BMJ Open Optimising the care for older persons with complex chronic conditions in home care and nursing homes: design and protocol of I-CARE4OLD, an observational study using real-world data

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ABSTRACT

To cite: Hoogendijk EO, Onder G, Smalbil L, *et al.* Optimising the care for older persons with complex chronic conditions in home care and nursing homes: design and protocol of I-CARE40LD, an observational study using real-world data. *BMJ Open* 2023;**13**:e072399. doi:10.1136/ bmjopen-2023-072399

Prepublication history for this paper is available online. To view these files, please visit the journal online (http://dx.doi. org/10.1136/bmjopen-2023-072399).

Received 31 January 2023 Accepted 08 June 2023

(Check for updates

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Dr Emiel O Hoogendijk; e.hoogendijk@amsterdamumc. nl **Introduction** In ageing societies, the number of older adults with complex chronic conditions (CCCs) is rapidly increasing. Care for older persons with CCCs is challenging, due to interactions between multiple conditions and their treatments. In home care and nursing homes, where most older persons with CCCs receive care, professionals often lack appropriate decision support suitable and sufficient to address the medical and functional complexity of persons with CCCs. This EUfunded project aims to develop decision support systems using high-quality, internationally standardised, routine care data to support better prognostication of health trajectories and treatment impact among older persons with CCCs.

Methods and analysis Real-world data from older persons aged ≥ 60 years in home care and nursing homes, based on routinely performed comprehensive geriatric assessments using interRAI systems collected in the past 20 years, will be linked with administrative repositories on mortality and care use. These include potentially up to 51 million care recipients from eight countries: Italy, the Netherlands, Finland, Belgium, Canada, USA, Hong Kong and New Zealand. Prognostic algorithms will be developed and validated to better predict various health outcomes. In addition, the modifying impact of pharmacological and non-pharmacological interventions will be examined. A variety of analytical methods will be used, including techniques from the field of artificial intelligence such as machine learning. Based on the results, decision support tools will be developed and pilot tested among health professionals working in home care and nursing homes. Ethics and dissemination The study was approved by authorised medical ethical committees in each of the participating countries, and will comply with both local and EU legislation. Study findings will be shared with relevant stakeholders, including publications in peer-reviewed journals and presentations at national and international meetings.

STRENGTHS AND LIMITATIONS OF THIS STUDY

- ⇒ This is a very large study involving older care recipients with complex chronic conditions in home care and nursing home settings from eight countries.
- ⇒ The study integrates real-world, high-quality data from interRAI comprehensive assessments with registry data on mortality, medications and care use.
- ⇒ Real-world data have high external validity and include relatively old and medically complex care recipients that are often excluded from randomised clinical trials.
- ⇒ Prognostic algorithms will be developed and validated using a variety of techniques, including artificial intelligence methods such as machine learning.
- \Rightarrow A potential limitation of the study is that successful linkage between interRAI assessment data and registry data cannot be guaranteed for 100% of the study population.

INTRODUCTION

In ageing societies, the number of older people with complex chronic conditions (CCCs, ie, the presence of co-occurring, chronic multimorbidities or chronic disease complications that require the attention of multiple healthcare professionals) is rapidly increasing.¹ Delivering appropriate care to these individuals is one of the greatest challenges for healthcare systems.^{2–4} Not only do older adults with CCCs suffer from multiple diseases, these diseases often interact with each other, as well as with their treatment.⁵ Moreover, older adults with CCCs regularly present with functional limitations and geriatric syndromes such as frailty.^{6–8} Insufficient management of these conditions may result in poor health-related outcomes, including impaired quality of life and premature mortality.^{9 10}

In the past few decades, progress has been made in evidence-informed care for older adults with CCCs.³ This has, for example, resulted in improved clinical guidelines for the management of multimorbidity.¹¹ However, important gaps in current care guidelines and procedures remain.¹² First, there is a lack of randomised controlled trials to inform care guidelines for older adults with CCCs, because most clinical trials focus on single diseases and the most vulnerable older people are often excluded from trials.¹³¹⁴ Therefore, these trials are not able to account for the complexity and needs of older adults with CCCs. Second, previous studies have mainly focused on disease-specific and physiologic outcomes, and much less on patient-centred outcomes such as functioning and quality of life, which are most valued by older adults.¹⁵ Third, it is often difficult to select subgroups of older adults with CCCs, due to a lack of statistical power. This means that in most studies, the effectiveness of treatments for this group cannot be reliably evaluated. Altogether, these issues hinder a more individualised approach to care for older adults with CCCs, resulting in care that is fragmented and not taking into account the complex interplay between conditions, thereby contributing to adverse health outcomes.

