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Reliability of Artificial Intelligence in Lateral Cephalometric Analysis

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Aim: The purpose of this study was to assess the reliability of lateral cephalometric analysis performed by an artificial intelligence-dependent software program.

Materials and Methods: One Hundred and Eighty digital cephalometric radiographs acquired by Vatech PaX-i X-ray machine, were used in the study. The anatomical landmarks of both Steiner and McNamara analyses were manually traced using a third-party software AudaxCeph Empower, version 6.6.12.4731 (Audax d.o.o., Ljubljana, Slovenia), the tracing was performed by two radiologists with more than 5 years of experience in digital cephalometry to determine the inter-reliability, then it was repeated with an interval of two weeks to determine the intra-reliability. The landmarks were retraced automatically through the fully automatic option on the same software program using convolutional neural network.

Results: Regarding McNamara analysis, the results of this study showed excellent reliability of the artificial intelligence measurements compared to the manual measurements, with an interclass correlation coefficient >0.9. Regarding Steiner analysis, our results showed excellent reliability of the artificial intelligence measurements compared to the manual measurements (0.75<ICC<1 excluding Positive 1/SN degree, Negative 1i/NB mm, Pg/NB mm, and S-L point mm, which show moderate reliability with 0.4<ICC<0.74). Two measurements showed poor reliability (Holdaway ratio and S-E point mm).

Conclusions: The results of this study showed that the AudaxCeph automated software program has excellent reliability regarding McNamara and Steiner analyses. While in Steiner analysis, manual confirmation should be made with some dental landmarks.

Keywords: Artificial Intelligence, Cephalometry, deep learning

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Introduction

Lateral cephalometric radiography has been extensively used in craniofacial analysis. It is employed to describe morphology and predict the facial skeleton's growth, evaluate the anteroposterior (AP) relationships between the maxilla and mandible, and assess skeletal and soft-tissue relationship.[1] It is also used in treatment planning, monitoring the progress of treatment, and treatment outcomes.[2-4] Conventional or traditional cephalometric analysis is performed on acetate sheets by hand tracing the anatomical landmarks on the cephalogram, and then these selected points are used to measure linear and angular measurements by the construction of planes, lines, and angles. Regardless of the widespread use of the traditional tracing method in orthodontics, the technique is time consuming and the manually acquired linear and angular cephalometric measurements with a ruler and protractor may be subjected to error.[5,6]

The conventional tracing method has been replaced by digital tracing, either using direct or indirect radiographic systems.[7,8] However, digitizing the cephalometric analysis still doesn't eliminate the manual landmark annotation process, which is a subjective process that requires clinician experience and, if done properly, can also be time-consuming, especially when using more than one type of analysis.[9]

Artificial intelligence (AI) is the assemblage of technologies that can imitate human intelligence or make effective and ethical decisions controlled by predetermined criteria.[10] Machine learning is a part of AI that can analyze data, allowing computer programs to improve through cognitive content automatically.[10] While deep learning is a subset of machine learning that depends on artificial neural network (ANN). This network consists of several layers, including input, output, and hidden layers.[11] So, a machine can learn from its own data processing, but in order to achieve that, it needs a large amount of training data, high-end computer resources, and a longer training time.[11]

Recently, AI has been investigated by many researchers regarding its integration in diagnosis and treatment planning, for example, its use in oral radiology to enhance the interpretation of the radiographs,[12,13] in the detection and categorization of bone lesions using deep learning algorithms,[14] in the classification of temporomandibular joint diseases,[15,16] in identifying oral cancer and lymph node metastasis,[17] and in identifying people at risk of osteoporosis.[18] Moreover, AI has been used in the detection of periodontal bone diseases,[19] teeth detection and segmentation [20] and tooth labelling and numbering.[21]

Besides, AI was used in the diagnostic procedures and treatment phases in orthodontics.[22] It was introduced into the field of cephalometric analysis to eliminate the need for an expert orthodontist to perform the manual anatomical landmark localization.[23]

So, we believe that fully automated software programs for cephalometric tracing would benefit practitioners by decreasing the percentage of errors in cephalometric analysis, as landmark identification is considered one of the main reasons for these errors [24]. Besides, these software programs will significantly save time for orthodontists as they will not need to place each landmark, especially when using multiple analyses. Therefore, it was necessary to evaluate the reliability of the fully automated software programs to allow orthodontists to use them with confidence.

