

Role of visual analytics in supporting mental healthcare systems research and policy: A systematic scoping review



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ABSTRACT

The availability of healthcare data has exponentially grown, both in quantity and complexity. The speed of this evolution has generated new challenges for translating complex data into effective evidence-informed policy. Visual analytics offers new capacity to analyze healthcare systems and support better decision-making. We conducted a systematic scoping review to look for evidence of visual analytics approaches being applied to mental healthcare systems and their use in driving policy. We found 79 relevant studies and categorized them in two ways: by study purpose and by type of visualization. The majority (67.1%) of the studies used geographical maps, and 11% conducted highly complex studies requiring novel visualizations. Significantly, only 15% of the studies provided information indicating high levels of usability for policy and planning. Our findings suggest that while visual analytics continues to evolve rapidly, there is a need to ensure this evolution reflects the practical needs of policy makers.

1. Introduction

Health planners and policy-makers face complex decisions requiring a deep knowledge of ‘healthcare systems’, which consist of all the organizations, people and actions involved in maintaining, restoring and enhancing human well-being. The characteristics of healthcare systems are considered as an important indicator of population health (e.g., quality of life for people in developing integrated smart systems for cities or regions) (Ismagilova, Hughes, Dwivedi, & Raman, 2019). There is significant variation in policy, funding and delivery of health care across regions (Griffin et al., 2016). Understanding these differences and how they impact on the health of communities requires reliable evidence, and health planners can use this evidence to drive systematic quality improvement of regional healthcare delivery.

The growing availability of healthcare data raises the prospect of better evidence-informed decision-making. Healthcare systems involve

complex interactions between structures, processes, outcomes and agents. They are characterized by nonlinearity, interconnectivity, self-organization, constant change, variability and uncertainty (Kannampallil, Schauer, Cohen, & Patel, 2011; Lipsitz, 2012; Long, McDermott, & Meadows, 2018). Mental health care epitomizes this complexity. Mental illness often has both health and social dimensions (Salvador-Carulla, Haro, & Ayuso-Mateos, 2006). For health planners to drive quality improvement, useful data must reflect the complexity of mental health care. However, capitalizing on this evolution has been hampered by difficulties in data analysis and limited human ability to process information. (Caban & Gotz, 2015).

Visual analytics plays an important role in more effectively analyzing mental healthcare data. It refers to the suite of tools combining automated analysis techniques with visualizations, and the analytical capabilities of users, to capitalize on complex data to improve understanding and decision-making (Keim, Kohlhammer, & Ellis, 2010;

Abbreviations: GIS, geographic information systems; KDD, knowledge discovery in databases; AI, artificial intelligence

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Kohlhammer, Keim, Pohl, Santucci, & Andrienko, 2011; Ruppert, 2018). While traditional data analysis approaches such as statistics and probabilities can be used to measure the complexity and uncertainty of data, they are notoriously difficult to communicate effectively to decision-makers (Spiegelhalter, Pearson, & Short, 2011). Visual analytics permits the synthesis of data from various sources, the communication and use of complex data in exploring information, generating understanding, eliciting implicit knowledge and developing evidence-informed decision-making (Lavis, Permanand, Oxman, Lewin, & Fretheim, 2009; McNerny et al., 2014; Robinson, 2016). It also provides new capacity to derive insight from massive, dynamic and uncertain data. It can detect expected and unexpected pattern information; provide timely, defensible and understandable assessments; and communicate these assessments effectively for action (Chung et al., 2018; Kohlhammer et al., 2011; Ola & Sedig, 2016). Over the last decade a range of visual analytics approaches have emerged and been widely applied to scientific discovery and innovation in health sciences such as infectious disease control (Carroll et al., 2014), personal health information of patients (Faisal, Blandford, & Potts, 2013), and healthcare ecosystems research (Furst, Gandré, Romero-Lopez-Alberca, & Salvador-Carulla, 2019). Despite the significance of these contributions, the role of visual analytics has been largely unexplored in the scientific literature on healthcare systems research and policy (Lavrač et al., 2007; Moraga, 2017; Sopan et al., 2012).

In this scoping review, we summarize and analyze this evidence. The objectives of this review are:

- i) to investigate and identify the existing literature regarding the application of visual analytics to mental healthcare systems;
- ii) to map and categorize this literature according to study purpose (its intended aim), data complexity, analytical methods, visualization types, analytical results and interpretation, policy implication, benefits and limitations of using visualizations; and
- iii) to synthesize evidence demonstrating the practical application of visual analytics to mental healthcare systems research and policy.

