International Journal of Information Management 50 (2020) 17–27

Contents lists available at ScienceDirect

International Journal of Information Management

journal homepage: www.elsevier.com/locate/ijinfomgt

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

Younjin Chung[a,*], Nasser Bagheri[a], Jose Alberto Salinas-Perez[b], Kayla Smurthwaite[c], Erin Walsh[d], MaryAnne Furst[a], Sebastian Rosenberg[a,e], Luis Salvador-Carulla[a]

[a] Centre for Mental Health Research, Research School of Population Health, College of Health and Medicine, Australian National University, 63 Eggleston Road, Acton ACT 2601, Australia
[b] Department of Quantitative Methods, Universidad Loyola Andalucía, Calle Energía Solar, 1, 41014 Sevilla, Spain
[c] Department of Health Services Research and Policy, Research School of Population Health, College of Health and Medicine, Australian National University, 62 Mills Road, Acton ACT 2601, Australia
[d] Centre for Research in Ageing, Health and Wellbeing, Research School of Population Health, College of Health and Medicine, Australian National University, 62 Mills Road, Acton ACT 2601, Australia
[e] Brain and Mind Centre, University of Sydney, 94 Mallett Street, Camperdown NSW 2050, Australia

ARTICLE INFO

Keywords:
Systematic scoping review
Mental healthcare system
Data complexity
Visualization
Visual analytics
Evidence-informed decision-making

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

* Corresponding author.
E-mail address: younjin.chung@anu.edu.au (Y. Chung).

https://doi.org/10.1016/j.ijinfomgt.2019.04.012
Received 4 December 2018; Received in revised form 21 April 2019; Accepted 21 April 2019

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; McInerny 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

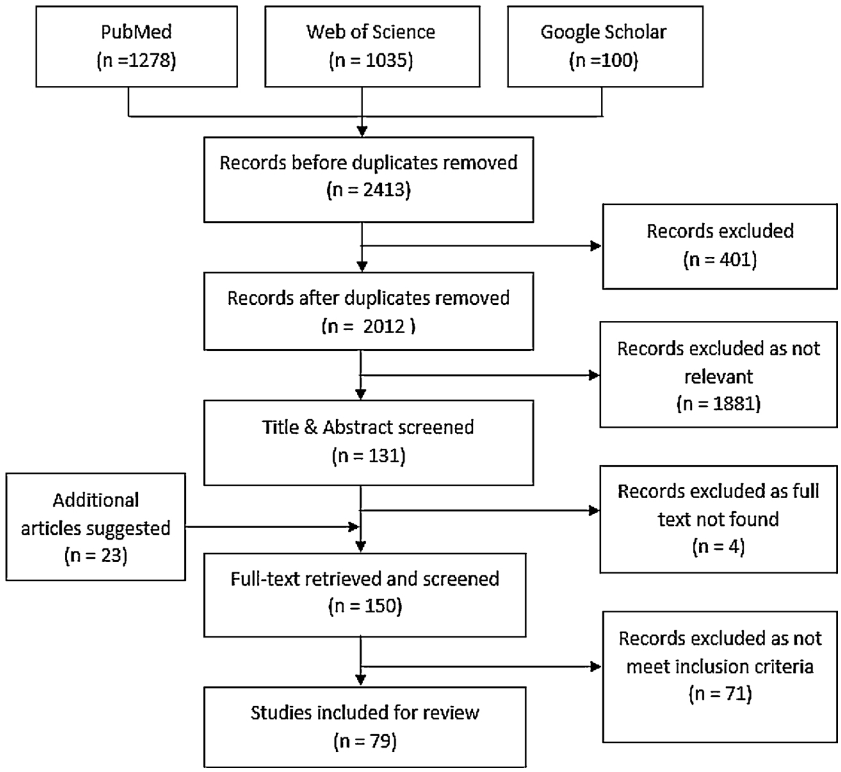

Fig. 1. The search decision and screening flowchart.