Up to our knowledge, there are contradicting studies testing the reliability of the fully automated cephalometric analysis compared to the manual analysis.[25-29] Accordingly, the aim of our study is to assess the reliability of lateral cephalometric analysis performed by AI dependent computer software program using Steiner and McNamara analyses. The null hypothesis is that cephalometric analysis performed by AI dependent computer software programs is not as reliable as the manual one.

Materials and Methods

This study is a retrospective analytical study carried on lateral cephalometric images. The study was exempted from the research ethical committee, exempt number FDASU-Rec EM012203, Faculty of Dentistry-Ain Shams University. Images were chosen from the database of the Oral and Maxillofacial Radiology Department from December 2021 to January 2023.

Sampling

A power analysis was designed to have adequate power to apply a two-sided statistical test of the null hypothesis that there is no difference between artificial intelligent cephalometric analysis and digital (manual). By adopting an alpha (α) level of (0.05), a beta (β) level of (0.2) (i.e. power = 80%), and an effect size (d) of (0.206) calculated based on results of similar study by Silva et al.[26] in which the average value measured in the control group was (2.643± 2.514) and in the test group it was (2.176±1.882)-; the predicted sample size (n) was found to be (187) cases. Sample size calculation was performed using G*Power version 3.1.9.7.[30]

Images have been acquired by PaX-i machine (Vatech, Seoul, Korea) applying 90 kVp, 10 mA, and 0.7-1.2 s exposure time. We included in our study images of patients aged 14-60 years of both sexes with fully erupted permanent dentition in both arches. We excluded images with artifacts, prosthetic restorations, patients with cleft palate, or patients with trauma. Images were transferred to a third-party software AudaxCeph Empower, version 6.6.12.4731 (Audax d.o.o., Ljubljana, Slovenia) for the digital cephalometric analysis. Image viewing was performed using 21.5-inch screen (Lenovo, Beijing, China) in a dimly lit room. Two radiologists with more than 5 years of experience in digital cephalometry performed the tracing procedure twice with two weeks interval.

Cephalometric analysis was performed using Steiner and McNamara analyses, which included the selection of thirty-five anatomical landmarks and eleven anatomical landmarks, respectively (Tables 1–2).[31] Each type of analysis was performed using two methods. First, manual tracing of the cephalometric images (using the concurrent tracing option in the software). Second, automatic tracing option using the SCN-EXT convolutional neural network of the AudaxCeph software program[32] (Figure 1). Data from both analyses was recorded and tabulated.

Statistical Analysis

Statistical analysis was performed with SPSS 20® (Statistical Package for Scientific Studies) Graph Pad Prism® and Microsoft Excel 365. Normality test exploration was performed using Shapiro-Wilk test and Kolmogorov-Smirnov test, as presented in Table 3. The comparison between the mean and standard deviation of both manual and AI measurements was executed using Mann-Whitney's test, which is used to compare two non-parametric measurements. Reliability was evaluated by using the interclass correlation coefficient (ICC) to evaluate the agreement between manual and AI measurements. ICC is a reliability index that reflects both the degree of correlation and agreement between measurements.[33]

Table (1) showing the anatomical landmarks of Steiner analysis.

