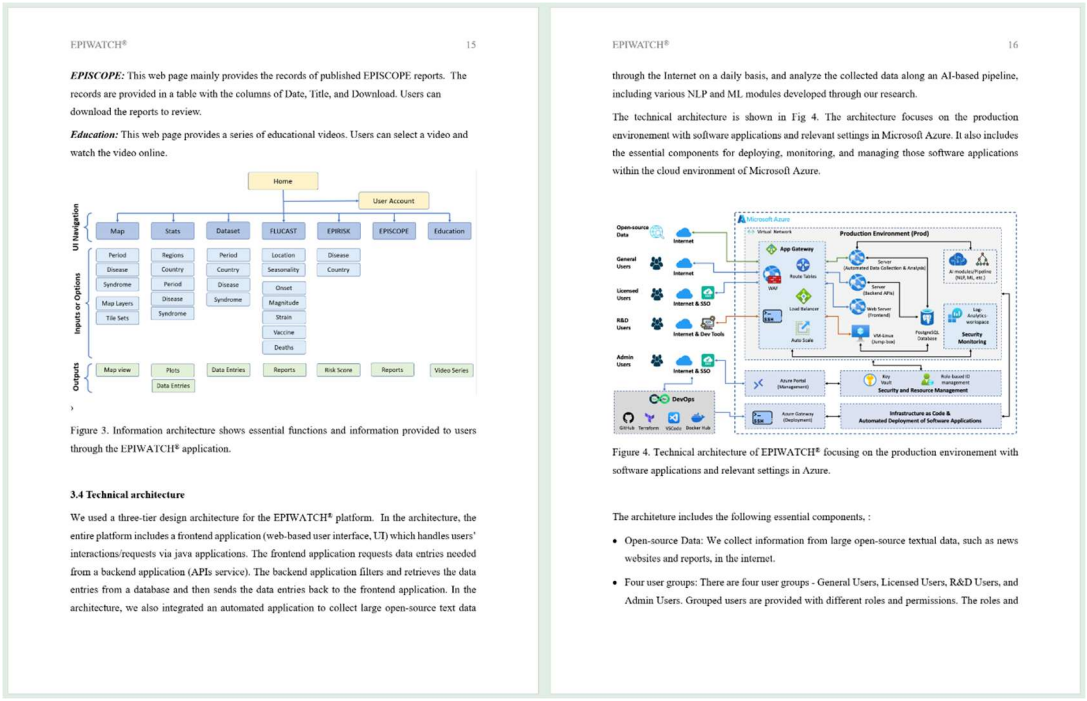
Demo of some previous projects

Appendix 1: A screenshot of the design document for the EPIWATCH project, showing the design architecture in Azure.



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EPISCOPE: This web page mainly provides the records of published EPISCOPE reports. The records are provided in a table with the columns of Date, Title, and Download. Users can download the reports to review.

Education: This web page provides a series of educational videos. Users can select a video and watch the video online.

Figure 3. Information architecture shows essential functions and information provided to users through the EPIWATCH® application.

3.4 Technical architecture

We used a three-tier design architecture for the EPIWATCH® platform. In the architecture, the entire platform includes a frontend application (web-based user interface, UI) which handles users' interactions/requests via java applications. The frontend application requests data entries needed from a backend application (APIs service). The backend application filters and retrieves the data entries from a database and then sends the data entries back to the frontend application. In the architecture, we also integrated an automated application to collect large open-source text data

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through the Internet on a daily basis, and analyze the collected data along an AI-based pipeline, including various NLP and ML modules developed through our research.