2. Material and methods

We conducted a systematic scoping review to identify and map the literature concerning the application of visualization tools for analysing healthcare systems and evidence-informed decision support in mental health. This review identified and selected relevant studies, mapped evidence; collated and summarized results and identified findings and gaps in the research. Following published guidance on scoping reviews (Arksey & O'Malley, 2005; Colquhoun et al., 2014; Levac, Colquhoun, & O'Brien, 2010; Peters, Godfrey, McInerney et al., 2015; Peters, Godfrey, Khalil et al., 2015), we used an iterative and parallel process to be flexible in the search, screening, mapping and reviewing phases.

2.1. Data selection and evaluation

The scoping review focused on examining the following question: to what extent are visualization tools applied to analyze mental healthcare systems in supporting evidence-informed decisions? The search strategy looked for studies where visualization tools were deployed to understand complex mental healthcare systems. This meant our criteria to identify studies in this review included several areas of mental health care:

- mental healthcare services (local, regional, national and international);
- population mental health and epidemiology;
- policy and legislation;
- resource availability and allocation; and
- involvement of domain experts in service delivery and planning.

Studies using visual analytics on clinical trials, genomic information, individual decision-making and dashboards were excluded, unless they addressed policy impact on mental healthcare resources and services. Due to cost and time constraints we mainly included English-language peer-reviewed studies (Arksey & O'Malley, 2005).

We identified the search terms and refined the selection criteria further by reviewing a random sample of publications from the search results. A comprehensive search was completed in July 2018 using the final combination of search terms, (visual* OR graph* OR geograph* OR geospatial OR spatial OR diagram* OR map*) AND (mental OR psychiatr*) AND (decision OR policy OR plan* OR provision) AND (health system OR health service OR health care), to three databases: PubMed, Web of Science and Google Scholar. Duplicated publications from different databases were arranged using a citation management system (EndNote) and manually. The studies were then selected in steps by title, abstract and full-text screening. For quality control purposes at each step, two independent researchers (YC and KS) reviewed and applied the selection criteria to the studies in parallel. A third researcher (JS) joined the agreement process to ensure that all relevant studies were included in the review. We also conducted a citation search from our own and colleagues' records to identify additional studies known to be missed from the database search. For inclusion in our search, access to full-text of the studies was required. When this was not freely available we made direct requests to authors.

Drawing on the search results, we collected evidence and iteratively developed summary to evaluate the identified literature, according to the following topics: study aim; study area (region); data type; layer of analytical information; methodology; computational analysis; visualization type; study results; policy implication; and benefits and limitations of using visualizations. Two independent researchers (EW and MF) applied the summary topics to all included studies, and the process was checked for consistency and accuracy by a third researcher (YC). Any changes were discussed by both researchers and a final decision arrived at through consensus with the third researcher.

2.2. Data analysis and mapping

We developed summary descriptions of the application of visualization tools to mental healthcare systems, showing the scope of the research found. We have presented our findings not only to show how visual analytics tools are currently used, but also to consider implications for future research and practice.

We developed a typology to categorize visualization types by the key purpose or analytical tasks of each study, aiming to demonstrate their variation as applied to mental healthcare systems. We then assessed the tendency of the studies over time to identify gaps for future work in mental healthcare systems research. The final aspect of this scoping review assessed the practical applicability of the visual analytics by evaluating the complexity and usability of the studies.

The complexity was measured using three attributes as seen in Table 1:

- 1) the number of information layers to be analyzed and viewed using visualizations;
- 2) the level of 'graphicacy' (the ability to understand and use a map or graph) (Kennedy, 2015) for visual interpretation and communication; and
- 3) the complexity of computational analysis method to produce analytical information.

The complexity attributes were scored with the values of 0 (low) and 1 (high) based on the sizes of data and variables used. We defined the values of graphicacy based on the types of visualization tools, divided into two categories (Pantazos, Lauesen, & Vatrapu, 2013):

- 1) tools that require advanced skills or knowledge from large audiences

Table 1
Measures of the study complexity and usability.

Study Evaluation	Attribute	Score	Note
Complexity	Information Layer	0 (low) / 1 (high)	Visualized information
	Graphicacy Level	0 (basic skill) / 1 (advanced skill)	Targeted domain experts
	Computational Complexity	0 (low) / 1 (high)	Applied algorithms
Usability	Funding Strategy	0 (no) / 1 (yes)	Health organization funding?
	Expert Participation	0 (no) / 1 (yes)	Non-academic experts?
	Policy Impact	0 (no) / 1 (yes)	Intention of policy impact?

for interpreting its visual information in an unfamiliar form; or
2) tools that produce the visual information in familiar and predefined way to large audiences requiring very basic skills or knowledge for its interpretation.

The graphicacy was scored 1 if a study used visualization tools that require advanced skill of knowledge, otherwise 0. Two researchers (YC and JS) separately scored the graphicacy of the main visualization graph used in each study. To make scoring fairer, the two researchers referred to the benefits and limitations of the visualization tools as discussed in the publications. The interrater reliability of the graphicacy scores was measured using the Kappa coefficient (k) to synthesize the quality of the evaluation results (Cohen, 1960; McHugh, 2012). For quality control and final decision on the scores, a third researcher (NB) joined the process. A final decision on the graphicacy scores was reached through consensus with the third researcher. The aggregation of these scores provided the complexity levels from 0 to 3 (from low to high) in our review.

