Predictive Data Analytics in Telecare and Telehealth: A Systematic Scoping Review

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Abstract

Background: Telecare and telehealth are important care at home services used to support individuals to live more independently at home. Historically, these technologies have reactively responded to issues. However, there has been a recent drive to make better use of the data from these services to facilitate more proactive and predictive care.

Objective: This review seeks to explore the ways in which predictive data analytics techniques have been applied in telecare and telehealth in at-home settings.

Methods: The PRISMA-ScR checklist was adhered to alongside Arksey and O'Malley's methodological framework. English language papers published in Medline, EMBASE and Social Science Premium Collection between 2012 and 2022 were considered and results were screened against inclusion/exclusion criteria.

Results: 86 papers were included in this review. The types of analytics featuring in this review can be categorised as anomaly detection (n=22), diagnosis (n=32), prediction (n=22) and activity recognition (n=10). The most common health conditions represented were Parkinson's disease (n=12) and cardiovascular conditions (n=11). The main findings include: a lack of use of routinely collected data; a dominance of diagnostic tools and barriers; opportunities that exist, such as including Patient Reported Outcomes (PROs), for future predictive analytics in telecare and telehealth.

Conclusions: All papers in this review were small-scale pilots and, as such, future research should seek to apply these predictive techniques into more routinely collected care data processes. Datasets used must be of suitable size and diversity, ensuring models are generalisable to a wider population and can be appropriately trained, validated and tested.

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Data Accessibility Statement

Data extraction table will be made available via PURE.

Declarations
This study was jointly funded as part of the Glasgow City Innovation District Project by University of Strathclyde, Digital Health and Care Innovation Centre, Glasgow City Council, and Tunstall, who were part of the project team.

ABSTRACT

Background:

Telecare and telehealth are important care at home services used to support individuals to live more independently at home. Historically, these technologies have reactively responded to issues. However, there has been a recent drive to make better use of the data from these services to facilitate more proactive and predictive care.

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This review seeks to explore the ways in which predictive data analytics techniques have been applied in telecare and telehealth in at-home settings.

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The PRISMA-ScR checklist was adhered to alongside Arksey and O'Malley's methodological framework. English language papers published in Medline, EMBASE and Social Science Premium Collection between 2012 and 2022 were considered and results were screened against inclusion/exclusion criteria.

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86 papers were included in this review. The types of analytics featuring in this review can be categorised as anomaly detection (n=21), diagnosis (n=32), prediction (n=22) and activity recognition (n=11). The most common health conditions represented were Parkinson's disease (n=12) and cardiovascular conditions (n=11). The main findings include: a lack of use of routinely collected data; a dominance of diagnostic tools; and barriers and opportunities that exist, such as including Patient Reported Outcomes (PROs), for future predictive analytics in telecare and telehealth.

Conclusions:

All papers in this review were small-scale pilots and, as such, future research should seek to apply these predictive techniques into larger trials. Additionally, further integration of routinely collected care data and PROs into predictive models in telecare and telehealth offer significant opportunities to improve the analytics being performed and should be explored further. Datasets used must be of suitable size and diversity, ensuring models are generalisable to a wider population and can be appropriately trained, validated and tested.

Key Words: telecare, telehealth, data analytics, predictive models, scoping review.

INTRODUCTION

Technologies can play a role in addressing the challenges associated with supporting people to live longer independently at home. Telecare services have existed since the 1970s and are systems designed to support vulnerable individuals living in their homes, enabling them to retain their autonomy while ensuring they are protected from any anomalous situations that may arise [1]. Telecare devices have gone through many iterations since their introduction as simple user-triggered alarms and now include, for example, bed occupancy sensors and automatic fall detectors [1]. Today, telecare systems can work as lifestyle monitors, collecting data relating to the individual and their home environment in real time. Telehealth services are used in the management of long-term conditions such as heart disease or diabetes. Users are given equipment, such as vital signs monitors, to allow them to record blood pressure, heart rate or blood glucose levels for example. This data is shared with care providers to allow remote assessment of the well-being of an individual and to intervene if necessary.

Technology-enabled services have been a feature of care at home for a number of years and demand for these services remains high. In Scotland alone, there are over 129,000 people (2.4% of the total population) who make use of a telecare service or community alarm [2], while an estimated 1.8 million people across the whole of the United Kingdom (2.7% of the total population) use either telecare or telehealth services [3]. In the USA, a total of 2.3 million veterans used telehealth services in 2022, representing more than a third of all veterans receiving care from the Department of Veterans Affairs [4].

Newer telecare and telehealth devices collect increasing amounts of data from a variety of connected sensors and systems. However, most services respond to an anomaly once it has been identified and do not intelligently use the data they receive to identify those at higher risk of an adverse event in order to pre-emptively plan what an individual may require. There are significant benefits to more proactive services such as a reduction in secondary care use including ambulance call outs or eventual hospital admissions for example [5, 6].

Recent policy has highlighted a desire to shift telecare and telehealth services towards a more proactive model. The UK Government state – in their plan for Digital Health and Social Care – that anticipatory care promoting prevention through machine learning-facilitated data analysis will be routinely implemented by 2028 [7]. This has similarly been highlighted in a number of other countries including Australia, Canada and New Zealand [8-10].

This scoping review therefore seeks to identify and explore the ways in which predictive data analytics techniques have been applied in the use of community-based telecare and telehealth devices and services in order to identify the current gaps and opportunities that exist for the future use of predictive analytics in telecare and telehealth.

METHODS

This review was conducted and presented in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) 2020 checklist [11]. The protocol was informed by the methodological framework proposed by Arksey and O'Malley [12].

Inclusion/Exclusion Criteria

This review considered any study utilising quantitative methods relating to the predictive use of data analytics in the fields of telecare and telehealth. Qualitative studies were excluded. The Population, Concept and Context (PCC) framework was applied. Database searches were conducted in August 2022 and restricted to papers published within 10 years of the initial searches being conducted. Only papers published in the English language were considered.

Population

Papers focussing on any and all users were included. All populations of users (anyone using a telecare and telehealth device or systems) including both adult and child services were valid for inclusion since the focus of this review was on the methods of analytics being applied, rather than the specific reason for accessing telecare or telehealth.

