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TECHNICAL REPORT

Digital technologies for the surveillance, prevention and control of infectious diseases

A scoping review of the research literature 2015–2019

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Contents

Figures

Tables

Abbreviations

AI	Artificial intelligence
CDC	US Centers for Disease Control and Prevention
EC	European Commission
ECDC	European Centre for Disease Prevention and Control
EEA	European Economic Area
EHR	Electronic health record
EU	European Union
ICT	Information and communication technologies
GIS	Geographic information systems
HIV/AIDS	Human immunodeficiency virus/acquired immunodeficiency syndrome
IoT	Internet of Things
LOC	Lab-on-chip
MERS-CoV	Middle East Respiratory Syndrome Coronavirus
MeSH	Medical Subject Heading
PRESS	Peer-Review of Electronic Search Strategies
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
QA	Quality assurance
UK	United Kingdom
USA	United States of America
WHO	World Health Organization

Executive summary

New developments in information and communication technologies (ICT), particularly in digital technologies, have the potential to significantly improve the speed and accuracy of key public health functions such as infectious disease diagnostics, surveillance, forecasting, outbreak detection and response. It is important to understand the range and types of digital technology available, as well as contextual insights such as disease and geographical areas of application, when attempting to assess the benefits and risks of digital technologies to deliver public health functions. The objective of this scoping review is to obtain an estimate of the size and nature of the scientific literature available on digital technologies with the potential to benefit or disrupt key public health functions, focusing on infectious disease surveillance, prevention and control.

We conducted a scoping review of the literature published between 2015 and 2019 on the use of digital technologies for the surveillance, prevention and control of infectious diseases. The scoping review protocol was developed following the PRISMA-ScR checklist. We ran peer-reviewed search strategies in PubMed, Scopus, the Cochrane Database of Systematic Reviews and the ACM Digital Library. We also searched CORDIS – the European Commission's primary public repository – to identify relevant EU-funded research projects and conducted targeted searches in Google. Study selection was based on pre-defined inclusion criteria and included a pilot screening exercise to ensure a consistent approach among all members of the study team. Using a pre-designed extraction template, we extracted data from each study on publication details, geographical context, digital technologies, infectious diseases, key public health functions, and the potential benefits, obstacles and negative impacts of using the digital technologies in the given context. Digital technologies were categorised according to 15 high-level technology groups. These include cognitive technologies such as artificial intelligence, and autonomous devices and systems such as drones. Technologies were also classified against six key public health functions of relevance to infectious disease control, for example surveillance, signal detection and outbreak response.

The database/repository searches returned a total of 5 780 unique references. A further 14 relevant articles were identified through CORDIS, and 31 from targeted Google searches. Of these, 502 articles were identified as eligible for inclusion.

The broad nature of the scoping review helped identify relevant knowledge gaps, highlight possible areas for future research (e.g. in-depth systematic reviews or reviews of reviews into the application of one or more technologies to support a specific public health function), and determine the next steps for ECDC’s strategy in relation to the use of digital technologies to deliver key public health functions. In some areas there appears to be sufficient primary studies to conduct a systematic review. These are: infectious disease surveillance and forecasting using either cognitive technologies such as artificial intelligence, data analytics including big data, or simulation technologies. For specific infectious diseases, there appears to be sufficient evidence to conduct systematic reviews on the use of digital technologies to forecast dengue, or malaria, and the same applies to for the forecasting and surveillance of influenza. In one area – use of data analytics for the surveillance, monitoring and detection of infectious disease trends and outbreaks – eight systematic reviews were identified, which may be sufficient to conduct a review of reviews.

The technologies identified (33 in this review) were grouped into 15 high-level technology groups to facilitate data extraction and presentation. However, the broad spectrum of technologies and the large variation of study designs and outcomes, suggest that it could be challenging to systematically collate sufficient information on the application of one or more technologies to a specific public health function. In addition, a large number (almost three quarters of the articles identified) described digital technology intervention at the conceptual or piloting phase, suggesting a lack of information relating to implementation and evaluation.

The review identified several barriers to successful roll-out of digital technologies for key public health functions as described in the articles selected. These were grouped into categories: access to good quality data; technological and human resources; physical and network infrastructure; safety and ethics, and a range of interrelated political, social and environmental issues. The broad spectrum suggests that the use of digital technologies to support and improve key public health functions will require a systems approach to be successful and have a positive impact on public health outcomes.

Despite the identification of several areas where the next step could be a systematic review, the points listed above suggest that additional desk searches and reviews would probably not be the most appropriate use of time and resources. A more appropriate next step would be to complement the scoping review by mapping the digital technologies being researched and/or implemented to support key public health functions. It would also be useful to gather lessons learned across the EU/EEA through surveys, interviews and consultations, given that a similar exercise had to be cancelled in 2020 due to a lack of resources as a result of the pandemic. At the same time, we would aim to establish closer contacts with different stakeholders active in those fields relevant to digital public health.

In 2021, ECDC is holding consultations with EU and Member State representatives to exploit the momentum that came with the COVID-19 pandemic in order to bring public health onto the digitalisation agenda at EU and national

level. This will help us to gain a better understanding of the current state of play, and facilitate contact and exchange between the relevant stakeholders in digital and health/public health policy, regulation and practice.

The COVID-19 pandemic has accelerated the digitalisation of many aspects of everyday life, and Europe has been one of the epicentres of the pandemic ever since the spring of 2020. It is therefore an appropriate time to explore the impact of COVID-19 on the digitalisation of health and public health in Europe, as well as the effectiveness of digital public health interventions in a more structured and systematic manner.

1. Background

Context

Outbreaks of infectious disease outbreaks are unpredictable and can have detrimental and long-lasting effects on society and the health of individuals [1]. For example, the 2014-15 outbreak of Ebola in West Africa had adverse consequences on both the health of the population and healthcare systems, the latter caused by factors such as healthcare worker deaths and the reallocation of scarce resources away from routine health services [2]. More recently, the outbreak of coronavirus disease (COVID-19) due to severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) in December 2019 [3] caused enormous loss of life and global economic repercussions, the full extent of which are still not completely understood. COVID-19 also has social implications for individuals and societies through the heavy burden imposed on health and social care systems, and the isolation and lockdown measures adopted to slow its spread [4, 5].

It is difficult to predict the timing and characteristics of future infectious disease outbreaks - for example their mode of transmission, incubation period and case fatality rate [6]. However, researchers note that, despite these uncertainties, there will probably be future regional and global outbreaks of infectious disease that could have similarly significant and long-term impact [7-9]. The above examples underline the numerous risks and challenges that infectious diseases continue to pose at regional, national and global level, highlighting the need for key public health functions such as surveillance, monitoring, outbreak detection, response and collaboration. Moreover, the diverse factors that influence the risk of infectious disease outbreaks, such as agriculture and land use, urbanisation, trade, travel, animal health and population growth, are constantly changing and evolving [10].

New developments in information and communication technologies (ICT) – particularly in the area of digital technologies – have the potential to significantly improve key functions associated with public health – e.g. the speed, reliability and reach of infectious disease surveillance, prevention and control [1]. Digital technologies can improve the ability to both detect and respond to emerging infectious diseases by providing automatic and real-time mapping, creating new sources of data, and facilitating the discovery of pathogens, while at the same time reducing costs [1, 10-13]. Digital technologies can also be harnessed to counter some of the risks that such technologies pose for infectious disease prevention and control, for example the rapid dissemination of misinformation on social media.

However, there are still challenges associated with understanding the potential use, benefits and limitations of digital technologies for the prevention, surveillance and control of infectious diseases. Novel technologies for health emergencies are often not standardised in public health functions and tend to be used on an ad hoc basis [1]. There are also varying capabilities in different geographical settings as the roll-out of technology depends on factors such as infrastructure, equipment and trained personnel [14]. It is therefore necessary to consider the range and types of digital technology, as well as contextual insights such as disease and geographical area of application, when attempting to assess the benefits and risks of using digital technologies to deliver public health functions.

Study objectives

The objective of the scoping review was to obtain an estimate of the size and nature of the scientific literature available on digital technologies with potentially beneficial or disruptive effects for key public health functions. The focus was on infectious disease surveillance, prevention and control – i.e. to identify and map a body of evidence in a given field, rather than to critically appraise it or provide an in-depth synthesised answer to a more specific question [15].

The specific research questions that form the basis of this scoping review are presented in Box 1. From a strategic perspective, the scoping review will serve to identify and collate evidence on digital technologies of potential relevance to public health – infectious diseases in particular – and ECDC's mandate. The review will be used as a source of information for ECDC and its key stakeholders to support strategic decision-making in the field. The outcomes of the study will help ECDC to develop its activities in this increasingly important and fast-evolving area, and to identify key topics that warrant further research.

Box 1. Research questions for the scoping review on digital technology for infectious disease surveillance, prevention and control

- What digital technologies have been discussed in the scientific literature over the last five years and in relation to which key public health functions?
- Do systematic reviews, comparative primary studies and/or modelling studies exist for the technologies identified and for key public health functions, and if yes, for which?
- What are the main study characteristics and findings of the studies identified, which countries and organisations contributed, and what obstacles/barriers were identified?

The second objective was to develop a glossary of terms relevant to the digital solutions and ICTs identified from analysis of the scoping review, related to infectious disease surveillance, prevention and control.

2. Methodology

The aim of the review was to develop a broad understanding of the evidence from recent research on the use of digital technologies for infectious disease surveillance, prevention and control.

The scoping review protocol was developed following the PRISMA-ScR checklist and, based on the broad scope of the research questions, the following databases and repositories of peer-reviewed scientific literature were chosen: (i) PubMed; (ii) Scopus; (iii) Cochrane Database of Systematic Reviews (Wiley); and (iv) ACM Digital Library. The search strategies followed the same broad format across the databases but were tailored to make use of each database's individual search functions (e.g. MeSH terms, proximity operators, etc.). Specific search strategies for each database/repository are detailed in the supplementary material (Annex C). The database/repository searches were run on 25 November 2019, and the results were collated using EndNote X8.2 reference management software. The search strategy was limited to five years (2015-2019), and was peer-reviewed using the PRESS approach (Peer-Review of Electronic Search Strategies) [16]. Searches were also performed in CORDIS – the European Commission's primary public repository – to identify relevant EU-funded research projects, and targeted searches were run in Google.

Study selection was based on pre-defined inclusion criteria and a pilot screening exercise ensured a consistent approach between all members of the study team. Study selection was based on the inclusion/exclusion criteria outlined in Table 1.

Table 1. Inclusion and exclusion criteria for studies in the scoping review

	Inclusion	Exclusion
Population/topic of interest	Infectious disease surveillance, prevention and control in humans	Infectious disease surveillance, prevention and control in plants and animals
Intervention	Any emerging or novel use of digital technologies for public health[1]	Any digital technologies that are not considered emerging within the past five years
Comparison	Any or no comparison	N/A
Outcome	Any potential benefit or disruption to key public health functions	No discussion of potential benefits or disruptions
Study	Completed research studies, research protocols, conference proceedings with full text, theoretical papers, commentaries, letters, working papers, books and book chapters.	Conference proceedings that do not include full text
Date	Published in the last five years (2015– 2019)	Published before 2015
Language	English articles included and extracted non-English articles included but data only extracted from the abstract	No exclusion based on language, but data only extracted from abstracts and articles available in English

Using a pre-designed extraction template, data were extracted from each included study on publication details, geographical context, digital technologies, infectious diseases, public health key functions, and the potential benefits, obstacles and negative impacts associated with using the digital technology of interest in the given context. Where possible, drop-down menus were assigned to columns to facilitate data filtering and analysis. During the data extraction phase, the research team communicated regularly with each other to make sure that any uncertainties about how to complete the template were resolved as early as possible.

All data recorded using drop-down menus or short-answer formats were analysed using Microsoft Excel. These analyses explored publication year, article/study type, geographical context, infectious disease, digital technology and public health key function, including cross-analysis of the relationships between these categories. These analyses were all conducted by two core members of the research team.

For the open-text data column on barriers to successful implementation of digital technologies, a rapid manual analysis was conducted in Excel to arrive at a set of key themes. The process to identify the key themes was undertaken qualitatively and in an iterative manner, coding the extracted open-text data on barriers under the identified themes while continuing to identify additional themes and to group the themes according to shared concepts. This process of verifying and refining the themes produced a final list of key overarching themes. (See supplementary material at the following link for further details on methodology including search strategies and the PRISMA checklist.)

[1] For the purposes of this study, we include digital technologies employed for public health in ways that were novel or innovative at the time of publication (i.e. within the last five years). This includes emerging technologies such as artificial intelligence and Internet of Things, but also novel uses of established technologies such as smartphones.

3. Key study variables

In this section, we set out the high-level technology groups and public health key functions against which we conduct multiple cross-analysis of other study variables in the coming sections.

High-level technology groups

The data extraction phase resulted in numerous digital technologies cutting across different areas and ranging from highly-specific to more generic technology. Some of the technology could be considered to belong to the same 'family' or high-level 'group'. To facilitate the analysis of the data, the digital technologies recorded in the data extraction template were matched against the most relevant technology descriptions from the European Commission's Digital Single Market glossary [17]. Drawing on this existing glossary, some additional sources and previous work by RAND Europe in the field, a set of 15 high-level technology 'groups' were produced to cluster the digital technologies recorded in the data extraction template. The mapping that resulted from this grouping is presented in Table 2. Some digital technologies appear in two groups because, when examining the use of the technology described in each individual paper, it was found that certain uses fell under one high-level technology group while others were more closely related to another. In the case of biosensors, for example, this technology was discussed by different sources as either part of an Internet of Things (IoT) network or an example of nanotechnology.

Table 2. Mapping of digital technologies into high-level technology groups

High-level technology group	Digital technology classification in extraction template
Advanced manufacturing technologies	3D-printing
Autonomous devices and systems	Drones
	Robotics
Blockchain/distributed ledger technology	Blockchain/distributed ledger technology
Cloud computing/cloud-based networks	Cloud computing/cloud-based networks
Cognitive technologies	Artificial intelligence (AI)
	Expert systems
	Machine learning
	Natural language processing
	(Artificial) neural networks
Crowdsourcing platforms	Crowdsourcing
Data analytics (including big data)	Big data analytics (incl. data mining)
	Health informatics
	Parallel computing
	Social media and mobile data analysis
e-health	Digital health/e-health/m-health
	Electronic health records (EHRs)
	Telemedicine
Imaging and sensing technologies (including GIS)	Geographic Information Systems (GIS)
	Health informatics
	Image processing
	Satellite communication/imaging (incl. earth observation and remote sensing)
Immersive technologies	Virtual/augmented reality
Integrated, ubiquitous fixed and mobile networks	Cellular networks
	Smartphones and tablet computing devices
Internet of things (IoT)	Biosensors
	Internet of things (IoT)
	Wireless sensor networks
Nanotechnology and microsystems	Biosensors
	Digital DNA/RNA/protein analysis
	Lab-on-chip (LOC)
	Nanotechnology
Simulation	Mathematical models/simulations
Wearables (including ingestibles)	Wearables (incl. smart fabrics, ingestibles)

Note: Some digital technologies appear in two groups, because when examining the use of the technology described in each individual paper, it was found that certain uses fell under one high-level technology group while others were more closely related to another.

Public health key functions

For the purpose of this scoping review six key public health function categories were devised.

1. Screening and diagnostics: identifying infectious disease in individuals.
2. Surveillance and monitoring: monitoring infectious disease patterns and trends in populations.
3. Forecasting: forecasting infectious disease outbreaks (e.g. for outbreak prediction).
4. Signal/outbreak detection and validation: detecting and validating infectious disease outbreaks.
5. Outbreak response: responding to infectious disease outbreaks.
6. Communication/collaboration: Communication involves informing, educating and empowering people in relation to infectious diseases through the use of digital technologies (e.g. social media). Collaboration refers to technology, platforms and tools used to improve reporting and communication across disciplines or sectors and the identification, selection and analysis of evidence.

These categories were arrived at by mapping a selection of high-level key public health functions (such as surveillance, monitoring, prevention, control, and prediction) against the World Health Organization's 10 essential public health operations [18] and the US Centers for Disease Control and Prevention's essential public health services [19] to identify areas of commonality that might help define key functions.

4. Results

Literature search and study selection

Database and repository searches

The database/repository searches returned a total of 5 780 references. A summary of the search results broken down by database/repository is presented in Table 3.

Table 3. Summary of search results from scientific database and repository searches

Database	Total number of results	Total number of results minus duplicates from previous database/repository searches
PubMed	3 147	3 147
SCOPUS	2 775	1 869
Cochrane Database of Systematic Reviews (Wiley)	357	297
ACM Digital Library	497	467
Total for PubMed, SCOPUS, Cochrane and ACM, excluding duplicates		5 780

After screening titles and abstracts picked up by the database/repository searches, 501 unique articles were identified as eligible for full-text review, and 5 279 were excluded.

Targeted searches

While conducting data extraction for the articles included from the main database and repository searches, we identified a total of 33 different digital technologies. Of these, 15 were discussed in fewer than ten articles. These were 3D-printing; biosensors; blockchain/distributed ledger technology; cellular networks; drones; expert systems; health informatics and electronic health records (EHRs); image and signal processing; lab-on-chip (LOC); natural language processing; parallel computing; robotics; telemedicine; virtual/augmented reality; and wireless sensor networks. Targeted searches were run for these technologies in Google, incorporating 'digital technologies' as keywords to complement the database searches. These targeted searches identified 31 additional papers for inclusion in the full-text review.

