Exploring the use of a Length Artificial Intelligence (LAI) algorithm to estimate children's length from smartphone images in a real-world setting

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Submitted to: JMIR Pediatrics and Parenting
on: June 21, 2024

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Abstract

Background: Length measurement in young children below 18 months is important for monitoring growth and development. Accurate length measurement requires proper equipment, standardised methods, and trained personnel. Additionally, length measurement requires young children's cooperation, making it a particular challenge during infancy and toddlerhood.

Objective: We developed a Length Artificial Intelligence (LAI) algorithm to aid users in determining recumbent length conveniently from smartphone images and explored its performance and suitability for personal and clinical use.

Methods: This pilot study in healthy children (0–18 months) was performed at KK Women's and Children's Hospital, Singapore from November 2021 to March 2022. Smartphone images were taken by parents and investigators. Standardised length-board measurements were taken by trained investigators. Performance was evaluated by comparing the tool's image-based length estimations with length-board measurements (bias [mean error, the mean difference between measured and predicted length]; absolute error [AE, magnitude of error]). Prediction performance was evaluated on an individual-image basis and subject-averaged basis. User experience was collected via questionnaires.

Results: A total of 215 subjects (median age 4 months) were included. The tool produced a length estimation value for 2211 (99%) of 2224 photos analysed. The mean AE was 2.47 cm for individual image predictions and 1.77 cm for subject-averaged predictions. Investigators and parents reported no difficulties in capturing the required photos for most subjects (85%, 182/215 subjects and 72%, 144/200 subjects, respectively).

Conclusions: LAI is a practical and novel way of estimating children's length from smartphone images without the need for specialised equipment or trained personnel. LAI's current performance and ease of use suggest its potential for use by parents/caregivers with an accuracy approaching that typically achieved in paediatric outpatient clinics. The results show that the algorithm is acceptable for use in a personal setting, and this serves as a proof of concept for use in clinical settings. Clinical Trial: The study was registered at ClinicalTrials.gov (https://clinicaltrials.gov/ct2/show/NCT05079776)

(JMIR Preprints 21/06/2024:59564)
DOI: https://doi.org/10.2196/preprints.59564

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TITLE PAGE

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ABSTRACT (297 words)

Background: Length measurement in young children below 18 months is important for monitoring growth and development. Accurate length measurement requires proper equipment, standardised methods, and trained personnel. Additionally, length measurement requires young children's cooperation, making it a particular challenge during infancy and toddlerhood. We developed a Length Artificial Intelligence (LAI) algorithm to aid users in determining recumbent length conveniently from smartphone images and explored its performance and suitability for personal and clinical use.

Methods: This pilot study in healthy children (0–18 months) was performed at KK Women's and Children's Hospital, Singapore from November 2021 to March 2022. Smartphone images were taken by parents and investigators. Standardised length-board measurements were taken by trained investigators. Performance was evaluated by comparing the tool's image-based length estimations with length-board measurements (bias [mean error, the mean difference between measured and predicted length]; absolute error [AE, magnitude of error]). Prediction performance was evaluated on an individual-image basis and subject-averaged basis. User experience was collected via questionnaires.

Results: A total of 215 subjects (median age 4 months) were included. The tool produced a length estimation value for 2211 (99%) of 2224 photos analysed. The mean AE was 2.47 cm for individual image predictions and 1.77 cm for subject-averaged predictions. Investigators and parents reported no difficulties in capturing the required photos for most subjects (85%, 182/215 subjects and 72%, 144/200 subjects, respectively).

Conclusions: LAI is a practical and novel way of estimating children's length from smartphone images without the need for specialised equipment or trained personnel. LAI's current performance and ease of use suggest its potential for use by parents/caregivers with an accuracy approaching that typically achieved in paediatric outpatient clinics. The results show that the algorithm is acceptable for use in a personal setting, and this serves as a proof of concept for use in clinical settings.

KEYWORDS: computer vision; length estimation; artificial intelligence; smartphone images; children

INTRODUCTION

Regular and accurate measurement of anthropometric parameters in young children is important for monitoring growth and development, and for facilitating timely interventions to ensure appropriate growth [1, 2]. Body length measurements are required for two key World Health Organization (WHO) growth standards: i) length-for-age and ii) weight-for-length [3]. Accurate length measurement requires specialised equipment (a properly calibrated length board), skilled personnel, and a cooperative child [4-7]. Studies have reported inaccuracy and variability of length measurements, even in clinical settings [5, 6, 8, 9]. Although parents and caregivers want to track their children's growth closely, many find measuring their child's length at home technically challenging. Thus, there is an unmet need to develop a tool that is easy to use and addresses the key obstacles in taking accurate length measurements. This can potentially be upscaled and deployed for both personal and clinical environments.

Mobile devices are increasingly used for fast and efficient collection of real-world data, especially through smartphone images. Advances in artificial intelligence (AI) and computer vision technology, particularly deep learning, have enabled complex image recognition and prediction tasks to be performed on such image data [10-14]. These include challenging tasks such as predicting the physical size of a three-dimensional object from one or more two-dimensional images, which could translate to clinical use in determining a person's anthropometric measurements. Most of the existing image-based approaches focus on predicting the standing height of adults [15, 16], although a couple of approaches for predicting the recumbent length of young children have been proposed [17, 18]. Unlike manual measurements, these automated image-based approaches do not rely on standardised positioning of the child's body but must overcome certain challenges to produce accurate predictions. The relevant body parts must be automatically identified within the image by locating key landmarks such as the head and limb joints. The length prediction method must also account for body parts having variable orientation and distance from the camera, which affects their apparent lengths in the image. Image artefacts, such as blurring due to the child's movement, must also be detected and accounted for. One group proposed a stereoscopic vision system that uses two cameras to photograph the child simultaneously from different angles and estimates the child's body length based on the two images using the parallax principle [17]. Another group proposed a method involving the detection of customised round markers placed on the child's body before image capture. The markers allow both the detection of body landmarks in the image and the estimation of their 3D position relative to the camera; these are used to predict overall body length [18]. However, neither approach fully overcomes all current challenges with child length measurement since they still require specialised equipment or additional manual setup.