Concept

Any telecare or telehealth innovation that gathers or generates data and electronically communicates it for use in an analytical manner was valid for inclusion. This could be 'passive' technology, such as sensors and wearables, or 'active' technology where data is intentionally entered into a device by a user. Papers investigating devices which do not directly monitor a health element of an individual, such as an educational app, were excluded. Any data analytics that make inference or predictions from the data they receive were included in this review. This includes diagnosis, classification and anomaly detection and does not exclusively consider predictions of future events. Additionally, this review only considers telecare and telehealth devices related to a somatic condition, i.e. physical condition of the body. Papers focussed on mental health and loneliness, for example, were excluded as these conditions may necessitate a very different management approach.

Context

Any paper which had a 'care in the community' setting was suitable for inclusion (patient's own home; assisted living facilities and sheltered accommodation). In-patient and non-home-based settings were excluded with the exception of papers that focus on technologies clearly designed for at-home use that have thus far only been tested on individuals in an in-patient setting.

Study Type

All reviews (systematic, literature and scoping) were excluded as this would cause duplicate data to be reviewed and could lead to bias through over reporting. Any paper outlining an entirely conceptual framework and not detail on how it would work in practice was excluded. The review also excluded editorials, summaries and opinion pieces.

Databases Searched

Databases relevant to health and social care – Medline [OVID], EMBASE [OVID] and Social Science Premium Collection [ProQuest] – were searched.

Search Strategy

Two key domains were identified for inclusion in the search strategy: data analytics and telecare/telehealth (see Table 1).

Search terms that were deemed most applicable to each database were applied. MeSH terms and free-text entries were considered as appropriate. Boolean operators such as ‘AND’, ‘OR’ and truncation codes were used to refine and improve searches. A copy of the full search strategy employed while searching the Medline database can be found in Multimedia Appendix 1.

Table 1 - Synonyms considered during literature searches for review.

Search Term Domains	Synonyms
Data analytics	Data analytics Big data Health analytics Electronic data capture Data management system Machine learning Data analysis Data mining
Telecare / Telehealth	Telecare Telehealth Remote healthcare services Remote monitoring Telemonitoring Telecommunication Advanced assistive technology

Study Screening

Results from each database search were imported to EndNote™ [13] where duplicates were removed. Studies were uploaded to Covidence™ [14] for screening. Title and abstract screening were completed by six reviewers (ML, NW, ED, DK, MR and LL). Every paper was screened independently by at least two researchers, with conflicts resolved through discussion. A third reviewer was consulted when agreement could not be reached.

Full-text versions of the accepted papers were obtained for full-text screening. There were 537 papers considered for full-text screening by the lead author. Of these 537, approximately 15% (n=80 out of 537) were screened collaboratively by the lead author (EA) and two other reviewers (NW and DK). Inter-rater agreement (all three reviewers coming to the same conclusion on inclusion or exclusion), was categorised through the following thresholds: <70% = poor, 70-79% = fair, 80-89% = good and ≥90% = excellent [15]. Of the papers that were collaboratively reviewed by all three researchers, there was an inter-rater agreement of 81%. This was a sufficient level of agreement for the remaining full-text papers to be independently screened by the primary author only. A second opinion was sought by the primary researcher during full-text screening when required. A PRISMA flow chart of the full screening process completed for this review can be found in Multimedia Appendix 2.

Data Charting Process

A data extraction table was created in Microsoft Excel® by the primary author. The data extraction table was piloted by the primary author for the first 10 papers before a discussion with secondary authors was conducted to ensure the appropriateness of the data being extracted. These discussions helped shape the table further with modifications made so that all relevant pieces of information were extracted. Data extracted related to key study characteristics, data analysed in the paper, the technology employed and the analytics techniques used.

Data Items and Synthesis of Results

Data was collected on paper characteristics (e.g. title, authors, year of publication, location of publication and country of origin) and study characteristics (e.g. study design, stage of implementation, study setting, primary/secondary analysis, participant description, duration of study and drop-outs). Data was also captured relating to the technology in use (e.g. what the technology is designed to assist with, the technology being employed and its function), the data used in the analyses (e.g. data streams, where the data is sent and what it is being used for) and the methods of analyses employed (e.g. the statistical method of analysis, the actions taken as a result of the analysis and outcome measures). Information on the key findings from each study and any potential limitations with the studies were also collected. A summary of the data extracted for each paper can be found in Multimedia Appendix 3.

RESULTS

Approximately one third of papers (n=28) considered telecare services, with the other two thirds considering telehealth services (n=58).

The data analytics tasks employed in the studies reviewed (with reference to Banaee et al. [16]) can generally be categorised into: anomaly detection (n=21, 24%), prediction (n=22, 26%) and diagnosis and decision-making (n=32, 37%). Additionally, this review identified a fourth data analytics task which relates to activity recognition systems (n=11, 13%). Table 2 provides a breakdown of the papers, categorised by type of data analytics task applied.

Table 2 - Categories of data analytics in included papers.

Type of Data Analytics Applied	**N**	**References**
Diagnosis and decision making	32	[17-48]
Prediction	22	[49-70]
Anomaly detection	21	[71-91]
Activity recognition	11	[92-102]

The most common areas of focus for overall technology systems were general monitoring systems (n=14, 16%) and activity recognition systems (n=11, 13%). The majority of the included papers focussed on the prevention, detection, treatment or monitoring of a specific health condition (n=53, 62%). Of these, the most commonly studied was Parkinson’s Disease (n=12, 14%), followed by conditions of the cardiovascular (n=11, 13%) and respiratory systems (n=8, 9%). Table 3 lists the number of papers considered by the paper’s focus, split between technology systems and by health condition.

Table 3 - Focus of papers included in review, grouped by monitoring systems and by health condition [a].