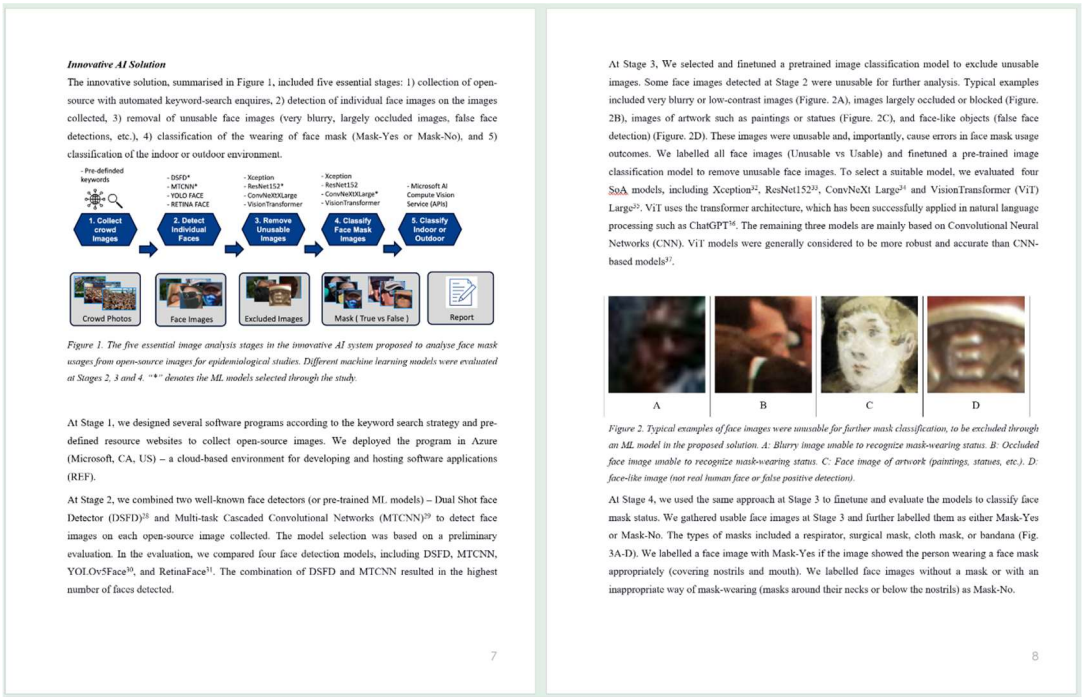
The technical architecture is shown in Fig 4. The architecture focuses on the production environement with software applications and relevant settings in Microsoft Azure. It also includes the essential components for deploying, monitoring, and managing those software applications within the cloud environment of Microsoft Azure.

Figure 4. Technical architecture of EPIWATCH® focusing on the production environement with software applications and relevant settings in Azure.

The architeture includes the following essential components, :

- Open-source Data: We collect information from large open-source textual data, such as news websites and reports, in the internet.
- Four user groups: There are four user groups - General Users, Licensed Users, R&D Users, and Admin Users. Grouped users are provided with different roles and permissions. The roles and

Appendix 2: A screenshot of the design document of the face-mask project, showing the pipeline to assess the face mask usage from large open-source data globally.



Innovative AI Solution

The innovative solution, summarised in Figure 1, included five essential stages: 1) collection of open-source with automated keyword-search enquires, 2) detection of individual face images on the images collected, 3) removal of unusable face images (very blurry, largely occluded images, false face detections, etc.), 4) classification of the wearing of face mask (Mask-Yes or Mask-No), and 5) classification of the indoor or outdoor environment.

Figure 1. The five essential image analysis stages in the innovative AI system proposed to analyse face mask usages from open-source images for epidemiological studies. Different machine learning models were evaluated at Stages 2, 3 and 4. "" denotes the ML models selected through the study.*

At Stage 1, we designed several software programs according to the keyword search strategy and pre-defined resource websites to collect open-source images. We deployed the program in Azure (Microsoft, CA, US) – a cloud-based environment for developing and hosting software applications (REF).

At Stage 2, we combined two well-known face detectors (or pre-trained ML models) – Dual Shot face Detector (DSFD)[28] and Multi-task Cascaded Convolutional Networks (MTCNN)[29] to detect face images on each open-source image collected. The model selection was based on a preliminary evaluation. In the evaluation, we compared four face detection models, including DSFD, MTCNN, YOLOv5Face[30], and RetinaFace[31]. The combination of DSFD and MTCNN resulted in the highest number of faces detected.

