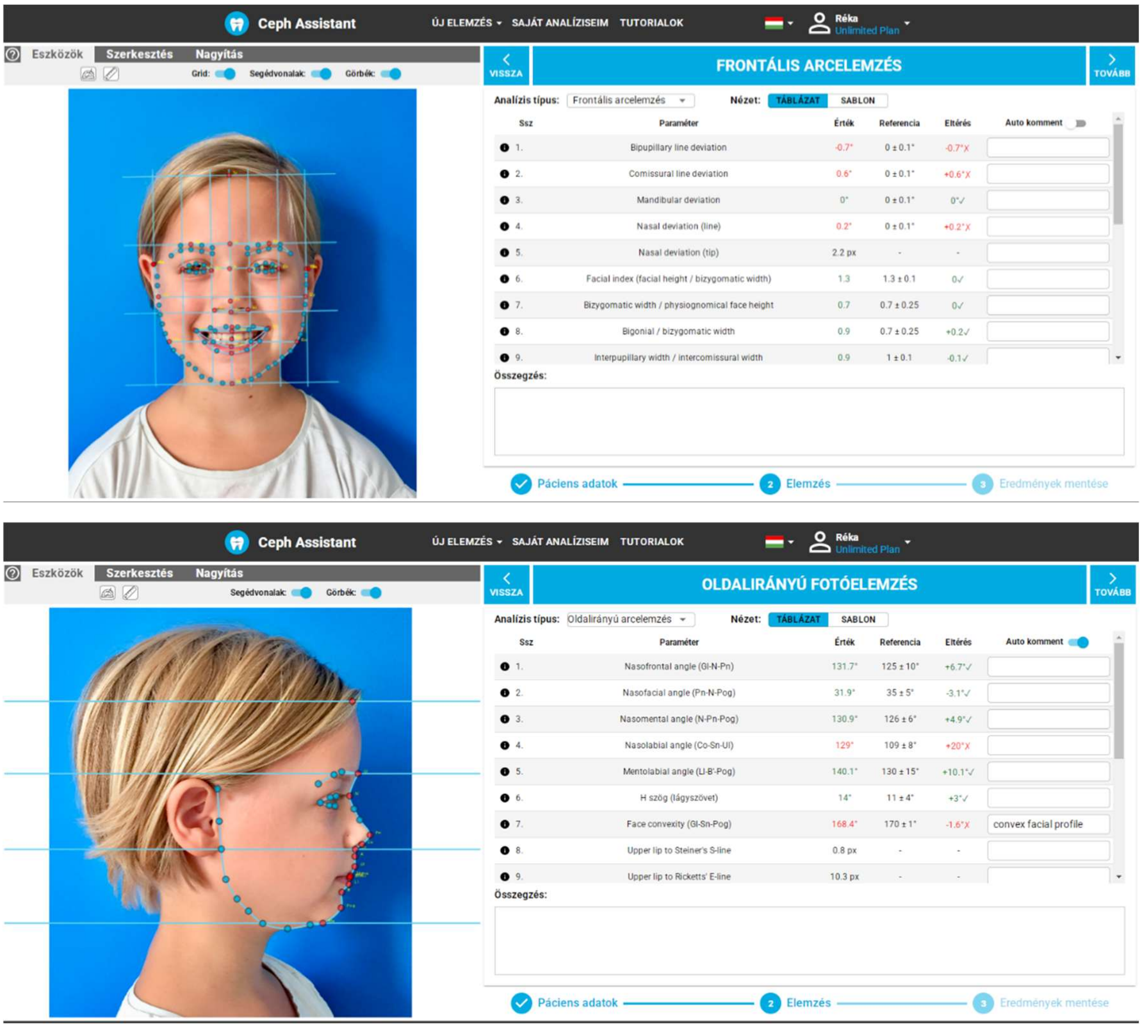


Figure 19. Automated photo analysis tool from the Ceph Assistant software.