Focus of Paper (Technology System)	**N**	**References**
General monitoring system	14	[30, 53, 55, 59, 71, 73-75, 80, 84-85, 88, 90-91]
Activity recognition system	11	[92-102]
Falls monitoring system	5	[51, 70, 86, 89, 100]
Focus of Paper (Health Condition)	**N**	**References**
Parkinson’s Disease	12	[20-21, 28, 32, 40-41, 43-44, 47-48, 76-77]
Cardiovascular system (heart disease, heart failure, atrial fibrillation, cardiovascular disease,	11	[23-24, 27, 46, 57, 63, 67-68, 70, 82-83]

blood pressure and anticoagulation)		
Respiratory system (lung transplant, chronic obstructive pulmonary disease and asthma)	8	[49, 56, 58, 60-62, 69, 79]
Sleep apnoea	4	[26, 29, 35, 78]
Diabetes (including Prediabetes)	4	[39, 64-65, 81]
Post-stroke rehab	3	[22, 25, 31]
Cognitive assessment/dependence	2	[18, 33]
Weight/diet	2	[36, 54]
Multiple Sclerosis	2	[37, 45]
Craniosynostosis	1	[17]
Gait	1	[19]
Pressure injuries	1	[34]
Alzheimer's Disease	1	[38]
Typhoid	1	[42]
Cancer	1	[50]
Pancreatectomy	1	[52]
COVID-19	1	[66]
Knee arthroplasty	1	[72]
Pain management	1	[87]

[a]*Table 3 does not sum to 86 as there are a small number of papers that have more than one area of focus.*

Studies featuring primary data sources accounted for just over half of the papers included (n=46, 53%). There were a further 36 papers (42%) that used data originating from secondary sources, such as data gathered over the course of a separate experiment or trial that was then applied to future studies, while four papers (5%) used a combination of both primary and secondary sources [27, 41, 85, 99]. There were a total of three papers that focussed on the predictive analytics of data that has been routinely collected in telehealth practice, while there were no such telecare papers [31, 42, 68]. Every paper reviewed was either in a pilot/feasibility study or was undergoing proof-of-concept tests. Table 4 displays the different types of technologies featured in this review. The most common technologies were wearable sensors (n=38, 44%). The majority of the papers (n=68, 79%) used at least one type of sensor – be it wearable, environmental/motion/pressure, smartphone or 3D motion scanners. Other technologies included self-reported symptoms via smartphone apps (n=17, 20%) and vital signs monitoring (n=11, 13%). These technologies do not map neatly onto the data analytics tasks shown in Table 2. For example, wearable sensors feature in papers that consider diagnosis and decision making, anomaly detection, prediction and activity recognition tasks.

Table 4 - Technology featured in papers under review [a].

Technology Used	N	Technology Used	N
Wearable sensors	38	Computer/Phone-based testing	2
Patient Reported Outcomes via app	17	Virtual glove	2
Environmental/pressure/motion sensors	16	Virtual knee sleeve	1
Vital signs monitoring	11	Video recording	1
Smartphone sensors	10	Voice recording	1
3D motion scanners	4	Images	1

[a] *Table 4 does not sum to 86 as a number of papers featured the usage of more than one technology.*

Machine learning (ML) techniques were the most commonly applied method of analysis of the data collected in the studies reviewed (n=76, 88%). Table 5 breaks down the machine learning techniques that have been reported in at least two paper in this review, highlighting the variety of different possible methods of analysis. For papers that consider multiple different machine learning methods, only the technique found to be most accurate has been selected. Other methods of analysis employed in this review were rules-based inference systems (n=4, 5%) and non-machine learning algorithms (n=3, 3%). The most commonly applied machine learning methods were decision trees (n=14, 16%), followed by neural networks (n=12, 14%) and support vector machines (n=11, 13%). Additionally, there are a number of papers (n=16, 21%) that consider highly bespoke algorithms, employed in one instance only, which do not feature in Table 5.

Table 5 - Machine learning techniques applied in relevant papers.

Machine Learning Technique	N	Machine Learning Technique	N
Decision trees	14	Ensemble (combination of models)	6
Neural networks	12	Logistic regression	5
Support vector machines	11	Hidden Markov Models	2
Random forests	8	k-Nearest neighbours	2

There were 68 papers (79%) in this review that reflected on potential limitations with their studies. Of these, two limitations were identified across multiple papers: small sample or study sizes (n=32, 47% of papers reporting limitations) and the issue of bias (n=13, 19% of papers reporting limitations). In total, there were only two included papers that considered the calculation of suitable sample sizes for their studies [31, 79].

The main limitation identified in the papers reviewed is that a significant number of papers are trained on very small datasets or samples. In total, there were 32 papers that acknowledged this as an issue. The other limitation that was identified a significant number of times was the possibility of the introduction of bias to the models. Bias presents a similar issue to small sample sizes as it can invalidate the findings of a study, as the model is trained on a group that is not representative of the wider population of interest. The types of bias identified in this review can be found in Table 6.

Table 6 - Sources of bias identified by researchers.

Type of Bias	N	References
Technology trialled on young, healthy individuals	5	[51, 71, 83, 93, 100]
Female dominated dataset	4	[18, 26, 39, 54]
More complete data received from healthier individuals	1	[24]
Participants almost all white and college educated	1	[44]
Participants all recruited from one church in urban area	1	[59]
Male dominated dataset	1	[67]

DISCUSSION

Within this review, the data analytics approaches can be categorised, with reference to Banaee et al [16], as: anomaly detection, prediction, and diagnosis/decision making. Additionally, a fourth analytics category, activity recognition systems, has been identified. Table 2 features a breakdown of the analytics approaches employed in the reviewed papers.

Diagnosis and decision-making systems were the most commonly occurring data analytics task performed in the literature (n=32, 37%), while systems designed to identify anomalous events that have already taken place accounted for 21 reviewed papers (24%). Systems designed to make temporal predictions – identify an anomaly or event in advance of it taking place – only accounted for 22 of the papers reviewed (26%). This branch of analytics approaches is of critical importance to researchers and care providers due to the potential healthcare savings that could be made through the timely and proactive identification and resolution of anomalies before the occur. As such, it would be expected that in the future, studies focussing on the prediction of anomalous events will become more frequently applied in the field of telecare and telehealth. This is supported by recent policy documents highlighting aspirations to move towards more proactive and predictive models of care [7-10].

The final identified branch of data analytics tasks is activity recognition systems (n=11, 13%). These systems typically use a classification model to identify the activity performed (e.g. walking, falling) which is very relevant in the field of telecare but found rarely in the literature. A few studies show how such systems could be advanced towards more predictive anomaly detection [92, 100] but they do not currently have a feedback loop whereby the recognition of an event taking place leads to an action by the care provider. This is of critical importance if aiming to identify people at risk of an adverse event and take preventative measures and is likely to become more commonly applied in telecare and telehealth moving forward.