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At Stage 3, We selected and finetuned a pretrained image classification model to exclude unusable images. Some face images detected at Stage 2 were unusable for further analysis. Typical examples included very blurry or low-contrast images (Figure. 2A), images largely occluded or blocked (Figure. 2B), images of artwork such as paintings or statues (Figure. 2C), and face-like objects (false face detection) (Figure. 2D). These images were unusable and, importantly, cause errors in face mask usage outcomes. We labelled all face images (Unusable vs Usable) and finetuned a pre-trained image classification model to remove unusable face images. To select a suitable model, we evaluated four SoA models, including Xception[32], ResNet152[33], ConvNeXt Large[34] and VisionTransformer (ViT) Large[35]. ViT uses the transformer architecture, which has been successfully applied in natural language processing such as ChatGPT[36]. The remaining three models are mainly based on Convolutional Neural Networks (CNN). ViT models were generally considered to be more robust and accurate than CNN-based models[37].

Figure 2. Typical examples of face images were unusable for further mask classification, to be excluded through an ML model in the proposed solution. A: Blurry image unable to recognize mask-wearing status. B: Occluded face image unable to recognize mask-wearing status. C: Face image of artwork (paintings, statues, etc.). D: face-like image (not real human face or false positive detection).

At Stage 4, we used the same approach at Stage 3 to finetune and evaluate the models to classify face mask status. We gathered usable face images at Stage 3 and further labelled them as either Mask-Yes or Mask-No. The types of masks included a respirator, surgical mask, cloth mask, or bandana (Fig. 3A-D). We labelled a face image with Mask-Yes if the image showed the person wearing a face mask appropriately (covering nostrils and mouth). We labelled face images without a mask or with an inappropriate way of mask-wearing (masks around their necks or below the nostrils) as Mask-No.

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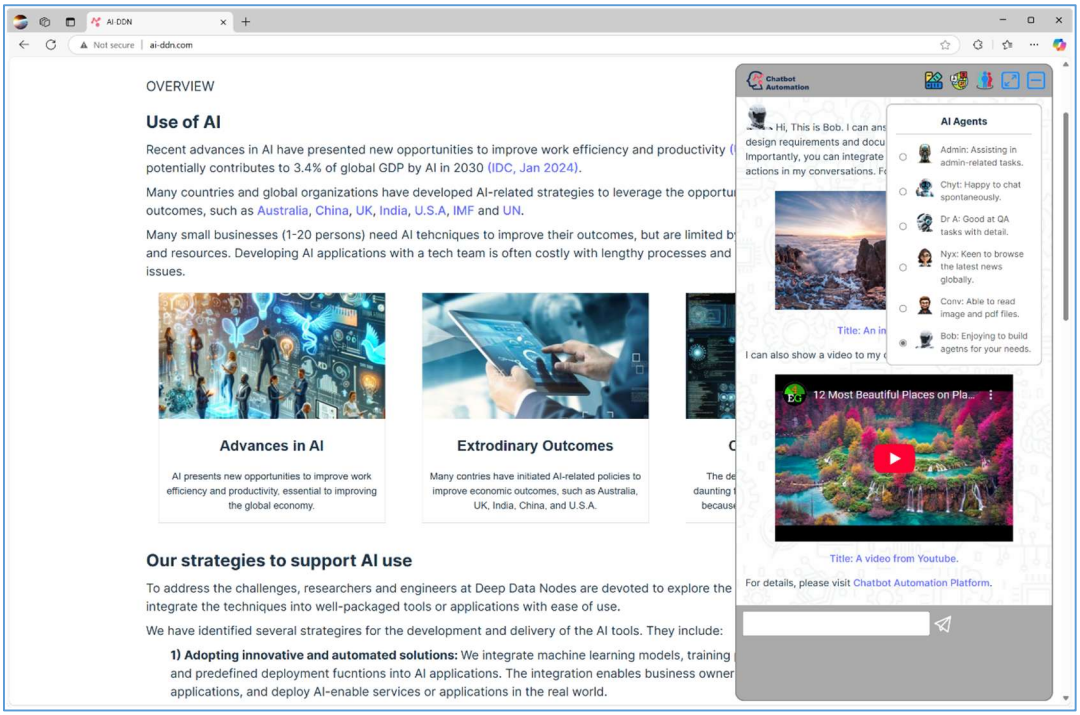
Appendix 3: A screenshot of a chatbot application, showing the use of LLMs and RAG to address various business' needs.