An appropriate approach to overcome the challenges observed in current care guidelines and procedures may be a combination of using real-world routine care data and artificial intelligence (AI) methods-which enable us to capture more complex relationships-to create a more accurate and individualised prognosis for older people with CCCs, including the impact of treatments. The results have potential to provide evidence that is complementary to that of randomised controlled trials. Using real-world data has several advantages, such as its high external validity and the availability of long-term follow-up on an extensive number of variables. Moreover, these data do include those very old and medically complex care users usually excluded from trials. AI applications in healthcare such as machine learning are highly promising.¹⁶ An important aspect of machine learning is the development of sophisticated algorithms for risk prediction. When applying these algorithms to very large, high-quality, real-world datasets, individualised decision support for older adults with CCCs may be developed.

The goal of the current project is to overcome the aforementioned gaps in care guidelines for older adults with CCCs. The Individualised CARE for OLDer persons with CCCs at home and in nursing homes (I-CARE4OLD) study is a European Union funded project (2021–2025) that aims to develop high-quality decision support for better prognostication of health trajectories, including treatment impact, in older care recipients with CCCs using high volumes of linked real-world data. The results may provide important insights for, among others, healthcare professionals, care recipients and policymakers, by delivering digital decision support tools or platforms for individualised prognosis, and decision support on appropriate, safe, and effective treatments. In this article, we describe the design, methodology and dissemination activities of I-CARE4OLD.

METHODS AND ANALYSIS Consortium and data sources

The multidisciplinary consortium of I-CARE4OLD consists of international experts in the fields of chronic diseases, geriatrics, gerontology, clinical pharmacy, longterm care, epidemiology, public health, mental health, biostatistics and AI. Figure 1 shows a map with participating countries. Ten countries are represented in the consortium, including six countries that provide data repositories and participate in analytical or dissemination work (Belgium, Canada, Finland, Italy, the Netherlands and USA), as well as four countries that participate only in analytical or dissemination work (Czech Republic, Israel, Poland and Sweden). Two countries only provide data for analyses (Hong Kong and New Zealand). Moreover, various international organisations (eg, European Geriatric Medicine Society, EUGMS) advise and participate in the dissemination of the results of the project.

For this study, real-life big data repositories will be used. The main data come from routinely performed comprehensive geriatric assessments (CGAs) of potentially up to 51 million older home care and nursing home care recipients (aged ≥ 60 years) in the eight data providing countries, which were collected in the past 20 years. We aim to use data from 2014 onwards, but in some cases older data will be used as well (eg, the consistency of results may be checked by comparing different countries and historical periods). All older care recipients were monitored and assessed using interRAI assessment instruments.¹⁷ These assessments contain between 200 and 400 standardised variables on clinical, functional, medical and psychosocial domains, as well as validated scales and triggers for clinical actions. Many also contain comprehensive information on medication use. Over the years, several editions of interRAI tools were issued, notable the MDS2.0 and the interRAI suite for home care and nursing homes. Data from interRAI assessments will be enriched by linking them to registry data on mortality, hospitalisation, medications and healthcare utilisation in each participating country. Table 1 provides an estimated overview of available interRAI data and linked repositories in each country.

Project structure

The I-CARE4OLD study started in June 2021 and will continue until the end of May 2025. The project consists of several components that will be implemented in a stepwise approach (figure 2).