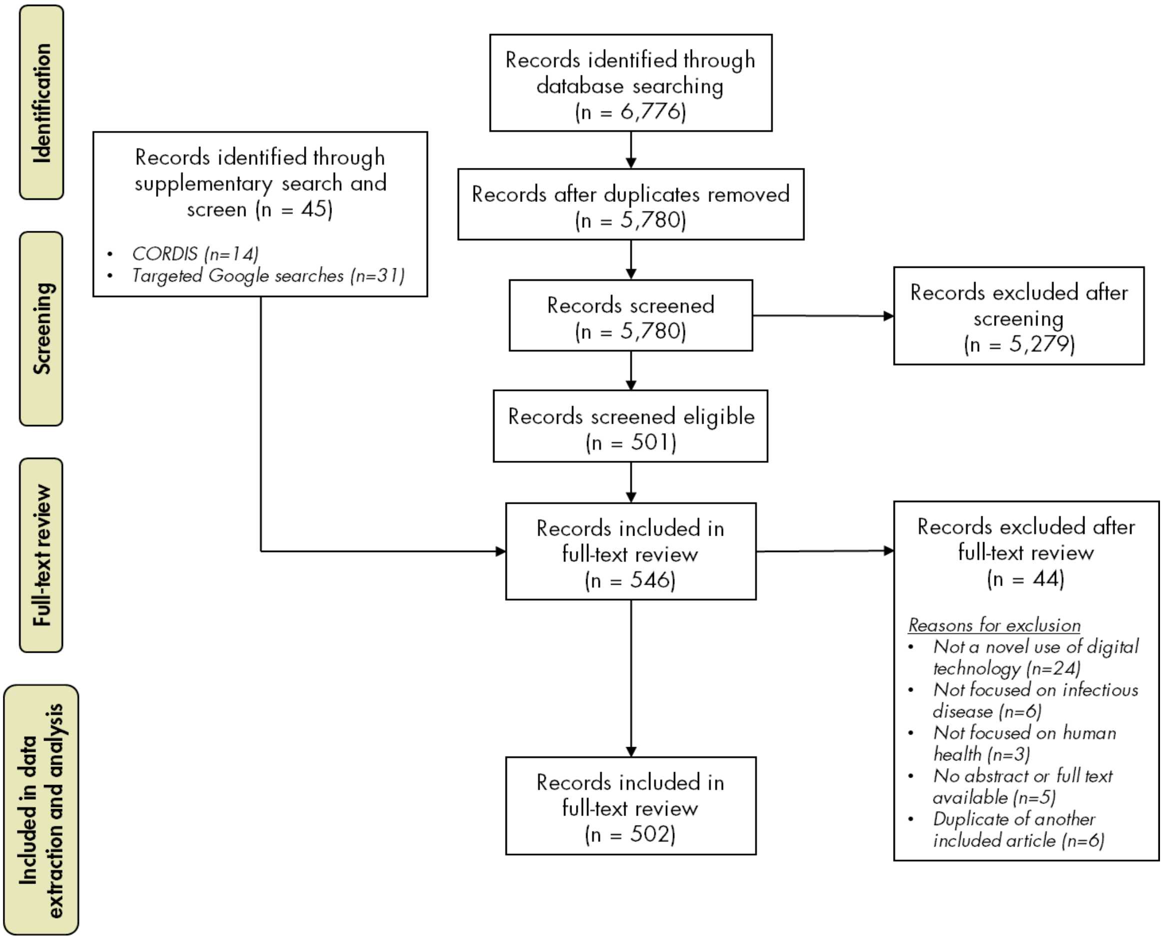
CORDIS search

The search of the CORDIS repository identified five relevant projects, from which 14 project documents were extracted for inclusion in the full-text review. In the case of two CORDIS projects, the search yielded no documents. In both cases this was due to the projects being at an early stage, with only basic technical reporting documents and no academic outputs. For both cases, summary information from the project abstract was extracted and recorded in a separate sheet.

Study selection

The process of study selection is summarised in the PRISMA diagram [20] presented in Figure 1. The screening of titles and abstracts identified 501 potential articles from the database/repository search, 14 from CORDIS and 31 from the targeted searches, resulting in 546 articles taken forward for full-text review. Of these 546 articles, 44 were excluded from data extraction and analysis (see Annex F in the supplementary material). The reasons for exclusion are summarised in Figure 1. This resulted in 502 unique articles for final inclusion and analysis.

Figure 1. PRISMA flow diagram [20] for the scoping review



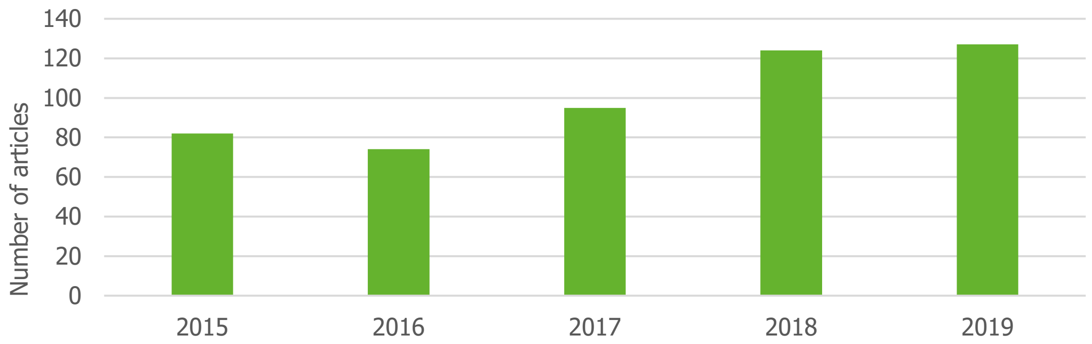
Overview of the literature included

This section presents an overview of the 502 articles included for data extraction and analysis, summarised in terms of publication date, article/study type and geographical context. Throughout this section, examples of articles are included in the scoping review, to illustrate a point and/or to add context to the analysis. Where possible, literature reviews were preferred for these examples, particularly systematic reviews, due to the wider body of evidence that they represent. Articles identified by full-text reviewers as being of particular interest were also used as examples, as were articles discussing or originating from EU/EEA countries, given ECDC's remit as an EU agency. Otherwise, the choice of articles referenced below was subjective and not intended to prioritise any article(s) over the rest of the literature.

Publication date

There appears to have been a slight increase in the number of publications of relevant literature in more recent years. Half of the 502 articles included were published in the last two years of the screening period: 2018 (124 articles) and 2019 (127 articles) (see Figure 2.)

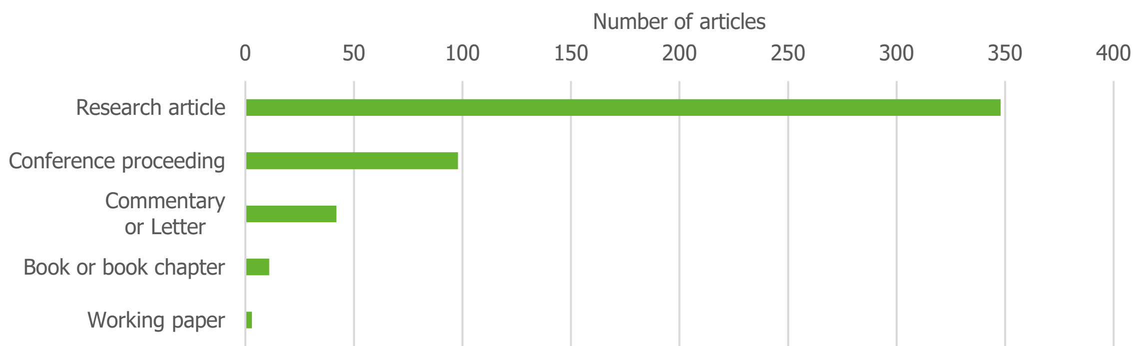
Figure 2. Number of included articles published in each year (2015–2019)



Article and study type

Articles were sorted according to the following types: i) research articles; ii) conference proceedings; iii) commentaries or letters; iv) books or book chapters and v) working papers. As shown in Figure 3, research articles constitute 348 of the 502 articles that were analysed. Of the remaining 154 articles, 98 were conference proceedings, 42 were commentaries or letters, 11 were books or book chapters, and three were working papers (Figure 3).

Figure 3. Number of each article type included in the reviewed literature



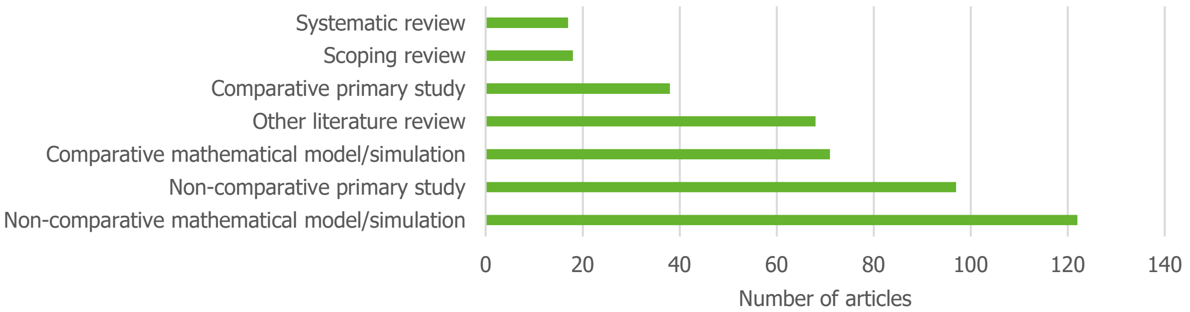
Study types were classified according to the following categories: (i) non-comparative mathematical model/simulation; (ii) comparative mathematical model/simulation; (iii) non-comparative primary study; (iv) comparative primary study; (v) systematic review; (vi) scoping review, and (vii) other literature review. In total, 431 of the 502 articles included reported findings from research studies. These included the 348 research articles noted above, along with 71 conference proceedings, six commentaries, five book chapters and one working paper. Research studies refer to studies that investigate variables and their characteristics to enhance understanding of a topic [21]. Of the 431 articles reporting on research studies, 193 represented mathematical modelling or simulation studies. The majority did not provide a comparison (122 articles), but a significant minority compared the proposed model's accuracy to that of an existing or alternative model (71 articles). One example of a comparative mathematical model/simulation study is Chae et al.'s work which used deep-neural-network (DNN) and long-short-term-memory (LSTM) learning models to forecast the incidence of three infectious diseases in South Korea [22]. The researchers compared the performance of their model, which incorporated social media and weather data and drew on deep learning analysis, to that of the existing autoregressive integrated moving average (ARIMA) model, to predict chickenpox (varicella), malaria and scarlet fever one week in the future [22].

Primary research studies (both observational and experimental) comprise a further 135 articles. Of these, the majority are again non-comparative (97 articles), with the remainder comparing the technology to an alternative, typically an existing or gold-standard approach to the same activity (38 articles). For example, Hoshi et al. field-tested a 3D-printed light trap designed to reduce the spread of vector-borne infectious diseases [23]. They compared the efficiency of their low-cost, light-weight mosquito trap to two existing gold-standard alternatives (the US Centers for Disease Control and Prevention (CDC) light trap and the BG Sentinel 2 trap), concluding that their 3D-printed model is cheaper, lighter and more easily customisable, but equally efficient at trapping mosquitos [23].

The remaining 103 research articles are literature reviews - 17 are systematic reviews, 18 are scoping reviews, and 68 are other literature reviews (primarily narrative reviews without a systematic search strategy). Systematic reviews seek to explore a range of relevant research topics, including the use of data from online social networks (Facebook, Twitter, etc.) to detect and track infectious disease pandemics worldwide [24], and the concepts and designs underpinning mobile phone applications developed in response to the 2014–15 Ebola outbreak in West Africa [25].

The number of different study types in the reviewed literature is illustrated in Figure 4.

Figure 4. Number of each study type included in the reviewed literature



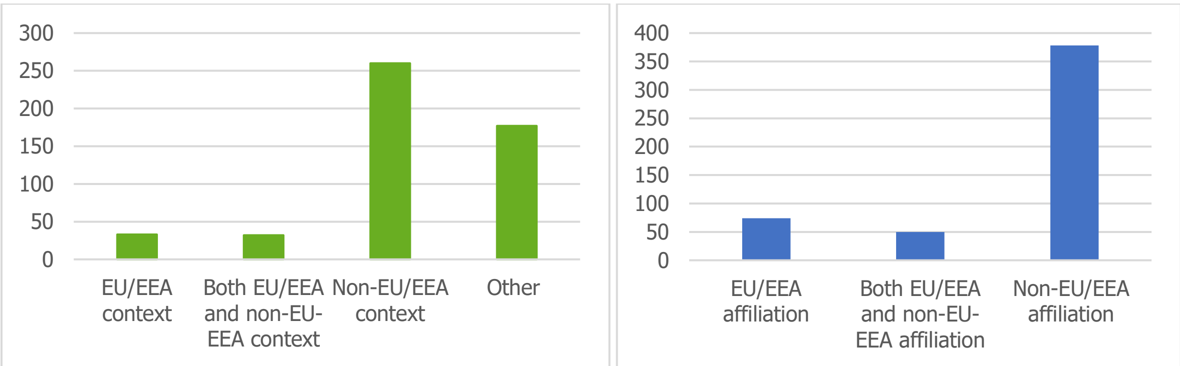
Geographical context

The geographical context in which the technology or technologies were discussed, and the location of the first and last authors' organisational affiliations were identified. For the purpose of this analysis, the first and last authors were considered to be the key contributing authors. Note also that because the search was run in November 2019 and much of the data extraction was completed before 31 January 2020, it was agreed that the UK would be treated as an EU/EEA country for the purposes of this analysis.

The geographical context was classified according to the following categories i) within the EU/EEA; ii) outside the EU/EEA; and iii) both within and outside the EU/EEA. A fourth category, iv) other, was used when the geographical context was either not applicable or not reported. This was the case in 177 of the 502 included articles (shown together as 'other'). The geographical context was not applicable when a model or technology was proposed, developed or tested without reference to a specific geographical context, instead using either laboratory settings or a hypothetical context. For example, Alessa and Faezipour (2019) use linear regression models to classify Twitter posts and historical reports from the CDC to predict flu outbreaks without specifying a country context in which the framework is tested [26].

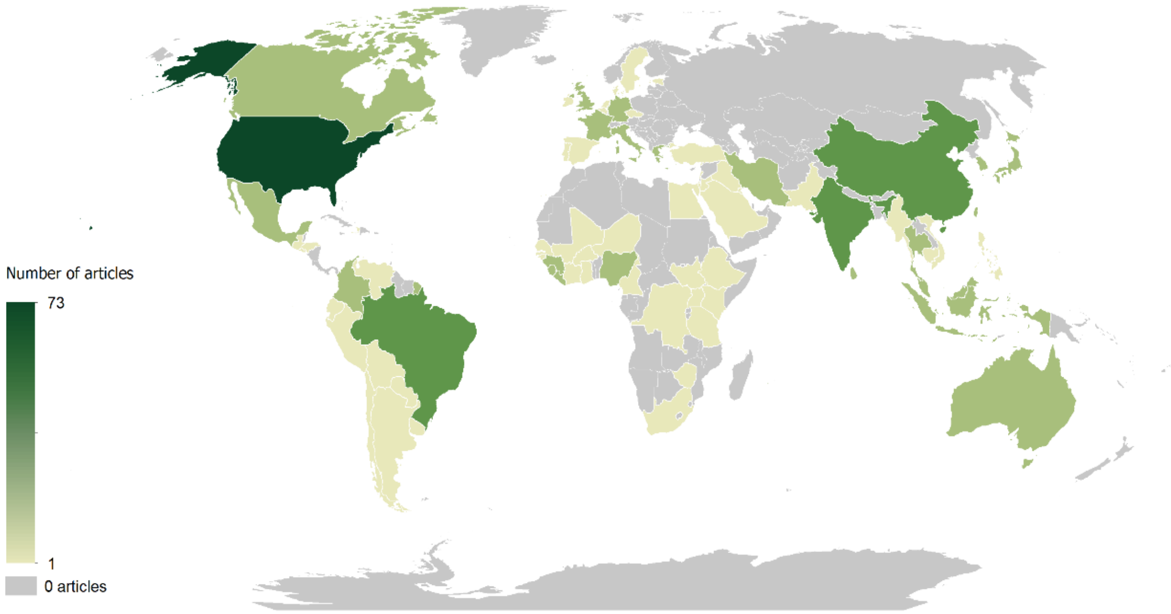
For the remaining 325 articles, the geographical context in which the technology was discussed was most often located outside of the EU/EEA (260 articles) (Figure 5, left frame). In total, 32 articles were identified discussing digital technologies in the context of both EU/EEA and non-EU/EEA countries, and 33 articles discussing digital technologies in EU/EEA countries only. Non-EU/EEA countries were also predominant when looking at the organisational affiliation of the first and last author (Figure 5, right frame).

Figure 5. Number of articles included by geographical focus of research (green) and by location of the first/last authors' organisational affiliation (blue)



Figures 6 and 7 present the number of articles discussing the use or application of digital technologies for infectious disease surveillance, prevention and control in each country. The map in Figure 6 provides an overview of the countries and regions receiving most research interest worldwide. Figure 7 presents the number of articles exploring the use of digital technologies in the 'top 20' countries discussed most frequently in the literature (a full list of all 80 countries included is provided in Annex H). The data also includes articles that discussed the use of digital technologies in several countries. For example, one article investigated the use of internet-based biosurveillance methods for vector-borne diseases in Brazil, India, Singapore, Indonesia, Bolivia, Argentina, Mexico, the Philippines, Thailand, Venezuela, and Australia [12], all of which are counted separately in the data underlying Figures 6 and 7.

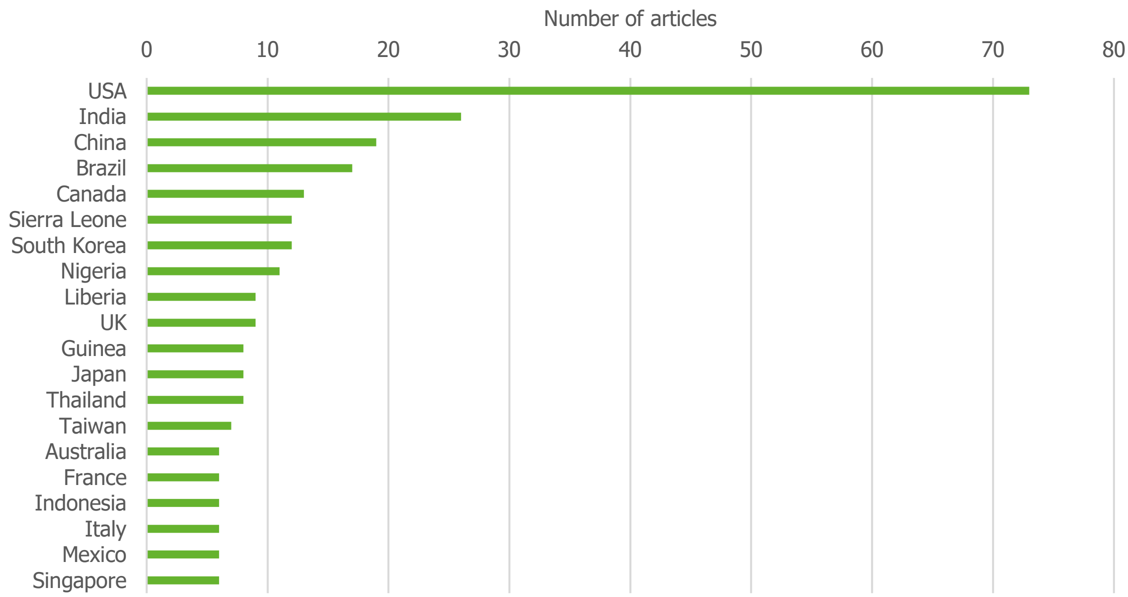
Figure 6. Geographical focus of digital technologies research



ECDC Administrative boundaries: © EuroGeographics © UN-FAO © Turkstat. The boundaries and names shown on this map do not imply official endorsement or acceptance by the European Union. Map produced 15 April 2021.