Our research demonstrated a clear improvement in time efficiency (5.25 minutes) and significant advancements in precision during the training process of the Ceph Assistant algorithm. Even when corrections are needed for landmarks predicted by models trained on smaller datasets, evaluation times were reduced to less than half compared to fully manual dot tracing. Furthermore, accuracy assessments showed that the corrected predictions of the most advanced AI model achieved high level of precision even under suboptimal imaging conditions, with landmark detection errors consistently remaining within the range of discrepancies observed between two experts or between repeated evaluations by the same specialist (~2 mm). In the case of high-quality images, the L2 distance was reduced to approximately 1 mm. Results support the hypothesis that examiners make minor corrections to AI predictions, indicating that AI assistance influences decision-making during cephalometric analysis. The accuracy of the latest model exceeded that of human examiners, with angular (0.05°–1.86°) and proportional (3.14%) errors considered clinically acceptable. This highlights the practicality of AI-assisted workflows in clinical settings. (1)

The extension of training data improved model precision, but the small improvements were occasionally clinically insignificant, as tool noise remained lower than examiner noise. Nevertheless, higher quality models are advantageous, as they produce better results with less correction. Previous studies report lower intra- and inter-examiner variability in some cases, which could be attributed to variations in exclusion criteria and the greater number of landmarks in our study. (60, 61) While our model's average prediction distance slightly exceeded the 2 mm criterion set by C. W. Wang et al. (62-64) for dental radiography analysis, the median prediction distance remained well within the clinically acceptable range. This discrepancy can likely be attributed to the inclusion of more difficult landmarks in our evaluation compared to other studies. Additionally, the angular and ratio errors between AI and human dot tracing showed promising results, supporting the clinical relevance of our model's accuracy. Further studies could investigate the therapeutic implications by examining the impact on treatment planning or evaluating the long-term outcomes of therapies guided by the model's predictions and expert assessments. (1)

In summary, based on accessible international literature and current knowledge, this work represents a pioneering effort in managing a complex and comprehensive structured database in dentistry, specifically in the field of orthodontics, enhanced with AI solutions and decision-support capabilities. We demonstrated that, with sufficient high-quality data, an AI model can serve as an accurate diagnostic tool across both spatial and temporal dimensions. This study highlighted both the advantages and potential limitations of the approach and showed, using clinically relevant data, that AI-predicted cephalometric landmarks enable more precise angular and proportional calculations. This facilitates accurate orthodontic diagnosis in a significantly reduced timeframe. Our most accurate model may serve as a robust baseline for analysing lateral cephalograms, substantially improving diagnostic efficiency in orthodontics. With the extensive and high-quality data generated through this combined system, a fully autonomous workflow could be developed, eventually eliminating the need for manual corrections. Future research should investigate how evaluation errors and biases influence therapeutic

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outcomes, while further refining AI models by incorporating malocclusion-specific datasets and diverse evaluation methods to enhance precision and clinical utility. (1,65)

My ultimate goal is to develop a comprehensive AI-driven solution capable of recognizing patterns, correlations, and connections between various data points. Such a tool could support clinical decision-making and facilitate the identification of relevant correlations for research purposes.

VI. CONCLUSIONS

1. *Our findings, along with those from individual studies, confirm that structured and standardized documentation substantially improves the quality of medical records, providing valuable opportunities for data reuse when required.* This approach benefits medical professionals by facilitating patient management, enabling effective utilization of their expertise, enhancing educational tasks, and contributing to scientific progress. However, the initial implementation of such methods may increase administrative burdens for healthcare professionals, prompting us to develop a user-friendly interface that is easy for our colleagues to learn and use.

2. *To the best of my knowledge and based on the currently available international literature, I am the first to develop a structured orthodontic reporting interface that is not only unique worldwide but also, due to its complexity and interdisciplinary nature, provides a novelty method both in research and clinical practice.* With potential future expansions and collaborations with other clinics, may help to refine diagnostic approaches, extend clinical utilities, optimize patient pathways and care, enhance medical education, and strengthen competitiveness in the academic field.