The usability was measured using another three attributes as described in Table 1:

- 1) the funding strategy (e.g., direct funding or co-funding from health organizations and public agencies);
- 2) the participation of domain experts (e.g., stakeholders with co-authorship); and
- 3) the policy impact of the study (e.g., reference to a specific policy problem in the study).

The usability attributes were also scored with the values of 0 and 1 based on 'no' and 'yes' categories, respectively. The funding strategy was scored 1 if a study was supported by any relevant local or global health organizations, otherwise 0. The participation of domain experts was scored 1 if any non-academic experts were involved in a study, otherwise 0. The policy impact was scored 1 if there was a specific statement linking the study to a policy problem. In order to assess the overall usability, we provided the aggregated scores of these three attributes from 0 to 3 (low to high).

3. Results

The database search yielded a total of 2413 publications. This was reduced to 2012 after removal of duplicates (see Fig. 1 for a summary of the screening process). After screening titles and abstracts from the search results, we found 131 publications and identified a further 23 publications based on our knowledge, meaning the initial selection included 154 publications for the full-text screening. We were unable to retrieve the full-text of four publications so they were excluded from the full-text screening. Another 71 publications were also excluded as they did not meet the inclusion criteria described above. After the full-text screening, a total of 79 publications were selected for final inclusion in the scoping review. The topic of the included studies was extracted for review and comparison in a summary table (refer to Appendix).

3.1. Conceptual mapping of visualizations

The 79 studies were mapped into a conceptual framework (see Table 2). This framework allowed us to apply the typology developed to categorize the studies by visualization type and study purpose/analytical tasks. Three main tasks were identified: descriptive; non-geospatial and geospatial analysis. The first two tasks involve abstract information that do not require geospatial information while the latter requires geospatial information for their data analyses (Tory & Moller, 2004). While descriptive analysis was defined for relatively simple bivariate data with statistical measures, non-geospatial analysis was defined for multivariate data with more complex measures (e.g., using multiple regression or multi-dimensional scaling methods) in this review. The visualizations were then further categorized into six broad types: geographical map; mixed geographical map and other graphs; association graphs; variation graphs; diagram; and novel visualizations, referring to analytical targets (e.g., data, attributes, network and geospatial) (Munzner, 2014). Graphs such as bar, curve and scatter plots were considered as 'association graphs' if they were used for studies on association analysis that included analysis of correlation, prediction, clustering, and pattern. Graphs such as bar, line and radar plots were considered as 'variation graphs' if they were used for studies on variation analysis that included analysis of spatial and/or temporal change and difference comparison.

As seen in Table 2, 40.5% of the included studies referred to geospatial studies related to service access, variation, association and utilisation. All these geospatial studies used geographical maps for visual analytics. Half of them also used other supported graphs for association analysis. Many of the descriptive studies focused on variation analysis and used variation graphs. Many of these descriptive studies also used geographical maps to present the descriptive information. Geographical maps were also used for some of non-geospatial studies. Overall, 67.1% of the studies in this review used geographical maps for analyzing healthcare systems in mental health. The rest of the studies used other visualization techniques (association or variation graphs based on their tasks). Only a small number of the studies (2.5%) attempted to use relatively novel visualization forms (e.g., Cluster Panel Map and Self-Organising Map) when analyzing complex patterns of mental healthcare systems.

3.2. Tendency mapping of studies

We mapped our evaluation of the 79 identified studies into the three main tasks (descriptive, geospatial and non-geospatial analysis), by 5-year periods. As shown in Fig. 2, the earliest study was conducted in 1988, analysing non-geospatial (abstract) information of mental healthcare systems. Studies on descriptive analysis were the most common task between 2000 and 2004. Since 2005 the most common task has been geospatial analysis, with non-geospatial analysis emerging more recently, reflecting increased demand for understanding complex mental healthcare systems at a high (abstract) level.

Using the same periods, we also mapped the studies by geographic origin. As shown in Fig. 3, the majority (32 studies, 41.25%) of the studies were European (Spain, UK, France, Italy, Germany, Switzerland, Sweden and Netherlands) with 36.25% (30 studies) from North