1. *Data linkage and harmonisation (A)*. A first step of the project is the harmonisation of datasets and linkage of CGAs with external data repositories (registry data). We will develop a methodology to link and harmonise



Figure 1 Participating countries in the I-CARE4OLD project.

interRAI data and external registry data collected in different data delivering countries participating in I-CARE4OLD. The use of interRAI assessment data is a major advantage for data harmonisation, because these data are based on a standardised family of instruments holding identical data elements across participating countries and various care settings. The data have already been collected and only need to be harmonised

Table 1 Availability of interRAI data (estimated) and linked repositories				
Country/geographic area	Sample size CGA- interRAI home care data	Sample size CGA-interRAI nursing home data	Available repositories for linkage	
1. Italy, Umbria region	10000*	20000*	Death registries, medications, hospital data	
2. The Netherlands	4000*	18000*†	Death registries, medications, hospital data, medical records primary care, reimbursed healthcare claims	
3. Finland	200000†	150000†	Death registries, medications, hospital data, primary healthcare contacts	
4. Belgium	13000*	3000*	Death registries, medications, hospital data, reimbursed healthcare claims	
5. Canada	4413724†	5044480†	Death registries, medications, hospital data, reimbursed healthcare claims	
6. USA	2 721 188*	37644492†‡	In nursing home only: death registries, hospital data	
7. Hong Kong	249237†	-	None	
8. New Zealand	35 1 89*	-	None	
Total (estimated)	7646338	42 879 972		
*interRAI suite version. †interRAI MDS2.0 version ‡interRAI MDS3.0 version CGA_comprehensive geri	I. I. jatric assessment			



Figure 2 Main elements and structure of the I-CARE4OLD project.

to make variables in the datasets uniform, as over time several editions were issued with slightly different variable names or labels, and country-specific elements may have been added. In this way, in all countries, datasets are comparable and common analytic strategies may be applied. Both developmental datasets and validation datasets will be created. Developmental datasets will be used to build models and train algorithms, while validation datasets will be used for testing the developed models and algorithms. Moreover, the harmonisation will enable algorithms developed with data from one country to be validated externally using data from other countries.

- 2. Identification of homogeneous groups of persons based on disease patterns (B). Diseases often co-occur in the same individuals due to common underlying risk factors, shared general pathophysiology and similar contextual factors. It is important to identify groups of older persons characterised by common disease patterns, as this may be a starting point of risk stratification, ultimately contributing to maximisation of effectiveness of interventions. Different patterns of diseases bring different risks of development of adverse health outcomes and healthcare utilisation.¹⁸⁻²⁰ Characterisation of homogeneous groups of older adults may allow for the assessment of individualised health trajectories and treatment options. Therefore, we will characterise home care and nursing home care recipients based on their patterns of complex conditions, and we will test the consistency of these patterns across settings and countries. Whether the use of common disease patterns contributes to improved models to predict health trajectories will be examined in parts C, D and E.
- 3. *Predictive models for health outcomes (C)*. The consequences of CCCs in terms of health outcomes cannot

solely be determined on the basis of the number of conditions present. Additional information is required to create profiles that predict health trajectories. Parameters such as physical functioning, cognitive abilities, social factors and contextual factors need to be considered as well. All these parameters are covered by the comprehensive interRAI assessment data in our datasets. In this part of the project, machine learning will be employed to develop and validate algorithms to predict various health outcomes, capitalising on the very large linked datasets of I-CARE4OLD.

- 4. Impact of pharmacological treatment on health outcomes (D). For individualised decision support it is important to know the pharmacological treatments used in older persons belonging to specific disease profiles. A crucial next step is to estimate the impact of pharmacological treatment on health trajectories and outcomes in older adults with CCCs. This information cannot be derived from randomised controlled trials, which usually focus on single diseases and average effects. For individualised decision support, different methods are needed to consider combinations of diseases and interactions between treatments. We will make a consensus-based list of pharmacological interventions regarded by professionals as most urgent and relevant for reliable impact estimates, and then we will apply a broad set of techniques such as machine learning to our linked datasets to develop and validate algorithms that estimate the impact and safety of these pharmacological interventions on health outcomes.
- 5. *Impact of non-pharmacological interventions on health outcomes (E)*. A large part of the interventions for older people in home care and nursing homes concern non-pharmacological interventions, such as physical activity, physiotherapy, occupational therapy and social activities.²¹ Similar to the procedures for pharmaco-

logical interventions, we will develop algorithms that inform appropriate and safe individualised decisionmaking on the benefits of (combinations of) nonpharmacological interventions for older care recipients with CCCs. Because we expect pharmacological and non-pharmacological interventions to interact, we will look at combinations of both types of interventions if necessary.