We developed a Length Artificial Intelligence (LAI) algorithm to automatically predict children's length from smartphone images. To our knowledge, the LAI is the first approach that does not require specialised equipment or precise placement of body segment markers for length prediction. This innovative approach could make it much more practical and convenient for parents or caregivers to take regular length measurements for their children. In this pilot study, we examined the LAI's performance for automated length prediction and compared its performance with WHO standards [19] and measurements taken in paediatric outpatient clinics [20]. These comparisons allowed us to assess the feasibility of using the LAI in scenarios where specialised equipment and skilled personnel are unavailable. In addition, we explored users' experience and expectations for a digital measurement tool that could be used in home or clinic environments.

METHODS

Study design and subjects

An exploratory, observational, cross-sectional pilot study was conducted between November 2021 and March 2022 at KK Women's and Children's Hospital, Singapore. The institution's independent ethics committee approved the study before its initiation. The study was conducted in accordance with Good Clinical Practice, the Declaration of Helsinki, and the local laws and regulations of Singapore. Written informed consent was obtained from the parents of each subject before any study-related procedures were performed. The study was registered at ClinicalTrials.gov (https://clinicaltrials.gov/ct2/show/NCT05079776).

Eligible subjects were children between 0 to 18 months whose parents i) had a smartphone or tablet with access to the internet, ii) were able to complete the study questionnaires, and iii) take and upload images onto an online form. Children who were unable to undergo length measurement by the standardised technique recommended by the World Health Organization (WHO) [21] (e.g., children with structural abnormalities of the lower limbs or orthopaedic conditions such as club foot and hip dysplasia) were excluded from the study.

The study duration was a maximum of two days. On Day 1 (clinic setting), investigators measured the subject's body length using the standardised WHO length measurement technique [21]. They then used a smartphone to take six top-view photos of the subject in a supine position. Each photo included a standard-size reference card. On Day 1 or 2 (home setting), parents took and uploaded six smartphone photos of the subject in a supine position with the reference card. Investigators and parents were given a list of image quality requirements and guidelines for capturing good quality images. Parents and investigators completed their respective user experience questionnaires after the image upload process.

Study assessments

Standardised length measurements

The body length of the subject was measured twice by investigators to the nearest 0.1 cm using the standardised WHO technique [21]. As children were under two years old, measurements were taken supine by two investigators using an infant length board. The average of the two measurements was recorded as the subject's body length and used as input to the LAI algorithm. If the two measurements differed by more than 0.5 cm, a third measurement was taken and the average of the three measurements was used.

User experience questionnaires

Customised questionnaires were used to capture user feedback from investigators and parents on their experience with taking suitable photos according to the study requirements and on other items relating to using a digital measurement tool, including expected accuracy and desirable features.

LAI overview

The LAI uses state-of-the-art imaging and machine learning techniques to estimate a subject's length from a single image, such as a smartphone photo. The current algorithm was designed to predict the length of children up to 18 months. The input to the algorithm is a digital image of the subject in a supine position and a reference object (standard CR80 reference card, 85.6 mm by 54.0 mm). The first step involves extracting image features for both the subject and the reference card (**Figure 1**). Landmark extraction models are used to detect landmarks on the subject's face and body (shoulders, hips, knees, ankles, heels, etc.) within the image. These estimate the length of individual body segments in pixels. The card detection and card segmentation models are used to locate the reference card in the image and compare its pixel dimensions against its known physical dimensions to generate a pixel per metric value. The feature extraction step thus generates a set of quantitative features used in the length prediction step (**Figure 1**). A model incorporating these features predicts the total body length in millimetres. The algorithm returns a predicted length value as output only if the key feature extraction steps (body and card features) are successful.

Image datasets

The Investigator (I) and Parent (P) datasets consisted of all images taken by the investigators and the parents, respectively.

Image requirements

To maximise the number of images usable for length prediction, photo-taking guidelines were given to investigators and parents. This included no clothing on the head or feet (e.g., cap, socks, etc.); no loose/baggy clothing to ensure that the body contour was visible; high contrast between the background, subject, and reference card; subject and reference card placed on the same flat and stable surface; subject positioned not more than 10 cm from the reference card; image taken at 90 degrees from the surface on which the subject and card were placed; subject's legs not bent with the entire body visible to the camera (**Supplementary Figure 1**). Images that fail to meet these requirements may fail to generate length predictions.