Appendix 4: A screenshot of a chatbot application for the self-management of whiplash, showing the program design and model training outcomes.

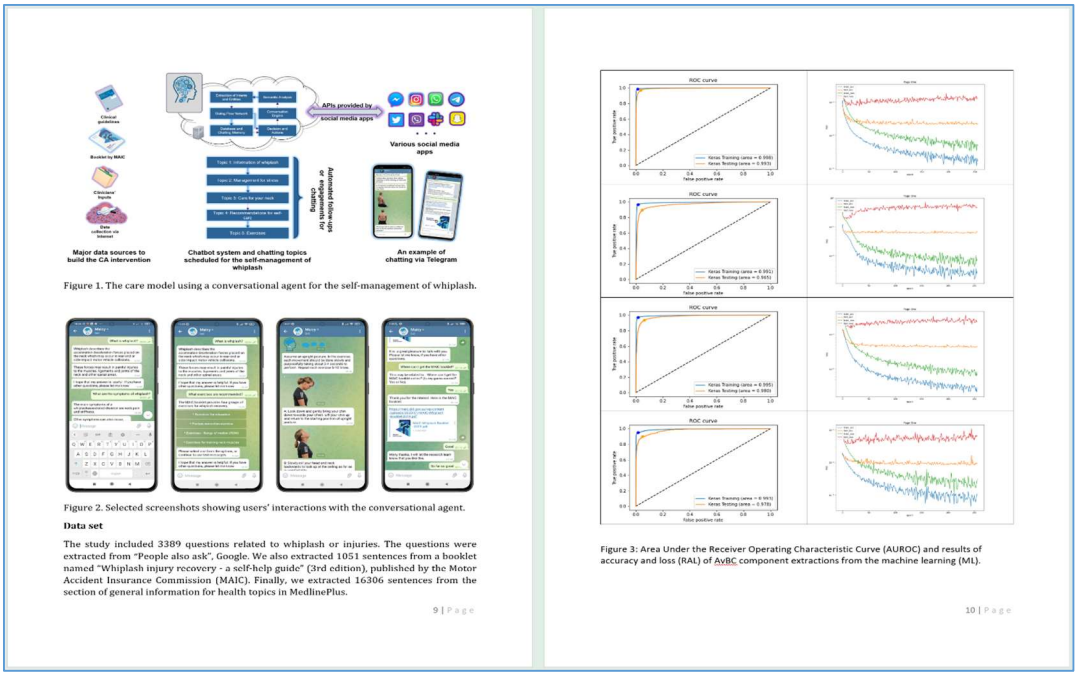


Figure 1. The care model using a conversational agent for the self-management of whiplash.

Figure 2. Selected screenshots showing users' interactions with the conversational agent.

Data set

The study included 3389 questions related to whiplash or injuries. The questions were extracted from "People also ask", Google. We also extracted 1051 sentences from a booklet named "Whiplash injury recovery - a self-help guide" (3rd edition), published by the Motor Accident Insurance Commission (MAIC). Finally, we extracted 16306 sentences from the section of general information for health topics in MedlinePlus.

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Figure 3: Area Under the Receiver Operating Characteristic Curve (AUROC) and results of accuracy and loss (RAL) of AvBC component extractions from the machine learning (ML).

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Appendix 5: Screenshots of an mHealth program for the self-management of diabetes, showing the care delivery model, clinical portal, and mobile app.

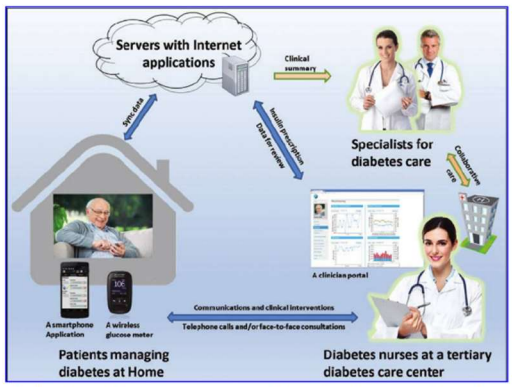

Fig. 1. The care model of the m-Health enabled home care program for clinical insulin dose adjustment. Color images available online at: www.liebertpub.com/tmj