Analytics Focus

This review also highlighted that there has been far more research into predictive analytics in telehealth (n=58) compared to telecare (n=28). Telehealth data may be more suitable to the application of predictive analytics because it is often more structured and numerical in nature whereas social care data more frequently relies on unstructured case notes.

Studies which considered a system or technology aimed at a specific disease or condition made up the majority of papers identified, with the most common disease of focus being Parkinson’s disease [31-42]. The reason for the large quantity of studies focussing on Parkinson’s disease might be due, in part, to the features and symptoms of the disease itself and their suitability for being measured by sensors and then modelled by data analytics techniques. For example, slowness of movement, uncontrollable shaking and gait problems are very common Parkinson's disease symptoms and are all well suited to being captured through wearable sensors. Such remote monitoring or assessment is also useful in diseases like Parkinson's disease where clinical features of the disease may be intermittent in the early stages and thus may not be present during a scheduled assessment [103].

Patient Reported Outcomes

While PROs were one of the more commonly featured tools in this review (n=17, 20%), they are not commonly used in telecare predictive data analytics models (n=3 out of 28 telecare papers, 11%). PROs can provide more nuanced information than solely using clinical indicators which can lead to an underestimation of the impact on a patient in combination with an overestimation of the effectiveness of treatment being provided [104-105]. As such, there is an argument to be made for further utilisation of PROs in predictive data analytics models, especially in the field of telecare.

The inclusion of PROs in predictive modelling work is challenging as it requires the marrying of objective and subjective data but this can help to strengthen model results as they will reflect the true reported experience and outcomes for the patient. Indeed, evidence shows that PRO measurements are of comparable accuracy to many objective clinical measures [106]. Appropriate testing, validation and re-evaluation of PROs can help to improve the quality and consistent collection of data while the move towards standardisation of PROs through the use of tools such as the National Institute of Health's Patient-Reported Outcome Measurement Information System (PROMIS) can enable a rise in data quality levels across the board, facilitating a greater integration of PROs in predictive modelling work [107].

Use of Routinely Collected Data

Routinely collected data can be defined as data that has not been specifically captured for research purposes. There are only three studies featured in this review using data that has been routinely collected in real world health and care practice, with all of these papers considering telehealth systems [31, 42, 68]. From a telehealth perspective, a lack of use of routinely collected data makes sense due to these systems focussing on highly specific features that need to be extracted about a given condition or illness. As such, the data considered in these systems tend to originate from bespoke, highly targeted data collection methods.

However, a significant amount of data is being generated by providers of telecare services globally as they deliver care and the application of data analytics in these real-world datasets needs to be explored further than it has been to date. One key barrier to the analytical use of routinely collected telecare data is that this data is typically siloed in different locations with a lack of interoperability between systems. For example, call handling data is frequently maintained in a different system to other social care data meaning that the outcomes of calls are not accessible to social care organisations. This has been identified by the Scottish Government as being a key issue preventing the use of data-driven care [108].

Additionally, work must be done to improve other issues surrounding the use of routinely collected data such as patient consent and data governance and security [109]. If researchers, care providers and any commercial suppliers in control of these rich data sources can collaboratively overcome these identified issues then a whole new avenue for the use of predictive data analytics will be opened.

Limitations within Studies

Limitations noted by researchers were typically specific to the technology employed. For example, low quality data being captured from sensors [84], the technology being uncomfortable to wear and with a short battery life [86] and there being a limited number of sensors employed [93]. Limitations related to the analytics techniques included low impact falls being missed by a model [89], large volumes of missing values [61] and a model that struggled to differentiate between an individual sitting and standing [101].

The main limitation identified in this review is that a significant number of papers are trained on very small datasets or samples. In total, there were 32 papers (47% of the total papers reporting limitations) that acknowledged this as an issue. This is a critical problem as having a small sample size could undermine the legitimacy of the findings of the paper – particularly when the outcome of interest is rare. Small sample sizes make it harder to accurately train, validate and test machine learning models with the findings less conclusive and less reliable.

To ensure that the strongest evidence base possible sample size calculations should be conducted prior to the study, however only two of the papers featured in this review reported prior sample size estimation [31, 79]. This could be due to the pragmatic nature of recruitment, with it being difficult to recruit significant numbers of individuals with a certain condition, but is no less of an issue to the validity of the findings.

The other limitation that was identified a significant number of times was the possibility of the introduction of bias to the models, as can be seen in Table 6. Bias could invalidate study findings as the model is trained on a group that is not representative (e.g. gender, age) of the target population meaning that its performance may not translate in reality. In the field of telecare and telehealth, it is critical that datasets consider individuals of appropriate age – generally elderly – and that disease-specific systems have been trialled on individuals with the illness or condition of interest. For example, a study using young, healthy volunteers to classify falls – and other activities – requires participants to simulate falls [100]. This may impact on the accuracy of the model and a dataset featuring genuine falls captured by elderly individuals would be significantly more appropriate. The key sources of bias identified in this review are the use of exclusively young, healthy adults to trial technologies that are designed for an older population and datasets which are dominated by women.

Limitations of this Review

The quality of the studies selected for inclusion in this review was not assessed using any official appraisal tool. This is typical of a scoping review, which seeks to synthesise the available literature rather than provide a systematic analysis, however, this means that the quality of the papers featuring in this review cannot be guaranteed. A further limitation of this review is that it may have missed commercially developed data analytics tools that have being implemented in practice, as these would not necessarily be contained in the research literature. Finally, only papers that were available in the English language were considered which may preclude a number of papers of relevance to this review.

CONCLUSION

Predictive data analytics have been widely used in the field of telecare and telehealth but all of the studies featured in this review are still small-scale pilot studies and must be extended to larger trials. Additionally, opportunities for predictive analytics revolving around routinely collected data and PROs should be explored further. Using larger and more diverse 'real world' data will enable models to be built that have less bias, can predict more accurately, and could be adapted more widely within other telecare or telehealth settings. Ultimately, appropriate consideration of these factors could lead us to more predictive and preventative data driven models of telecare and telehealth.

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REFERENCES

1. Doughty K, Cameron K, Garner P. Three Generations of Telecare of the Elderly. Journal of Telemedicine and Telecare. 1996;2(2):71-80.