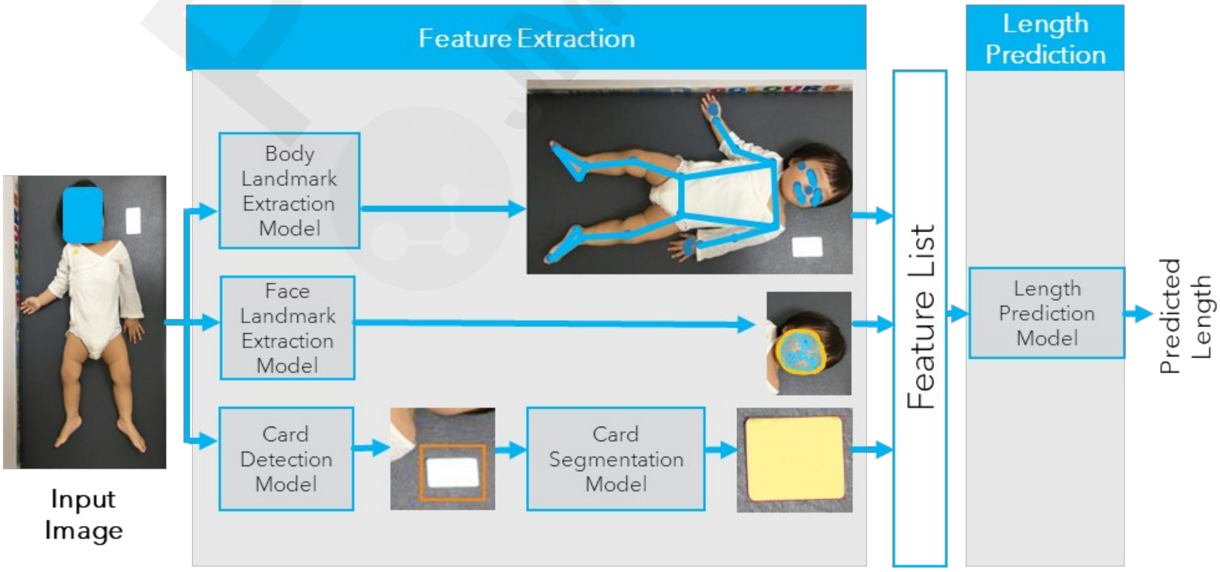
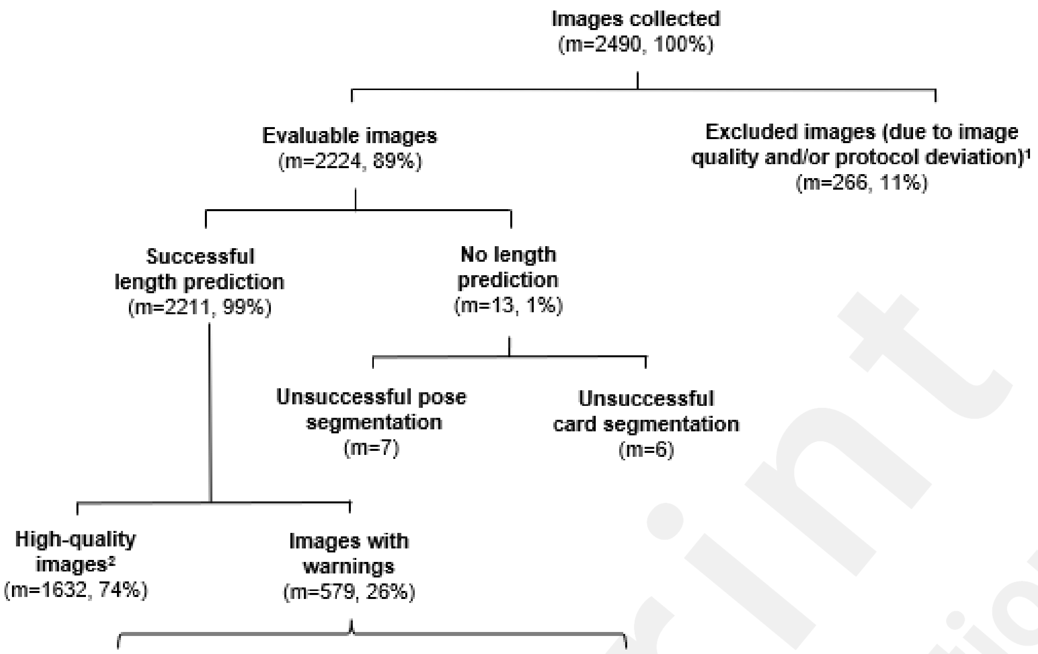


Figure 1. LAI algorithm overview. From an input image of a child in a supine position and

a standard reference object, anthropomorphic landmarks of the body and face are extracted, along with the detection and segmentation of the reference object. These are used by the LAI to predict the length of the child.

Following further testing and optimisation, automated flags/warnings were incorporated into the LAI (**Figure 2**). This allows the tool to detect uploaded images that do not meet the specified requirements and warn users that length prediction may be unsuccessful. Four different types of warnings were implemented.



Warning Labels	Warning Description
W0	Card and body overlap
W1	Card aspect ratio is wrong
W2	Improper card segmentation
W3	Width pixel size and height pixel size are too far

Warnings	No. of images affected
W0	88
W1	105
W2	174
W0, W1	9
W0, W2	64
W1, W2	94
W1, W3	3
W0, W1, W2	39
W1, W2, W3	2
W0, W1, W2, W3	1
Total	579

[1] Due to protocol violations, including resubmission of data, uploading of images out-of-visit window and image requirements not met.
[2] High-quality images refer to images that did not generate any warnings.
m (%), number and percentage of images in the category

Figure 2. Schematic diagram of image flow. A total of 2490 images were collected in this study and 2224 images were analysed. A total of 266 images were not analysed due to protocol deviations (resubmission of images, submission of images outside the stipulated visit window, or images that did not meet the requirements). Of 2224 images analysed, 2211 images produced a length prediction. The algorithm did not produce a prediction for 13 images due to unsuccessful pose segmentation (m=7) or unsuccessful card segmentation

(m=6).

Model training and performance metrics

The LAI model was trained on the combined set of images collected by investigators and parents (I+P datasets) and the investigator-generated length measurements. As described above, a set of features was generated, along with warnings. Only images that did not produce warnings were used to train the model. A 5-fold cross-validation was used. Cross-validation is a statistical resampling method commonly used in applied machine learning to evaluate model performance with limited datasets [22, 23]. Each fold contained images from the same individual only, and the same distribution of measured lengths was maintained in all folds. A bagged model was used for prediction. Hyperparameter optimisation (HPO) incorporated a random feature selection step and was implemented using a state-of-the-art HPO framework [24]. Training was performed only on images taken by the investigators using a two-step process. In the first step, a model was trained on all images from the investigators in the current training fold. Subsequently, a subset of these images within the 90th percentile of the training error was selected, and the model was retrained on these images to ensure that outliers did not affect the training. Finally, all test images (from the investigators and parents) without warnings within the current fold were used to predict and calculate validation errors. The average validation error from all folds was used to drive the HPO framework to find the best model.