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

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

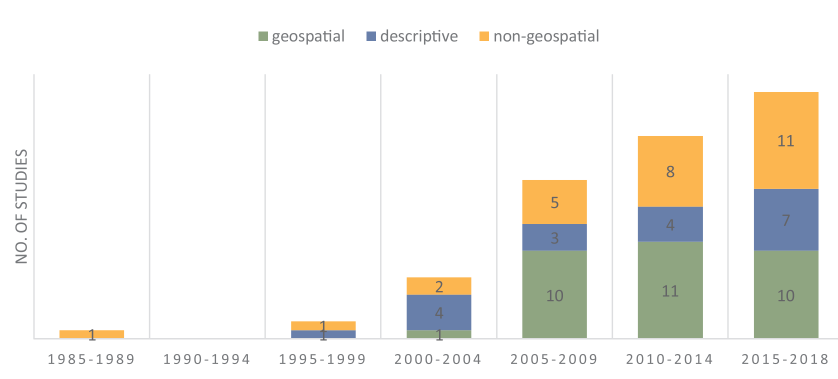

Fig. 2. The tendency of the studies based on 5-year periods for different analytical tasks.

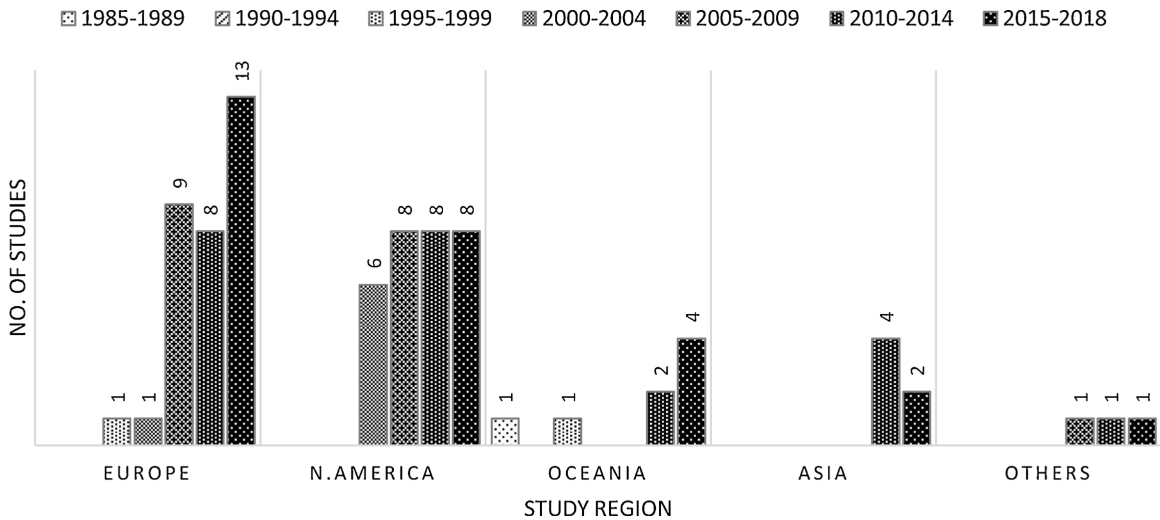

Fig. 3. The tendency of the studies based on 5-year periods worldwide.

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

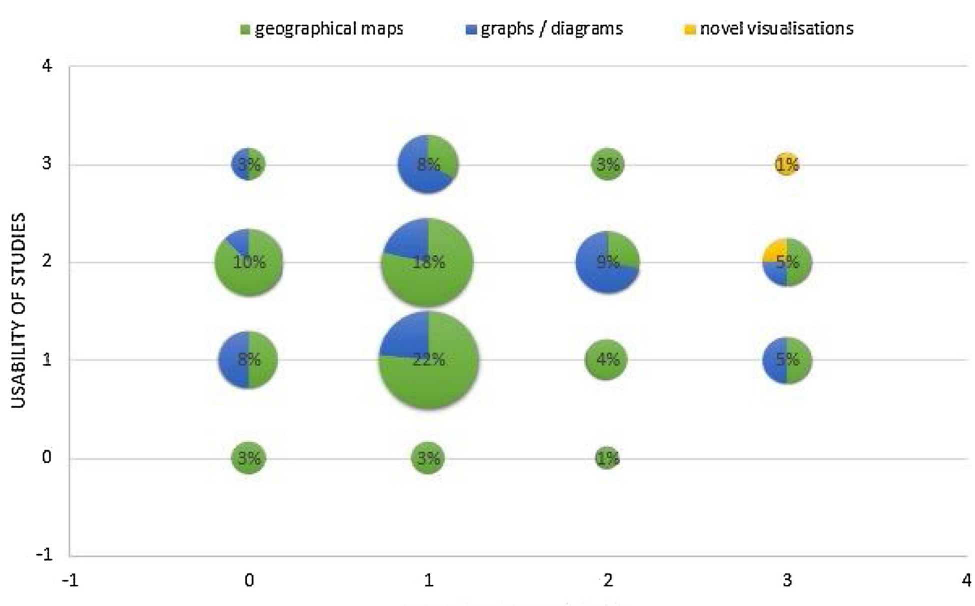

Fig. 4. The practical applicability levels of visual analytics for mental healthcare systems research and policy. The bubble size indicates the percentage of studies at each level.