Non-EU/EEA countries are much more commonly discussed as the focus of the interventions than EU/EEA countries. The most commonly referenced country by a wide margin is the USA (73 articles), followed by India (26 articles), China (19 articles), Brazil (17 articles), Canada (13 articles), and Sierra Leone and South Korea (12 articles each). Examples of non-EU/EEA research include an article investigating how Google search trends can be used to predict disease outbreaks in the Chandigarh Union territory and Haryana state of India [27]. An example of an article with a wider geographical scope explores the use of a machine learning method analysing flu-related internet search data for influenza surveillance in eight Latin American countries [28].

Figure 7. 'Top 20' countries in terms of numbers of included articles discussing the use of digital technologies in the context of these countries



Far fewer articles discuss the use of digital technologies in countries within the EU/EEA. The most commonly discussed countries are the UK (nine articles), France (six articles) and Italy (six articles). These are the only EU/EEA countries that appear in the 'top 20' shown in Figure 7. Examples of research from these countries include a study investigating the use of sensors and peripheral temperature measurements for febrile patients in France [29], and a study using Bayesian analysis to explore the mechanisms influencing the spread of the 2009 influenza pandemic in England [30].

Table 4 summarises the number of articles discussing digital technologies for each key public health function in the EU/EEA countries for which publications were identified. Note that, because some articles cover more than one key public health function and, in some cases, more than one country, the numbers presented in Table 4 cannot be directly compared with those presented above.

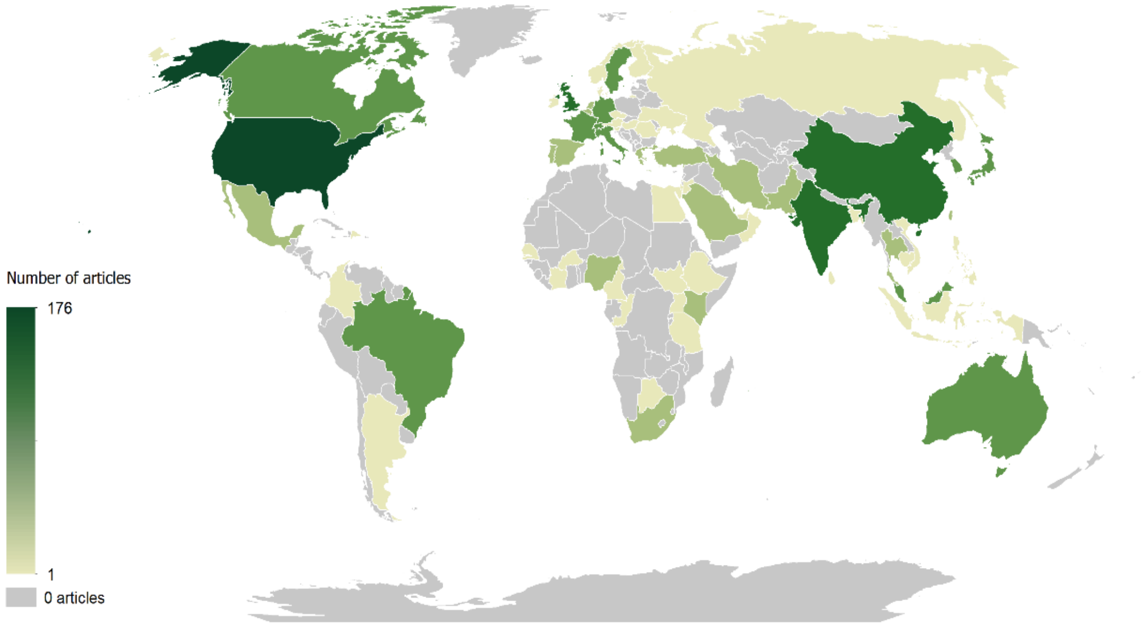
Table 4. Heat table of articles discussing digital technologies with geographical context in EU/EEA countries, organised by key public health function

NUMBER OF ARTICLES INCLUDED		Public health key function					
		Screening and diagnostics	Surveillance and monitoring	Forecasting	Signal/outbreak detection and validation	Outbreak response	Communication/collaboration
EU/EEA Country	Belgium		2	1			
	Czech Republic		1				
	Denmark		1				
	Estonia		1				
	France	1	5				
	Germany	2		1	1		
	Greece	2					
	Ireland		1				
	Italy	1	5		1		
	Netherlands		1				
	Spain		1				
	Sweden		2	2			
	UK	1	7	1	1		

When looking at author affiliation, almost three quarters of all the articles analysed (378 articles) had first and last authors from exclusively non-EU/EEA organisations.

(Figure 8 and Figure 9 break down information on contributing authors to country level. The geographical map presented in Figure 8 shows the location of contributing authors' organisational affiliations. Figure 9 goes on to provide the number of articles for which first and/or last authors are affiliated with organisations based in each of the most commonly represented countries (a full list of all contributing countries is provided in Annex G of the supplementary material.)

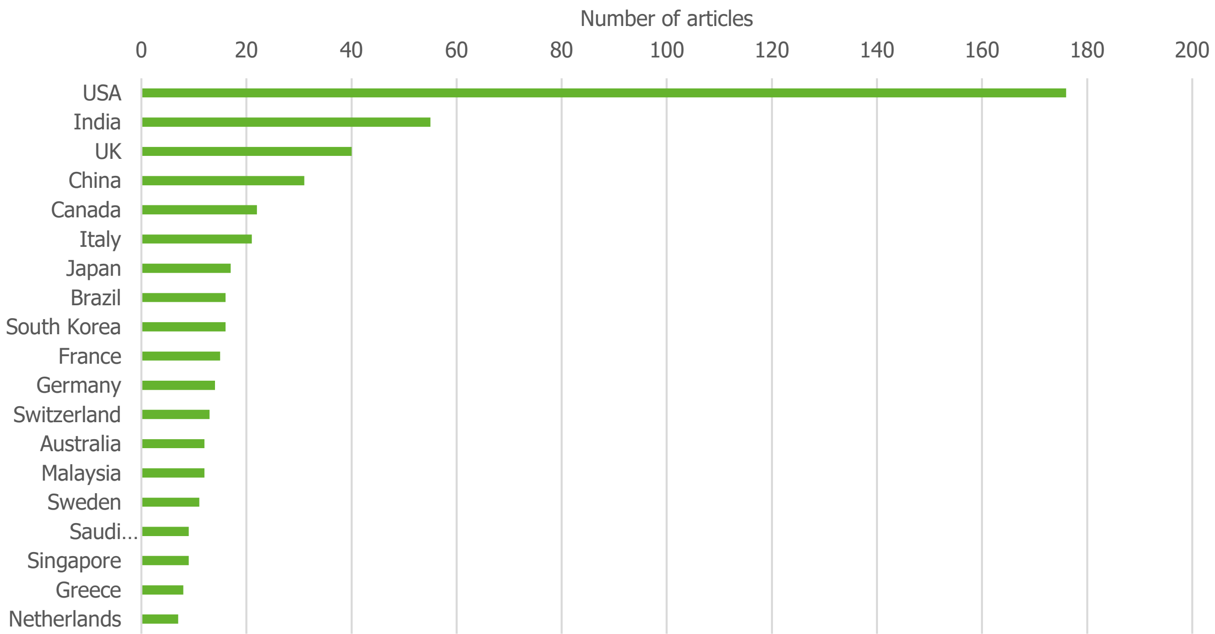
Figure 8. Map showing the number of articles and location of first and/or last author's organisational affiliations for each country



ECDC Administrative boundaries: © EuroGeographics © UN-FAO © Turkstat. The boundaries and names shown on this map do not imply official endorsement or acceptance by the European Union. Map produced 15 April 2021.

Non-EU/EEA countries that appear prominently in Figures 6 and 7 (i.e. the figures presenting the geographical focus of the research) dominate in Figures 8 and 9 as well. The USA is again the front-runner by a large margin (176 articles), followed by India (55 articles), China (31 articles) and Canada (22 articles).

Figure 9. 'Top 19' countries in terms of number of articles included and location of first and/or last author's organisational affiliations for each country[2]



[2] Six countries were the location of first and/or last author organisational affiliations for six articles, and therefore tied in 20th place. Therefore these countries (Iran, Nigeria, Portugal, South Africa, Spain and Turkey) were omitted from the figure.

If we focus on EU/EEA countries and the UK, those that make the 'top 20' are the UK (40 articles, the third most frequent contributor after the USA and India), Italy (21 articles), France (15 articles), Germany (14 articles), Sweden (15 articles), Greece (eight articles) and the Netherlands (seven articles). Other EU/EEA countries that do not make the 'top 20' but are nonetheless represented in the data on first/last author affiliations are Portugal (six articles), Spain (six articles), Belgium (four articles), Hungary (two articles), Romania (two articles), Slovenia (two articles), and one article each from Austria, Czech Republic, Denmark, Finland and Ireland. Table 5 summarises the number of articles written by first/last authors with organisational affiliations in EU/EEA countries, focusing on each key public health function. Note that because some articles cover more than one key public health function, the numbers presented in Table 5 cannot be directly compared with those presented above.

Table 5. Heat table of articles authored by first/last authors with organisational affiliations in EU/EEA countries, organised by key public health function

		Public health key function					
	NUMBER OF ARTICLES INCLUDED	**Screening and diagnostics**	**Surveillance and monitoring**	**Forecasting**	**Signal/outbreak detection and validation**	**Outbreak response**	**Communication /collaboration**
EU/EEA Country	Austria	1					
	Belgium	1	1	2			
	Czech Republic		1				
	Denmark		1				
	Finland						1
	France	3	9	4	1		1
	Germany	2	7	3	1	1	
	Greece	4	2	3			
	Hungary		2				
	Ireland				1		
	Italy	2	13	4	2	1	
	Netherlands	1	1	3	1	1	
	Norway		1	1			
	Portugal	2	3	1			
	Romania	2					
	Slovenia	1	1			1	
	Spain	3		1	1		1
	Sweden	1	6	4	1	2	
	UK	12	18	6	2	6	1

Examples of digital technology applications for public health discussed in EU/EEA country contexts include Influenzanet, which uses participatory surveillance by citizens of 10 EU countries via crowdsourcing platforms to monitor the incidence of influenza-like illness [31], and technology to forecast the risk of mosquito-borne infectious disease in European countries. Big data from air passenger logs and Twitter, along with estimates of *Aedes albopictus* mosquitoes' ability to act as vectors for disease transmission, have been used to forecast outbreaks of chikungunya in Europe [32]. Furthermore, the use of environmental data collected through remote sensing and geographical information systems (GIS) has been proposed for the identification of conditions favourable to mosquitoes to facilitate the prediction of West Nile virus outbreaks in Europe and neighbouring countries [33].

Box 2. Key takeaways – overview of the literature included

In general, the number of relevant papers published per year increased during the period 2015−2019, although the five-year period studied was short. A total of 502 articles on the use of digital technology for infectious disease surveillance, prevention and control were identified for the purpose of this scoping review.

The bulk of the literature included comprised research articles (348 articles) and conference proceedings (98 articles). A total of 193 mathematical model/simulation studies, 135 primary studies and 17 systematic reviews were identified. Most of the studies were non-comparative.

Only 65 articles explored the use of digital technologies for infectious disease in EU/EEA countries (sometimes alongside their use elsewhere). The study authors were also more commonly affiliated with organisations based in non-EU/EEA countries, but EU/EEA countries were represented in 128 articles. The USA accounted for the largest share of articles by a wide margin, for both technology context and key contributor affiliations.

Infectious diseases targeted by the digital technologies

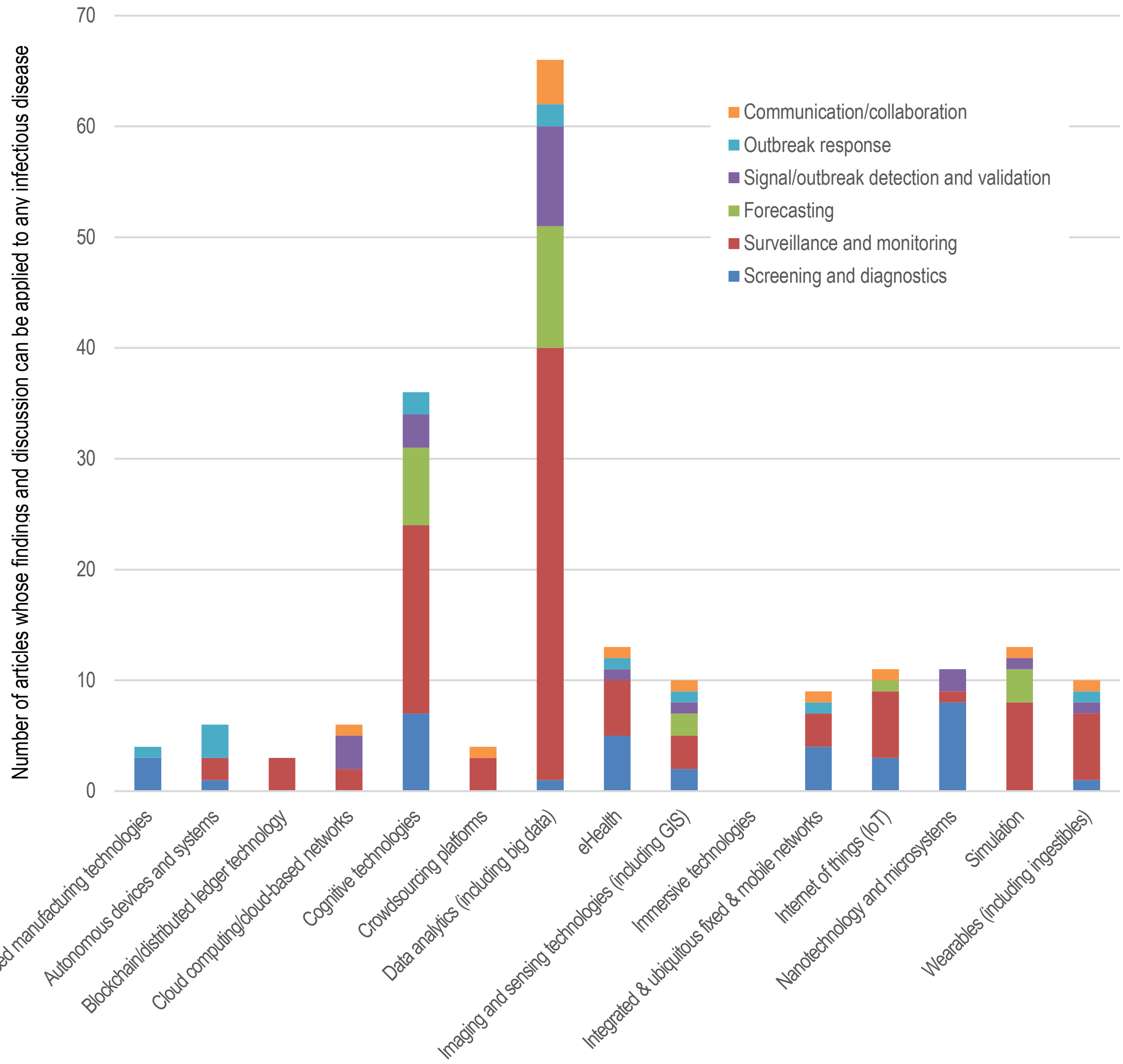
This section provides a descriptive analysis of the infectious diseases discussed in the literature included. Some articles discussed the use of digital technologies for individually named infectious diseases, while others considered the potential for digital technologies to improve infectious disease surveillance, prevention and control more generally. The articles were therefore grouped according to their different focuses: (i) individually named infectious disease(s); (ii) named groups of infectious diseases as defined by the authors, for example vector-borne, sexually transmitted, or healthcare-associated diseases; and (iii) any (unspecified) infectious disease. Over half of the analysed articles focus on the application of digital technologies in the context of one or more individually named infectious diseases (275 articles). For example, Lopez and Manogaran (2016) propose a 'big data architecture' that can analyse big data on spatial climate in order to understand the impact of climate change on possible future dengue outbreaks [34].

A further 67 articles also have a named disease focus, but the focus is on a named group of infectious diseases rather than named individual infections. For example, de Souza Silva et al. (2018) propose integrating a number of digital technologies related to the IoT to monitor and respond to any spread of infectious disease by *Aedes aegypti* or *Aedes albopictus* mosquitoes [35].

The remaining 160 articles fall under the category of 'any infectious disease'. This is defined as an article which mainly discusses a digital technology's potential for application to infectious diseases very broadly, without reference to particular diseases. For example, Feldman et al. (2019) use a combination of natural language processing, machine learning and human expertise to develop a database of global infectious disease activity, based on information extracted from online media reports that can be used for the surveillance and monitoring of any infectious disease [36]. In some cases, these articles do draw on examples involving individually named diseases to illustrate a point, but since the diseases are mentioned as examples rather than the focus of the article, the article was classified as being about any infectious disease and not individually named infectious diseases.

Figure 10 only represents the data from papers exploring the use of digital technologies for key public health functions without specifying any named disease or disease group. These data therefore show the number of articles published on the use of each high-level technology group for each key public health function that can be applied to any infectious disease context. Most of these articles report on the use of cognitive technologies and data analytics (including big data), and the most commonly discussed key public health function is surveillance and monitoring, followed by forecasting. Section 4.5.3 contains a broader cross-cutting analysis of digital technologies against key public health functions for all articles, irrespective of their infectious disease focus.