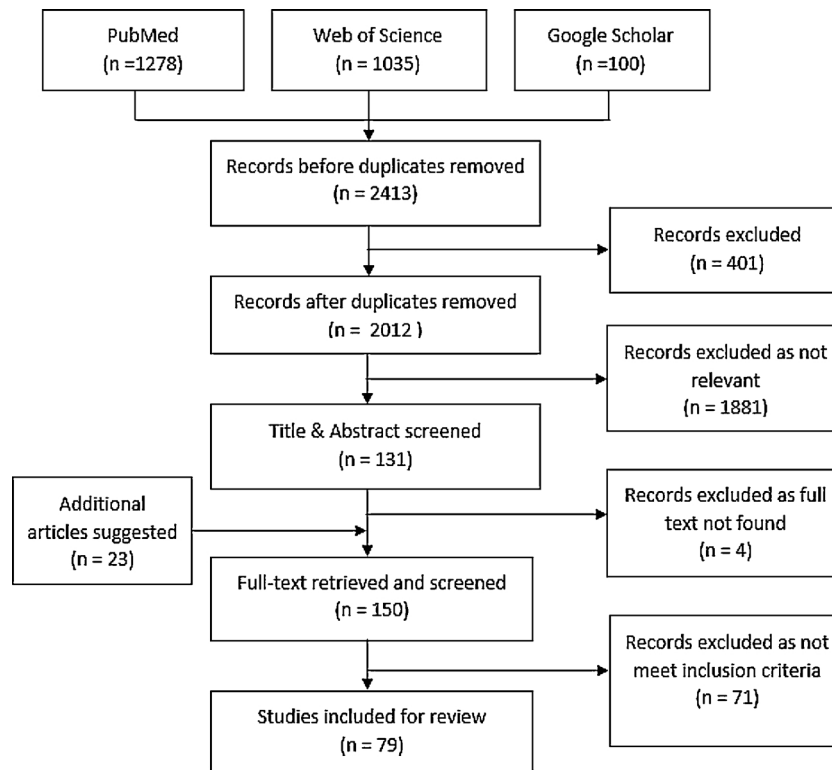


Fig. 1. The search decision and screening flowchart.

Table 2

The conceptual mapping of visualization types based on analytical tasks of the studies (associated with Table 3).

Analytical tasks		Visualization Type					No. of studies	Total No. of studies (%)	
		Geographical map	Geographical map + other graphs	Association graphs	Variation graphs	Diagram			Novel visualizations
Descriptive	Variation	9 [1][2][5] [7][11][17] [21][28][49]	2 [20][39]		7 [18][19][33] [36][52] [64][75]			18	21 (26.6%)
	Association	1 [26]		1 [50]				2	
	Pathway	1 [3]						1	
Non-geospatial	Variation		1 [15]		4 [12][22] [23][57]			5	26 (32.9%)
	Association	6 [24][31][37] [41][53][60]	1 [56]	9 [6][9][30] [35][62][68] [69][74][79]		1 [61]	2 [14][27]	19	
	Pathway					2 [32][66]		2	
Geospatial	Variation	4 [4][16] [38][76]	2 [13][54]					6	32 (40.5%)
	Association	8 [10][43][48] [51][63][65] [72][78]	8 [45][46][47][58] [59] [67] [71][77]					16	
	Hotspot	9 [8][29][34] [40][42][44] [55][70][73]	1 [25]					10	
Total No. of studies (%)		38 (48.1%)	15 (19.0%)	10 (12.7%)	11 (13.9%)	3 (3.8%)	2 (2.5%)	79 (100%)	79 (100%)

Table 3
The list of publications included in the review and associated with Table 2.