Performance metrics were calculated on a per-image and per-subject basis. For a given image i, the body length (p_i) predicted by the trained model was compared with the corresponding subject's WHO-standardised length measurement (m_i) to derive the following performance metrics: error (E_i, cm: difference between measured and predicted length, $E_i=¿$); absolute error (AE_i, cm: absolute value of the error, $AE_i=¿E_i\vee¿$); and absolute percentage error

(APE$_i$, %: absolute error as a percentage of the length measurement, $APE_i = 100 \times \frac{AE_i}{m_i}$). Bias (average of E, cm; $bias = \frac{1}{M} \sum AE_i$), mean AE (average of AE, cm), mean APE (average of APE, %), percentages at each AE cut-off (≤1 cm, ≤2 cm, ≤5 cm and ≤10 cm) and percentages at each APE cut-off (≤2%, ≤5%, ≤10% and ≤20%) were also calculated. Missing values due to errors, where the model did not return a predicted length value, were counted and reported separately. For subjects with successful length predictions based on at least nine images, the predictions for each image were averaged to generate a single predicted length for that subject.

The performance of the LAI model was evaluated using five-fold cross-validation performed on the combined I+P datasets and investigator-generated length measurements. To assess the LAI's performance relative to measurements in paediatric outpatient clinic settings, the appropriate performance metrics were compared with published values for the technical error of measurement (TEM), an index commonly used in anthropometry to assess the accuracy and reliability of measurements [19, 20].

Statistical analysis

Due to the exploratory nature of this study, there was no formal sample size calculation. It was estimated that a complete data set from 200 subjects (standardised length measurements, images taken by investigators, images taken by parents, and completed questionnaires from investigators and parents) would allow model performance to be adequately assessed. Assuming a 20% dropout rate, 250 subjects were planned for enrolment.

Descriptive statistics were used to summarise subject characteristics and user experience questionnaire responses. Continuous variables were summarised using mean, median, and minimum and maximum values. Discrete variables were summarised using percentages and frequencies by category, including missing values. No statistical testing of formal hypotheses was conducted.

RESULTS

Characteristics of subjects and image data

In total, 215 subjects were enrolled in the study, of whom 51% were female. The mean age was 6.1 months (range: 0.0, 17.7) and the median age was 4.4 months. All subjects completed the clinic-based data collection procedures, and 200 subjects completed both clinic-based and home-based data collection procedures to provide a complete dataset of length measurements, images and questionnaires.

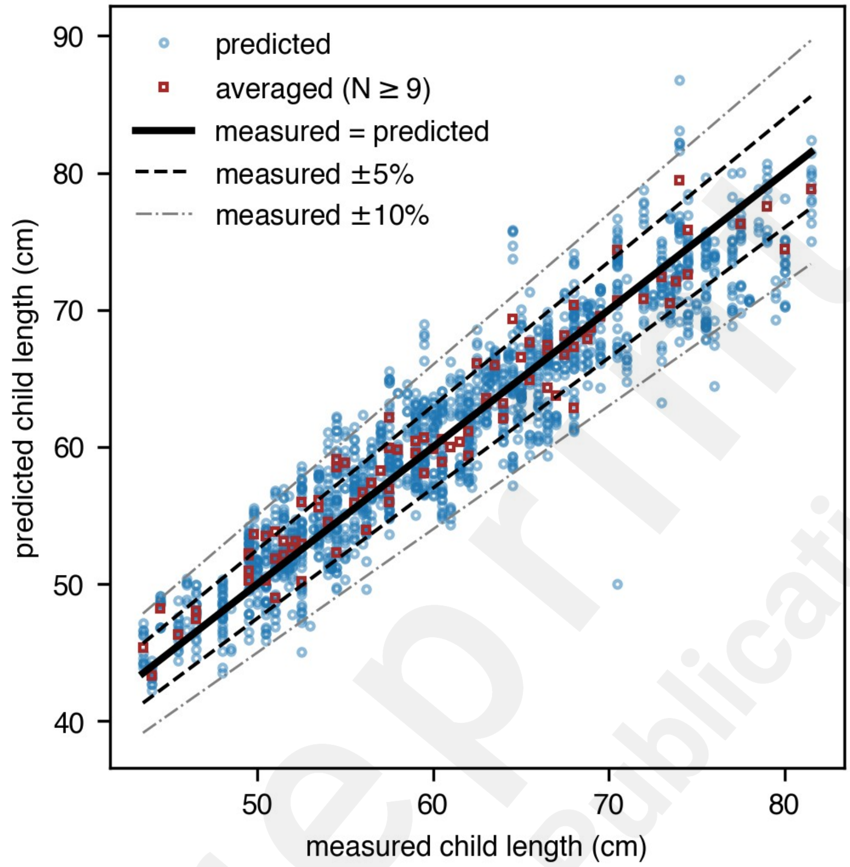
A total of 2490 images were taken and uploaded (1290 images by eight investigators at the clinic and 1200 images by 200 parents at home) (**Figure 2**). Of these, 2224 images (89%) were analysed, and 266 (11%) were excluded due to image quality and/or protocol deviations.

Length prediction performance of the LAI

The LAI produced a length prediction for 2211 (99%) of 2224 images (**Figure 2**). Thirteen images (1% of 2224) did not produce a prediction due to either unsuccessful pose segmentation (seven images) or unsuccessful card segmentation (six images).