Figure 10. High-level technology groups and key public health functions of papers written on any infectious disease



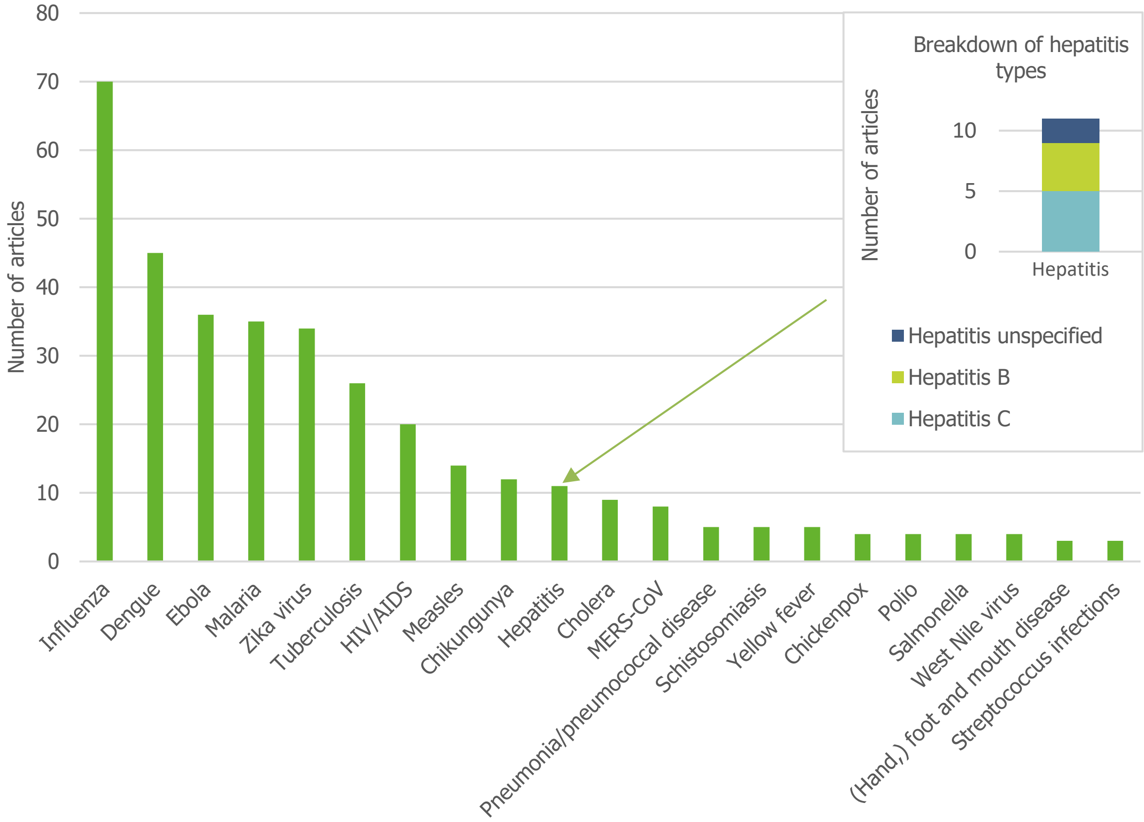
Individually named diseases of interest

In Figure 11, we present the number of articles on the use of digital technologies to address the 'top 20' infectious diseases discussed most frequently in the literature (see Annex G in the supplementary material for a full list of all 57 individually-named infectious diseases included). When an article discusses the application of a digital technology for multiple diseases, all the disease mentions are counted individually. For example, Liu et al. (2015) develop a software application that uses environmental data from satellite remote sensing that is open-source and client-based and can provide early-warning systems for West Nile virus and malaria [37]. Both West Nile virus and malaria are therefore counted in the data for this paper. The data also include cases where an article primarily discusses the use of digital technologies for any infectious disease but draws on individually named diseases in a case study. For example, Deodhar et al. (2015) present an integrated web application that uses big data analytics to forecast global epidemics of any infectious disease, using the example of the 2014 Ebola outbreak in West Africa to illustrate the technology's potential use [38]. This mention of Ebola is included in the data underpinning Figure 11.

The most commonly mentioned infectious disease in the articles is influenza (70 articles), followed by dengue (45 articles), Ebola (36 articles), malaria (35 articles) and Zika virus (34 articles). Examples of articles exploring the use of digital technologies for these infectious diseases include scoping reviews of artificial intelligence (AI) for the surveillance and forecasting of influenza [39] and malaria [40], and a systematic review of 58 mobile applications for managing the 2014–15 outbreak of Ebola in West Africa [25]. One literature review covering a wider range of technologies implemented during the same Ebola outbreak discusses the use of social media surveillance, population mapping through mobile phone data, forecasting and outbreak detection through Google Trends data, and the use of Earth-observation satellite data to track disease dynamics [41].

A number of articles discuss tuberculosis (26 articles), human immunodeficiency virus/acquired immunodeficiency syndrome (HIV/AIDS) (20 articles), measles (14 articles), chikungunya (12 articles), and hepatitis (11 articles). Fewer than 10 articles discuss cholera (nine articles), Middle East respiratory syndrome coronavirus (MERS-CoV) (eight articles), pneumonia/pneumococcal disease (five articles), schistosomiasis (five articles), yellow fever (five articles), chickenpox (varicella) (four articles), polio (four articles), West Nile virus (four articles), (hand,) foot and mouth disease (three articles), and streptococcal infections (three articles). A further 36 individually named infectious diseases are included in our dataset, 10 of which are mentioned in two articles and 26 in just one. A full list of all infectious diseases included is provided in Annex G of the supplementary material.

Figure 11. Number of articles included discussing the use of digital technologies for an individually named infectious disease



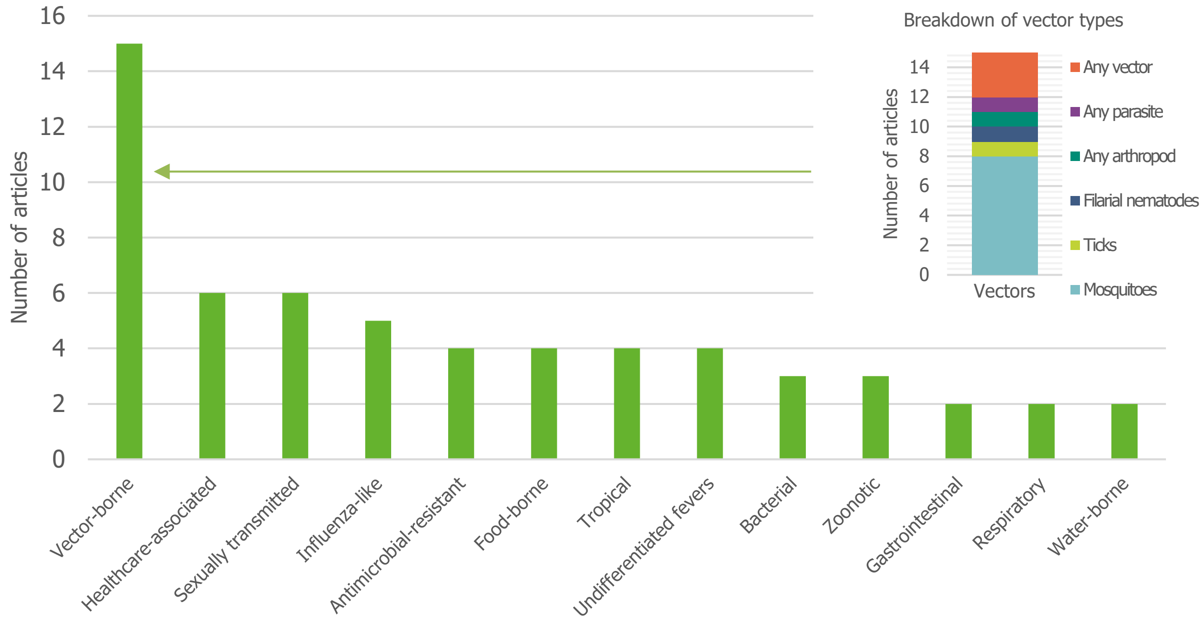
Disease groups of interest

This section looks more closely at the 67 articles on the use of digital technologies for infectious disease groups. The infectious disease groups presented here mirror those selected by authors for focus in the articles. They do not represent any form of grouping or disease classification conducted by the members of this study team. Several of the groups overlap, in that there are individual infectious diseases that fall within multiple groups. Nonetheless, these data are useful for the reader who wishes to explore the evidence available on the use of digital technologies for one or more defined groups of infectious disease.

As illustrated in Figure 12, vector-borne diseases are the subject of 15 of these articles, with over half of them focussing on mosquito-borne diseases. For example, Silva and Braga (2019) report findings from systematic literature mapping of the use of IoT applications to combat the spread of infectious diseases transmitted by the *Aedes aegypti* mosquito [42]. The next most commonly discussed infectious disease groups are healthcare-associated infections and sexually transmitted diseases, which are the focus of six articles each. For example, Daher et al. (2017) conducted a systematic review of the effectiveness of m-health and e-health applications for the prevention and treatment of HIV and other sexually transmitted diseases [43]. It is not possible to provide a further breakdown of subgroups for these infectious disease groups as they do not exist.

Five articles discuss influenza-like illnesses, while four discuss anti-microbial-resistant infections, food-borne pathogens, tropical infectious diseases and undifferentiated fevers, respectively. Three articles focus on bacterial infections and zoonotic diseases, while gastrointestinal, respiratory and water-borne infectious diseases are discussed in two articles each. A further 11 infectious disease types are the focus of one article each. These include, but are not limited to, blood-borne diseases, diarrhoeal diseases and vaccine-preventable diseases. A full list of all infectious disease groups included is provided in Annex G of the supplementary material.

Figure 12. Number of articles included discussing use of digital technologies for infectious disease groups



Cross-analysis of named infectious diseases and key public health functions

This section presents three heat tables from which it is possible to determine the volume and type of evidence available for individually named infectious diseases and disease groups. The three heat tables summarise the number of primary studies, mathematical modelling/simulation studies and systematic reviews included in this scoping review for each combination of key public health function and individually named infectious diseases (from the 'top 20' individual diseases) or disease groups (from the 'top 10' disease groups).

The surveillance and monitoring of influenza is the most common focus of the primary studies included (10 articles), along with mathematical modelling/simulation studies (19 articles). Mathematical modelling/simulation studies focusing on the forecasting of influenza (14 articles), dengue (10 articles) and malaria (10 articles) are also common. There is no combination of key public health function and individually named infectious disease or disease group for which more than one systematic review was identified.

Table 6. **Heat table of primary studies exploring the use of digital technologies for key public health functions related to the 'top 20' infectious diseases and 'top 10' disease groups**

Number of primary studies included		Key public health function					
		Screening and diagnostics	Surveillance and monitoring	Forecasting	Signal/outbreak detection and validation	Outbreak response	Communication/collaboration
Individually named infectious disease	Chickenpox		1				
	Chikungunya	2	1	1			
	Cholera	1	1				
	Dengue	1	4			1	
	Ebola	2	4			4	2
	Hepatitis			1			
	HIV	1				2	
	Influenza	2	10	4	4		1
	Malaria	5	3				
	Measles		2		1		1
	MERS-CoV		3			1	
	Polio		4				
	Salmonella	3					
	Schistosomiasis	1	2				
	Tuberculosis	3					
	Zika virus	2	4	2	1	2	2
Named group of infectious diseases	Antimicrobial-resistant organisms	1		1			
	Foodborne illnesses	1	1				
	Sexually transmitted infections	1					1
	Tropical diseases	1					
	Undifferentiated fevers	4					
	Vector-borne diseases	2	6				

Table 7. Heat table of included mathematical modelling/simulation studies exploring the use of digital technologies for key public health functions related to the 'top 20' infectious diseases and 'top 10' disease groups

Number of mathematical modelling/simulation studies included		Key public health function: Screening and diagnostics	Surveillance and monitoring	Forecasting	Signal/outbreak detection and validation	Outbreak response	Communication/collaboration
Individually named infectious disease	Chickenpox			1			
	Chikungunya	1	1	4			
	Cholera				1	1	
	Dengue	4	7	10	2		
	Ebola		4	4			
	(Hand,) foot and mouth disease			1		1	
	Hepatitis	3	2	1			
	HIV	1	1	5			
	Influenza		19	14	2		1
	Malaria	5	1	10	1		
	Measles		1	2	2		
	MERS-CoV		1	2			1
	Pneumonia/pneumococcal disease	2					
	Tuberculosis	8	1	2			
	West Nile virus			3			
	Yellow Fever	1	1		1		
	Zika virus		5	4		1	1
Named group of infectious diseases	Foodborne illnesses		1		1		
	Healthcare-associated infections	1	1				
	Influenza-like illness			4			
	Vector-borne diseases		1				

Table 8. Heat table of included systematic reviews exploring the use of digital technologies for key public health functions related to the 'top 20' infectious diseases and 'top 10' disease groups

Systematic reviews included		Key public health function: Screening and diagnostics	Surveillance and monitoring	Signal/outbreak detection and validation	Outbreak response	Communication/collaboration
Individually named infectious disease	Ebola		1			
	Influenza		1			
	Pneumonia/pneumococcal disease		1			
Named group of infectious diseases	Antimicrobial-resistant organisms		1			
	Healthcare-associated infections		1			
	Influenza-like illness		1			
	Sexually transmitted infections				1	1
	Tropical diseases		1	1		
	Vector-borne diseases	1	1			

Box 3. Key takeaways – infectious diseases targeted by the digital technology

Most articles identified discuss digital technology in the context of individually named infectious diseases, particularly influenza and dengue fever.

Fewer digital technologies were discussed more broadly, either without reference to any particular disease, or in a few instances, with reference to a named group of infectious diseases such as vector-borne diseases or sexually transmitted diseases.

When considering the use of digital technology to address public health functions in the case of individually named infectious diseases or disease groups, surveillance and monitoring of influenza was the most common focus for the primary studies included (10 articles), along with mathematical modelling/simulation studies (19 articles).

There was no combination of key public health function and individually named infectious disease or disease group for which more than one systematic review was identified.

Digital technologies and key public health functions

High-level technology groups

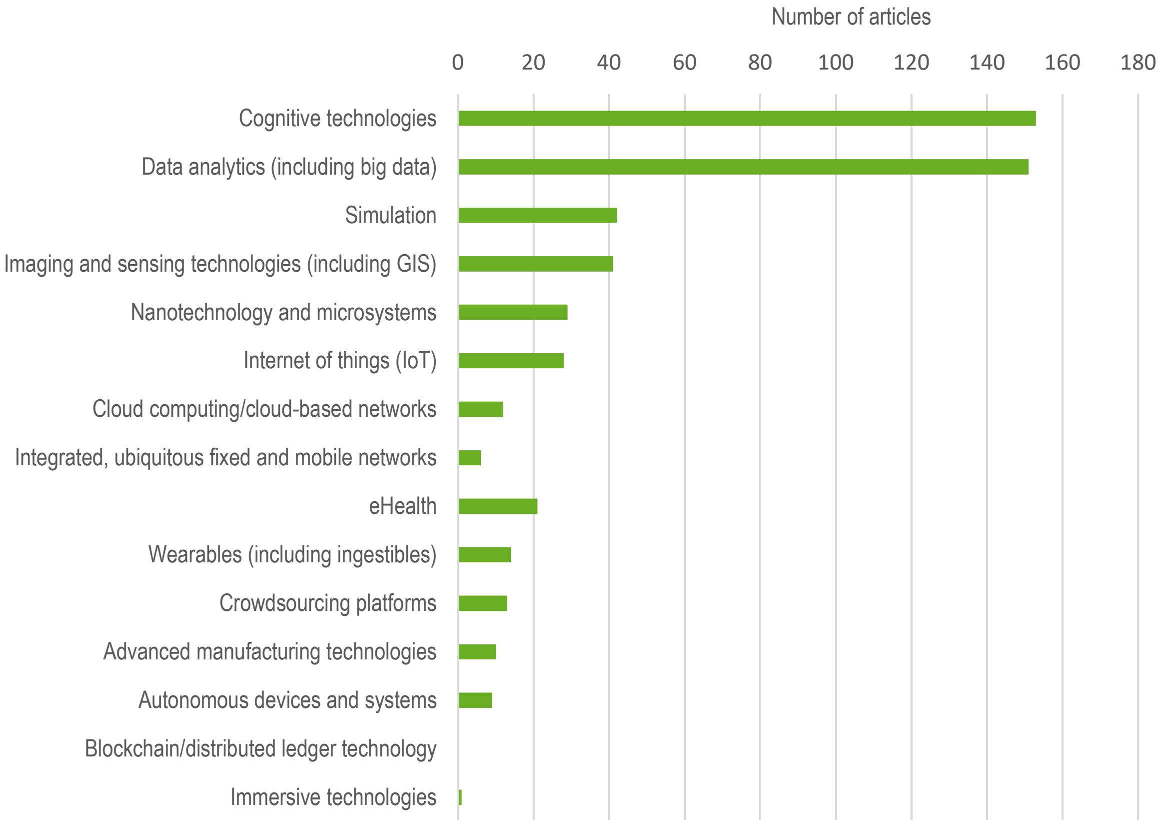
Figure 13 presents the number of included articles discussing digital technologies from each high-level technology group (see Section 3.2.5 and Annex E for further information on the technology groups). The data include cases where an article discusses the use of several technology groups.

A large proportion of the technologies either come under the category 'cognitive technologies' (153 articles) or 'data analytics (including big data)' (151 articles). The 'cognitive technologies' group includes technology such as artificial intelligence, expert systems, machine learning, natural language processing, and artificial neural networks. For example, Kulkarni and Jha (2019) review the use of artificial intelligence and machine learning for diagnosis of tuberculosis [44]. The cognitive technologies identified in this scoping review range from basic diagnostic systems supported by computers to complex deep learning algorithms [44]. The 'data analytics' group includes technology such as big data analytics, data mining, parallel computing, and social media and mobile data analysis. One book chapter reviews the use of big data from various sources – including some non-traditional – to facilitate reliable and timely surveillance, forecasting, molecular epidemiology and pathogen phylodynamics [45].

The next most commonly discussed high-level technology groups are 'simulation' (42 articles) and 'imaging and sensing technologies' (41 articles). Simulation papers report on mathematical models/simulations, while imaging and sensing technologies include geographic information systems, image processing, and satellite communication or imaging, which also includes earth observation and remote sensing.

The 'nanotechnology and microsystems', 'Internet of Things', and 'cloud computing or cloud-based networks' technology groups comprise a similar number of articles (between 26 and 29 articles each). The 'integrated and ubiquitous fixed and mobile networks' (22 articles) and 'e-health' (21 articles) groups have slightly fewer articles, followed by 'wearables' (14 articles), 'crowdsourcing platforms' (13 articles), 'advanced manufacturing' (10 articles), and 'autonomous devices and systems' (nine articles). We identified only a small number of articles related to 'blockchain and distributed ledger technology' (three articles) and 'immersive technologies' (one article).