(1) (Allard, Rosen, & Tolman, 2003)	(44) (Moreno et al., 2008; Stulz, Pichler, Kawohl, & Hepp, 2018)
(2) (Allard, Tolman, & Rosen, 2003)	(45) (Moriarty, Zack, Holt, Chapman, & Safran, 2009)
(3) (Allen, LeMaster, & Deters, 2004)	(46) (Moscone & Knapp, 2005)
(4) (Almog, Curtis, Copeland, & Congdon, 2004)	(47) (Moscone, Knapp, & Tosetti, 2007)
(5) (Andrilla, Patterson, Garberson, Coulthard, & Larson, 2018)	(48) (Ngui, Apparicio, Moltchanova, & Vasiliadis, 2014)
(6) (Asthana, Gibson, Hewson, Bailey, & Dibben, 2011)	(49) (Okoro et al., 2011)
(7) (Baldwin et al., 2006)	(50) (Pedersen & Lilleeng, 2000)
(8) (Banta, Wiafe, Soret, & Holzer, 2008)	(51) (Qi, Hu, Page, & Tong, 2012)
(9) (Borgoni, Smith, & Berrington, 2015)	(52) (Raja, Wood, de Menil, & Mannarath, 2010)
(10) (Campbell & Ballas, 2016)	(53) (Rodero-Cosano et al., 2016)
(11) (Carson et al., 2016)	(54) (Ronzio, Guagliardo, & Persaud, 2006)
(12) (Chang et al., 2014)	(55) (Salinas-Perez, Garcia-Alonso, Molina-Parrilla, Jorda-Sampietro, & Salvador-Carulla, 2012)
(13) (Cheung, Spittal, Pirkis, & Yip, 2012)	(56) (Stahler, Mennis, Cotlar, & Baron, 2009)
(14) (Chung et al., 2018)	(57) (Strum, Ringel, & Andreyeva, 2003)
(15) (Coldefy & Curtis, 2010)	(58) (Stulz et al., 2018)
(16) (Cummings, Allen, Clennon, Ji, & Druss, 2017)	(59) (Takahashi et al., 2017)
(17) (Ellis, Konrad, Thomas, & Morrissey, 2009)	(60) (Tibaldi et al., 2005)
(18) (Fernandez et al., 2017)	(61) (Trani, Ballard, Bakhshi, & Hovmand, 2016)
(19) (Fernandez et al., 2015)	(62) (Vazquez-Polo et al., 2005)
(20) (Fleming, McGilloway, & Barry, 2016)	(63) (Walker, Hurvitz, Leith, Rodriguez, & Endler, 2016)
(21) (Foley & Platzer, 2007)	(64) (Wu et al., 2016)
(22) (Gandre et al., 2018b)	(65) (J. Zhang et al., 2014)
(23) (Gandre et al., 2018a)	(66) (W. Zhang et al., 2013)
(24) (Garrido-Cumbrera et al., 2008)	(67) (Zulian et al., 2011)
(25) (Ghosh, Sterns, Drew, & Hamera, 2011)	(68) (Hudson, 2010)
(26) (Gleeson, Hay, & Law, 1998)	(69) (Alvarez-Galvez, Salinas-Perez, Rodero-Cosano, & Salvador-Carulla, 2017)
(27) (Green & Aarons, 2011)	(70) (Bagheri, Wangdi, Cherbuin, & Anstey, 2018)
(28) (Green et al., 2013)	(71) (Chaix et al., 2006)
(29) (Guerrero & Kao, 2013)	(72) (Curtis et al., 2006)
(30) (G. Hall et al., 2016)	(73) (García-Alonso, Salvador-Carulla, Negrín-Hernández, & Moreno-Küstner, 2010)
(31) (G. B. Hall, 1988)	(74) (Gibert, García-Alonso, & Salvador-Carulla, 2010)
(32) (Hashimoto et al., 2015)	(75) (Gutiérrez-Colosía et al., 2017)
(33) (He et al., 2016)	(76) (Kirkbride et al., 2007)
(34) (Wong & Stanhope, 2009)	(77) (Ngui et al., 2013)
(35) (Jia, Muennig, Lubetkin, & Gold, 2004)	(78) (Salinas-Pérez, Rodero-Cosano, García-Alonso, & Salvador-Carulla, 2015)
(36) (Johnson, LaForest, Lissenden, & Stern, 2017)	(79) (Torres-Jiménez, García-Alonso, Salvador-Carulla, & Fernández-Rodríguez, 2015)
(37) (Koizumi, Rothbard, & Kuno, 2009)	
(38) (Law & Perlman, 2018)	
(39) (Lin, Chen, & Chou, 2012)	
(40) (Mathis, Woods, & Srihari, 2018)	
(41) (Maylath, Seidel, Werner, & Schlattmann, 1999)	
(42) (Mayne, Morgan, Jalaludin, & Bauman, 2018)	
(43) (Metraux, Brusilovskiy, Prvu-Bettger, Irene Wong, & Salzer, 2012; Moreno, Garcia-Alonso, Hernandez, Torres-Gonzalez, & Salvador-Carulla, 2008)	

America (USA and Canada), followed by 11.25% (8 studies) from Oceania (Australia and New Zealand). While New Zealand in Oceania was responsible for the earliest study (1988) recorded in this review, most of the studies across all regions have been conducted since 2005. Visual analytics is a contemporary phenomenon. The studies on mental healthcare systems in Europe began in 1995 increasing from 2005 to be the main source of the research worldwide. North America showed a steady pattern, with minimal study rates in other world regions such as Asia and Africa.

3.3. Practical applicability evaluation of visual analytics

This part of our study focused on assessing the extent to which the 79 visual analytics studies could be seen to be practically influencing policy and decision-making. Based on the complexity and usability levels measured for all 79 studies, a matrix with 16 different value combinations was developed to assess the practical applicability of visual analytics for mental healthcare systems research and planning. The interrater reliability of the graphicacy scores given to the visualization

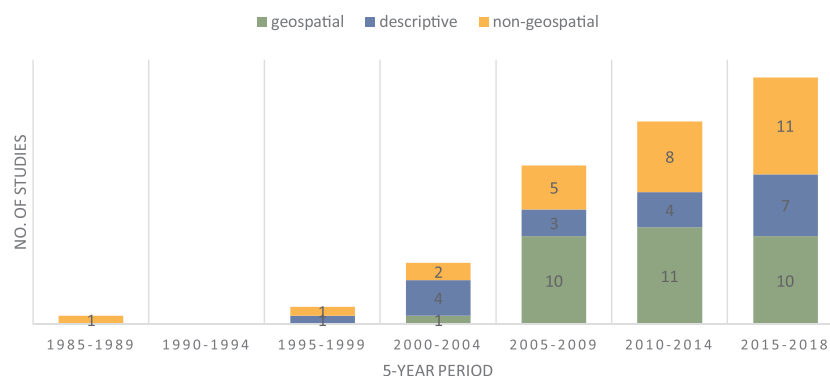


Fig. 2. The tendency of the studies based on 5-year periods for different analytical tasks.