2. Public Health Scotland. Insights in social care: statistics for Scotland. In: Scotland PH, editor. 2022.
3. FarrPoint. The Digital Shift and its Impact on the Telecare Sector in England Study Report November 2022. 2022.
4. Lutes T. With telehealth, Veterans can access care when and where they need it VA News: United States Department of Veterans Affairs; 2022 [Available from: https://news.va.gov/108453/telehealth-access-care-when-where-need/.
5. Contreras WA-O, Sarquella E, Binefa E, Entrambasaguas M, Stjerne A, Booth P. The Impact on Ambulance Mobilisations of an Increasing Age Profile of Telecare Service Users Receiving Advanced Proactive, Personalised Telecare in Spain-a Longitudinal Study 2014-2018. (2509-4971 (Print)).
6. Cund A, Hendry A, Ritchie L, H.; F, M.; T, Struthers J, et al. Evaluating Proactive Telecare Outbound Calling in Scotland Report. 2022.
7. NHS England. A Plan for Digital Health and Social Care. In: Care DoHaS, editor. 2022.
8. Australian Government. Safe, seamless and secure: evolving health and care to meet the needs of modern Australia. Australia's National Digital Health Strategy. In: Agency ADH, editor. 2017.
9. Government of Canada. Health Canada Data Strategy. In: Canada H, editor. 2019.
10. New Zealand Government. NZ Vision for Health Technology. In: Zealand TWOHN, editor. 2020.
11. Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. (1539-3704 (Electronic)).
12. Arksey H, O'Malley L. Scoping studies: towards a methodological framework. International Journal of Social Research Methodology. 2005;8(1):19-32.
13. The EndNote Team. EndNote. EndNote X9 ed. Philadelphia, PA: Clarivate; 2013.
14. Veritas Health Innovation. Covidence Systematic Review Software. 2023.
15. Cicchetti DV. Methodological Commentary The Precision of Reliability and Validity Estimates Re-Visited: Distinguishing Between Clinical and Statistical Significance of Sample Size Requirements. Journal of Clinical and Experimental Neuropsychology. 2001;23(5):695-700.
16. Banaee H, Ahmed Mu Fau - Loutfi A, Loutfi A. Data mining for wearable sensors in health monitoring systems: a review of recent trends and challenges. (1424-8220 (Electronic)).
17. Bookland MJ, Ahn ES, Stoltz P, Martin JE. Image processing and machine learning for telehealth craniosynostosis screening in newborns. J Neurosurg Pediatrics. 2021;27(5):581-8.
18. Garcia-Moreno FM, Bermudez-Edo M, Rodriguez-Garcia E, Perez-Marmol JM, Garrido JL, Rodriguez-Fortiz MJ. A machine learning approach for semi-automatic assessment of IADL dependence in older adults with wearable sensors. Int J Med Inf. 2022;157:104625.
19. Altilio R, Rossetti A, Fang Q, Gu X, Panella M. A comparison of machine learning classifiers for smartphone-based gait analysis. Med Biol Eng Comput. 2021;59(3):535-46.
20. Guo R, Shao X, Zhang C, Qian X. Sparse Adaptive Graph Convolutional Network for Leg Agility Assessment in Parkinson's Disease. IEEE Trans Neural Syst Rehabil Eng. 2020;28(12):2837-48.
21. Tunc HC, Sakar CO, Apaydin H, Serbes G, Gunduz A, Tutuncu M, et al. Estimation of Parkinson's disease severity using speech features and extreme gradient boosting. Med Biol Eng Comput. 2020;58(11):2757-73.
22. Chae SH, Kim Y, Lee KS, Park HS. Development and Clinical Evaluation of a Web-Based Upper Limb Home Rehabilitation System Using a Smartwatch and Machine Learning Model for Chronic Stroke Survivors: Prospective Comparative Study. JMIR Mhealth Uhealth. 2020;8(7):e17216.
23. Shao M, Zhou Z, Bin G, Bai Y, Wu S. A Wearable Electrocardiogram Telemonitoring System for Atrial Fibrillation Detection. Sensors (Basel). 2020;20(3):22.
24. Meng Y, Speier W, Shufelt C, Joung S, J EVE, Bairey Merz CN, et al. A Machine Learning

Approach to Classifying Self-Reported Health Status in a Cohort of Patients With Heart Disease Using Activity Tracker Data. IEEE j. 2020;24(3):878-84.
25. van Ommeren AL, Sawaryn B, Prange-Lasonder GB, Buurke JH, Rietman JS, Veltink PH. Detection of the Intention to Grasp During Reaching in Stroke Using Inertial Sensing. IEEE Trans Neural Syst Rehabil Eng. 2019;27(10):2128-34.
26. Mosquera-Lopez C, Leitschuh J, Condon J, Hagen CC, Rajhbeharrysingh U, Hanks C, et al. Design and Evaluation of a Non-ContactBed-Mounted Sensing Device for AutomatedIn-Home Detection of Obstructive Sleep Apnea:A Pilot Study. Biosensors (Basel). 2019;9(3):22.
27. Kruger GH, Latchamsetty R, Langhals NB, Yokokawa M, Chugh A, Morady F, et al. Bimodal classification algorithm for atrial fibrillation detection from m-health ECG recordings. Comput Biol Med. 2019;104:310-8.
28. Prince J, Andreotti F, De Vos M. Multi-Source Ensemble Learning for the Remote Prediction of Parkinson's Disease in the Presence of Source-Wise Missing Data. IEEE Trans Biomed Eng. 2019;66(5):1402-11.
29. Gutierrez-Tobal GC, Alvarez D, Crespo A, Del Campo F, Hornero R. Evaluation of Machine-Learning Approaches to Estimate Sleep Apnea Severity From At-Home Oximetry Recordings. IEEE j. 2019;23(2):882-92.
30. Mlakar M, Puddu PE, Somrak M, Bonfiglio S, Lustrek M, Chiron, et al. Mining telemonitored physiological data and patient-reported outcomes of congestive heart failure patients. PLoS ONE. 2018;13(3):e0190323.
31. Standen PJ, Threapleton K, Richardson A, Connell L, Brown DJ, Battersby S, et al. A low cost virtual reality system for home based rehabilitation of the arm following stroke: a randomised controlled feasibility trial. Clin Rehabil. 2017;31(3):340-50.
32. Arroyo-Gallego T, Ledesma-Carbayo MJ, Sanchez-Ferro A, Butterworth I, Mendoza CS, Matarazzo M, et al. Detection of Motor Impairment in Parkinson's Disease Via Mobile Touchscreen Typing. IEEE Trans Biomed Eng. 2017;64(9):1994-2002.
33. Dawadi PN, Cook DJ, Schmitter-Edgecombe M. Automated Cognitive Health Assessment From Smart Home-Based Behavior Data. IEEE j. 2016;20(4):1188-94.
34. Gabison S, Pupic N, Evans G, Dolatabadi E, Fernie G, Dutta T. Measuring Repositioning in Home Care for Pressure Injury Prevention and Management. medRxiv. 2022;21.
35. Iwasaki A, Fujiwara K, Nakayama C, Sumi Y, Kano M, Nagamoto T, et al. R-R interval-based sleep apnea screening by a recurrent neural network in a large clinical polysomnography dataset. Clinical Neurophysiology. 2022;139:80-9.
36. Adhikary S, Ghosh A. e-BMI: A gait based smart remote BMI monitoring framework implementing edge computing and incremental machine learning. Smart Health. 2022;24 (no pagination).
37. Creagh AP, Simillion C, Bourke AK, Scotland A, Lipsmeier F, Bernasconi C, et al. Smartphone- and Smartwatch-Based Remote Characterisation of Ambulation in Multiple Sclerosis during the Two-Minute Walk Test. IEEE Journal of Biomedical and Health Informatics. 2021;25(3):838-49.
38. Alberdi A, Weakley A, Schmitter-Edgecombe M, Cook DJ, Aztiria A, Basarab A, et al. Smart Home-Based Prediction of Multidomain Symptoms Related to Alzheimer's Disease. IEEE Journal of Biomedical and Health Informatics. 2018;22(6):1720-31.
39. Ramesh J, Aburukba R, Sagahyroon A. A remote healthcare monitoring framework for diabetes prediction using machine learning. Healthcare Technology Letters. 2021;8(3):45-57.
40. Sajal MSR, Ehsan MT, Vaidyanathan R, Wang S, Aziz T, Mamun KAA. Telemonitoring Parkinson's disease using machine learning by combining tremor and voice analysis. Brain Informatics. 2020;7(1) (no pagination).