Figure 13. Number of articles discussing digital technologies from each high-level technology group



Specific digital technologies

As shown in Figure 14, the most commonly included technologies are big data analytics (including data mining) (103 articles) and machine learning (98 articles). An example of an article on big data analytics describes a predictive model for MERS-CoV using the data mining techniques Naïve Bayes classifiers and J48 decision tree algorithms [46]. An example of a machine learning article discusses the testing of a prediction model for influenza supported by machine learning and long short-term memory networks [47].

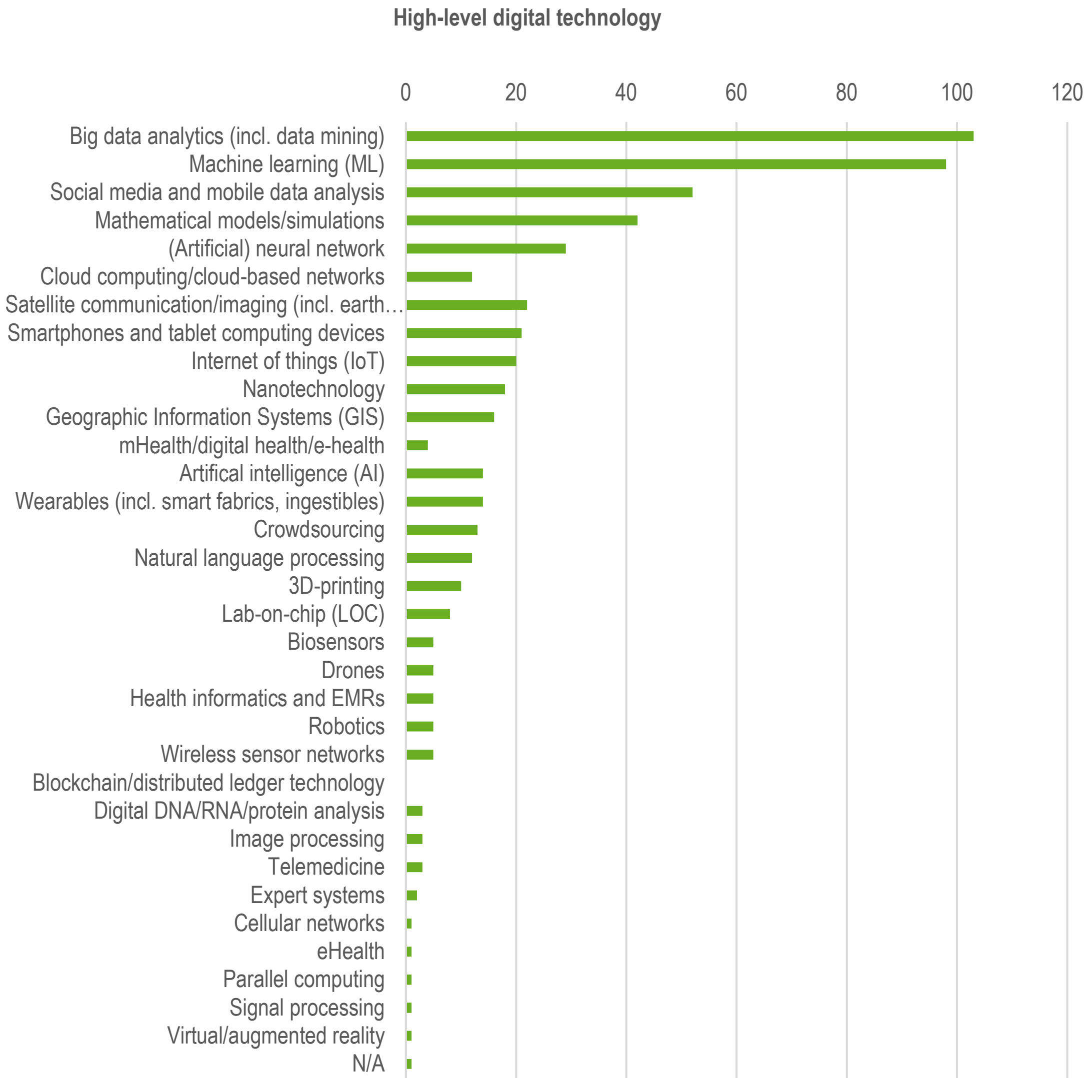
Compared to data analytics and machine learning, approximately half as many articles discuss technology involving social media and mobile data analysis (52 articles). For example, one article examines the potential use of data derived from call detail records and short message services to respond to infectious disease outbreaks [48]. A further 42 articles explore the use of mathematical models and simulations.

Between 20 and 30 articles fall within the following digital technology categories: artificial neural networks (29 articles); cloud computing or cloud-based networks (26 articles); satellite communication or imaging (including earth observation and remote sensing) (22 articles); smartphones and tablet computing devices (21 articles); and IoT (20 articles).

Many of the remaining digital technology categories are each represented by 10–20 articles: nanotechnology (18 articles); GIS (16 articles); m-health or digital health or e-health (16 articles); artificial intelligence (14 articles); wearables, including ingestibles and smart fabrics (14 articles); crowdsourcing (13 articles); natural language processing (12 articles); and 3-D printing (10 articles). Slightly fewer articles focus on lab-on-chip technology (eight), with the remaining technology categories each having five articles (biosensors, drones, health informatics and EHRs, robotics, and wireless sensor networks).

Several articles discuss multiple technologies of relevance to key public health functions, and these multiple categories are taken into account in our analysis. For example, a scoping review of digital technologies implemented in response to the 2014 outbreak of Ebola in West Africa discusses the use of data analytics (including big data), mathematical models/simulation, m-health, nanotechnology and microsystems, and imaging and sensing technologies, all of which are counted separately in our analysis [49]. The review concludes that these digital technologies facilitate increased speed and precision in the execution of tasks related to screening and diagnostics, surveillance and monitoring, forecasting, and communication and collaboration [49].

Figure 14. Number of articles discussing the use of specific digital technologies



Implementation phase of the technology

Most of the articles included discuss interventions that are 'proposed' (362 articles) – i.e. concepts, models, techniques and prototypes that have not yet been implemented in a wider public health context. This category also captures articles that use datasets from a specific context, but where the digital technology has not been used for public health purposes beyond the study context of the article. For example, Almazidy et al. (2016) propose using an IoT approach to extract and mine information related to disease outbreaks from Twitter data [50]. At the time of publication, their approach was at a conceptual stage and had not yet been applied in a wider public health context. We also identified articles discussing digital technology interventions that are 'implemented' (i.e. have been used for public health functions outside of the study context.) These constitute a quarter of the articles included (123 articles). For example, Bhatele et al. (2017) describe a code, EpiSemdemics, that employs agent-based modelling to map disease spread in large and co-evolving interaction networks [51]. The code has already provided support for US federal agencies during influenza H1N1 and Ebola outbreaks [51]. The remaining 17 articles discuss multiple technologies, some of which are implemented and others proposed. Note that all interventions included in this scoping review are tagged as either implemented or proposed, based on their implementation status at the time of the source article's publication. It is beyond the scope of this study to comment on whether interventions proposed at the time of publication of the articles have since been implemented.

Box 4. Key takeaways – digital technology groups

A total of 23 types of digital technology were identified and placed into 15 high-level technology groups. The most commonly discussed technology groups were cognitive technologies (153 articles) and data analytics (including big data) (151 articles). Simulation (42 articles) and imaging and sensing technologies (41 articles) were also frequently mentioned.

The most commonly featured digital technology in the articles were big data analytics (including data mining) (103 articles), machine learning (98 articles) and social media and mobile data analysis (52 articles). Other technologies that featured prominently were mathematical models and simulations (42 articles); artificial neural networks (29 articles) and cloud computing and cloud-based networks (26 articles).

Eight systematic reviews explored data analytics (including big data); two systematic reviews looked at e-health and integrated and ubiquitous fixed and mobile networks and one systematic review explored each of the groups autonomous devices and systems, imaging & sensing technologies (including GIS), IoT and nanotechnology & microsystems.

In total, 362 articles proposed technological solutions for public health that, at the time of article publication, had not yet been implemented. These articles discuss concepts, models, prototypes and pilot studies, but since the digital technology of interest had not yet been implemented or adopted in a wider public health context, they are classed as 'proposed'. A total of 123 articles present digital technology for public health that has been implemented outside the study context. In all, 17 articles discuss multiple interventions, some of which have been implemented and others are proposed.

There was no combination of key public health function and individually named infectious disease or disease group for which more than one systematic review was identified.

Overview of key public health functions

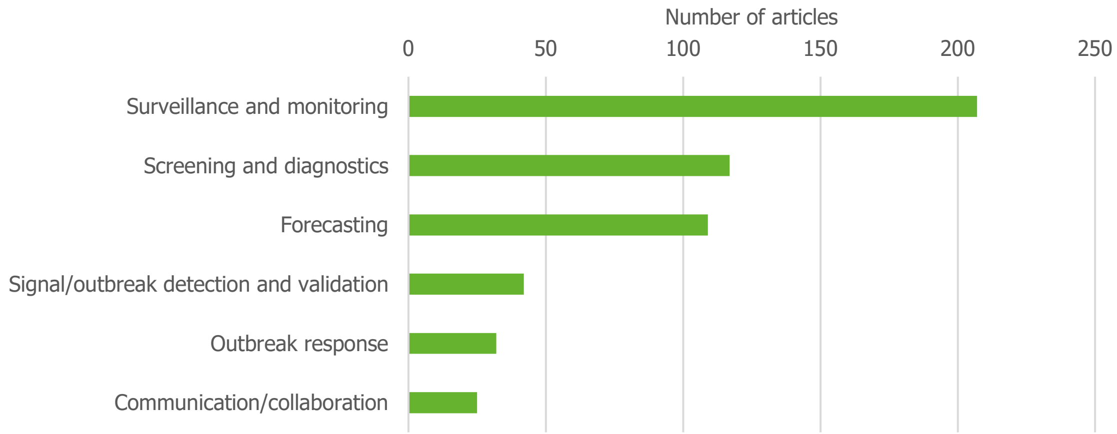
The number of articles that discuss each of the key public health functions of interest, sorted into the following six categories: (i) screening and diagnostics; (ii) surveillance and monitoring; (iii) forecasting; (iv) signal/outbreak detection and validation; (v) outbreak response and (vi) communication/collaboration, are shown in Figure 15. The overview of articles accounts for instances where an article focuses on digital technology used for several key public health functions. For example, Thapen et al. (2016) introduce a software system that combines data from social and news media with algorithms for outbreak detection, improved situational awareness and forecasting, thereby fulfilling three key public health functions: signal/outbreak detection and validation, surveillance and monitoring and forecasting [52].

As shown in Figure 15, a large number of articles examine the use of digital technologies for the surveillance and monitoring of infectious disease (207 articles). For example, one article reviews methods of traditional and syndromic surveillance, including big data analytics, to produce an inventory of the data, strategies and systems employed for infectious disease surveillance worldwide [53].

A number of articles explore the use of digital technologies for screening and diagnostics (117 articles) and/or forecasting (109 articles). Articles focusing on these key public health functions include narrative reviews of the use of biomedical and electrochemical sensors for rapid and accurate diagnosis [54-56], and a scoping review of the use of satellite earth observation data to model and forecast malaria, dengue and West Nile virus [57].

Fewer articles focus on signal/outbreak detection and validation (42 articles). For example, there is one systematic review of outbreak detection algorithms used to signal nosocomial outbreak worldwide [58]. A relatively small number of articles focus on outbreak response (32 articles), including reviews of digital innovations, such as e-health and m-health interventions for HIV and STIs [43] and technologies, including IoT applications, to combat *Aedes* mosquitos [35]. The least commonly discussed public health function is communication and collaboration (25 articles). Examples of digital technologies used for this function include controlling the spread of infectious disease scares using social networking information [59], and a sub-regional information system where patients, doctors and social assistants can discuss issues related to HIV [60].

Figure 15. Number of articles discussing each key public health function



Box 5. Key takeaways – public health key functions

Six categories of public health key function were agreed between RAND Europe and ECDC prior to data extraction and analysis: screening and diagnostics; surveillance and monitoring; forecasting; signal/outbreak detection and validation; outbreak response; and communication and collaboration.

The most commonly discussed key public health function was the surveillance and monitoring of infectious disease with 207 articles, followed by screening and diagnostics (117 articles), forecasting (109 articles), signal/outbreak detection and validation (42 articles), outbreak response (32 articles) and communication and collaboration (25 articles).

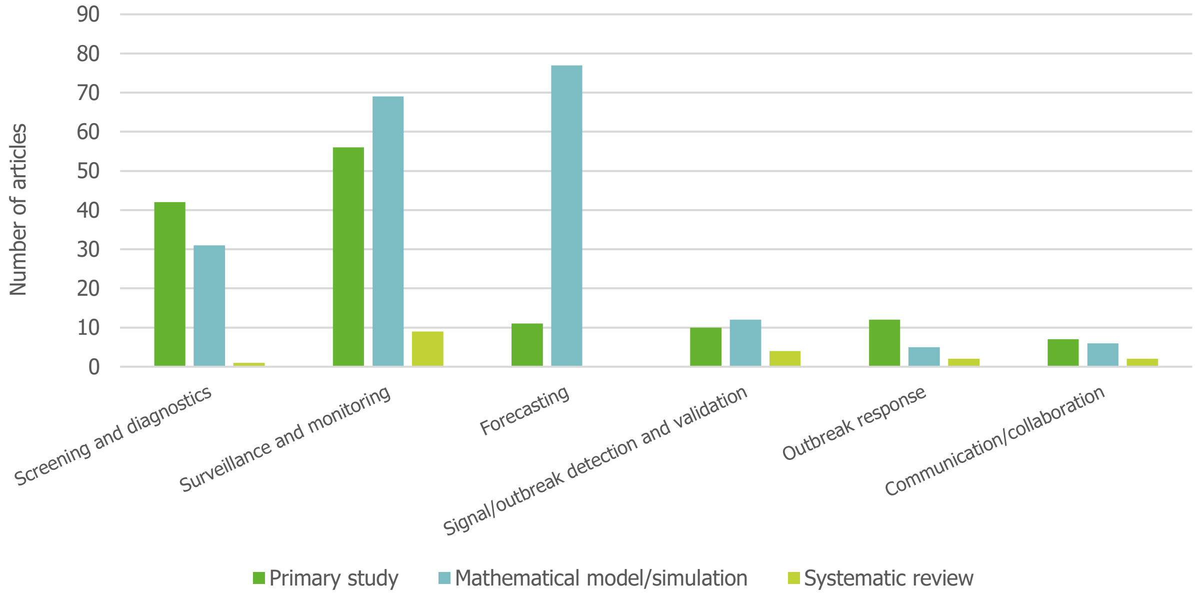
The systematic reviews included most commonly investigated digital technology for surveillance and monitoring (nine systematic reviews). Four systematic reviews discussed signal/outbreak detection and validation; two each looked at communication/collaboration and outbreak response; and one review discussed digital technology for screening and diagnostics. The scoping review did not pick up any systematic reviews exploring the use of digital technology for infectious disease forecasting.

Cross-analysis

Cross-analysis by study type

As shown in Figure 16, most of the articles within each category of public health key function of interest were either mathematical models/simulations or primary studies. Mathematical models/simulations constituted a large share of the articles in the following categories of key public health functions: forecasting (77 models/simulations), surveillance and monitoring (69 models/simulations), and signal/outbreak detection and validation (12 models/simulations). The remaining three public health key function categories were better represented by primary studies, including screening and diagnostics (31 primary studies), communication/collaboration (six studies), and outbreak response (five studies). Systematic reviews constituted a very small share of articles for all the key public health function categories: surveillance and monitoring (nine systematic reviews), signal/outbreak detection and validation (four systematic reviews), outbreak response (two systematic reviews), screening and diagnostics (one systematic review), and communication/collaboration (one systematic review). There were no systematic reviews of the use of digital technologies for infectious disease forecasting.

Figure 16. Number of included mathematical models/simulations, primary studies and systematic reviews for each key public health function



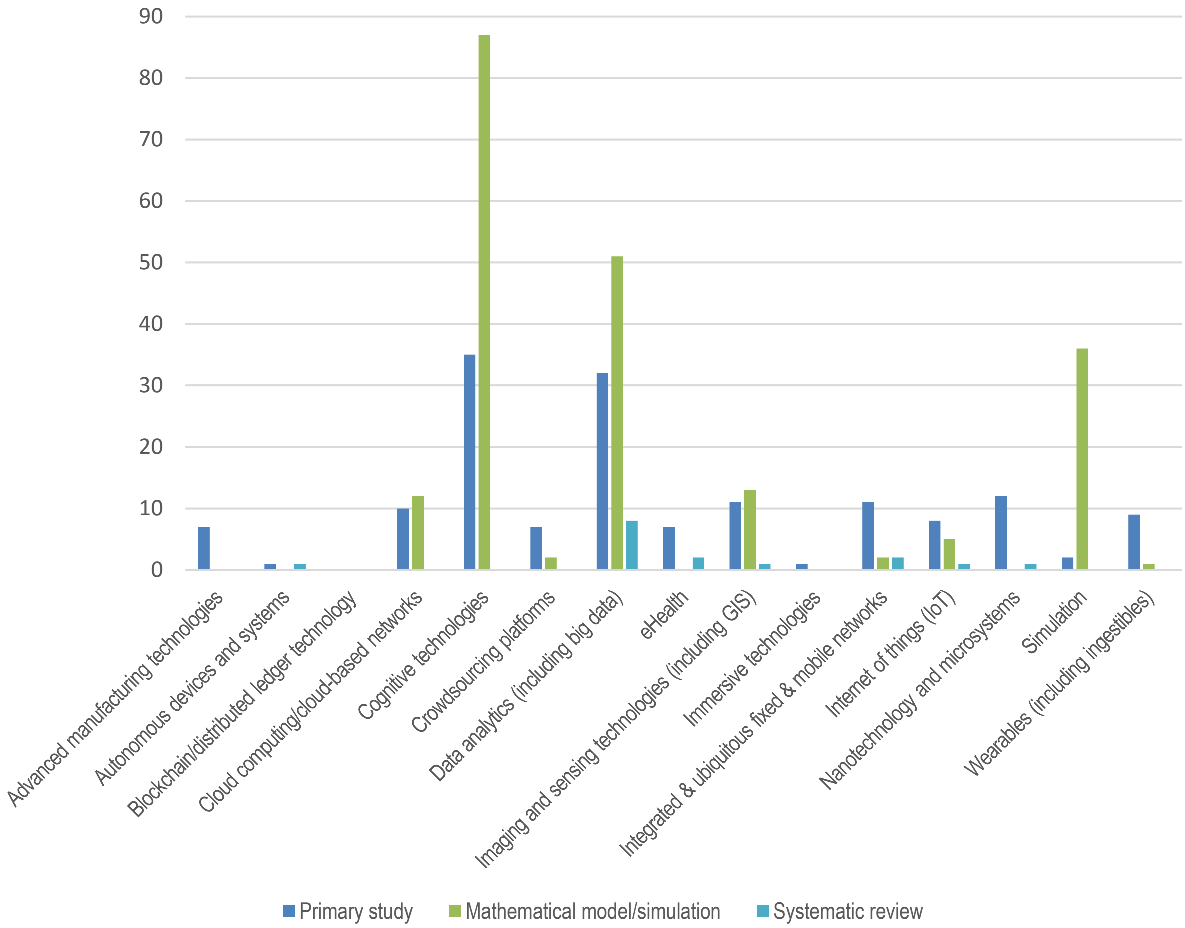
Study types by high-level technology group

As shown in Figure 17, primary studies were included for all the high-level technology groups identified, except blockchain/distributed ledger technology. They were the most common source of information for eight of the 15 high-level digital technology groups. Although not the main source of information for either 'cognitive technologies' (35 primary studies) or 'data analytics including big data' (32 primary studies), these are the technology groups for which primary studies were the most numerous.