For the set of 1632 high-quality images (those that did not generate any warnings; **Figure 2**), the bias for individual length predictions was minimal (0.02 cm) (**Supplementary Table 1**). Most of the length predictions for these individual images (95%; 1557 of 1632) were within 10% of the measured length (**Figure 3 and Supplementary Table 1**). We found that length prediction was improved by averaging across multiple images for a subject. For 88 subjects who had predictions for ≥nine images, the majority of these averaged length predictions (81%; 71 of 88) were within 5% of the measured length (**Figure 3 and Supplementary Table 1**). The overall distributions of errors for individual image predictions and subject-averaged predictions are illustrated in **Figure 4**. Published TEM values for length measurements from WHO (0.48 cm) [19] and paediatric outpatient clinics (1.41 cm) [20] are indicated on the figure for comparison. The MAE for individual image predictions was 2.47

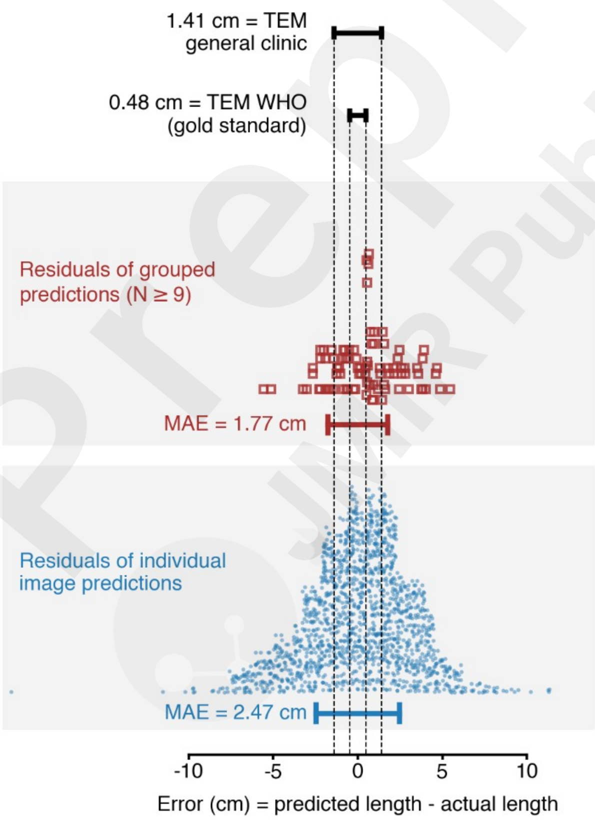
cm and the MAE for subject-averaged predictions was 1.77 cm, which approaches the TEM value reported in paediatric outpatient clinics [20].



Blue circles represent predictions from all individual images. Red squares represent averaged predictions for children who had predictions from at least 10 images. A thick black line indicates the ideal prediction (i.e., length prediction = measured length). Dotted lines represent 5% and 10% deviations from the ideal prediction.

Figure 3. Scatter plot depicting length predictions made by the model versus gold-standard length measurements made by the investigators. For length predictions on individual images, the majority fell within 10% of the subject's measured length. For averaged length predictions (per-subject, for subjects who had predictions from ≥9 images), the majority fell within 5% of the measured length.

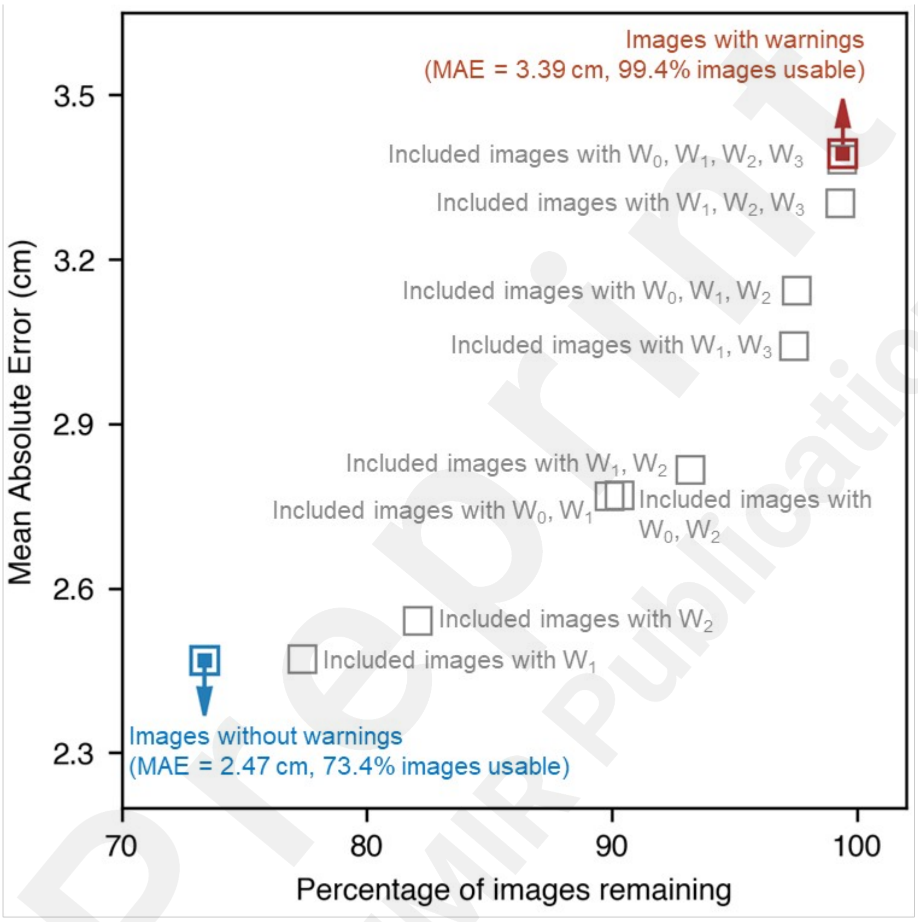
A quarter of the images with successful length predictions (26%; 579 of 2211 images) generated at least one warning **(Figure 2)**. For this study dataset, the most common warning was improper card segmentation. The numbers of images affected by each type of warning are shown in **Figure 2**. **Figure 5** illustrates the percentages of images available for length prediction under scenarios where different warning types are ignored, and the corresponding MAE values. The length prediction workflow can be adjusted to use more or less stringent settings, which affects the number of images retained for prediction and prediction error. Retaining fewer but higher quality images (fewer warnings) for prediction resulted in smaller MAE values (2.47 cm on images without any warnings); conversely, ignoring more warning types allowed more images to be used, but led to an increased MAE (3.39 cm using all images regardless of warnings). Similarly, the MAE for subject-averaged predictions decreased from 2.48 cm (N=155) to 1.77 cm (N=88) when only high-quality images without warnings were used for prediction (**Supplementary Table 1**).