- 6. Development of platform for individualised decision support (F). Based on the algorithms that were derived from parts C, D and E, a digital platform for decision support will be developed. The e-platform will provide information on the individual risk of adverse health outcomes for older adults with CCCs, and will suggest best treatment options for each individual that may improve health outcomes. We will pilot test the feasibility and acceptability of this digital platform for individualised decision support among front-line healthcare professionals, older care recipients and their close relatives. Pilot testing is needed to ensure that the algorithms are working in real life, and that they contribute to better quality decision-making as well as possible increasing effectiveness of treatments. The pilot testing will be done in five countries (Belgium, Finland, Italy, the Netherlands and USA). A protocol for the pilot will be developed separately (not covered by the current paper).
- 7. *Dissemination and exploitation (G)*. The results of the I-CARE4OLD project have relevance for many external stakeholders in Europe, USA and Canada. Therefore, we will invest in dissemination activities as of the start of the project. Various groups will be targeted, including policy makers, healthcare professionals, researchers and the general public. A dissemination plan has been developed, in which target audience and methods have been specified.

Main outcome measures

In the analyses on health trajectories (C, D, E), at least six outcome measures will be investigated (table 2). These outcomes are based on validated interRAI measurement scales and registry data, and include death, acute hospital admission, change in self-care functioning,²² change in cognitive functioning,²³ change in clinical (in) stability²⁴ and change in health-related quality of life.²⁵ Additionally, other outcomes such as changes in locomotion, mental health and frailty may be derived from the interRAI assessment data.^{26–28}

Statistical analyses

For the identification of homogeneous groups (B), various analytical approaches will be employed, such as various types of cluster, factor and latent class analyses. The analyses on health trajectories (C, D, E) are primarily focused on supervised machine learning.²⁹ This means that a supervised learning algorithm is provided with feedback during the learning phase. The model can test its intermediate performance by comparing its predicted output with actual labelled output from the data. All datasets used for analyses will be standardised and harmonised, but analyses will be done in each country separately following a common analytic strategy. Predictive models for specific health outcomes (C) will be evaluated in several ways. First, existing machine learning models will be evaluated in the harmonised real-life datasets across countries and settings. Second, novel supervised machine learning strategies will be developed to predict various health outcomes. Some outcomes are represented in the data as categorical variables, others are continuous. As such, we expect to use both regression and classification models. Classification-based models such as Random Forest Classifiers, XGBoost or Support-Vector Machines can be used to predict discrete health outcomes (eg, death).³⁰ Regression algorithms such as multivariate linear regression models can be used to predict continuous outcomes. The impact of pharmacological (D) and non-pharmacological (E) interventions on health outcomes will be analysed using supervised and reinforcement learning. In reinforcement learning, the model learns by optimising a certain goal (eg, preventing cognitive decline). Causality-inspired algorithms such as Causal Decision Trees and propensity score matching-based methods that estimate the impact of the interventions on our outcome measures (expressed by metrics such as

Table 2 I-CARE4OLD main health outcome measures				
Health outcome	Definition	Data source		
1. Death	Date of death during follow-up	Death registry, interRAI MDS item on discharge reasons		
2. Hospital admission	Date of acute admission during follow-up	Hospital registry, interRAI MDS item on acute admission in past 90 days		
3. Change in self-care functioning	≥1 point at follow-up on ADLH, change	MDS from interRAI assessment		
4. Change in cognitive functioning	≥1 point change at follow-up in CPS	MDS from interRAI assessment		
5. Change in clinical (in)stability	\geq 1 point change at follow-up in CHESS	MDS from interRAI assessment		
6. Change in health-related quality of life	$\geq \frac{1}{2}$ SD change at follow-up in HUI3	MDS from interRAI assessment		
ADLH. Activities of Daily Living Hierarchy Scale: CHESS. Changes in Health. End-Stage Disease. Signs. and Symptoms Scale: CPS.				

ADLH, Activities of Daily Living Hierarchy Scale; CHESS, Changes in Health, End-Stage Disease, Signs, and Symptoms Scale; C Cognitive Performance Scale; HUI3, Health Utility Index III; MDS, Minimal Data Set; SD, Standard deviation.

the average treatment effect) will also be considered. An added benefit of these models compared with standard supervised methods is that these techniques are designed to reason about the underlying causal structure of a problem. As such, these methods are well suited for estimating impact of an intervention or group of interventions on a certain health outcome. Moreover, models that incorporate domain knowledge from medical experts will also be developed and tested. The richness of our datasets allows for the accounting of many clinical, functional and contextual parameters that may influence the impact of interventions. When evaluating models across countries, between-country differences in healthcare practices and organisation of care in home care and nursing homes will be taken into account.