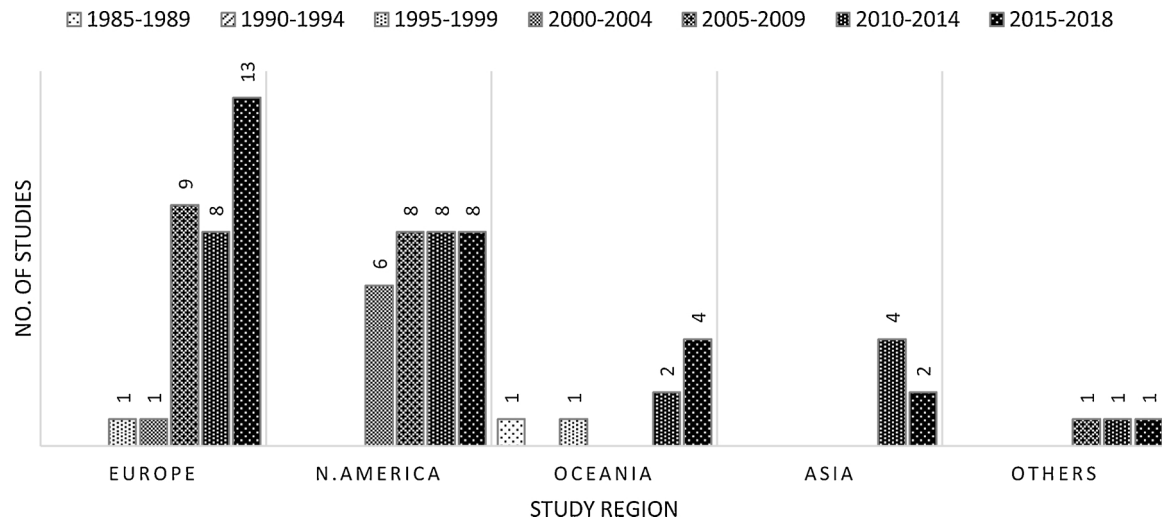


Fig. 3. The tendency of the studies based on 5-year periods worldwide.

tools showed substantial agreement ($k = 0.71$) for measuring the complexity of the studies.

As shown in Fig. 4, visual analytics was applicable for most of the moderately useable studies through all levels of the study complexity ($10\% + 18\% + 9\% + 5\% + 8\% + 22\% + 4\% + 5\% = 81\%$). However, the practical applicability of visual analytics appeared relatively low for highly complex studies ($5\% + 5\% + 1\% = 11\%$) and very low for these studies even if they were able to demonstrate strong support from relevant health organisations. Only 15% ($3\% + 8\% + 3\% + 1\%$) of the studies provided information that indicated high levels of usability in policy and practice. The practical applicability of visual analytics also appeared very low for studies that were not able to demonstrate any support from a relevant health organization and none if they were very complex. Fig. 4 also shows the distribution of three main visualization types (geographical maps, graphs/diagrams, novel visualizations) used for the studies by impact rating. This demonstrates low practical applicability of visual analytics involving high complexity and usability, as more novel visualization approaches were required to generate impact.

4. Discussion

Given the growing availability of data in health care, there is an increasing need for investment in visual analytics approaches to assist evidence-informed decision-making (Robinson, 2016). Mental health should be a high priority area for these developments due to: its mixture of health and social care needs; the complexity and ambiguity of mental disorders; and the interface between mental and physical care (Salvador-Carulla et al., 2006). To our knowledge, this is the first attempt to conduct a scoping of the literature related to the application of visual analytics to mental healthcare systems. It has incorporated a method for categorizing and assessing the literature on this topic.