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, Sànchez-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 (McInerny 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; McInerny 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.

Funding

This work was partially supported by ANU cross college grant, the Research School of Population Health, Australian National University (ANU) [grant numbers RPH41006, 2018].

Declaration of interest

None.

Acknowledgements

None.

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.

References

Allard, S. W., Rosen, D., & Tolman, R. M. (2003). Access to mental health and substance abuse services among women receiving welfare in Detroit. *Urban Affairs Review, 38*(6), 787–807. https://doi.org/10.1177/1078087403251912.

Allard, S. W., Tolman, R. M., & Rosen, D. (2003). Proximity to service providers and service utilization among welfare recipients: The interaction of place and race. *Journal of Policy Analysis and Management, 22*(4), 599–613. https://doi.org/10.1002/pam.10157.

Allen, J., LeMaster, P. L., & Deters, P. B. (2004). Mapping pathways to services: Description of local service systems for American Indian and Alaska Native children by Circles of Care. *American Indian and Alaska Native Mental Health Research, 11*(2), 65–87.

Almog, M., Curtis, S., Copeland, A., & Congdon, P. (2004). Geographical variation in acute psychiatric admissions within New York City 1990–2000: Growing inequalities in service use? *Social Science & Medicine, 59*(2), 361–376. https://doi.org/10.1016/j.socscimed.2003.10.019.

Alvarez-Galvez, J., Salinas-Perez, J. A., Rodero-Cosano, M. L., & Salvador-Carulla, L. (2017). Methodological barriers to studying the association between the economic crisis and suicide in Spain. *BMC Public Health, 17*(1), 694.

Andrilla, C. H. A., Patterson, D. G., Garberson, L. A., Coulthard, C., & Larson, E. H. (2018). Geographic variation in the supply of selected behavioral health providers. *American Journal of Preventive Medicine, 54*(6s3), S199–s207. https://doi.org/10.1016/j.amepre.2018.01.004.

Arksey, H., & O'Malley, L. (2005). Scoping studies: Towards a methodological framework. *International Journal of Social Research Methodology, 8*(1), 19–32.

Asthana, S., Gibson, A., Hewson, P., Bailey, T., & Dibben, C. (2011). General practitioner commissioning consortia and budgetary risk: Evidence from the modelling of' fair share' practice budgets for mental health. *Journal of Health Services Research & Policy, 16*(2), 95–101. https://doi.org/10.1258/jhsrp.2010.010086.

Bagheri, N., Wangdi, K., Cherbuin, N., & Anstey, K. J. (2018). General practice clinical data help identify dementia hotspots: A novel geospatial analysis approach. *Journal of Alzheimers Disease, 61*(1), 125–134.

Baldwin, L. M., Patanian, M. M., Larson, E. H., Lishner, D. M., Mauksch, L. B., Katon, W. J., ... Hart, L. G. (2006). Modeling the mental health workforce in Washington State: Using state licensing data to examine provider supply in rural and urban areas. *The Journal of Rural Health, 22*(1), 50–58. https://doi.org/10.1111/j.1748-0361.2006.00003.x.

Banta, J. E., Wiafe, S., Soret, S., & Holzer, C. (2008). A spatial needs assessment of indigent acute psychiatric discharges in California. *The Journal of Behavioral Health Services & Research, 35*(2), 179–194. https://doi.org/10.1007/s11414-007-9103-1.

Borgoni, R., Smith, P. W. F., & Berrington, A. M. (2015). Simulating interventions in graphical chain models for longitudinal data. *Quality & Quantity, 49*(2), 599–616. https://doi.org/10.1007/s11135-014-0011-1.

Caban, J. J., & Gotz, D. (2015). *Visual analytics in healthcare–opportunities and research challenges.* Oxford University Press.

Campbell, M., & Ballas, D. (2016). SimAlba: A spatial microsimulation approach to the analysis of health inequalities. *Frontiers in Public Health, 4*. https://doi.org/10.3389/fpubh.2016.00230.