Mathematical models/simulations are by a large margin the most common source of information on the following high-level technology groups: 'cognitive technologies' (87 models/simulations), 'data analytics including big data' (51 models/simulations) and 'simulation' (36 models/simulations). They are also slightly more common than primary studies for the following technology groups: 'imaging and sensing technologies including GIS' (13 models/simulations), and 'cloud computing/ cloud-based networks' (12 models/simulations). Mathematical models/simulations are included in this scoping review for a further four of the technology groups, but in these groups primary studies are more common: 'IoT' (five models/simulations), 'crowdsourcing platforms' (two models/simulations), 'integrated, ubiquitous fixed and mobile networks (two models/simulations), and 'wearables' (one model/simulation).

The systematic reviews included explore seven of the 15 high-level digital technology groups. There are eight systematic reviews exploring 'data analytics (including big data)'; two systematic reviews exploring each of 'e-health' and 'integrated and ubiquitous fixed and mobile networks'; and one review exploring each of the groups 'autonomous devices and systems', 'imaging and sensing technologies (including GIS)', 'Internet of Things', and 'nanotechnology and microsystems'.

Figure 17. Number of mathematical models/simulations, primary studies and systematic reviews for each high-level technology group



Study types by high-level technology group and key public health function

The three heat tables presented in this section summarise the number of primary studies, mathematical modelling/simulation studies and systematic reviews included in this scoping review for each combination of high-level technology group and key public health function. They are designed to be read in isolation, and the colours should therefore not be compared across tables.

The tables can be used to identify areas that have been the subject of particular research interest, and may therefore be suitable topics for potential future research. For example, Table 11 indicates that topics for future systematic reviews might include (i) the use of cognitive technologies for screening and diagnostics; (ii) the use of cognitive technologies for surveillance and monitoring; (iii) the use of data analytics for surveillance and monitoring; and (iv) the use of nanotechnology and micro-systems for screening and diagnostics. Table 12 highlights further topics for which there is evidence available to potentially conduct a systematic review: (i) the use of cognitive technologies for forecasting; (ii) the use of data analytics for forecasting; (iii) the use of simulation for surveillance and monitoring and (iv) the use of simulation for forecasting. From Table 13, we can determine that the only viable area for attempting a review of reviews is the use of data analytics for the surveillance, monitoring and detection of infectious disease trends and outbreaks.

Table 9. Heat table of primary studies exploring the use of high-level technology groups for key public health functions

		Public health key function					
	Number of primary studies included	**Screening and diagnostics**	**Surveillance and monitoring**	**Forecasting**	**Signal/outbreak detection and validation**	**Outbreak response**	**Communication/collaboration**
High-level technology group	Advanced manufacturing technologies	5	2				
	Autonomous devices and systems		1				
	Blockchain/distributed ledger technology						
	Cloud computing/cloud-based networks		7	2		2	
	Cognitive technologies	12	14	3	3	1	2
	Crowdsourcing platforms		6				1
	Data analytics (including big data)	2	14	6	4	3	4
	e-health	2	5				
	Imaging and sensing technologies (including GIS)	3	6		2		
	Immersive technologies					1	
	Integrated, ubiquitous fixed and mobile networks	4	3			4	
	Internet of things (IoT)	3	5				
	Nanotechnology and microsystems	12					
	Simulation	1			1		
	Wearables (including ingestibles)	3	5			1	

Table 10. Heat table of included mathematical modelling/simulation studies exploring the use of high-level technology groups for key public health functions

Number of mathematical modelling/simulation studies		Public health key function					
		Screening and diagnostics	Surveillance and monitoring	Forecasting	Signal/outbreak detection and validation	Outbreak response	Communication/collaboration
High-level technology group	Advanced manufacturing technologies						
	Autonomous devices and systems						
	Blockchain/distributed ledger technology						
	Cloud computing/cloud-based networks	1	6	4	1		1
	Cognitive technologies	25	20	34	6	2	1
	Crowdsourcing platforms		2				
	Data analytics (including big data)	2	27	18	3	2	4
	e-health						
	Imaging and sensing technologies (including GIS)	1	2	9		1	
	Immersive technologies						
	Integrated, ubiquitous fixed and mobile networks	1	1				
	Internet of things (IoT)	1	3	1			1
	Nanotechnology and microsystems						
	Simulation	1	17	15	2		1
	Wearables (including ingestibles)		1				1

Table 11. Heat table of included systematic reviews exploring the use of high-level technology groups for key public health functions

		Public health key function					
Number of systematic reviews		Screening and diagnostics	Surveillance and monitoring	Forecasting	Signal/outbreak detection and validation	Outbreak response	Communication/collaboration
High-level technology group	Advanced manufacturing technologies						
	Autonomous devices and systems		1			1	
	Blockchain/distributed ledger technology						
	Cloud computing/cloud-based networks						
	Cognitive technologies						
	Crowdsourcing platforms						
	Data analytics (including big data)		3		4		1
	e-health		1			1	
	Imaging and sensing technologies (including GIS)		1				
	Immersive technologies						
	Integrated, ubiquitous fixed and mobile networks		1				1
	Internet of things (IoT)		1				
	Nanotechnology and microsystems	1					
	Simulation						
	Wearables (including ingestibles)						

Cross-analysis of high-level technology groups and key public health functions

A high-level overview of the association between technology groups and key public health functions is illustrated in Table 12 which presents the key public health functions discussed in the articles for each high-level technology group.

Table 12. Key public health function discussed in each technology group

High-level technology group	Key public health function No.1 (most frequently discussed in included articles)	Key public health function No.2 (second most frequently discussed in included articles)
Advanced manufacturing technologies	Screening and diagnostics	Surveillance and monitoring
Autonomous devices and systems	Outbreak response	Surveillance and monitoring
Blockchain/distributed ledger technology	Surveillance and monitoring	N/A
Cloud-computing/cloud-based networks	Surveillance and monitoring	Forecasting
Cognitive technologies	Screening and diagnostics	Surveillance and monitoring
Crowdsourcing platforms	Surveillance and monitoring	Communication/collaboration
Data analytics (including big data)	Surveillance and monitoring	Forecasting
e-health	Surveillance and monitoring	Screening and diagnostics
Imaging and sensing technologies (incl. GIS)	Surveillance and monitoring	Forecasting
Immersive technologies	Outbreak response	N/A

High-level technology group	Key public health function No.1 (most frequently discussed in included articles)	Key public health function No.2 (second most frequently discussed in included articles)
Integrated, ubiquitous fixed and mobile networks	Screening and diagnostics and Surveillance and monitoring	
Internet of things (IoT)	Surveillance and monitoring	Screening and diagnostics
Nanotechnology and microsystems	Screening and diagnostics	Surveillance and monitoring
Simulation	Surveillance and monitoring	Forecasting
Wearables (including ingestibles)	Surveillance and monitoring	Screening and diagnostics

Surveillance and monitoring was discussed in almost every high-level technology group, the only exception being 'immersive technologies'. It was also the most frequently discussed key public health function for nine high-level technology groups, including 'blockchain/distributed ledger technology' (all three articles), 'cloud computing or cloud-based networks' (14 of 28 articles), 'crowdsourcing platforms' (10 of 13 articles), 'data analytics (including big data)' (80 of 151 articles), 'e-health' (12 of 26 articles), 'imaging and sensing technologies (including GIS)' (17 of 43 articles), 'Internet of Things (IoT)' (16 of 26 articles), 'simulation' (18 of 42 articles), and 'wearables (including ingestibles)' (eight of the 16 articles). The largest number of articles discussing surveillance and monitoring for any one high-level digital technology came in the 'data analytics (including big data)' technology group. An example of an article discussing use of data analytics for surveillance and monitoring includes a review of the use of social media to monitor and predict infectious disease, and for public health education to prevent the spread of infectious diseases (Aduragba & Cristea, 2019).

For the following high-level technology groups, articles primarily looked at possible use for screening and diagnostics: 'cognitive technologies', 'nanotechnology and microsystems', and 'advanced manufacturing technologies'. A total of 48 articles (out of 152) in the 'cognitive technologies' group, 26 articles (out of 29) in the 'nanotechnology and microsystems' group, and seven articles (out of 10) in the 'advanced manufacturing technologies' group discuss screening and diagnostics. One example of using cognitive technologies for screening and diagnostics is an article that looks at the application of artificial intelligence in diagnosis and medicine prescription (Das et al 2018).

The 'integrated, ubiquitous fixed and mobile networks' technology group was discussed in the same number of articles in relation to both 'screening and diagnostics' and 'surveillance and monitoring' (eight articles on each topic out of the 22 articles that discussed 'integrated, ubiquitous fixed and mobile networks'). Screening and diagnostics was not discussed in the following high-level technology groups: 'blockchain/distributed ledger technologies', 'crowdsourcing platforms', and 'immersive technologies', but constituted a reasonably large share of articles in the 'Internet of Things (IoT)' (eight of 26 articles), 'advanced manufacturing technologies' (four of 10 articles), and the 'wearables (including ingestibles)' (four of 16 articles) technology groups.

Although forecasting was not the focus of the majority of articles for any of the high-level technology groups, a significant share of articles in many groups still addressed this subject. These groups included 'cognitive technologies' (39 of 154 articles), 'data analytics (including big data)' (37 of 151 articles), 'imaging and sensing technologies' (16 of 43 articles), and 'simulation' (17 of 42 articles). Forecasting was not addressed in the following technology groups: 'advanced manufacturing technologies', autonomous devices and systems', 'blockchain/distributed ledger technology', 'crowdsourcing platforms', 'e-health, 'immersive technologies', 'integrated, ubiquitous fixed and mobile networks', 'nanotechnology and microsystems', and 'wearables (including ingestibles)'.

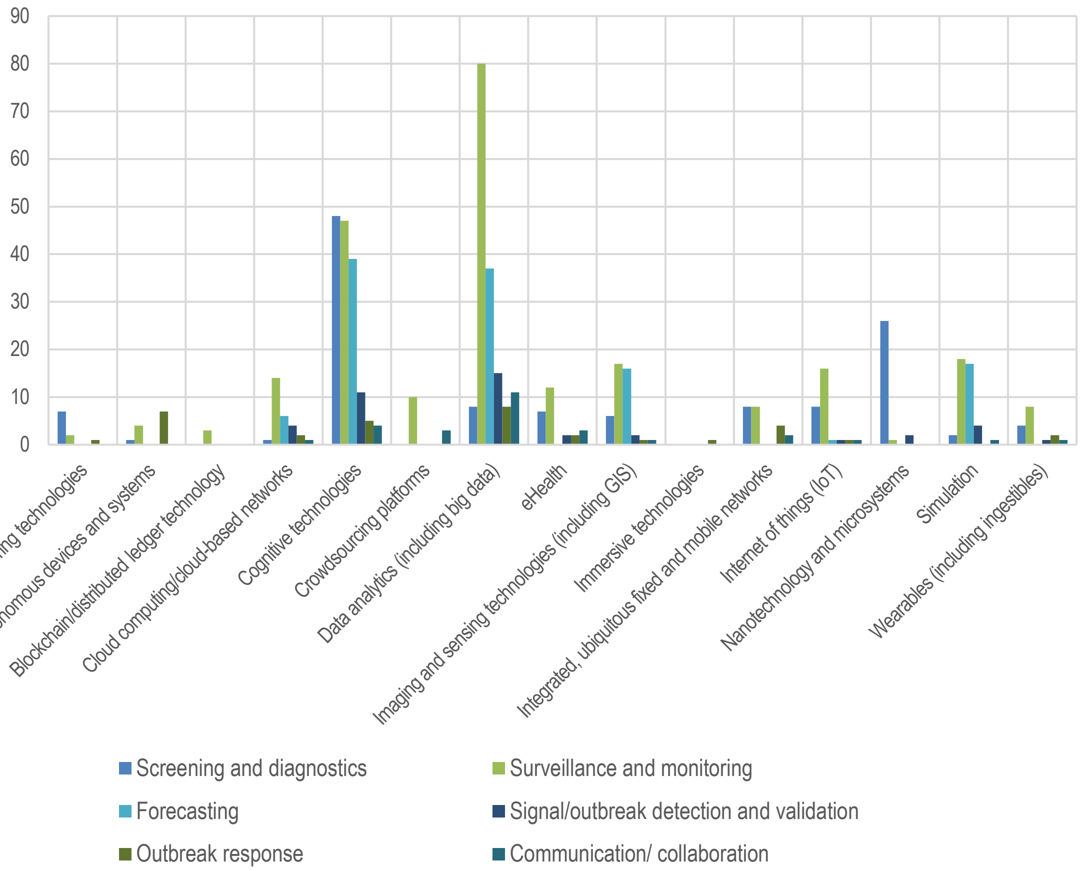
Signal/outbreak detection and validation constituted a reasonable share of the articles in the following high-level technology groups: 'cloud computing/cloud-based networks' (4 out 28 articles), 'cognitive technologies' (11 of 154 articles), and 'data analytics (including big data)' (15 of 159 articles). A smaller number of articles considered signal outbreak detection and validation in the following high-level technology groups: 'simulation' (four articles), 'e-health' (two articles), 'imaging and sensing technologies (including GIS)' (two articles), nanotechnology and microsystems' (two articles), 'Internet of Things (IoT)' (one article), and 'wearables (including ingestibles)' (one article).

There were not many articles on the subject of outbreak response and the majority of them occurred within the autonomous devices and systems technology group (seven out 12 articles articles). There was a similar number of articles in the 'data analytics (including big data)' technology group (eight articles). Outbreak response was also discussed in the 'cognitive technologies' (five articles), 'integrated, ubiquitous fixed and mobile networks (four articles), 'cloud computing/cloud-based networks' (two articles), 'e-health' (two articles), 'wearables (and ingestibles)' (two articles), 'immersive technologies' (one article), 'IoT' (one article), 'advanced manufacturing technologies' (one article) and 'imaging and sensing technologies (including GIS)' (one article).

Communication/collaboration was only addressed in eight of the high-level technology groups and constituted a small share of the articles. Communication/collaboration was only addressed once or twice in the following technology groups: 'crowdsourcing platforms' (two articles), 'integrated, ubiquitous fixed and mobile networks (two articles), 'cloud computing/cloud-based networks' (one article), 'imaging and sensing technologies (including GIS)' (one article), 'IoT' (one article), 'simulation' (one article), and 'wearables (including ingestibles)' (one article). There were more articles in the 'data analytics (including big data)' group on the subject of communication/collaboration (11 articles), although these still only represented a small proportion of the total number of articles in this technology group (151 articles).

Figure 18 illustrates the number of articles discussing the use of each high-level digital technology group for the key public health functions.

Figure 18. Number of articles discussing the use of each high-level digital technology group for the key public health functions



Box 6. Key takeaways – cross-analysis of technology groups and key public health functions

The following high-level technology groups, listed in order of number of articles discussing the technology, are those most commonly employed for surveillance and monitoring: data analytics (including big data); simulation; imaging and sensing technologies (including GIS); Internet of Things; cloud computing/ cloud-based networks; e-health; crowdsourcing platforms; wearables; and blockchain/distributed ledger technology.

Screening and diagnostics were the most commonly reported key public health functions for the following high-level technology groups: cognitive technologies; nanotechnology and microsystems and advanced manufacturing technologies.

Autonomous devices and systems and immersive technologies were the only high-level technology groups for which outbreak response is the most reported key public health function.

No technology was predominantly employed for forecasting, but the technologies most commonly employed for this purpose are cognitive technologies; data analytics (including big data); simulation and imaging and sensing technologies (including GIS).

No technology was predominantly employed for signal/outbreak detection and validation, but this function appears to be carried out most frequently using data analytics (including big data) and cognitive technologies.

Communication was the least commonly discussed key public health function in the included articles, but those technology groups in which it features more prominently are data analytics (including big data) and e-health.

Two high-level technology groups were only employed for one key public health function each: blockchain/distributed ledger technology for surveillance and monitoring; and immersive technologies for outbreak response.

Barriers to effective implementation of digital technologies for key public health functions

This section summarises the key barriers to the use of digital technologies for infectious disease surveillance, prevention and control discussed in the articles identified for this scoping review. Qualitative analysis of the data recorded during data extraction identified five over-arching themes: (i) issues with the availability and quality of the data on which many digital technologies depend; (ii) issues with the availability and cost of requisite resources, including technological and human resources; (iii) issues with the physical and network infrastructure without which many digital technologies are unable to function, most notably a stable power supply and internet connection; (iv) safety and ethical issues, along with associated issues relating to legal regulation and acceptance of digital technologies by healthcare professionals and the public and (v) a range of interrelated social, political and environmental issues.

Barriers associated with the data supply appear to be a cross-cutting issue. The subsequent sections each include a comment about how the theme under discussion impacts the availability and quality of data, while also discussing the direct barriers associated with that theme. For example, issues with public acceptance can be a direct barrier to the implementation of technology such as drones [61] and robotics [62], but they can also indirectly affect the success of implementation by having an impact on the volume and quality of data collected – e.g. through crowdsourcing platforms [63] or wearable tracking devices [64, 65].