3. *Additionally, I contributed to the development of clinically acceptable AI software for cephalometric analysis, which underwent rigorous validation through extensive scientific research prior to its implementation in clinical practice and market introduction.* Our study demonstrates that a well-trained AI algorithm effectively supports radiological diagnostics. Modern prediction tools, particularly in cephalometric evaluation, provide notable time efficiency benefits. As automatic prediction models continue to improve through advanced training, AI-assisted predictions enable clinicians to identify landmarks with greater accuracy and speed compared to traditional manual techniques. These results highlight the potential of AI models to optimize clinical workflows. Further

research is required to assess the long-term treatment implications of these advancements.

4. *Following the successful validation of the AI tool through a comprehensive study, the software was integrated into our structured template, enabling effortless access to its results.* This integration has produced a tool that addresses a critical procedural, technical, and conceptual gap in dentistry, particularly within orthodontics. Its interdisciplinary relevance extends beyond research, offering value to healthcare, medicine, economics, IT, and even policymaking in Hungary.

5. *Together, these findings and innovations provide substantial benefits that are expected to drive the present and future development of the Faculty of Dentistry.* However, this work extends beyond its current scope. The establishment of the structured database has created opportunities for extensive follow-up studies on large populations, various anomalies and an expanding range of tools driven by rapid advancements in digitalization. These studies aim to identify correlations between diagnostic and therapeutic procedures, patient groups, and long-term outcomes - marking the beginning of a new phase of exploration.

VII. SUMMARY

Working at a globally renowned university that prioritizes patient care, education, and research, I recognized that achieving maximum effectiveness requires return to the fundamental principles - specifically optimizing clinical workflows through structured and standardized medical recording. This dissertation addresses the urgent need for innovative data processing systems in healthcare, exploring both the current and future applications of EHRs and their potential integration with AI tools in diagnostic procedures, particularly in orthodontics to improve both efficiency and quality of medical services.

The study involved a systematic review, supplemented by original empirical research conducted within our clinic. The findings emphasize the significance of advancing diagnostic practices and the broader field of medical data management. This work lead to the establishment of a structured database and the development and integration of an AI algorithm for automated cephalometric analysis, which underwent a rigorous validation through a comprehensive study. However, my work does not end here. The foundation of the structured database has created opportunities for extensive follow-up studies on large populations, various anomalies, and an increasing number of tools enabled by rapid development and digitalization. These studies aim to find correlations between diagnostic procedures, groups of anomalies, and the results of long-term treatment outcomes, signalling the beginning of a new phase in data-driven medical research.

To the best of my knowledge and based on a recent review of medical literature, no other structured reporting template for orthodontics matches the complexity and comprehensiveness of the one I developed and published. However, my efforts have never been driven by the desire for pioneering status. Instead, my primary goal has been to develop a model that can be widely adopted as a fundamental component of clinical and research methodologies. I hope that this work will soon be integrated into standard practice, rather than persist as a novel innovation.

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Declaration on the Use of Generative Artificial Intelligence and AI-Based Technologies During the Writing Process

In the preparation of this dissertation, I used the artificial intelligence tool ChatGPT to support translation, refine language, and improve clarity. The tool was used exclusively for the refinement of certain sentences and expressions. The dissertation is the result of my own independent work. All text was subsequently reviewed and edited by me, and I take full responsibility for its final content.

IX. BIBLIOGRAPHY OF THE CANDIDATE'S PUBLICATIONS

IX.1 BIBLIOGRAPHY RELATED TO THE THESIS

- Bagdy-Bálint R, Szabó G, Zováthi ÖH, Zováthi BH, Somorjai Á, Köpenczei Cs, Rózsa NK. Accuracy of automated analysis in cephalometry. J Dent Sci. 2025;20(2):830-84.
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IX.2 OTHER RELATED SCIENTIFIC WORK

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IX.3 NONRELATED SCIENTIFIC PUBLICATIONS

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1. The total impact factor of original publications related to the dissertation: IF: **3.4**

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"Az a sok adat, amit az ember fejébe belepréselnek, úgyis elpárolog, abból semmi sem marad, azt az ember mind elfelejti. Ami megmarad, az a tudomány vagy a művészet, vagy a szépség szeretete. A probléma megoldásának vágya, a tettre készség, ezek az egyéni kvalitások fontosak."

Szent-Györgyi Albert