MAE, mean absolute error; TEM, technical error measurement; WHO, World Health Organization

Figure 4. Overall distribution of errors (residuals) for individual image predictions (blue dots) and averaged predictions made by the model. These were presented alongside published

technical error of measurements (TEMs) of length measurements from WHO [19] and paediatric outpatient clinics [20]. The MAE of individual image predictions was 2.47 cm. When averaged, the predictions had a MAE of 1.77 cm, which approaches the TEM (1.41 cm) of typical measurements from paediatric outpatient clinics.



MAE, mean absolute error
[1]Warning description: W_0, card and body overlapping; W_1, incorrect card aspect ratio; W_2, improper card segmentation; W_3, width and height pixel size are too different

Figure 5. A plot illustrating the percentage of images available for length prediction and the corresponding MAE under varying scenarios where combinations of different warning signals were ignored. Ignoring more warning types allowed more images to be used, but the less accurate the length predictions would be.

User experience

In most cases, investigators and parents reported that they did not find it difficult to capture the required images (**Figure 6**). Investigators and parents rated the photo-taking process as very easy/easy/normal for most subjects (85%, 182/215 subjects and 72%, 144/200 subjects, respectively).

Views on the use of a digital tool for length measurement

Seven of eight investigators (88%) indicated that they would be likely/very likely to use a digital tool that could automatically measure a child's length from an image, if available for clinical use (**Supplementary Figure 2**). A similar proportion (88%, 7/8 investigators) reported that they would be likely/very likely to recommend a digital length measurement tool to parents for home use, if available.

As for parents, most (73%) were not currently taking length measurements regularly (at least once a month or more frequently) at home, where 57% never measured length at home and 16% measured less frequently than once a month (**Figure 7A**). However, 92% felt that a digital tool that could automatically predict length from an image would be useful or very useful for them to measure their child's length at home (**Figure 7B**), and 89% of parents reported that they would use such a tool at least once a month or more frequently (**Figure 7A**).

85%

72%

N represents the number of subjects for which the investigator or parent provided a rating.

Figure 6. Ease of collecting images as rated by investigators and by parents.