41. Chen OY, Lipsmeier F, Phan H, Prince J, Taylor KI, Gossens C, et al. Building a Machine-Learning Framework to Remotely Assess Parkinson's Disease Using Smartphones. IEEE Transactions on Biomedical Engineering. 2020;67(12):3491-500.
42. Djawad YA, Suhaeb S, Ridwansyah, Jaya H, Fathahillah, Saharuddin. Development of an Intelligent Mobile Health Monitoring System for the Health Surveillance System in Indonesia. Irbm. 2021;42(1):28-34.
43. Abujrida H, Agu E, Pahlavan K. Machine learning-based motor assessment of Parkinson's disease using postural sway, gait and lifestyle features on crowdsourced smartphone data. Biomedical Physics and Engineering Express. 2020;6(3) (no pagination).
44. Zhan A, Mohan S, Tarolli C, Schneider RB, Adams JL, Sharma S, et al. Using smartphones and machine learning to quantify Parkinson disease severity the mobile Parkinson disease score. JAMA Neurology. 2018;75(7):876-80.
45. Supratak A, Datta G, Gafson AR, Nicholas R, Guo Y, Matthews PM. Remote monitoring in the home validates clinical gait measures for multiple sclerosis. Frontiers in Neurology. 2018;9(JUL) (no pagination).
46. Alshraideh H, Otoom M, Al-Araida A, Bawaneh H, Bravo J. A Web Based Cardiovascular Disease Detection System. Journal of Medical Systems. 2015;39(10) (no pagination).
47. Tucker CS, Behoora I, Nembhard HB, Lewis M, Sterling NW, Huang X. Machine learning classification of medication adherence in patients with movement disorders using non-wearable sensors. Computers in Biology and Medicine. 2015;66:120-34.
48. Cook DJ, Schmitter-Edgecombe M, Dawadi P. Analyzing Activity Behavior and Movement in a Naturalistic Environment Using Smart Home Techniques. IEEE journal of biomedical and health informatics. 2015;19(6):1882-92.
49. Zhang O, Minku LL, Gonem S. Detecting asthma exacerbations using daily home monitoring and machine learning. J Asthma. 2021;58(11):1518-27.
50. Rossi LA, Melstrom LG, Fong Y, Sun V. Predicting post-discharge cancer surgery complications via telemonitoring of patient-reported outcomes and patient-generated health data. J Surg Oncol. 2021;123(5):1345-52.
51. Greene BR, McManus K, Ader LGM, Caulfield B. Unsupervised Assessment of Balance and Falls Risk Using a Smartphone and Machine Learning. Sensors (Basel). 2021;21(14):13.
52. Cos H, Li D, Williams G, Chininis J, Dai R, Zhang J, et al. Predicting Outcomes in Patients Undergoing Pancreatectomy Using Wearable Technology and Machine Learning: Prospective Cohort Study. J Med Internet Res. 2021;23(3):e23595.
53. Fritz RL, Dermody G. A nurse-driven method for developing artificial intelligence in "smart" homes for aging-in-place. Nurs Outlook. 2019;67(2):140-53.
54. Forman EM, Goldstein SP, Zhang F, Evans BC, Manasse SM, Butryn ML, et al. OnTrack: development and feasibility of a smartphone app designed to predict and prevent dietary lapses. Transl Behav Med. 2019;9(2):236-4577.
55. Hela S, Amel B, Badran R. Early anomaly detection in smart home: A causal association rule-based approach. Artif Intell Med. 2018;91:57-71.
56. Orchard P, Agakova A, Pinnock H, Burton CD, Sarran C, Agakov F, et al. Improving Prediction of Risk of Hospital Admission in Chronic Obstructive Pulmonary Disease: Application of Machine Learning to Telemonitoring Data. J Med Internet Res. 2018;20(9):e263.
57. Krumm H, Reiss N, Burkert M, Schmidt T, Biehs S, Bohr C, et al. Development of a Computer-Aided Dosage and Telemonitoring System for Patients Under Oral Anticoagulation Therapy. Stud Health Technol Inform. 2018;248:188-95.
58. Finkelstein J, Jeong IC. Machine learning approaches to personalize early prediction of