Sample size and model generalisability

Given the large samples used in this project, we did not perform any sample size calculation for the chosen endpoints. The subsamples range from a few thousand care recipients (eg, nursing home data from Belgium) to millions of cases (eg, home care data from Canada and the USA). Therefore, we believe that our samples are more than sufficient in size to perform the planned analyses. Moreover, in AI, having a large enough sample is, by itself, not the main issue. What matters is that there are enough data points to achieve a good predictive performance on unseen cases. This is called generalisability, a key concept in (supervised) machine learning. An algorithm generalises well if it achieves a good out-of-sample performance. Thus, instead of computing the sample size (which is technically possible using sample complexity calculations), AI practitioners are mainly concerned with how well the model performs in the real-world (eg, how well the model predicts cognitive decline in previously unobserved long-term care recipients). To test the out-ofsample performance of a model, we split the data into two subsets, a training set and a test set. The model trains (ie, learns) on the training set. After training, we test its outof-sample performance on the test set. The performance on the test set can therefore be understood as a proxy for how well the model would perform when presented with new data points. For the current project, we must take special care of cases where algorithms are applied to very small groups, such as interventions or diseases with very low prevalence. In those cases, we may have to rely on data-efficient machine learning methods to achieve adequate performance.³¹

Progress so far

In the first 1.5 years of the project, progress has been made with the data linkage and harmonisation as well as with the characterisation of homogeneous groups in terms of disease patterns. We expect the data linkage and harmonisation to be ready before the end of 2023. Moreover, first steps have been made in the methodological development of the predictive models and the selection of pharmacological and non-pharmacological BMJ Open: first published as 10.1136/bmjopen-2023-072399 on 29 June 2023. Downloaded from http://bmjopen.bmj.com/ on August 14, 2023 at Terveyden ja hyvinvoinnin laitos Tietopalvelu. Protected by copyright.

interventions. Dissemination activities in the first 1.5 years involved, among others, the delivery of the project website (www.icare4old.eu).

Our project started when daily life of many older adults was still heavily affected by the COVID-19 pandemic (June 2021), especially those living in nursing homes. Therefore, we thought it would be important to pay attention to the COVID-19 situation in relation to our study population and outcomes. In the first year of the project, it was decided to add a new work package to the project with the aim to study the effect of COVID-19 on a diverse range of clinical outcomes in community and facility-based care settings. For this purpose, home care and nursing home interRAI data from Canada linked with hospital records, emergency room data, physician billing data and medication data will be used. The statistical models developed in parts C, D and E will be replicated and applied to data covering the pandemic period in Canada compared with prepandemic data. We will examine both the main effects of COVID-19 on persons in home care and nursing home settings, as well as the interactive effects of COVID-19 with various aspects of CCCs. The outcomes of interest include mortality; however, I-CARE4OLD researchers have the capacity to extend the investigation to a much broader range of outcomes including functional decline, frailty, mental health and quality of life. In addition, the impact of COVID-19 on trajectories of change and clinical indicators of quality of care will be studied.

Patient and public involvement

Representatives of healthcare professionals have participated in the design of the I-CARE4OLD project. Further, we promote active participation of end-users including healthcare professionals and care recipients in local workshops and at conferences. For the development of the decision support digital platform, healthcare professionals and older care recipients will be involved in the developing and testing phases. The results of the study will be shared with stakeholders, including patient organisations, healthcare professionals, policy makers and the general public.