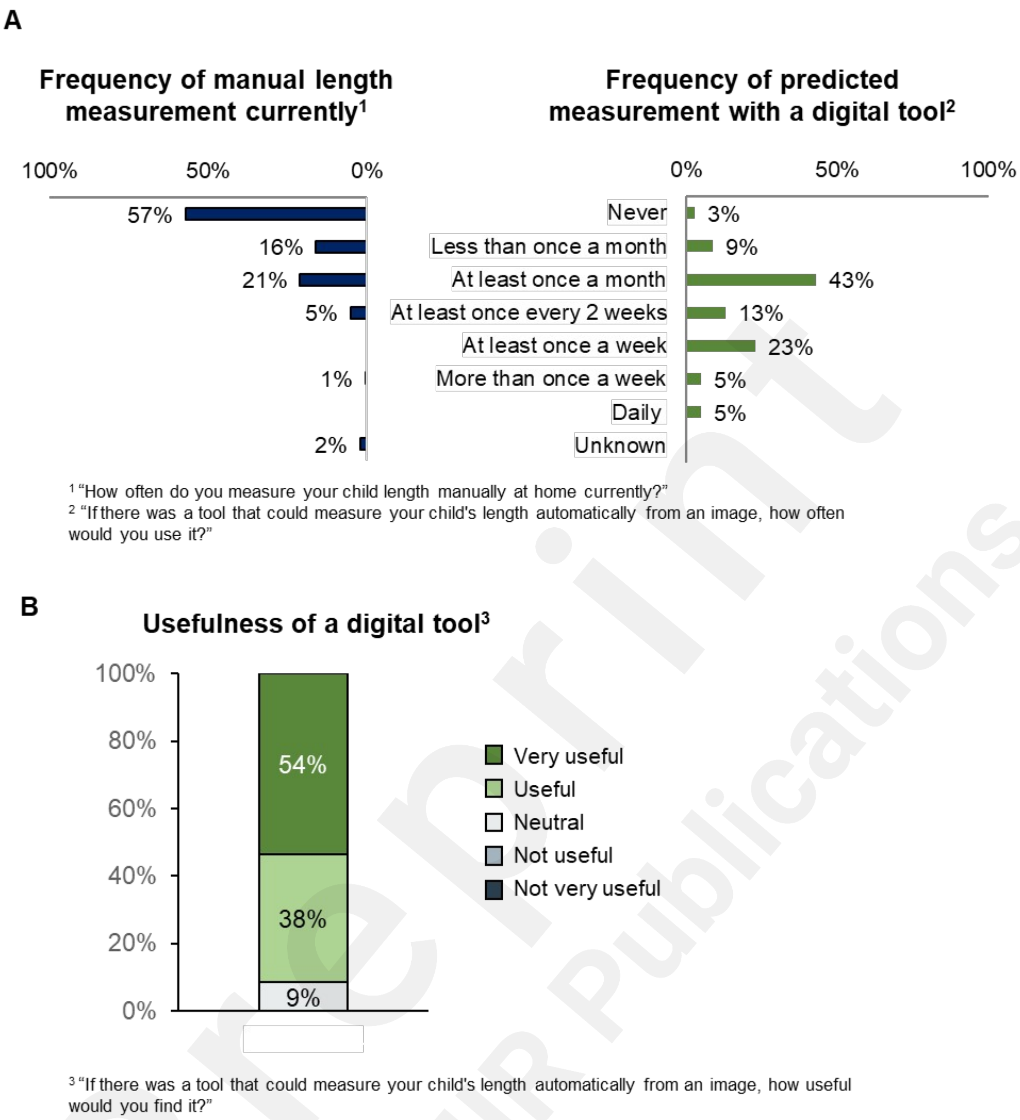


Figure 7. Parents' (N=200) assessment on the (A) frequency of length measurement in the home in terms of how often parents currently measure their child's length manually at home and how often they would measure their child's length if there was a digital tool that could automatically measure length from an image, and (B) usefulness of such a digital tool. N represents number of respondents.

Investigators and parents were asked about the magnitude of difference between standard clinic measurements and the length predicted by a digital tool that they would find acceptable in their typical use settings. For all investigators, only differences of ≤1 cm (4/8 investigators) or ≤2 cm (4/8 investigators) with respect to clinic measurements were considered acceptable (**Figure 8**). For most parents, differences of ≤1 cm (32%) or ≤2 cm (46%) were deemed acceptable, although a small proportion of parents considered differences of up to 5 cm acceptable.

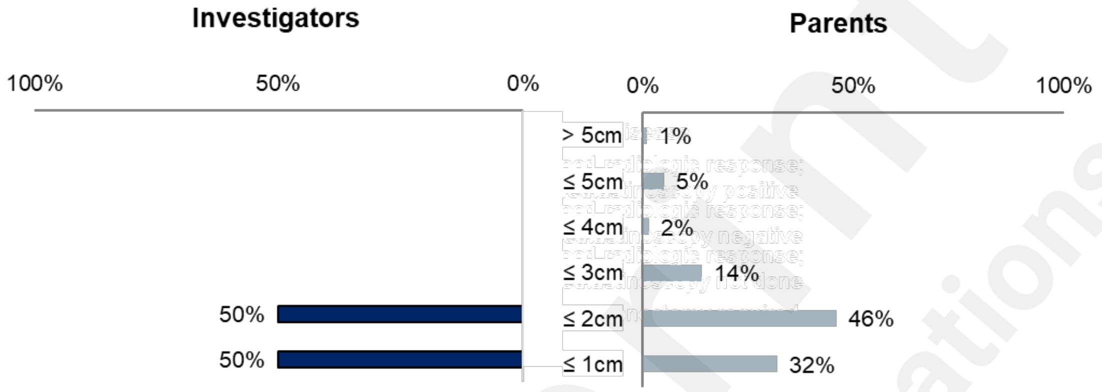


Figure 8. Acceptable magnitude of difference between AI-predicted length and standardised length measurement for investigators (N=8) and parents (N=200).

N represents number of respondents.

Additional features for an automated growth measurement tool

Apart from automated length measurement, investigators and parents highlighted several additional features that would be desirable in an image-based tool. The key features included estimating other anthropometric measurements, such as weight, head circumference, and growth-tracking functionality. Half of the investigators (4/8) suggested it would be useful to estimate other anthropometric parameters. A quarter (2/8) of investigators indicated that having a growth-tracking function would help detect growth abnormalities. In addition, 16% of parents wanted the tool to be able to estimate weight. Forty percent of the parents wanted to be able to track their child's height/length over time and have these measurements presented alongside the corresponding WHO height/length-for-age charts.

DISCUSSION

Regular and accurate recording of body length and other parameters is crucial for monitoring the growth and development of children [1, 2]. Length measurement is challenging in clinical practice, especially among those younger than two years of age, where inaccuracy and inter-observer variability in length measurements have been documented in various primary care and community health settings [5, 8, 25]. Without proper equipment and training, it is impractical to expect parents and caregivers to take accurate and reliable length measurements at home regularly.

Approaches for computer-assisted body length estimation from digital images have been proposed, but involve elaborate requirements for data capture or procedures that may cause disturbances to the child [17, 18]. These requirements limit the feasibility and applicability in real-world settings. In contrast, the LAI was designed with minimal requirements in terms of equipment and user training: only a smartphone and a readily available reference object (standard-size reference card) are required for data collection. This considerably increases the practicality of the LAI as a tool for real-world use. In our study, both parents and investigators found it easy to take the required photos for automated length estimation.

Our results show that the LAI, trained on high-quality length measurements and image data, can predict children's body length with minimal systematic error and accuracy approaching that achieved in paediatric outpatient clinic settings. In this study, we report that the MAE for individual image predictions was 2.47 cm. The results also suggest that length prediction could be improved by averaging across multiple images of a child: subject-averaged predictions had a smaller MAE of 1.77 cm, which approaches the published TEM value (1.41 cm) reported in paediatric outpatient clinics [20]. Thus, the LAI would enable parents to estimate their child's length using images captured using their smartphones, with accuracy comparable to length measurements at paediatric outpatient clinics. Published reports indicate that the level of accuracy considered acceptable ranges from ±0.5 cm to ±2.0 cm, depending on the clinical indication for which length measurements are required [5, 6, 9, 19, 20, 25]. This is consistent with the views of the study investigators, who indicated that they considered an accuracy of within 1–2 cm acceptable in a general clinical setting.