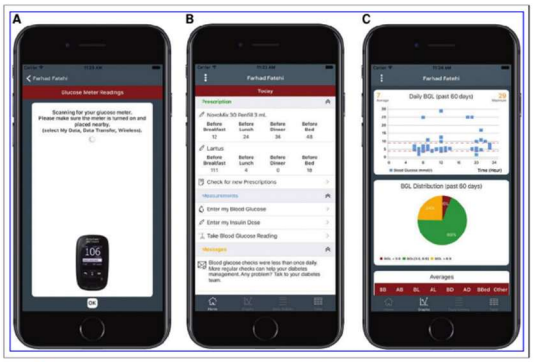

Fig. 2. (A) The user interface of the mobile phone application for the users to wirelessly transfer BGL entries from a glucose meter to the mobile application. (B) The user interface to review insulin prescribed by the diabetes nurses from a tertiary diabetes care center. (C) Smartphone plots to show the status of BGL control. BGL, blood glucose level. Color images available online at: www.liebertpub.com/tmj

smartphone was incompatible with the app and/or the glucose meter, the participant was provided with a compatible smartphone. A diabetes nurse trained each participant face to face. During the training, the nurse used the clinician portal to register the participant and enter insulin types and dosages according to his/her insulin prescription. After the registration, the m-Health system automatically sent to the trial glucose meter to measure BGL three to four times per day (before breakfast, lunch, dinner, or bed) and use the app to record insulin dosages taken and comments on a daily basis. The nurse reviewed the participants' data twice a week through the clinician portal and sent up to two text messages to test the messaging feature of the system.

the trial due to change of health status. Nine participants completed the trial, aged 58 ± 14 years (mean ± SD), with HbA1c of 8.6% ± 2.9% (mean ± SD) at baseline. During the trial period, the participants on average recorded 3.1 BGL entries, 1.2 insulin dosage entries, and 1.0 comment entry every day. The results of BGL entries during the trial period are shown in *Table 1*. Seven participants (78% of the participants) were considered to adhere to the program. The system achieved 100% precision in automatic transmission of the BGL entries ($n = 390$) from the glucose meters to the clinical portal.

supportive of the program with both these questions scoring highly at 4.3.

The participants were positive and disagreed that participation in this study took too much time (score = 1.7). They would continue to use the system if possible (score = 4.2). Importantly, they considered that using the system gave them confidence to manage their diabetes (score = 4.1). Finally, they were generally satisfied in using the system (score = 4.3), although some participants experienced technical issues during the trial (score = 2.6). We reviewed the responses to the free-text question asking participants what could be improved and

Appendix 6: Research grants.

1. Experienced Researcher Grants from The Prince Charles Hospital Foundation – a randomized controlled trial for COPD (Prof Ian Yang, CI, The Prince Charles Hospital; **Dr Hang Ding**, CI, CSIRO; $100,000; and 2015 – 2019).
2. Health Market Validation – multicentre randomized controlled trial for home-based heart failure care. (Mr Iain Edwards, CI, Peninsula Health; **Dr Hang Ding**, AI, CSIRO; Dr Mohan Karunanithi, AI, CSIRO; Dr Rajiv Jayasena, AI, CSIRO; MEAPACS, Medtech Global; $1,500,000; and 2013-2018).
3. Health Market Validation, Feasibility Study– Heart Failure. Medtech Global, Peninsula Health, CSIRO (**Dr Hang Ding**, Dr Rajiv Jayasena; $100,000; and 2013-2016).
4. The Enterprise Connect Researchers in Business program, CSIRO, (**Dr Hang Ding**, Dr Mohan Karunanithi, Dr Rajiv Jayasena; $100,000; and in 2013).

Appendix 7: Selected journal publications (A the First Author)

1. **H Ding**, J Simmich, A Vaezipour, N Andrews, T Russell. Evaluation framework for conversational agents with artificial intelligence in health interventions: a systematic scoping review. Journal of the American Medical Informatics Association 31 (3), 746-761. 2024.