Landmark	Definition
Sella Turcica (S)	The midpoint of the sella turcica or hypophyseal fossa.
Nasion (N)	The most anterior point on the frontonasal suture.
Posterior Nasal Spine (PNS)	Tip of the posterior spine of the palatine bone of the hard palate.
Anterior Nasal Spine (ANS)	Tip of the anterior nasal spine of the maxilla at the level of nasal base.
Point A (A)	The deepest point on the curved contour of the maxilla between the anterior nasal spine and the incisor.
Point B (B)	The deepest midline point on the contour of the mandible between the incisor and the bony chin
Pogonion (Pg)	Most anterior point of mandibular symphysis.
Gnathion (Gn)	The most antero-inferior point on the bony chin in the midsagittal plane.
Menton (Me)	Lower most point of the contour of the chin.
Articulare(Ar)	A point where the ramus meets the basilar portion of the occipital bone on its posterior border.
Mandibular Notch (Md)	A midline point on the concave groove at the top of the ramus of the mandible.
Constructed Gonion (tGo)	A crossection of a line tangent to the mandible's inferior border and the rami's posterior border.
Gonion (Go)	The most inferior point on the curvature of the angle of the mandible.
Apex of upper incisor (+1a)	The root apex of the most anterior maxillary central incisor.
Incisal edge of upper incisor(+1i)	The incisal edge of the maxillary central incisor.
Incisal edge of lower incisor(-1i)	The incisal edge of the most prominent mandibular central incisor.
Apex of lower incisor (-1a)	The root apex of the most anterior mandibular central incisor.
L1	The most labial point on the crown of the mandibular central incisor.
First molar (M6)	Tip of the mesiobuccal cusp of the maxillary 1st molar.
I1	Point defining Occlusal plane between incisors.
Glabella (Gl')	The most prominent point at the level of the superior orbital ridges in the midsagittal plane of the forehead.
Soft Nasion (N')	The concave or retruded point of the tissue overlying the area of the frontonasal suture.
Pronasale (Pn')	The most prominent point of the nose.
Subnasale (Sn')	The point at which the nasal septum merges with the upper cutaneous tip in the midsagittal plane.
Point Soft A (A')	The point of deepest concavity in the midline of the upper lip between subnasale and labrale superius.
Labrale Superior (Ls')	The most anterior point of the margin of the upper membranous lip.
Upper Stomion (+St')	The lowest midline point of the upper lip.
Lower Stomion (-St')	The highest midline point of the lower lip.
Labrale Inferior (Li')	The most anterior point of the margin of the lower membranous lip.
Point Soft B (B')	The point of greatest concavity in the midline of the lip between labrale inferius and soft tissue pogonion.
Point Soft Pogonion	The most prominent point of the soft tissue chin in the midsagittal plane.

Table (2) showing the anatomical landmarks of McNamara analysis.

Share with Steiner analysis N, S, Ar, ANS, PNS, A, +1i, -1i, Pg, Gn, Me, Go and tGo points. In addition to:	
Orbitale (Or)	The most inferior point of the external border of the orbital cavity.
Pt point	The most posterior and superior point on the pterygomaxillary fissure.
Porion (Po)	Most superior point of the outline of the external auditory meatus.
Basion (Ba)	Most inferior point on the anterior margin of the foramen magnum in the median plane.

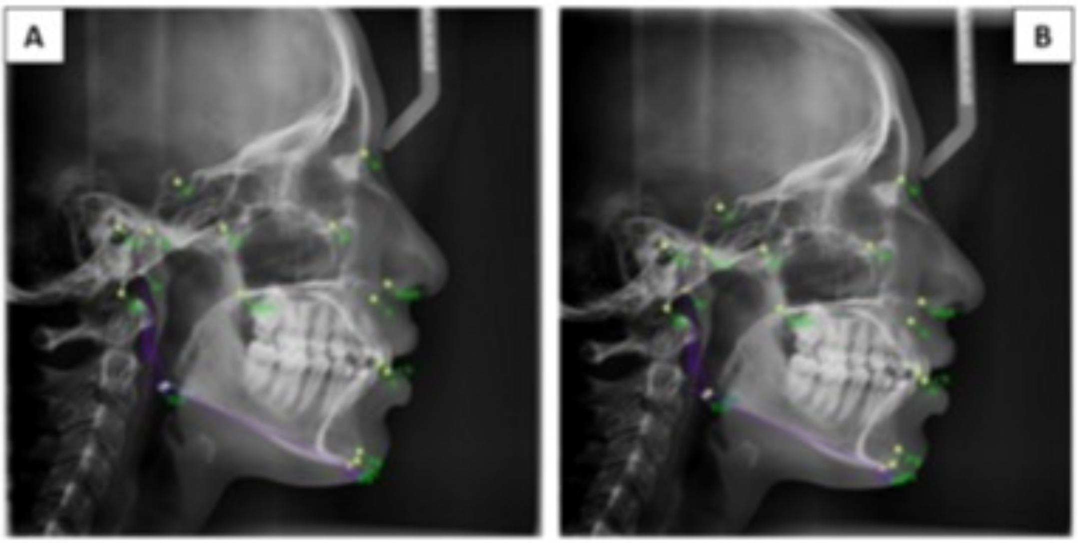

Fig (1) McNamara analysis. (A) Manual cephalometric tracing, (B) AI cephalometric tracing.