Carroll, L. N., Au, A. P., Detwiler, L. T., Fu, T.-c., Painter, I. S., & Abernethy, N. F. (2014). Visualization and analytics tools for infectious disease epidemiology: A systematic review. *Journal of Biomedical Informatics, 51*, 287–298.

Carson, D., Bidargaddi, N., Schrader, G., Allison, S., Jones, G. M., Bastiampillai, T., ... Strobel, J. (2016). Geography of primary mental health care through the Better Access initiative in South Australia 2006–2010. *The Australian Journal of Rural Health, 24*(3), 188–192. https://doi.org/10.1111/ajr.12237.

Chaix, B., Leyland, A. H., Sabel, C. E., Chauvin, P., Råstam, L., Kristersson, H., ... Merlo, J. (2006). Spatial clustering of mental disorders and associated characteristics of the neighbourhood context in Malmö, Sweden, in 2001. *Journal of Epidemiology and Community Health, 60*(5), 427–435.

Chang, S. S., Chen, Y. Y., Yip, P. S., Lee, W. J., Hagihara, A., & Gunnell, D. (2014). Regional changes in charcoal-burning suicide rates in East/Southeast Asia from 1995 to 2011: A time trend analysis. *PLoS Medicine, 11*(4), e1001622. https://doi.org/10.1371/journal.pmed.1001622.

Cheung, Y. T., Spittal, M. J., Pirkis, J., & Yip, P. S. (2012). Spatial analysis of suicide mortality in Australia: Investigation of metropolitan-rural-remote differentials of suicide risk across states/territories. *Social Science & Medicine, 75*(8), 1460–1468. https://doi.org/10.1016/j.socscimed.2012.04.008.

Chung, Y., Salvador-Carulla, L., Salinas-Perez, J. A., Uriarte-Uriarte, J. J., Iruin-Sanz, A., & Garcia-Alonso, C. R. (2018). Use of the self-organising map network (SOMNet) as a decision support system for regional mental health planning. *Health Research Policy and Systems, 16*(1), 35. https://doi.org/10.1186/s12961-018-0308-y.

Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and Psychological Measurement, 20*(1), 37–46.

Coldefy, M., & Curtis, S. E. (2010). The geography of institutional psychiatric care in France 1800-2000: Historical analysis of the spatial diffusion of specialised facilities for institutional care of mental illness. *Social Science & Medicine, 71*(12), 2117–2129. https://doi.org/10.1016/j.socscimed.2010.09.028.

Colquhoun, H. L., Levac, D., O'Brien, K. K., Straus, S., Tricco, A. C., Perrier, L., ... Moher, D. (2014). Scoping reviews: Time for clarity in definition, methods, and reporting. *Journal of Clinical Epidemiology, 67*(12), 1291–1294.

Cummings, J. R., Allen, L., Clennon, J., Ji, X., & Druss, B. G. (2017). Geographic access to specialty mental health care across high- and low-income US communities. *JAMA Psychiatry, 74*(5), 476–484. https://doi.org/10.1001/jamapsychiatry.2017.0303.

Curtis, S., Copeland, A., Fagg, J., Congdon, P., Almog, M., & Fitzpatrick, J. (2006). The ecological relationship between deprivation, social isolation and rates of hospital admission for acute psychiatric care: A comparison of London and New York City. *Health & Place, 12*(1), 19–37.

Dattée, B., & Barlow, J. (2010). Complexity and whole-system change programmes. *Journal of Health Services Research & Policy, 15*(2_suppl), 19–25.

Desjardins, J. (2018). *The amazonification of healthcare.* Retrieved 15 April, 2019, fromhttps://www.visualcapitalist.com/amazonification-healthcare.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. *International Journal of Information Management, 48*, 63–71.

Dwivedi, Y. K., Shareef, M. A., Simintiras, A. C., Lal, B., & Weerakkody, V. (2016). A generalised adoption model for services: A cross-country comparison of mobile health (m-health). *Government Information Quarterly, 33*(1), 174–187.

Ellis, A. R., Konrad, T. R., Thomas, K. C., & Morrissey, J. P. (2009). County-level estimates of mental health professional supply in the United States. *Psychiatric Services, 60*(10), 1315–1322. https://doi.org/10.1176/ps.2009.60.10.1315.