Data

The first barrier associated with data is availability. Without an adequate volume of data, several digital technologies are unable to function as intended. For example, a barrier to the successful implementation of a Zika virus surveillance technology using Deep Neural Networks to analyse Instagram images was the lack of mosquito photographs that the technology was able to gather from Instagram [66]. Sufficiently large data sets were also highlighted as a requirement for data analytics [10, 67-69], crowdsourcing platforms [70], and other cognitive technologies [22, 71]. For example, Christaki et al. (2015) note that surveillance tools based on Internet search queries require large data sets and are therefore less effective for the surveillance of diseases with relatively low prevalence [10]. Finally, there is the barrier posed by a lack of other relevant data on which digital technologies such as mathematical modelling and simulation depend. In their study of a forecasting tool for Crimean-Congo haemorrhagic fever in Turkey, based on a machine learning algorithm, Ak et al. (2019) raise the issue of unavailable or incomplete covariate data (in this case livestock statistics) as a barrier to successful implementation [72].

In cases where the required data do exist, barriers may still occur in the form of access or delays. One study, combining hospital big data and machine learning methods for real-time monitoring of influenza, notes that such clinical data are rarely publicly accessible [73], and the deep neural network approach to epidemic forecasting employed by EpiDeep relies on CDC data that has a delay of roughly two weeks [47]. Imaging and sensing technology is also impacted by data delay, with a lack of continuously available and timely remote sensing data reported as a potential barrier to the use of satellite hyperspectral imagery for the surveillance of tick-borne diseases [74].

Even once data have been acquired, there are still other barriers associated with data quality and reliability. For example, a scoping review of the use of satellite Earth observation data in predictive models for malaria, dengue and West Nile Virus names the quality of input data as the key barrier to accurate forecasting [57]. Multiple papers covering a variety of digital technologies and key public health functions raise the issue of missing data [75-78]. Moreover, several papers exploring the use of data analytics and data mining for infectious disease surveillance and forecasting highlight the very large quantities of noise in the data, most commonly in data derived from Internet search queries [79] or tweets [80-82]. Finally, biases in the data are an important barrier to the effective implementation of digital technologies. Simulations incorporating data mined from Internet search engines and Twitter suffer from the inherent population biases associated with the user base for these technologies [83], and data from other sources are skewed by population trends in phone ownership, care-seeking behaviour, and access to medical insurance [84].

Once data of an adequate quality and availability have been identified, there is a final barrier to its use in infectious disease surveillance, prevention and control - understanding (i.e. making sense of the data.) Raw data will often need to be combined with pre-processing tools before it can be analysed [85]. For example, raw data from certain IoT devices require several rounds of pre-processing to extract meaning [86]. The processing and interpretation of the data relies on both technological and human resources. This leads into a discussion of the technological and human resource barriers to successful implementation of digital technologies, which is the subject of the next section.

Resources

Key barriers to the use of big data analytics are data storage and processing [87]. Making sense of increasingly large, noisy datasets requires high performance computing [64, 88] and teams of skilled, multidisciplinary experts [88, 89]. These both represent potential resource barriers.

However, the demands of data analytics are just one of many examples of how digital technologies for infectious disease surveillance, prevention and control can be impacted by resource barriers. The potential use of drones for surveillance and outbreak response is called into question by their significant energy consumption and concerns about battery life [90, 91]. Multiple drones are required to cover wide areas in a short period of time [90], and the transportation of drugs or vaccines necessitates a temperature-controlled supply chain to be maintained by incorporating cooling capabilities into the drone [91]. The literature included in this review also makes numerous mentions of the need for skilled human resources who have received adequate, or often ongoing training. Digital technologies associated with this requirement includes 3D printing [23], drones [91], data analytics [92], simulation [89] and imaging and sensing technology [74].

Finally, resource barriers frequently represent cost barriers. Demand for smarter drones involves increasing costs [91], as do surveillance strategies relying on increasing numbers of drones to improve accuracy and effectiveness [90]. Discussions in the area of blockchain technology have focussed on the subject of costs, as its cost-effectiveness remains to be proven, both in the context of public health and more widely [93, 94]. Further examples include costs associated with establishing 3D printing capabilities [1], and the need to invest significantly in the equipment, supplies and ongoing maintenance of diagnostic capabilities, such as genetic sequencing [1].

Infrastructure

Infrastructure barriers refer to limitations in both the physical infrastructure and, more commonly in the case of digital technologies, network infrastructure. Inconsistent mobile phone coverage is raised as a potential barrier to technology based on e-health [95] and those relying on mobile phone data to track issues such as human mobility [96, 97]. A lack of Internet connectivity, or where connectivity is available, poor Internet quality and stability are significant barriers to the implementation of digital technologies, particularly in areas that are low resource and/or remote. Internet connectivity barriers have a negative impact on imaging and sensing technologies relying on Google Maps [98], drones utilising Google Earth [90], and telemedicine initiatives based on video appointments [99]. The lack of a reliable network and Internet connection can also affect the availability and quality of data underlying other digital technologies, as mentioned in articles discussing Internet-based biosurveillance of vector-borne diseases [12] and the use of online search trends as a proxy for vaccine compliance [100].

Although we identified fewer references to physical infrastructure barriers in the included literature, the lack of a stable power supply does feature. For example, the central server of the cloud-based Surveillance and Outbreak Response Management System (SORMAS) is hosted in Germany due to the lack of a stable power supply across most of Africa [101], and unstable electricity supplies in some regions are a barrier to producing 3D-printed mosquito light traps, which take 12 hours to make [23]. Further physical barriers include infrastructure such as runways, as reported in Laksham (2019)'s SWOT (Strengths, Weaknesses, Opportunities and Threats) analysis of drones [91].

Safety, ethics and regulation

The barrier that is discussed most with respect to the safety and ethics of digital technologies, and therefore often features in considerations of legal regulations and public acceptance of such technology for public health, is privacy. Accessing data without breaching ethical privacy boundaries is a challenge [64, 102]. Even in cases where social media data is publicly available, study authors note that there are privacy concerns due to users not intending or knowingly consenting to the use of their data for research purposes [103]. These concerns manifest in regulations that may limit the use of relevant data for infectious disease surveillance. For example, many countries limit access to mobile phone data through their telecommunication regulations [104].

Regulations also impede the use of other types of digital technology, most notably drones. Further research into the safety of drones is required [91], and study authors note that their potential use is significantly restricted by national airspace legislation [61, 91]. Other safety issues include the potential psychological consequences of feeling that personal data is being monitored [105], and the risk of AI being used as a justification for human rights abuses [106].

Finally, acceptance of the above issues and others affects the extent to which digital technologies can be successfully implemented for infectious disease surveillance, prevention and control. A lack of acceptance by the public and/or healthcare professionals is a significant barrier to participation in initiatives based on technologies such as crowdsourcing platforms [63], telemedicine [99] and wearable tracking devices [64, 107]. Similarly, barriers to regulatory changes that might facilitate the adoption of digital technologies for key public health functions exist in the form of a lack of public trust in technology such as drones [61] and robots [62]. This lack of trust is sometimes influenced by cultural issues, leading us into the discussion of social barriers discussed below.

Social, political and environmental aspects

The willingness to adopt digital technologies for public health can be negatively affected by community attitudes and cultures [61, 64]. Social barriers can also have a more nuanced impact on the effectiveness of digital technologies for infectious disease surveillance, prevention and control. One barrier referred to many times in the literature is the unavailability of accurate data analytics caused by mobile phone and SIM card practices in low- and middle-income countries. Experience from Sierra Leone's 2014-16 Ebola epidemic showed that many people share mobile phones with others and/or have multiple mobile phones per activity. Consequently data from one mobile phone or SIM card do not represent one individual [96]. Similarly, other studies have found that the tendency for individuals to own multiple SIM cards used in different locations throughout the day seriously complicates surveillance and monitoring activities incorporating these data [48, 84].

Another notable social issue that acts as a barrier to the use of digital technologies for public health is the 'digital divide' [49, 108]. There are population biases associated with phone ownership [104] and access to technology in general [108]. For example, the greater use of technology by males than females in low- and middle-income countries [49], and the widening gap between the 'AI haves' and 'AI have-nots' worldwide [106]. These biases skew the data on which many surveillance, detection and forecasting technologies depend, as discussed in the above section on 'Data'. There is also a risk that the growing use of digital technologies in the field of public health could lead to a sort of 'digital Darwinism' that increasingly excludes the 'have-not' groups from the process and benefits of public health research [109].

Perhaps the most important political barriers are based on the need for international cooperation and collaboration to tackle infectious diseases. Data sharing is essential for effective disease surveillance, modelling and forecasting, requiring transparency both within and between countries [89]. Unfortunately, competing political priorities in areas such as trade act as a barrier to the required international collaboration [10].

Finally, environmental factors can render certain digital technologies inoperable in some contexts. The widespread use of drones is restricted by global differences in climate and topography [61]. Moreover, conditions such as wind, turbulence and electromagnetic interference may impact the ability to maintain signal connection and monitor drones from the ground [91]. Drones and other technology incorporating image sensing may be jeopardised by heavy rain obstructing the camera lens [90]. High or wide-ranging temperatures, sunlight, humidity and/or contaminants can also act as barriers to the successful implementation of technology such as biosensors [110], nanotechnology and mosquito light traps [23].

5. Discussion

The aim of this study was to map the field of digital technologies for key public health functions in the area of infectious disease surveillance, prevention and control by providing a structured overview of the published research literature for a five-year period from 2015 to 2019. The ultimate objective of the scoping review was to identify promising technology areas and those public health functions that could benefit most from the use of digital technologies. We also aimed to identify potential gaps in the available research literature.

Limitations of the analysis

When discussing and interpreting the findings of this scoping review, it is important to bear certain caveats in mind. The limitations of the review broadly fall into two categories: those that are inherent in scoping reviews due to their focus on breadth rather than depth of evidence [15], and those that are specific to this review, given the limits placed on its scope.

In this scoping review, we aimed to provide a broad characterisation of the evidence associated with the use of digital technologies for infectious disease surveillance, prevention and control. We were interested in understanding the quantity of relevant evidence, the article types and study designs employed, the countries in which evidence is being accumulated, the types of technology in use and being researched, and the key public health functions potentially facilitated by the technology. High-level data were extracted using a pre-determined and piloted data extraction template, but we have not assessed the quality of the evidence. However, although we extracted data on relevant study findings where available, these data will only provide indicative evidence of the feasibility, acceptability, efficacy and effectiveness of any technology identified. In addition, we did not contact study authors or country representatives to ascertain and complement information in order to compensate for possible reporting or publication bias. The initial idea to combine the scoping review with surveys and interviews in 2020 to map the situation in the EU/EEA countries and identify further examples of digital technology use for public health key functions was hampered by the COVID-19 pandemic. Similarly, the expert consultation meeting, originally planned to take place in March 2020 over 1.5 days at ECDC premises, ultimately had to be cancelled at the last minute.

Although we adopted broad inclusion criteria to maximise the scope of the included evidence, it was still necessary to place some limits on the scope of the review to keep it manageable. While we maintained a broad scope in most areas (e.g. any digital technology, any country, any infectious disease), we only included literature published in English for the data extraction and analysis phases. We also restricted the search to include literature published in the last five years, but since the topic of interest is *emerging* use of digital technologies for public health, we did not feel that this would limit our findings.

Finally, the analysis identified numerous digital technologies, some of which were more specific than others. We established a set of high-level technology groups to cluster similar or related digital technologies recorded in our data extraction template. However, these high-level technology groups and the associated glossary are not intended to be definitive. They were simply created to aid the analysis, and help with the presentation of a varied set of often technical data.

Discussion of the main findings

Around two thirds of the identified articles provided information on the geographical context of the digital technology intervention. The research focus of most publications was outside of the EU/EEA, with only 33 articles discussing interventions in the context of EU/EEA countries. An additional 32 articles discussed interventions in the context of both EU/EEA and non-EU/EEA countries. The USA was the most represented country in the reviewed literature, both in terms of geographical context of the digital technologies and author affiliations. The USA was followed by India and China, in terms of geographical context of the technology, and by India and the UK in terms of first and last author affiliation.

The USA appears to also be leading research in digital technologies in terms of potential use for public health. However, it should be noted that this scoping review was restricted to English language outputs at data extraction level. As described under limitations, no extensive search was performed for grey literature in addition to CORDIS and conference proceedings, and no authors and country representatives were contacted to complement the findings with additional information from EU/EEA countries. Plans to do so were ultimately abandoned in 2020 due to reduced availability of country representatives who were busy with the COVID-19 pandemic response. Publication bias cannot be ruled out and examples may have been missed. The COVID-19 pandemic has accelerated the digitalisation of many aspects of daily life. For example, the transition to remote working and virtual medical appointments has occurred at a faster rate than would otherwise have been the case without the COVID-19 pandemic. Since Europe was one of the epicentres of the pandemic for long periods from the spring of 2020 onwards, it is expedient to explore the impact of COVID-19 on the digitalisation of health and public health in Europe, and the effectiveness of digital public health interventions, in a more structured and systematic manner.

Over half of the included articles looked at the application of digital technologies in the context of one or more individually named infectious diseases, with influenza leading the list, followed by dengue, Ebola, malaria and Zika. A total of 67 articles discussed digital technologies to address a group of infectious diseases, where the group in question was defined by a shared disease characteristic, such as mode of transmission or symptomology. The most frequently discussed infectious diseases groups were vector-borne diseases, in particular mosquito-borne diseases, sexually transmitted illnesses, and healthcare-associated infections.

The most commonly discussed key public health function was the surveillance and monitoring of infectious disease and this was the focus of around 40% of the articles. This was followed by screening and diagnostics, and forecasting, which were both the focus of around one fifth of the articles. Signal/outbreak detection and validation and outbreak response appear to have attracted less research interest. The key public health function communication and collaboration was the least discussed public health function.

The range of digital technologies discussed in the articles identified was very broad, making it challenging to determine the technology category. A total of 33 types of digital technologies were identified and grouped under 15 high-level technology groups. The most commonly featured high-level technology group was cognitive technologies, which includes machine learning, (artificial) neural networks, artificial intelligence, natural language processing and expert systems. This was closely followed by the data analytics technology group, which comprises big data analytics (including data mining), social media and mobile data analysis, health informatics and parallel computing.

When looking at the technology groups and key public health functions combined, the technology groups most frequently employed for surveillance and monitoring (listed according to number of articles) were data analytics (including big data); simulation; imaging and sensing technologies (including GIS); Internet of Things; cloud computing/ cloud-based networks; e-health; crowdsourcing platforms; wearables; and blockchain/distributed ledger technology. With regard to the key public health function screening and diagnostics, the most commonly reported technology groups were cognitive technologies; nanotechnology and microsystems; and advanced manufacturing technologies. Outbreak response was mostly discussed in connection with autonomous devices and immersive technologies.

One of the aims of the scoping review was to identify already existing systematic reviews as well as potential topics for future systematic reviews - i.e. areas for which sufficient primary studies would be available that could be summarised to draw conclusions on the effectiveness of single technologies and their possible use for specific public health functions.

A total of 17 systematic reviews were identified, eight of which explored data analytics, including big data. Two systematic reviews each explored e-health and integrated and ubiquitous fixed and mobile networks; and one review looked at autonomous devices and systems, imaging and sensing technologies (including GIS), IoT, and nanotechnology and microsystems respectively.

Based on the number of reviews and primary research articles identified, it appears that there could be sufficient evidence to perform a review of reviews on data analytics, for which eight systematic reviews were identified, and sufficient primary evidence is available to potentially conduct a systematic review on the use of cognitive technologies, data analytics (including big data), and simulation technologies for infectious disease surveillance and forecasting. With regard to specific infectious diseases, sufficient evidence appears to exist to conduct systematic reviews on the use of digital technologies for the forecasting of dengue and malaria and forecasting and surveillance of influenza (Table 13).

Table 13. Overview of potential topics for future systematic reviews

		Public health key function		
		Screening and diagnostics	Surveillance and monitoring	Forecasting
High-level digital technology group	Cognitive technologies	√	√	√
	Data analytics (including big data)		√	√
	Nanotechnology and micro-systems	√		
	Simulation		√	√
Infectious disease	Dengue			√
	Influenza		√	√
	Malaria			√

However, the reviews and primary studies identified varied significantly in terms of research questions and methodological approach, technology or combination of technologies applied and the type of outcomes measured, making any summative qualitative or quantitative assessment in the form of a systematic review extremely challenging.

In total, 72% of the articles included discussed possible uses or 'proposed' interventions, meaning that these articles discussed concepts, models, techniques and prototypes that have not yet been implemented in a wider public health context. This category also captures articles that use datasets from a specific context, but where the digital technology has not been used for public health purposes outside of the article's study context. For example, Almazidy et al. (2016) proposed using an IoT approach to extract and mine information related to disease outbreaks from Twitter data [50]. At the time of publication, their approach was at a conceptual stage and had not yet been applied in a wider public health context.

The publication of interventions at conceptual or piloting phase contrasts with the limited amount of publications describing their broader application, implementation and prospective follow-up of desired and unintended effects. This, in combination with the large variation of technologies and outcomes assessed and the low number of comparative studies, makes it difficult to build on lessons learned and draw conclusions in relation to the use of digital technologies to support key public health functions. For this, systematic reviews would be required focusing on depth rather than breadth of understanding, and exploring the evidence available on the effectiveness of digital technologies for key public health functions.

Around one quarter of the articles discussed digital technology interventions that have been 'implemented' - i.e. used or operationalised for public health functions outside of the study or experimental context. For example, Bhatele et al. (2017) describe a code, EpiSemdemics, that employs agent-based modelling to map disease spread in large and co-evolving interaction networks [51]. The code has already provided support to US federal agencies during influenza H1N1 and Ebola outbreaks [51].

The review also identified several barriers to successful implementation of digital technologies for key public health functions. These were grouped into the categories of access to good quality, unbiased data; technological and human resources; physical and network infrastructure; safety and ethics, and a range of interrelated political, social and environmental issues.

No one doubts that technology and innovation offer opportunities for increased efficiency of processes related to key public health functions. Examples include the management and analysis of large and complex data sets as well as increased accessibility to information and services. Digital technologies therefore have a great potential to positively impact health and public health. However, the market is largely driven by solutions from providers and vendors, and the lack of robust and timely evaluations makes it difficult for health providers and public health professionals to determine the credibility of the proposed solutions.