Table (3): Normality exploration of both groups

		McNamara	Steiner
Manual (1st observer)	1st read	<0.05*	<0.05*
	2nd read	<0.05*	<0.05*
Manual (2nd observer)	1st read	<0.05*	<0.05*
	2nd read	<0.05*	<0.05*
Artificial intelligence		<0.05*	<0.05*

***Significant difference (non-parametric data).**

Results

I. McNamara cephalometric analysis:

Intra-observer and inter-observer reliability were evaluated by using the interclass correlation coefficient (ICC). The results of this study showed excellent intra-observer and inter-observer reliability with an ICC > 0.9.

A comparison between the mean and standard deviation of both McNamara manual measurements and AI measurements was performed using Mann-Whitney's test, which revealed an insignificant difference between them (P > 0.05), as presented in Table 4.

Reliability was evaluated by using the interclass correlation coefficient (ICC) to evaluate the agreement between manual McNamara measurements and AI measurements, which revealed significant (P<0.0001) and excellent reliability (ICC > 0.9).

II. Steiner cephalometric analysis:

Intra-observer and inter-observer reliability were evaluated by using the interclass correlation coefficient (ICC). The results of our study showed excellent intra-observer reliability (ICC > 0.9). While the inter-observer reliability revealed excellent to moderate reliability (0.9>ICC > 0.7), (0.4>ICC>0.7) respectively.

A comparison between the mean and standard deviation of both Steiner manual measurements and AI measurements was performed using Mann-Whitney's test, which revealed an insignificant difference between them (P > 0.05), as presented in Table 5.

Reliability was evaluated by using the interclass correlation coefficient (ICC) to evaluate the agreement between manual Steiner measurements and AI measurements, which revealed significant (P<0.0001), excellent reliability (0.7<ICC < 0.9), moderate reliability (0.4<ICC<0.7) of Positive 1/SN degree, Negative 1i/NB mm, Pg/NB mm and S-L point mm measurements, and two measurements showing poor reliability (Holdaway Ratio and S-E point mm).

Discussion

With the significant application of AI in the dental field, AI has been introduced in orthodontics, especially in the field of cephalometric analysis. It allows easier and more practical localization of the anatomical landmarks without the need for an expert orthodontist.[23] For this purpose, our study is aiming to determine to what degree the AI is reliable for cephalometric tracing.

We chose to use AudaxCeph automated cephalometric tracing software program in our study as it offers a fully automated cephalometric tracing depending on convolutional neural networks for the identification of the anatomical landmarks.[32] In accordance with our study, Ristau et al [9] used AudaxCeph to test the reliability of the AI cephalometric analysis. However, they only selected certain anatomical landmarks (including A point, B point, Orbitale, Gonion, L1 apex, L1 tip, U1 apex, U1 tip, etc.) instead of using a specific analysis.

Likewise, Savc et al[32] used AudaxCeph to describe the development of the convolutional neural network in the automatic detection of the anatomical landmarks without using a certain analysis as well, and they selected 72 landmarks including (+1i—Upper incisal incisor, −1i—Lower incisal incisor, ANS—Anterior Nasal Spine, Go—Gonion, S—Sella Turcica, PNS—Posterior Nasal Spine, Pg'—Point Soft Pogonion, etc.).