Although smartphones greatly facilitate data collection for LAI, it is not always possible to consistently capture high-quality images of a child in actual settings, which affects the accuracy of the prediction. A commonly encountered image quality issue includes the visibility of body landmarks obscured by clothing or limb position. Within the current LAI, we implemented a system that detects issues with uploaded images and provides warnings on whether these could affect length prediction (**Supplementary Table 1**). The settings can be tuned to ignore warnings and allow more images to be used for length prediction, but at the cost of generating less accurate predictions. Valuable future improvements to the tool would include functions to guide parents/caregivers in positioning the baby and standard-size reference card to capture usable, high-quality images.

This pilot study suggests that the LAI's current performance may be compatible with personal use, such as general growth tracking, as its performance approaches that of manual length measurement in paediatric outpatient clinics. If more accurate predictions are required, such as in a clinical setting, the tool can be adjusted to use more stringent settings and high-quality images. With the LAI, parents could record length measurements more frequently and conveniently at home. This idea is consistent with feedback from parents of the children in our study. Most parents reported that they did not manually measure their child's length at home; on the other hand, they indicated that an automated measurement tool would be more desirable and would use it at least monthly or more frequently. Besides automated length measurement, parents indicated they wanted the tool to estimate other anthropometric parameters and to allow them to track their child's growth with reference to WHO growth charts [3]. This user feedback provides valuable insights that can guide future development of the tool.

One of the main strengths of the current LAI approach is its simplicity and practicality for non-expert end-users. Data collection requires no specialised equipment or training; physical discomfort and disturbance to the child are minimised. This innovative approach forges new standards for automated body length estimation that can be conveniently performed in a wide range of physical settings by any user. The feedback on the tool collected from both parents and clinicians will inform future versions of the tool to better cater to the unique requirements of different users. It should be noted that the LAI's performance was evaluated only using data from healthy children (those without known growth-related conditions). Further studies with different subject populations will be needed to guide the design and optimisation of the LAI for use in more specialised clinically-oriented tasks such as monitoring for abnormal growth.

Our study detailed the performance and usability of LAI and demonstrated its acceptability for estimating body length in young children (<18 months) in a personal setting. Although the tool does not currently meet the requirements for highly accurate measurement in specialist clinical settings, the tool can be tuned for more stringent image requirements to achieve more accurate length predictions. The current performance of LAI, coupled with its ease of use, suggests it has potential applicability to be a feasible method of measuring a child's length for use by parents with accuracy approaching that of paediatric outpatient clinic settings.

ACKNOWLEDGEMENTS

Medical writing and editorial support were provided by Tech Observer Asia Pacific Pte Ltd.

FUNDING

The study was funded by Danone Nutricia Research, Singapore.

CONFLICT OF INTEREST DISCLOSURE STATEMENT

Matthew Hadimaja, Jill Wong, Sankha Mukherjee, Umesh Nandal and Agathe Foussat are employees of Danone Nutricia Research Singapore. Mei Chien Chua, Daniel Chan, and Fabian Yap are investigators of this study.

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FIGURE LEGENDS

Figure 1. LAI algorithm overview. From an input image of a child in a supine position and a standard reference object, anthropomorphic landmarks of the body and face are extracted, along with the detection and segmentation of the reference object. These are used by the LAI to predict the length of the child.

Figure 2. Schematic diagram of image flow. A total of 2490 images were collected in this study and 2224 images were analysed. A total of 266 images were not analysed due to protocol deviations (resubmission of images, submission of images outside the stipulated visit window, or images that did not meet the requirements). Of 2224 images analysed, 2211 images produced a length prediction. The algorithm did not produce a prediction for 13 images due to unsuccessful pose estimation (m=7) or unsuccessful card segmentation (m=6).

Figure 3. Scatter plot depicting length predictions made by the model versus gold-standard length measurements made by the investigators. For length predictions on individual images, the majority fell within 10% of the subject's measured length. For averaged length predictions (per-subject, for subjects who had predictions from ≥nine images), the majority fell within 5% of the measured length.

Figure 4. Overall distribution of errors (residuals) for individual image predictions (blue dots) and averaged predictions made by the model. These were presented alongside published technical error of measurements (TEMs) of length measurements from WHO [19] and paediatric outpatient clinics [20]. The MAE of individual image predictions was 2.47 cm. When averaged, the predictions had a MAE of 1.77 cm, which approaches the TEM (1.41 cm) of typical measurements from paediatric outpatient clinics.

Figure 5. A plot illustrating the percentage of images available for length prediction and the corresponding MAE under varying scenarios where combinations of different warning signals were ignored. Ignoring more warning types allowed more images to be used, but the less accurate the length predictions would be.

Figure 6. Ease of collecting images as rated by investigators and by parents.

Figure 7. Parents' (N=200) assessment on the (A) frequency of length measurement in the home in terms of how often parents currently measure their child's length manually at home and how often they would measure their child's length if there was a digital tool that could automatically measure length from an image, and (B) usefulness of such a digital tool. N represents number of respondents.

Figure 8. Acceptable magnitude of difference between AI-predicted length and standardised length measurement for investigators (N=8) and parents (N=200). N represents number of respondents.

Supplementary Figure 1. Images that pose challenges for length prediction by LAI include (A) angle of the image not taken at 90 degrees from the top, (B) subject and reference card not placed on a flat surface, (C) blurring or glare, (D) baggy clothes on subject affecting visibility of body contour, (E) low contrast of subject with background and (F) face and body not fully visible.

Supplementary Figure 2. Likelihood that investigators (N=8) will use and recommend a digital tool to measure a child's length in the clinical setting. N represents number of respondents.

Supplementary Files

Untitled.

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