Faisal, S., Blandford, A., & Potts, H. W. (2013). Making sense of personal health information: Challenges for information visualization. *Health Informatics Journal, 19*(3), 198–217.

Fayyad, U., Piatetsky-Shapiro, G., & Smyth, P. (1996). From data mining to knowledge discovery in databases. *AI Magazine, 17*(3), 37.

Fernandez, A., Gillespie, J. A., Smith-Merry, J., Feng, X., Astell-Burt, T., Maas, C., ... Salvador-Carulla, L. (2017). Integrated mental health atlas of the Western Sydney Local Health District: Gaps and recommendations. *Australian Health Review, 41*(1), 38–44. https://doi.org/10.1071/ah15154.

Fernandez, A., Salinas-Perez, J. A., Gutierrez-Colosia, M. R., Prat-Pubill, B., Serrano-Blanco, A., Molina, C., ... Grp, G.-S. (2015). Use of an integrated Atlas of Mental Health Care for evidence informed policy in Catalonia (Spain). *Epidemiology and Psychiatric Sciences, 24*(6), 512–524. https://doi.org/10.1017/s2045796014000511.

Fleming, P., McGilloway, S., & Barry, S. (2016). Day service provision for people with intellectual disabilities: A case study mapping 15-year trends in Ireland. *Journal of Applied Research in Intellectual Disabilities: JARID*. https://doi.org/10.1111/jar.12249.

Foley, R., & Platzer, H. (2007). Place and provision: Mapping mental health advocacy services in London. *Social Science & Medicine, 64*(3), 617–632. https://doi.org/10.1016/j.socscimed.2006.09.014.

Forsman, A. K., Wahlbeck, K., Aarø, L. E., Alonso, J., Barry, M. M., Brunn, M., ... Eberhard-Gran, M. (2015). Research priorities for public mental health in Europe: Recommendations of the ROAMER project. *European Journal of Public Health, 25*(2), 249–254.

Furst, M., Gandré, C., Romero-Lopez-Alberca, C., & Salvador-Carulla, L. (2019). Healthcare ecosystems research in mental health: A scoping review of methods to describe the context of local care delivery. *BMC Health Services Research, 19*(1), 173.

Gandre, C., Gervaix, J., Thillard, J., Mace, J. M., Roelandt, J. L., & Chevreul, K. (2018a). Thirty-day readmission rates and associated factors: A multilevel analysis of practice variations in french public psychiatry. *The Journal of Mental Health Policy and Economics, 21*(1), 17–28.

Gandre, C., Gervaix, J., Thillard, J., Mace, J. M., Roelandt, J. L., & Chevreul, K. (2018b). Understanding geographic variations in psychiatric inpatient admission rates: Width of the variations and associations with the supply of health and social care in France. *BMC Psychiatry, 18*(1), 174. https://doi.org/10.1186/s12888-018-1747-2.

García-Alonso, C. R., Salvador-Carulla, L., Negrín-Hernández, M. A., & Moreno-Küstner, B. (2010). Development of a new spatial analysis tool in mental health: Identification of highly autocorrelated areas (hot-spots) of schizophrenia using a Multiobjective Evolutionary Algorithm model (MOEA/HS). *Epidemiology and Psychiatric Sciences, 19*(4), 302–313.

Garrido-Cumbrera, M., Almenara-Barrios, J., Lopez-Lara, E., Peralta-Saez, J. L., Garcia-Gutierrez, J. C., & Salvador-Carulla, L. (2008). Development and spatial representation of synthetic indexes of outpatient mental health care in Andalusia (Spain). *Epidemiologia E Psichiatria Sociale, 17*(3), 192–200.

Gatto, M. A. (2015). *Making research useful: Current challenges and good practices in data visualisation*.

Ghosh, D., Sterns, A. A., Drew, B. L., & Hamera, E. (2011). Geospatial study of psychiatric mental health-advanced practice registered nurses (PMH-APRNs) in the United States. *Psychiatric Services (Washington, DC), 62*(12), 1506–1509. https://doi.org/10.1176/appi.ps.000532011.

Gibert, K., García-Alonso, C., & Salvador-Carulla, L. (2010). Integrating clinicians, knowledge and data: Expert-based cooperative analysis in healthcare decision support. *Health Research Policy and Systems, 8*(1), 28.

Gibert, K., Sànchez-Marrè, M., & Codina, V. (2010). *Choosing the right data mining technique: Classification of methods and intelligent recommendation*.