In our study, we chose to apply McNamara and Steiner analyses. A study performed by Keim et al in the Journal of Clinical Orthodontics (JCO) [34] showed that Steiner analysis was the most used analysis in 45.1% of the orthodontic practice, and its relative popularity as compared to other

Table (4): Reliability between manual and artificial intelligence measurements using McNamara analysis

McNamara		Manual		AI		P-value	AI reliability			
							ICC	95% CI		P value
		M	SD	M	SD			L	U	
Maxilla to Cranial Base	A-NP distance mm	2.12	3.26	2.39	3.36	0.41	0.967	0.96	0.98	<0.0001*
	SNA angle	82.14	3.73	81.22	7.00	0.27	0.964	0.41	0.67	<0.0001*
Mandible to Maxilla	Co-A mm	82.81	5.61	82.97	5.62	0.82	0.959	0.94	0.97	<0.0001*
	Co-Gn mm	110.08	8.07	109.59	7.99	0.62	0.975	0.97	0.98	<0.0001*
	Max-Mand mm	27.34	5.75	26.58	5.50	0.21	0.994	0.99	1.00	<0.0001*
	ANS-Me mm	65.81	6.81	65.81	6.76	0.99	0.986	0.98	0.99	<0.0001*
	NL/ML Anatomic angle	27.37	6.02	26.43	6.08	0.16	0.965	0.95	0.97	<0.0001*
	Facial axis angle	89.52	4.98	88.69	4.71	0.08	0.976	0.97	0.98	<0.0001*
Mandible to Cranial Base	Pg-Np distance mm	3.32	6.23	2.51	6.33	0.21	0.969	0.96	0.98	<0.0001*
Dentition	Positive 1/A II FH mm	5.53	3.21	5.98	3.03	0.17	0.980	0.97	0.99	<0.0001*
	Negative 1/Apg mm	4.22	2.97	4.47	2.86	0.41	0.961	0.95	0.97	<0.0001*

analyses remained the same over the years. In addition, a survey done for Dutch orthodontists [35] showed that Steiner analysis was the most commonly used analysis by 58%.

Moreover, Nouri et al and Bansal et al [36,37] proved that McNamara analysis showed superior features compared to other analyses as it is based on the natural head position instead of the Frankfort plane which made it of high reproducibility in different age groups. Besides, McNamara Jr [38] stated that McNamara analysis has superior advantages over other analyses, it provides linear evaluation of apical base and dental to apical base discrepancies.

In our study, we selected two full analyses in order to minimize the potential confounding factor of reproducibility and variability of different landmark identifications.[39] Likewise, Silva et al [26] used Arnett's analysis for the same target. However, they used a different software program (CEFBOT).

The results of the current study showed excellent reliability of the AI measurements with the manual measurements regarding McNamara analysis with interclass correlation coefficient >0.9.

Moreover, the results of our study showed excellent reliability of the AI measurements compared to the manual measurements regarding Steiner analysis with 0.75<ICC<1 except for Positive 1/SN degree, Negative 1i/NB mm, Pg/NB mm and S-L point mm measurements which showed moderate reliability with 0.4<ICC<0.74. Besides, there were two measurements had poor reliability (Holdaway Ratio and S-E point mm). These later results may be due to the difficulty in detecting points such as Pogonion, the labial surface of the

Table (5): Reliability between manual and artificial intelligence measurements using Steiner analysis

Steiner	Manual		AI		P-value	AI reliability			
						ICC	95% CI		P value
	M	SD	M	SD			L	U	
Angle SNA degree	82.55	4.46	81.67	3.59	0.03*	0.912	0.883	0.935	<0.0001*
Angle SNB degree	78.89	4.40	77.56	3.90	0.004*	0.951	0.934	0.964	<0.0001*
ANB degree	3.67	3.54	4.07	2.92	0.41	0.923	0.897	0.943	<0.0001*
SND degree	76.17	4.30	74.99	5.38	0.001*	0.756	0.672	0.818	<0.0001*
Interincisal angle degree	118.98	12.96	120.63	16.93	0.02*	0.774	0.697	0.832	<0.0001*
SN/OcP degree	17.17	6.00	17.71	4.31	0.29	0.831	0.773	0.874	<0.0001*
SN/GoGn degree	33.31	7.10	34.28	6.25	0.08	0.934	0.911	0.951	<0.0001*
Positive 1/ NA degree	26.34	8.46	23.36	9.84	0.01*	0.790	0.719	0.844	<0.0001*
Positive 1/SN degree	108.87	9.11	103.68	12.35	0.01*	0.690	0.585	0.769	<0.0001*
Negative 1/NB degree	31.07	7.96	30.72	7.81	0.71	0.922	0.895	0.942	<0.0001*
Positive 1i/NA mm	5.57	3.49	5.19	3.46	0.37	0.763	0.682	0.824	<0.0001*
Negative 1i/NB mm	6.78	3.10	7.87	5.94	0.09	0.548	0.393	0.663	<0.0001*
Pg/NB mm	0.70	1.82	0.58	4.00	0.57	0.542	0.386	0.659	<0.0001*
Holdaway Ratio	10.59	18.96	32.69	194.54	0.98	0.284	0.144	0.413	<0.0001*
S-L point mm	46.90	9.63	45.02	19.22	0.01*	0.442	0.252	0.584	<0.0001*
S-E point mm	18.65	4.52	21.07	10.12	0.001*	0.101	0.206	0.330	<0.0001*