2. **H Ding**, SH Chen, I Edwards, R Jayasena, J Doecke, J Layland, IA Yang, et. al. Effects of different telemonitoring strategies on chronic heart failure care: Systematic review and subgroup meta-analysis. Journal of Medical Internet Research 22 (11), e20032, 2020.
3. **H Ding**, R Jayasena, SH Chen, A Maiorana, A Dowling, J Layland, et. al. The effects of telemonitoring on patient compliance with self-management recommendations and outcomes of the innovative telemonitoring enhanced care program for chronic heart failure. Journal of medical Internet research 22 (7), e17559, 2020.
4. **H Ding**, F Farhad, A Maiorana, et al. Digital Health for COPD care: the current state of play. Journal of thoracic disease. Vol 11, Supplement 17 (October 2019).
5. **H Ding**, M Karunanithi, D Ireland, et al. Evaluation of an innovative mobile health programme for the self-management of chronic obstructive pulmonary disease (MH-COPD): protocol of a randomised controlled trial. BMJ Open. 2019;9(4): e025381.
6. **H Ding**, F Fatehi, AW Russell, et al. User Experience of an Innovative Mobile Health Program to Assist in Insulin Dose Adjustment: Outcomes of a Proof-of-Concept Trial. Telemedicine and E-Health, 1 July 2018; Vol. 24, No.7.
7. **H Ding**, R Jayasena, A Maiorana, et al. Innovative Telemonitoring Enhanced Care Programme for Chronic Heart Failure (ITEC-CHF) to improve guideline compliance and collaborative care: protocol of a multicentre randomised controlled trial. BMJ Open 2017; 7(10): 8.
8. **H Ding**, M Karunanithi, Y Kanagasingam, J Vignarajan, Y Moodley. A pilot study of a mobile-phone-based home monitoring system to assist in remote interventions in cases of acute exacerbation of COPD. Journal of Telemedicine and Telecare 2014; 20: 128-34.
9. **H Ding**. Characterization of local complex structures in a recurrence plot to improve nonlinear dynamic discriminant analysis. Physical Review E 2014; 89.
10. **H Ding**, S Crozier, S Wilson. Optimization of Euclidean distance threshold in the application of recurrence quantification analysis to heart rate variability studies. Chaos Solitons & Fractals 2008; 38(5): 1457-67.
11. **H Ding**, S Crozier, S Wilson. A new Heart rate variability analysis method by means of quantifying the variation of nonlinear dynamic patterns. Ieee Transactions on Biomedical Engineering 2007; 54(9): 1590-7.

Appendix 8: Selected conference papers (As the first author)

1. **H.Ding**, A. Quigley, and R. MacIntyre. Analysing Open-source Images to Assess Face Mask Usage for Epidemiological Studies. Oral presentation, International Congress on Infectious Disease, 2024, Cape Town, South Affrica.

2. **H Ding**, M Gonzalez-Garcia, M Varnfield, et al. Limited functional capacity and physical activity associated with patient withdrawals from cardiac rehabilitation. ESC Congress 2019 - European Society of Cardiology. 31 August - 4 September 2019, Paris, France.
3. **H Ding**, I Yang, D Ireland, L McCarthy, et al. Use of mobile health to improve patient adherence to the management of chronic obstructive pulmonary disease. HIC 2016. Brisbane, QLD, Australia.
4. **H Ding**, M Karunanithi, F Fatehi, A Menon, D Bird, A Russell. User acceptance of an innovative mobile health enhanced delivery of insulin initiation and titration program for patients with type 2 diabetes. Successes and Failures in Telehealth-7th Annual Meeting of the Australasian Telehealth Society. Auckland, New Zealand: the Australasian Telehealth Society; 2016.
5. **H Ding**, M Karunanithi, M Duncan, D Ireland, M Noakes, and C Hooker, "A mobile phone enabled health promotion program for middle-aged males," Conference proceedings : Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference, vol. 2013, pp. 1173-6, 2013, 2013.
6. **H Ding**, Y Moodley, Y Kanagasingam, and M Karunanithi, "A mobile-health system to manage chronic obstructive pulmonary disease patients at home," Conference proceedings: Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference, vol. 2012, pp. 2178-81, 2012, 2012.