Gleeson, B., Hay, C., & Law, R. (1998). The geography of mental health in Dunedin, New Zealand. *Health & Place, 4*(1), 1–14.

Grant, J. (2015). *The nature, scale and beneficiaries of research impact: An initial analysis of Research Excellence Framework (REF) 2014 impact case studies*London, UK: Research Report 2015/01, King's College Access via: https://www.

Green, A. E., & Aarons, G. A. (2011). A comparison of policy and direct practice stakeholder perceptions of factors affecting evidence-based practice implementation using concept mapping. *Implementation Science, 6*. https://doi.org/10.1186/1748-5908-6-104.

Green, S. A., Poots, A. J., Marcano-Belisario, J., Samarasundera, E., Green, J., Honeybourne, E., ... Barnes, R. (2013). Mapping mental health service access: Achieving equity through quality improvement. *Journal of Public Health, 35*(2), 286–292. https://doi.org/10.1093/pubmed/fds071.

Griffin, P. M., Nembhard, H. B., DeFlitch, C. J., Bastian, N. D., Kang, H., & Munoz, D. A. (2016). *Healthcare systems engineering.* John Wiley & Sons.

Guerrero, E. G., & Kao, D. (2013). Racial/ethnic minority and low-income hotspots and their geographic proximity to integrated care providers. *Substance Abuse Treatment, Prevention, and Policy, 8*, 34. https://doi.org/10.1186/1747-597x-8-34.

Gutiérrez-Colosía, M. R., Salvador-Carulla, L., Salinas-Perez, J., Garcia-Alonso, C., Cid, J., Salazzari, D., ... Chevreul, K. (2017). Standard comparison of local mental health care systems in eight European countries. *Epidemiology and Psychiatric Sciences,* 1–14.

Hall, G. B. (1988). Monitoring and predicting community mental health centre utilization in Auckland, New Zealand. *Social Science & Medicine, 26*(1), 55–70.

Hall, G., Jessup, J., Lim, S., Olson, D., Seligson, A. L., He, F. T., ... Gwynn, C. (2016). Spatial shift in the utilization of mental health services after hurricane sandy among New York City residents enrolled in Medicaid. *Disaster Medicine and Public Health Preparedness, 10*(3), 420–427. https://doi.org/10.1017/dmp.2016.58.

Hashimoto, N., Fujisawa, D., Giasuddin, N. A., Kenchaiah, B. K., Narmandakh, A., Dugerragchaa, K., ... Sartorius, N. (2015). Pathways to mental health care in Bangladesh, India, Japan, Mongolia, and Nepal. *Asia-Pacific Journal of Public Health, 27*(2), Np1847–1857. https://doi.org/10.1177/1010539510379395.

Hazo, J.-B., Gandré, C., Leboyer, M., Obradors-Tarragó, C., Belli, S., McDaid, D., ... Wykes, T. (2017). National funding for mental health research in Finland, France, Spain and the United Kingdom. *European Neuropsychopharmacology, 27*(9), 892–899.

He, F. T., De La Cruz, N. L., Olson, D., Lim, S., Seligson, A. L., Hall, G., ... Gwynn, C. (2016). Temporal and spatial patterns in utilization of mental health services during and after hurricane sandy: Emergency department and inpatient hospitalizations in New York City. *Disaster Medicine and Public Health Preparedness, 10*(3), 512–517. https://doi.org/10.1017/dmp.2016.89.

Hudson, C. G. (2010). A predictive model of the development of national mental health systems. *The Journal of Mental Health Policy and Economics, 13*(4), 175–187.

Iruin-Sanz, A., Pereira-Rodríguez, C., & Nuño-Solinís, R. (2015). The role of geographic context on mental health: Lessons from the implementation of mental health atlases in the Basque Country (Spain). *Epidemiology and Psychiatric Sciences, 24*(1), 42–44.

Ismagilova, E., Hughes, L., Dwivedi, Y. K., & Raman, K. R. (2019). Smart cities: Advances in research. An information systems perspective. *International Journal of Information Management, 47*, 88–100.

Jia, H., Muennig, P., Lubetkin, E. I., & Gold, M. R. (2004). Predicting geographical variations in behavioural risk factors: An analysis of physical and mental healthy days. *Journal of Epidemiology and Community Health, 58*(2), 150–155.