4.1. Findings and gaps

This review reveals three main findings. First, much of the existing literature refers to the use of geographical maps in understanding mental healthcare systems. This has limited capacity to represent complex non-geospatial information at a high level. The second notable

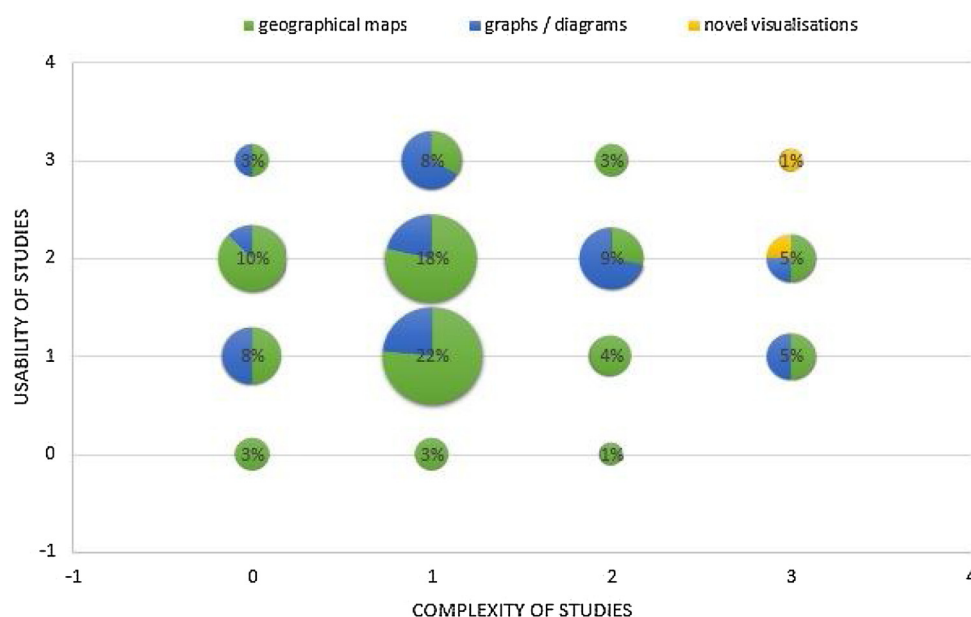


Fig. 4. The practical applicability levels of visual analytics for mental healthcare systems research and policy. The bubble size indicates the percentage of studies at each level.

finding is the increase of non-geospatial studies. This shows that a key emerging challenge for researchers is to select the visualization tools best suited for the study task and audience. The third interesting finding is the absence of literature indicating where the application of visual analytics with highly complex data has actually driven policy or funding decisions. In other words, it is not easy to find clear evidence that visualization techniques have actually been useful to decision-makers. There is clearly a need to ensure that health organizations and public agencies better understand the value of visual analytics so that it becomes part of routine practice in decision-making. Other findings to note are the regional differences identified in the number and sophistication of studies using visualization tools. Although this issue was not a key part of the scope of this review it is interesting to note European leadership in the field.

Our review suggests that studies using only geographical maps may not be the best way to present complex information and associations. Throughout the 1990s, the Geographic Information System (GIS) technology has been widely adopted for geospatial studies both in research and practice (Tate, 2018). Its application in mental healthcare systems planning took off in the 2000s, as data became more available across Europe, North America and Oceania. However, the increase of literature on non-geospatial analysis of large and complex mental healthcare systems has required novel visualization technologies with the use of Artificial Intelligence (AI) techniques for evidence-informed knowledge discovery and decision support (Duan, Edwards, & Dwivedi, 2019). Most visualization tools face considerable challenges in trying to display complex and multidimensional information that is analysed using AI techniques but does not require geospatial information. It is difficult to incorporate necessary abstract information into geographical maps given these maps rely on fixed geospatial information. Surmounting this problem requires incorporating additional visualizations (e.g., graphs or symbols) into geographical maps, using alternatives, or developing novel visualization approaches. Various visualization methods are available and can be tailored depending on the task. This review indicates that the diversity of visualization tools applied to mental healthcare systems is still low considering the alternatives available (Spiegelhalter et al., 2011). Common visualization tools currently used in other thematic areas, such as alluvial diagrams, rose-like graphs and roulette wheels (Grant, 2015), are rarely used in mental healthcare systems research and evidence-informed policy planning.

Visualisation plays an important role in incorporating domain experts in the whole process of Knowledge Discovery in Databases (KDD) and supporting evidence-informed decisions by domain experts (Fayyad, Piatetsky-Shapiro, & Smyth, 1996; Gibert, Sánchez-Marrè, & Codina, 2010; López, Sanchez, & Micó, 2014; Thornicroft, Ruggeri, & Goldberg, 2013). Understanding complex mental healthcare data also requires the engagement of domain experts in the process of KDD (pre-, mid- and post-processing phases) (Chung et al., 2018). The interactive capacity of visual analytics enables domain experts to sort, filter and explore data. There is evidence that this interaction leads to better understanding, clearer communication and increased likelihood that the analysis will effectively influence practical decision-making (Gatto, 2015). This has increasingly filled a crucial information gap when analysts and domain experts come to explore and communicate the wealth of information being produced particularly in the mid-processing phase of KDD, between the development of expert prior knowledge and the interpretation of analytical results (McInerney et al., 2014; Salvador-Carulla et al., 2010).