The broad spectrum of identified barriers suggests that the use of digital technologies to support and improve key public health functions will require a systems approach to be successful, which corresponds with the assessment of several researchers in the field. For example, in a 2019 review on behalf of the European Public Health Association (EUPHA), Odone et al. concluded that a successful European strategy for public health digitalization should integrate the pillars of political commitment, normative frameworks, technical infrastructure, targeted economic investments, education, research, monitoring and evaluation [111]. Meanwhile, Budd et al. state in their 2020 review of digital technologies in the public health response to COVID-19 that 'digital data sources, like any data source, need to be integrated and interoperable, such as with electronic patient records. Analysis and use of these data will depend on the digital infrastructure and readiness of public-health systems, spanning secondary, primary and social-care systems. The logistics of delivery to ensure population impact are often given too little attention and can lead to over-focus on the individual technology and not its effective operation in a system'. They also stressed the need for 'a systems-level approach for the vision of the ideal fit-for-purpose digital public-health system' [112].

6. Conclusions

This scoping review has highlighted several possible areas for future research, including those where sufficient research appears to have been conducted to make a systematic review feasible. These areas include the use of cognitive technologies, data analytics (including big data), and simulation technologies for infectious disease surveillance and forecasting. When focusing on specific infectious diseases, sufficient evidence appears to exist to conduct systematic reviews on the use of digital technologies for the forecasting of dengue, malaria and influenza. In one area – the use of data analytics for the surveillance, monitoring and detection of infectious disease trends and outbreaks – eight systematic reviews were identified which suggest it may be feasible to conduct a review of systematic reviews.

On the other hand, the reviews and primary studies identified varied significantly in terms of methodological approach, technology or combination of technologies applied and the type of outcomes measured, which would make any qualitative or quantitative assessment, in form of a systematic review or review of reviews, quite challenging. The review also identified a lack of information in the published research literature in terms of implementation and evaluation, with almost three-quarters of the identified literature describing digital technology interventions at the conceptual or piloting phase.

A more appropriate next step would therefore appear to be to go back to the original plan of complementing the scoping review with a mapping exercise of the situation in the EU/EEA countries. This exercise, which had to be cancelled in 2020 due to pandemic-induced lack of resources, would also help to establish closer contacts with different stakeholders active in the fields relevant to a digital public health approach.

During 2021, ECDC is holding a set of consultations involving EU and Member States' representatives to make use of the momentum that came with the COVID-19 pandemic. The aim is to bring public health onto the digitalisation agenda at EU and national level, obtain a better understanding of the current state of play, and facilitate the contact and exchange among the relevant stakeholders in policy and regulation relating to digital technologies and infrastructure, as well as health informatics and health and public health policy and practice.

With the COVID-19 pandemic accelerating the digitalisation of many aspects of daily life, it would also be interesting to explore the impact of COVID-19 on the digitalisation of health and public health in Europe, a region which was one of the epicentres of the pandemic for a long period from spring 2020 onwards. This would also facilitate an exploration of the effectiveness of digital public health interventions in a more structured and systematic manner.

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Glossary of digital technologies

This analysis identified a variety of areas of digital technology, some more specific than others. Several of the technologies identified from the articles could be considered part of the same broad high-level technology group. To help with the presentation of the data, we developed a set of high-level technology groups under which to group similar or conceptually-related types of digital technology recorded in our data extraction template. In the table below we include a glossary of these high-level technology groups, preceded by a description of the method used to develop the glossary.

To categorise the digital technologies, we used a multi-step approach, drawing on additional, bespoke desk research to develop the glossary of the high-level technology groups used.

- As a first step, the Digital Single Market (DSM) glossary [17] was used as a baseline for several of the digital technology areas identified.
- Where the DSM glossary did not directly correspond to a digital technology classification, we drew on relevant material from the articles considered as part of full-text review and relevant RAND Europe reports published in the last two years.
- In cases where we were unable to find relevant definitions in RAND Europe reports, we searched for definitions in academic and grey literature (including documents published by the European Commission).
- For technology in the very early stages of adoption, we examined some peer-reviewed journal articles and books in resources such as ScienceDirect and the OECD glossary for statistical terms.

Before finalising the conceptualisation of the glossary, we cross-checked the descriptions internally to assess them for accuracy and appropriateness for inclusion in the current study.

Table E1. Glossary of high-level technology groups

High-level technology group	Definition	Technologies	Definition
Advanced manufacturing technologies	Advanced manufacturing technologies include computer-controlled or micro-electronics-based equipment used to design, manufacture or process a product. This technology group includes the following technology areas captured in the data extraction template: 3D printing. *Based on OECD (2013) [113]*	3D-printing	3D-printing or additive manufacturing refers to the process of combining materials to make parts from 3D model data, usually by joining layers onto layers. *Based on Lee, J-y et al. (2017) [114]*
Autonomous devices and systems	Autonomous devices and systems include systems and devices that can properly understand and perceive their environment, translate this into action that is meaningful, and then perform these actions without human interference. This technology group includes the following technology areas captured in the data extraction template: drones, and robotics. *Based on European Commission (n.d.) [17]*	Drones	Drones or unmanned aircrafts refer to aircrafts that do not have a pilot. Drones are often used for surveillance. *Based on European Aviation Safety Agency (2015) [115]; Kardasz et al. (2016) [116]*
		Robotics	Robotics refers to the science of engineering, designing and use of intelligent machines that can 'sense, act purposefully, and perform work autonomously, and their control and processing systems' *Based on European Commission (n.d.) [17]*
Blockchain/ distributed ledger technology	Blockchain technology is one of the most well-known uses of distributed ledger technologies (DLT), in which the 'ledger' comprises 'blocks' of transactions, and it is the technology that underlies a cryptocurrency such as Bitcoin. This technology group includes the following technology areas captured in the data extraction template: blockchain/distributed ledger technology. *Based on Deshpande et al. (2017) [117]*	Blockchain/ distributed ledger technology	See second column
Cloud computing/ cloud-based networks	Cloud computing refers to a model that aims to enable online on-demand network access to a pool of computing resources (including networks, servers, storage, applications and services). Storage and processing take place in the cloud rather than on individual devices. Cloud networks constitute the mechanisms that facilitate the properties of elasticity, scalability and flexibility of the resources delivered on the cloud. This technology group includes the following technology areas captured in the data extraction template: cloud computing/cloud-based networks. *Based on European Commission (n.d.) [17]*	Cloud computing/cloud -based networks	See second column
Cognitive technologies	Cognitive technologies are defined as artificial technologies or systems that can 'perceive their environment, understand the situation and execute tasks efficiently even in challenging situations'. These systems are capable of adapting to changing conditions and new users and can work with different degrees of autonomy, either on their own or by cooperating with people This technology group includes following technologies: artificial intelligence, expert systems, machine learning, natural language process, (artificial) neural networks. *Based on European Commission (n.d.) [17]*	Artificial intelligence (AI)	Artificial intelligence refers to a collection of technologies that combine data, algorithms and computing power to enable systems to analyse their environment and take decisions with a certain degree of autonomy *Based on European Commission (2020) [118] and European Commission (2020) [119]*
		Expert systems	Expert systems are defined as computer programmes that employ AI to solve problems that commonly require human interference and expertise. They rely on two components: i) a knowledge base, and ii) an inference engine. The knowledge base consists of an organised collection of facts about the domain of the system. The engine interprets these facts to arrive at an answer. *Based on Abu-Nasser (2017) [120]*

High-level technology group	Definition	Technologies	Definition
		Machine learning	Machine learning refers to a software or a computer's ability to learn from very big data sets or its environment without being explicitly programmed, which enables systems to change their behaviour under changing circumstances or to carry out tasks. *Based on European Commission (n.d.) [17]; European Commission (2020) [118]; and Parreco et al. (2018) [121]*
		Natural language processing	Natural Language Processing (NLP) refers to research and applications that address how computers manipulate and understand natural language text or speech to perform desired tasks. *Based on Chowdhury, G. (2003) [122]*
		(Artificial) neural network	(Artificial) neural networks (ANNs) stimulate the networks and information, learning and generalisation processing strategies of nerve cells in the human central nervous system for computational networks. *Based on ScienceDirect (n.d.) [123]; Mukhopadhyay (2011) [124]; Mahesh et al. (2015) [125]*
Crowd-sourcing platforms	Crowdsourcing platforms refer to online platforms that enable many individuals network and share their resources online to support initiatives by other people or organisations. This technology group includes the following technology areas captured in the data extraction template: crowdsourcing. *Based on European Commission (n.d.) [17]*	Crowdsourcing	Crowdsourcing refers to when many individuals network and share their resources to collect information or complete tasks, often online. *Based on European Commission, (n.d.) [17], Quade and Nsoesie (2017) [126]*
Data analytics (including big data)	Data analytics involves the techniques used to extract and categorise data to identify and analyse behavioural data and patterns This technology group includes big data analytics, which refers to data analytics tools used to measure large amounts of data produced quickly that comes from diverse sources. This technology group includes following technologies: big data analytics, data mining, parallel computing, and social media and mobile data analysis. *Based on European Commission (n.d.) [17]*	Big data analytics (incl. data mining)	Big data analytics refers to data analytics tools used to measure large amounts of unstructured and structured data that comes from diverse sources. This data is defined by three 'Vs': i) volume, ii) variety, and iii) velocity. These data analytics tools can include data mining, which is an automated research technique that employs algorithms to extract information from unstructured data *Based on European Commission (n.d.) [17]; Chuchra & Chhabra (2016) [127]; and Asokan & Asokan (2015) [92]*
		Parallel computing	Parallel computing refers to the use of multiple computer resources simultaneously to solve a problem that is computational. The process breaks down computational problems so that they can be solved simultaneously, the parts are broken down to further instructions that can be executed concurrently in different processors, with a control mechanism for the whole system. *Based on European Commission (n.d.) [17]*
		Social media and mobile data analysis	Social media and mobile data analysis comprises the analysis carried out on data generated from mobile devices, online applications, platforms and media that aims to facilitate interactions, collaboration and the sharing of content *Based on Bernadas & Minchella (2016) [128]; Naef et al. (2014) [129]*

High-level technology group	Definition	Technologies	Definition
E-health	E-health refers to the suite of ICT tools that can improve 'prevention, diagnosis, treatment, monitoring and management' in health. It also includes: i) information and data sharing between patients and health service providers, hospitals, health professionals and health information networks, ii) electronic health records; telemedicine services, and iii) portable patient-monitoring devices, operating room scheduling software, robotised surgery and blue-sky research on the virtual physiological human. This technology group includes the following technology areas captured in the data extraction template: digital health/e-health/ m-health, electronic health records, and telemedicine. *Based on European Commission (n.d.) [17]*	M-health/digital health/e-health	M-health refers to the support of medical and public health practice by mobile devices, including patient monitoring devices, personal digital assistants, mobile phones, and other wireless devices. *Based on European Commission (n.d.) [17]* e-health refers to the ICT tools that can improve 'prevention, diagnosis, treatment, monitoring and management' in health. *Based on European Commission (n.d.) [17]*
		Health informatics and EHRs	Health informatics refers to the study and use of methods aimed at improving the management of clinical knowledge, population data, patient data, and other information that is relevant to patient care and community health. *Based on Wyatt & Liu (2002) [130]* Electronic health records (EHRs) are data in a digital format, which has health information on individual patients or a population, and which can be shared in different health settings. *Based on European Commission (n.d.) [17]*
		Telemedicine	Telemedicine refers to electronic communication and technologies used to provide or support clinical care at a distance. This includes case management, patient counselling, and supervision of patients by health professionals. *Based on European Commission (n.d.) [17]*
Imaging and sensing technologies (including GIS)	Imaging and sensing technologies use techniques, hardware, software and algorithms to analyse images or geocoded data often acquired through satellites or remote sensing devices to analyse, enhance, and optimise images. This technology group includes geographic information systems (GIS), image processing, satellite communication/imaging, earth observation and remote sensing. *Based on Ganney et al. (2014) [131]; Goodchild (2009) [132]; Johnson et al. (2008) [133]; and Tran et al. (2002) [134]*	Geographic Information Systems (GIS)	Geographic information systems (GIS) refer to the hardware and software systems employed to capture, store, check, integrate, manipulate, display, and analyse data that is spatially referenced (or geocoded). *Based on Goodchild (2009) [132]*
		Image processing	Image processing refers to the application of different techniques and algorithms to a digital image with the purpose of analysing, enhancing, or optimising image characteristics. *Based on Ganney et al. (2014) [131]*
		Satellite communication /imaging (incl. earth observation and remote sensing)	Satellite communication is defined as the use of satellites to communicate between different points on Earth and satellite imagery is the gathering of images of Earth by imaging satellites (NASA). This includes remote sensing and earth observation. Remote sensing refers to the acquisition of information from a distance . *Based on Johnson et al. (2008) [133]; Tran et al. (2002) [134]; and Batallán et al. (2015) [135]* Earth observation refers to the use of remote sensing technologies to gather information about the physical, chemical and biological properties of the Earth *Based on EU Science Hub (n.d.) [136]*

High-level technology group	Definition	Technologies	Definition
Immersive technologies	Immersive technologies immerse users in digitally generated or enhanced realities and transcends traditional formats and include virtual reality (which includes a completely virtual, digitally-generated environment) and augmented reality (which includes a partial digitally-generated environment mixed with real-world environment). This technology group includes the following technology areas captured in the data extraction template: virtual/augmented reality. *Based on Mateos-Garcia et al. (2018) [137]*	Virtual/augmented reality	Virtual reality is a computer-generated scenario that simulates a real-world experience. *Based on Steuer (1992) [138]* Augmented reality combines real-world experience with computer-generated content. *Based on Azuma (1997) [139]*
Integrated, ubiquitous fixed and mobile networks	Integrated, ubiquitous fixed and mobile networks refer to the use of a combination of fixed broadband and local access wireless technologies. Ubiquitous networks refer to networking characterised by the '4As' - it can happen anywhere, anytime, by anything and anyone. This technology group includes the following technology areas captured in the data extraction template: cellular networks and smartphones and tablet computing devices. *Based on European Commission (n.d.) [17]*	Cellular networks	Cellular networks refer to voice and data communication networks that are high-speed and high capacity. These networks support cellular networks with enhanced seamless roaming and multimedia capabilities. *Based on Liu et al. (2014) [140]*
		Smartphones and tablet computing devices	Smartphones refer to mobile phones that can be used as small computers and that have an internet connection. *Based on Islam & Want (2014) [141]* Tablet computing devices are devices that are smaller than a notebook, but larger than a smartphone. *Based on Watson & Jones (2013) [142]* These devices typically come with a touchscreen and no keyboard. Based on Techopedia (n.d.) [143]
Internet of things (IoT)	The IoT refers to a global network infrastructure with standardised and interoperable protocols that enable devices on the network to communicate with one another. Physical objects are fitted with software, sensors and other technologies that exchange data and integrate seamlessly into the information network. This technology group includes the following technology areas captured in the data extraction template: biosensors(IoT, and wireless sensor networks. *Based on European Commission (n.d.) [17]*	Biosensors	Biosensors refers to a device with an integrated receptor and transducer, that can provide analytical information based on a biological recognition element that can be used for both biological or non-biological matrices. An electrochemical biosensor uses a biological reception element that is in direct contact spatially with a transduction element that is electrochemical. *Based on Thevenot et al. (1999) [144]*
		IoT	See second column

High-level technology group	Definition	Technologies	Definition
		Wireless sensor networks	Wireless sensor networks refers to wireless networks that are self-configuring and operate without an infrastructure that aim to monitor physical or environmental conditions. The data that is collected is passed through the network to a main location where the data is analysed and observed. *Based on Matin & Islam (2012) [145]*
Nano-technology and microsystems	Nanotechnology and microsystems refer to the technology used to investigate matter on micro, atomic and molecular scales. - Nanotechnology addresses structures that are 100 nanometers or smaller in one dimensions and the development of both devices and materials that are the same size. - Microsystems are miniaturized systems that can accommodate specifications of small space, light weight and enhanced portability. This includes digital DNA/RNA/protein analysis, lab-on-chip technologies, and nanotechnology. This group includes the following technology areas captured in the data extraction template: biosensors, digital DNA/RNA/protein analysis, lab-on-chip, and nanotechnology. *Based on European Commission (n.d.) [17]; and Luttge (2011) [146]*	Biosensors	Biosensors refers to a device with an integrated receptor and transducer, that can provide analytical information based on a biological recognition element that can be used for both biological and non-biological matrices. An electrochemical biosensor uses a biological reception element that is in direct contact spatially with a transduction element that is electrochemical *Based on Thévenot et al. (1999) [144]*
		Digital DNA/RNA/protein analysis	Digital DNA/RNA/protein analysis refers to the use of novel digital technologies for DNA, RNA and/or protein analysis, including technologies such as digital microarrays for point-of-care testing. *Based on Bouzas et al. (2018) [147]; and O'Sullivan et al. (2019) [71]*
		Lab-on-chip (LOC)	Lab-on-chip refers to the integration of micro(nano) fluidic functionalities and components onto monolithic platform for biochemical or chemical processes. The form of lab-on-chip technologies that are the most integrated include all processes and devices on a single card or chip so that the collection, analysis, and production of outputs from data or a sample happens on the same chip or card. *Based on Garcia-Cordero & Ricco (2008) [148]*
		Nanotechnology	Nanotechnology refers to the technology used for matter on atomic and molecular scales. Nanotechnology addresses structures that are 100 nanometers or smaller in one dimensions and the development of both devices and materials that are the same size. *Based on European Commission (n.d.) [17]*
Simulation	A simulation is a digital programme or a suite of programmatic approaches that use step-by-step methods to approximate the behaviour of a mathematical model This technology group includes mathematical models/simulations. *Based on Stanford Encyclopaedia of Philosophy (2019) [149]*	Mathematical models/simulations	Mathematical models use mathematical concepts and language for the explanation of a system to study the effects of different system components and to make predictions. A computer simulation uses step-by-step methods derived from a mathematical model to approximate the model's behaviour (often modelling real-world systems). *Based on Abramaowitz & Stegun (1968) [150]; Stanford Encyclopaedia (2019) [149]*

High-level technology group	Definition	Technologies	Definition
Wearables (including ingestibles)	'Wearables' are technology devices comprised of an ensemble of electronics, software and sensors, which are either designed to be worn on the body or potentially held inside the body for short durations (i.e. ingestibles). This technology group includes the following technology areas captured in the data extraction template: wearables (including smart sensors and ingestibles). *Based on Billinghurst and Starner (1999) [151]*	Wearables (incl. smart fabrics, ingestibles)	See second column

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