asthma exacerbations. Ann N Y Acad Sci. 2017;1387(1):153-65.
59. Alshurafa N, Sideris C, Pourhomayoun M, Kalantarian H, Sarrafzadeh M, Eastwood JA. Remote Health Monitoring Outcome Success Prediction Using Baseline and First Month Intervention Data. IEEE j. 2017;21(2):507-14.
60. Riis HC, Jensen MH, Cichosz SL, Hejlesen OK. Prediction of exacerbation onset in chronic obstructive pulmonary disease patients. J Med Eng Technol. 2016;40(1):1-7.
61. Mohktar MS, Redmond SJ, Antoniades NC, Rochford PD, Pretto JJ, Basilakis J, et al. Predicting the risk of exacerbation in patients with chronic obstructive pulmonary disease using home telehealth measurement data. Artif Intell Med. 2015;63(1):51-9.
62. Fernandez-Granero MA, Sanchez-Morillo D, Leon-Jimenez A, Crespo LF. Automatic prediction of chronic obstructive pulmonary disease exacerbations through home telemonitoring of symptoms. Biomed Mater Eng. 2014;24(6):3825-32.
63. Karvounis EC, Tsipouras MG, Tzallas AT, Katertsidis NS, Stefanou K, Goletsis Y, et al. A Decision Support System for the Treatment of Patients with Ventricular Assist Device Support. Methods Inf Med. 2014;53(02):121-36.
64. Jensen MH, Christensen TF, Tarnow L, Johansen MD, Hejlesen OK. An information and communication technology system to detect hypoglycemia in people with type 1 diabetes. Stud Health Technol Inform. 2013;192:38-41.
65. Patel MS, Polsky D, Small DS, Park SH, Evans CN, Harrington T, et al. Predicting changes in glycemic control among adults with prediabetes from activity patterns collected by wearable devices. npj Digital Medicine. 2021;4(1) (no pagination).
66. Richards DM, Tweardy MKJ, Steinhubl SR, Chestek DW, Hoek TLV, Larimer KA, et al. Wearable sensor derived decompensation index for continuous remote monitoring of COVID-19 diagnosed patients. npj Digital Medicine. 2021;4(1) (no pagination).
67. Stehlik J, Schmalfuss C, Bozkurt B, Nativi-Nicolau J, Wohlfahrt P, Wegerich S, et al. Continuous wearable monitoring analytics predict heart failure hospitalization: The link-hf multicenter study. Circulation: Heart Failure. 2020;(no pagination).
68. Han L, Askari M, Altman RB, Schmitt SK, Fan J, Bentley JP, et al. Atrial fibrillation burden signature and near-term prediction of stroke: A machine learning analysis. Circulation: Cardiovascular Quality and Outcomes. 2019;12(10) (no pagination).
69. Kronborg T, Mark L, Cichosz SL, Secher PH, Hejlesen O. Population exacerbation incidence contains predictive information of acute exacerbations in patients with chronic obstructive pulmonary disease in telecare. International Journal of Medical Informatics. 2018;111:72-6.
70. Melillo P, Orrico A, Scala P, Crispino F, Pecchia L. Cloud-Based Smart Health Monitoring System for Automatic Cardiovascular and Fall Risk Assessment in Hypertensive Patients. Journal of Medical Systems. 2015;39(10) (no pagination).
71. Saeedi R, Sasani K, Gebremedhin AH. Collaborative Multi-Expert Active Learning for Mobile Health Monitoring: Architecture, Algorithms, and Evaluation. Sensors (Basel). 2020;20(7):30.
72. Ramkumar PN, Haeberle HS, Ramanathan D, Cantrell WA, Navarro SM, Mont MA, et al. Remote Patient Monitoring Using Mobile Health for Total Knee Arthroplasty: Validation of a Wearable and Machine Learning-Based Surveillance Platform. J Arthroplasty. 2019;34(10):2253-9.
73. Ismail WN, Hassan MM. Mining Productive-Associated Periodic-Frequent Patterns in Body Sensor Data for Smart Home Care. Sensors (Basel). 2017;17(5):26.
74. Benharref A, Serhani MA, Nujum AR. Closing the loop from continuous M-health monitoring to fuzzy logic-based optimized recommendations. Annu Int Conf IEEE Eng Med Biol Soc. 2014;2014:2698-701.
75. Serhani MA, Benharref A, Nujum AR. Intelligent remote health monitoring using evident-

based DSS for automated assistance. Annu Int Conf IEEE Eng Med Biol Soc. 2014;2014:2674-7.
76. Sama A, Perez-Lopez C, Rodriguez-Martin D, Moreno-Arostegui JM, Rovira J, Ahlrichs C, et al. A double closed loop to enhance the quality of life of Parkinson's Disease patients: REMPARK system. Stud Health Technol Inform. 2014;207:115-24.
77. Tzallas AT, Tsipouras MG, Rigas G, Tsalikakis DG, Karvounis EC, Chondrogiorgi M, et al. PERFORM: a system for monitoring, assessment and management of patients with Parkinson's disease. Sensors (Basel). 2014;14(11):21329-57.
78. Sannino G, De Falco I, De Pietro G. An automatic rules extraction approach to support OSA events detection in an mHealth system. IEEE j. 2014;18(5):1518-24.
79. Finkelstein SM, Lindgren BR, Robiner W, Lindquist R, Hertz M, Carlin BP, et al. A randomized controlled trial comparing health and quality of life of lung transplant recipients following nurse and computer-based triage utilizing home spirometry monitoring. Telemed J E Health. 2013;19(12):897-903.
80. Don S, Chung D, Choi E, Min D. An awareness approach to analyze ECG streaming data. J Med Syst. 2013;37(2):9901.
81. Suh MK, Moin T, Woodbridge J, Lan M, Ghasemzadeh H, Bui A, et al. Dynamic self-adaptive remote health monitoring system for diabetics. Annu Int Conf IEEE Eng Med Biol Soc. 2012;2012:2223-6.
82. Guidi G, Pettenati MC, Miniati R, Iadanza E. Heart failure analysis dashboard for patient's remote monitoring combining multiple artificial intelligence technologies. Annu Int Conf IEEE Eng Med Biol Soc. 2012;2012:2210-3.
83. Ganti VG, Carek AM, Nevius BN, Heller JA, Etemadi M, Inan OT. Wearable Cuff-Less Blood Pressure Estimation at Home via Pulse Transit Time. IEEE Journal of Biomedical and Health Informatics. 2021;25(6):1926-37.
84. Rahman MJ, Morshed BI, Harmon B, Rahman M. A pilot study towards a smart-health framework to collect and analyze biomarkers with low-cost and flexible wearables. Smart Health. 2022;23 (no pagination).
85. Lin YF, Shie HH, Yang YC, Tseng VS. Design of a real-time and Continua-based framework for Care Guideline Recommendations. International Journal of Environmental Research and Public Health. 2014;11(4):4262-79.
86. Al-Kababji A, Amira A, Bensaali F, Jarouf A, Shidqi L, Djelouat H. An IoT-based framework for remote fall monitoring. Biomedical Signal Processing and Control. 2021;67 (no pagination).
87. Fritz RL, Wilson M, Dermody G, Schmitter-Edgecombe M, Cook DJ. Automated smart home assessment to support pain management: multiple methods analysis. Journal of Medical Internet Research. 2020;22(11) (no pagination).
88. Grguric A, Mosmondor M, Huljenic D. The SmartHabits: An Intelligent Privacy-Aware Home Care Assistance System. Sensors. 2019;19(4).
89. Geertsema EE, Visser GH, Viergever MA, Kalitzin SN. Automated remote fall detection using impact features from video and audio. Journal of Biomechanics. 2019;88:25-32.
90. Mora N, Matrella G, Ciampolini P. Cloud-Based Behavioral Monitoring in Smart Homes. Sensors. 2018;18(6).
91. Lopez-Guede JM, Moreno-Fernandez-De-Leceta A, Martinez-Garcia A, Grana M. Lynx: Automatic Elderly Behavior Prediction in Home Telecare. BioMed Research International. 2015;2015 (no pagination).92. Abbas M, Somme D, Le Bouquin Jeannes R. D-SORM: A digital solution for remote monitoring based on the attitude of wearable devices. Comput Methods Programs Biomed. 2021;208:106247.
93. Chapron K, Lapointe P, Bouchard K, Gaboury S. Highly Accurate Bathroom Activity