However, identifying and displaying meaningful abstract information using visualizations remains a challenge for several reasons. First, some domain experts may have limited graphicacy skills. Their skills may be further tested due to the size and complexity of the data presented. Also, some visual analytics tools might be difficult for the targeted audience (e.g., policy-makers) to use and understand. The richer and more complex information presented using visual analytics tools might make it difficult to establish clear understanding about what to

do or what messages to communicate. This might influence the late adoption and diffusion of visual analytics in healthcare systems research and policy. A multidisciplinary collaboration (e.g., infography, visual arts and marketing) with domain experts in the development of visual analytics can be highly relevant for improving the use of novel visualization tools by decision-makers. There will be huge opportunities for studies to engage domain experts, improve the use of visualizations and drive increased research efforts (Kohlhammer et al., 2011; McInerney et al., 2014).

4.2. Strengths and limitations

The key strength of this scoping review is its originality - the practical applicability of visual analytics to mental healthcare systems. It is hoped our findings allow researchers and domain experts to obtain a strategic view of the potential power of visual analytics to drive better policy and decision-making in mental health care. Our approach requires corroboration by other research groups. Our strong involvement in mental healthcare systems research may have produced a selection bias. We have tried to overcome this issue by incorporating independent raters (KS and EW) who were not previously involved in this research. The review should trigger continued debate about the direction of growth of visual analytics for evidence-informed decision-making in mental health and beyond.

The main limitation of our review is the extent to which the search strategy does not list all visualization types currently available. Our search strategy put more weight on the geospatial terms for visualization and, as a result, we may have missed some relevant literature on novel visualizations. Similarly, since we focused on visual analytics for mental healthcare systems, other mental health studies were not considered in this review. This could have resulted in missing some relevant studies from the initial screening phases, or the search terms could not index them properly in the database search. To address any gap, we conducted a citation search for the review and considered a further 23 publications at the full-text screening phase. A final limitation was that overall there seemed to be a paucity of relevant literature, meaning our eventual sample size was small.

4.3. Future work

The emergence of specialists and visual analytics laboratories both in academia and in the public sector is already apparent and important. The increasing interest in this topic will guide the next stage of evolution of visual analytics technology and eventually result in better tools to influence policy, funding and the quality of services for people with mental illnesses. This could include the suitability of visual analytics technologies in response to the recent evolution of digital health services towards gamification (Koivisto & Hamari, 2019), amazonification (Desjardins, 2018) and real-time dashboard initiative (Kitchin, Lauriault, & McArdle, 2015). These techniques are critical in developing, monitoring and supporting digital health services and activities to design effective mental healthcare interventions for right people at right places (Dwivedi, Shareef, Simintiras, Lal, & Weerakkody, 2016). The great challenges ahead are developing novel visualizations; increasing the graphicacy skills of domain experts in relation to visual analytics technology; and improving the quality of information generated by new visualization tools.

Another area for future research is a detailed analysis of specific areas of visualization such as the use of geographical maps over other visualizations. Given its predominance in the sector, a systematic review on this type of visualization would be desirable. It may also be relevant to explore national and regional differences in the development and use of visualization tools identified in this review. The adoption of systems thinking and complexity approaches to mental health planning in Europe and the priorities of European health funding schemes could have played a role in these findings (Dattée & Barlow,

2010; Forsman et al., 2015; Hazo et al., 2017; Iruin-Sanz, Pereira-Rodríguez, & Nuño-Solinís, 2015).

Finally, this scoping review can contribute to the future development of a framework or guidelines for the use of visual analytics tools in mental healthcare systems research. Such a framework would help researchers and decision-makers capitalize on these tools, choosing the most appropriate and useful to meet their needs.

5. Conclusions

This systematic scoping review was conducted to illustrate the application of visual analytics to data analysis and decision support in mental health systems settings. It presents a sample of the variety of work being performed around the world. This review demonstrates the complexity of data, the type of study, the type of visualizations and the impact of visual analytics as practically applied to mental healthcare systems and policy planning. Our findings indicate that most of the studies used geographical maps for visual analytics of mental healthcare systems. The dearth of visualization tools providing abstract information for highly complex data indicates a major gap between existing and novel visualization methods as applied to mental health. Continuing to develop visual analytics approaches, engaging domain experts in better understanding the role of visual analytics and ensuring their genuine impact in better decision-making are the key next steps for this emerging research area.

Authors' contributions

YC contributed to the study design, data search, data mapping, and data review and analysis; wrote the original draft manuscript; and incorporated revisions from each of the co-authors. NB and LS contributed to the conception of this research and the study design and provided critical reviews of the manuscript for important intellectual content with SR, who also contributed to English correction of the manuscript. KS contributed to the data search and screening; EW and MF contributed to data mapping; and JS contributed to data review and analysis. All authors read and approved the final manuscript.

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Declaration of interest

None.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:<https://doi.org/10.1016/j.ijinfomgt.2019.04.012>.

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