Ethics and dissemination

Ethical considerations

In the I-CARE4OLD project, real-life data will be reused for data analysis, in compliance with both local and EU legislation. Existing routine care data from interRAI assessments will be linked with registry data from various repositories. Although in several care sites opt-in (informed consent) or opt-out procedures are in place, the vast amount of data portions targeted in I-CARE4OLD were collected without explicit consent. There is no realistic way of obtaining such consent from the subjects of the data. This is permitted according to EU regulations when data are anonymised in such a way that the data subject is deidentified. Personal data will be pseudoanonymised before linkage, and analytical samples will be appropriately deidentified, secured and governed. The I-CARE4OLD study was approved by authorised medical ethical committees in each of the participating countries. Italy: Comitato Etico del Instituto Superiore di Sanità (No. 2021_0017777) and Università Cattolica del Sacro Cuore Ethical Committee (No. 2021 4327), the Netherlands: Medical Ethics Review Committee of VU University Medical Center (No. 2021.0358), Finland: Institutional Review Board (IRB) of The Finnish Institute for Health and Welfare (No. THL/1118/6.02.00/2021), Belgium: Commissie Medisch Ethiek van de Universitair Medische Ziekenhuizen Katholieke Universiteit Leuven (No. G-2023-6216-R5(MIN)), Canada: Human Research Ethics Board of the University of Waterloo (No. 43618), United States: Advarra Institutional Review Board (No. PRO00054430). For Hong Kong and New Zealand, no additional ethical approval is needed, since data from these countries will not be linked with other sources. There is a signed agreement between the governments from these sites and interRAI that supports the transmission of deidentified data to the interRAI data repositories. In addition, the complex linked dataset used for Canadian data was prepared with the support of the Canadian Institute for Health Information.

Dissemination

The results of the study will be published in peer-reviewed journals. Further, results will be disseminated during national and international scientific and professional conferences and meetings. Stakeholders will also be informed via the project website and social media, and through targeted methods such as webinars, factsheets and (feedback) workshops. We strive to publish as much as possible open access, including analytical scripts. Databases will not become publicly available, but datasets used and/or analysed as part of the project can be made available on reasonable request and with permission of the I-CARE4OLD consortium.

DISCUSSION

This study on older adults with CCCs has the potential to majorly advance long-term care research, by benefitting from opportunities that arise from international collaboration and interdisciplinary cooperation. Data from up to 51 million care users in home care and nursing home settings in eight countries will be used to develop highquality decision support. Routinely collected geriatric assessment data from interRAI will be linked to registry data on mortality, medications and care use. A major strength of the study includes the use of supervised machine learning to create more accurate and more individualised prognostication of health trajectories, including the impact of treatment. Moreover, the study focuses on relatively old and medically complex older persons who are often excluded from clinical trials.

The study also has some limitations. The analyses will be performed on high-quality, real-world data. However, these are all existing data, which means we depend on the availability of variables included in these data. We have no means to obtain additional data when information on a certain topic is lacking. Furthermore, our real-world data have been collected over an extended time period. During this observational period, diagnostic criteria or tools may have changed for some chronic conditions. Although disease assessments are based on international standards (eg. International Classification of Diseases), it is important to note that there might be differences in the diagnosis of certain chronic conditions over time and between countries. Another limitation is that beforehand we do not know for how many care recipients linkable data are available from repositories. Therefore, successful linkage between assessment data and registry data cannot be guaranteed for 100% of the study population, especially in the countries where probability linkage will be applied based on identifiers such as date of birth and postal code.

In conclusion, this unique study will use real-world data to develop next generation decision support for professionals, care recipients and close relatives, thereby making an important contribution to improved care for older adults with CCCs in home care and in nursing homes.

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Contributors EOH drafted the manuscript. LS contributed to the writing of the statistical analysis sections. EOH, GO, LS, DLV, JPH, EPH, JNM, DF, KS, ECMK, MH, AD, JDAM, R-LL, JH, JE, GR, RL, KJJ and HvH contributed to the conception and design of the study, critically revised drafts of the manuscript and approved the final version of the manuscript.

Funding The I-CARE40LD project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 965341. Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European Union. Neither the European Union nor the granting authority can be held responsible for them. More information on the I-CARE40LD project can be found at www.icare40le.u and https:// cordis.europa.eu/project/id/965341. Additional funding to support the Canadian participation in the work was provided by Canada's New Frontiers Research Fund - Global Fund (grant agreement No. 177780). The work of DF was supported by the institutional program Cooperatio of the Faculty of Pharmacy, Charles University, Prague.

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Competing interests None declared.

Patient and public involvement Patients and/or the public were involved in the design, or conduct, or reporting or dissemination plans of this research. Refer to the Methods section for further details.

Patient consent for publication Not applicable.

Provenance and peer review Not commissioned; externally peer reviewed.

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