mandibular central incisor, and the apices of the upper and lower incisors.

The decreased reliability is probably due to the difficulty in detecting points such as pogonion, the labial surface of the mandibular central incisor, the apex of the upper incisor, incisal edge of the lower incisor. Besides, Holdaway ratio, which has the least reliability, is the ratio between the linear distance from the labial surface of the mandibular central incisor to the NB line, over the linear distance of the pogonion to the same line (L1-NB/ Pg-NB).

In accordance with our results, Ristau et al[9] showed no statistically significant difference between the manual tracing and

AudaxCeph, except for the x- and y-dimension of Porion and U1 apex points, the y-dimension of L1 apex and B points and the x-dimension of the Orbitale point . In our study, there is difficulty in detecting B point presented in NB line (nasion-point B line), U1 apex (+1/ SN °) as well.

Similarly, a study done by Savc et al [32], who developed a modified Spatial Configuration-Net network (SCN-EXT) to localize 72 landmarks using AudaxCeph, showed high accuracy of detection of the landmarks except for 10 landmarks which showed the least accuracy including (Glabella, Point soft Gnathion, Temporale, etc.).. Likewise, Papievis et al [40], who evaluated the reliability of AudaxCeph, showed high reliability of detection of the anatomical landmarks except for 6 landmarks which showed statistical significant difference (SN-Pg, AN-Pg, SN/ANS-PNS, ANS-PNS/GoGn, U1/ANS-PNS and U1-L1 measurements).

Another study by Jeon et al [27] using different software program showed no statistically significant difference between the manual and automated measurements except for 3 measurements (linear measurements of maxillary incisor to NA line, mandibular incisor to NB line, and saddle angle). Jeon et al mentioned that the surrounding superimposing anatomical structures can affect landmark identification. In addition, the difficulty is more in tracing the mandibular incisor due to overbite and overjet. In our study, the linear measurements of the mandibular incisor to the NB line showed moderate reliability as well.

In accordance with our study, a study done by Mahto et al [41] showed that 7 out of 12 measurements had higher ICC values, while 5 measurements showed lower ICC values (UL to E-line, U1 to NA (mm), SNA, SNB, U1 to NA (°) than the rest of measurements).

From the previous studies, including ours, we could suggest that there is difficulty in detecting root apices of both upper and lower incisor teeth, including +1/SN°, -1/NB mm, U1 apex point, L1 apex point, maxillary incisor to NA line, and mandibular incisor to NB line measurements.

Likely, a study by Tsolakis [42] showed high ICC values between the automated cephalometric analysis and the manual one except for FMA, L1-MP, ANS-PNS/GoGn, and U1-L1 which were statistically significant.

Moreover, a study done by Panesar et al [28] revealed excellent accuracy of AI-derived measurements, 10 out of 26 measurements had the least reliability. Four of these measurements included gonion point (L1-MP, FMA, posterior face height and SN-MP).

Our results suggest that AudaxCeph is a very promising software program for the automatic identification of cephalometric landmarks, according to McNamara and Steiner analyses. However, care should be taken regarding some points in Steiner analysis, including the apex of upper incisor, the incisal edge, and labial surface of the lower central incisor, Pogonion. We recommend testing the reliability of these cephalometric landmarks within different analyses.

Conclusion

The results of this study showed that the AudaxCeph automated software program has excellent reliability regarding McNamara and Steiner analyses. While in Steiner analysis, manual confirmation should be made with some points.

Conflict of Interest

The authors have no conflict of interest.

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