Recognition Using Infrared Proximity Sensors. IEEE j. 2020;24(8):2368-77.
94. Kantoch E. Recognition of Sedentary Behavior by Machine Learning Analysis of Wearable Sensors during Activities of Daily Living for Telemedical Assessment of Cardiovascular Risk. Sensors (Basel). 2018;18(10):24.
95. O'Brien MK, Shawen N, Mummidisetty CK, Kaur S, Bo X, Poellabauer C, et al. Activity Recognition for Persons With Stroke Using Mobile Phone Technology: Toward Improved Performance in a Home Setting. J Med Internet Res. 2017;19(5):e184.
96. Ghose S, Mitra J, Karunanithi M, Dowling J. Human Activity Recognition from Smart-Phone Sensor Data using a Multi-Class Ensemble Learning in Home Monitoring. Stud Health Technol Inform. 2015;214:62-7.
97. Gal N, Andrei D, Nemes DI, Nadasan E, Stoicu-Tivadar V. A Kinect based intelligent e-rehabilitation system in physical therapy. Stud Health Technol Inform. 2015;210:489-93.
98. Calzada A, Liu J, Nugent CD, Wang H, Martinez L. Sensor-based activity recognition using extended belief rule-based inference methodology. Annu Int Conf IEEE Eng Med Biol Soc. 2014;2014:2694-7.
99. Jalal A, Kamal S, Kim D. A depth video sensor-based life-logging human activity recognition system for elderly care in smart indoor environments. Sensors (Basel). 2014;14(7):11735-59.
100. Saho K, Hayashi S, Tsuyama M, Meng L, Masugi M. Machine Learning-Based Classification of Human Behaviors and Falls in Restroom via Dual Doppler Radar Measurements. Sensors. 2022;22(5).
101. Alaraj R, Alshammari R. Utilizing machine learning to recognize human activities for elderly and homecare. Acta Informatica Medica. 2020;28(3):196-201.
102. Zhu H, Chen H, Brown R. A sequence-to-sequence model-based deep learning approach for recognizing activity of daily living for senior care. Journal of Biomedical Informatics. 2018;84:148-58.
103. Nadia K, Morris H. Clinical Features and Differential Diagnosis of Parkinson’s Disease. 2017. p. 103-15.
104. Pakhomov SV, Jacobsen Sj Fau - Chute CG, Chute Cg Fau - Roger VL, Roger VL. Agreement between patient-reported symptoms and their documentation in the medical record. (1936-2692 (Electronic)).
105. Bunzel EW, Park HY, Goz V, Spina N. Patient Reported Outcomes Measures and the Evolving Role of Predictive Analytics in Spine Care. Operative Techniques in Orthopaedics. 2019;29(2):100712.
106. Hahn EA, Cella D, Chassany O, Fairclough DL, Wong GY, Hays RD, Clinical Significance Consensus Meeting Group. Precision of health-related quality-of-life data compared with other clinical measures. InMayo Clinic Proceedings 2007 Oct 1 (Vol. 82, No. 10, pp. 1244-1254).
107. Bevans, M., A. Ross, and D. Cella, Patient-Reported Outcomes Measurement Information System (PROMIS): efficient, standardized tools to measure self-reported health and quality of life. (1528-3968 (Electronic)).
108. COSLA and the Scottish Government. Greater access, better insight, improved outcomes: a strategy for data-driven care in the digital age. The Scottish Government; 2023. p. 43.
109. Lugg-Widger FV, Angel L, Cannings-John R, Hood K, Hughes K, Moody G, Robling M. Challenges in accessing routinely collected data from multiple providers in the UK for primary studies: Managing the morass. Int J Popul Data Sci. 2018 Sep 21;3(3):432.

Supplementary Files

Multimedia Appendixes

Example literature search strategy employed in Medline.
URL: http://asset.jmir.pub/assets/6ddeac821feb549a8903ed7552c5eb95.docx

A copy of the PRISMA flow diagram for the full screening process.
URL: http://asset.jmir.pub/assets/de202229b32ccddc77d752719182e6d3.docx

A summary of the data extracted for each paper included in this review.
URL: http://asset.jmir.pub/assets/d611c7f3d9132cb456fd9907f8dc1580.docx

CONSORT (or other) checklists

Completed PRISMA-ScR checklist.
URL: http://asset.jmir.pub/assets/894760d499eeae8769da424f7dec11e3.pdf