Johnson, W. C., LaForest, M., Lissenden, B., & Stern, S. (2017). Variation in mental illness and provision of public mental health services. *Health Services & Outcomes Research Methodology, 17*(1), 1–30. https://doi.org/10.1007/s10742-016-0167-3.

Kannampallil, T. G., Schauer, G. F., Cohen, T., & Patel, V. L. (2011). Considering complexity in healthcare systems. *Journal of Biomedical Informatics, 44*(6), 943–947.

Keim, E. D., Kohlhammer, J., & Ellis, G. (2010). *Mastering the information age: Solving problems with visual analytics.* Eurographics Association.

Kennedy, H. (2015). Seeing Data: Visualisation design should consider how we respond to statistics emotionally as well as rationally. *Impact of Social Sciences Blog*.

Kirkbride, J. B., Fearon, P., Morgan, C., Dazzan, P., Morgan, K., Murray, R. M., ... Jones, P. B. (2007). Neighbourhood variation in the incidence of psychotic disorders in Southeast London. *Social Psychiatry and Psychiatric Epidemiology, 42*(6), 438–445.

Kitchin, R., Lauriault, T. P., & McArdle, G. (2015). Knowing and governing cities through urban indicators, city benchmarking and real-time dashboards. *Regional Studies Regional Science, 2*(1), 6–28.

Kohlhammer, J., Keim, D., Pohl, M., Santucci, G., & Andrienko, G. (2011). Solving problems with visual analytics. *Procedia Computer Science, 7*, 117–120.

Koivisto, J., & Hamari, J. (2019). The rise of motivational information systems: A review of gamification research. *International Journal of Information Management, 45*, 191–210.

Koizumi, N., Rothbard, A. B., & Kuno, E. (2009). Distance matters in choice of mental health program: Policy implications for reducing racial disparities in public mental health care. *Administration and Policy in Mental Health, 36*(6), 424–431. https://doi.org/10.1007/s10488-009-0233-z.

Lavis, J. N., Permanand, G., Oxman, A. D., Lewin, S., & Fretheim, A. (2009). SUPPORT Tools for evidence-informed health Policymaking (STP) 13: Preparing and using policy briefs to support evidence-informed policymaking. *Health Research Policy and Systems, 7*(1), S13.

Lavrač, N., Bohanec, M., Pur, A., Cestnik, B., Debeljak, M., & Kobler, A. (2007). Data mining and visualization for decision support and modeling of public health-care resources. *Journal of Biomedical Informatics, 40*(4), 438–447.

Law, J., & Perlman, C. (2018). Exploring geographic variation of mental health risk and service utilization of doctors and hospitals in Toronto: A shared component spatial modeling approach. *International Journal of Environmental Research and Public Health, 15*(4), https://doi.org/10.3390/ijerph15040593.

Levac, D., Colquhoun, H., & O'Brien, K. K. (2010). Scoping studies: Advancing the methodology. *Implementation Science, 5*(1), 69.

Lin, J. D., Chen, Y. C., & Chou, Y. C. (2012). Longitudinal analyses of geographic differences in utilization rates of children with developmental delays who participation in early intervention services. *Research in Developmental Disabilities, 33*(6), 1757–1762. https://doi.org/10.1016/j.ridd.2012.05.007.

Lipsitz, L. A. (2012). Understanding health care as a complex system: The foundation for unintended consequences. *JAMA, 308*(3), 243–244.

Long, K. M., McDermott, F., & Meadows, G. N. (2018). Being pragmatic about healthcare complexity: Our experiences applying complexity theory and pragmatism to health services research. *BMC Medicine, 16*(1), 94.

López, J. C., Sanchez, L. A., & Micó, R. J. (2014). *Mathematical modeling in social sciences and engineering.* Nova Science Publishers Incorporated.

Mathis, W. S., Woods, S., & Srihari, V. (2018). Blind Spots: Spatial analytics can identify nonrandom geographic variation in first episode psychosis program enrollments. *Early Intervention in Psychiatry*. https://doi.org/10.1111/eip.12681.

Maylath, E., Seidel, J., Werner, B., & Schlattmann, P. (1999). Geographical analysis of the risk of psychiatric hospitalization in Hamburg from 1988-1994. *European Psychiatry, 14*(8), 414–425. https://doi.org/10.1016/s0924-9338(99)00226-6.

Mayne, D. J., Morgan, G. G., Jalaludin, B. B., & Bauman, A. E. (2018). Does walkability contribute to geographic variation in psychosocial distress? A spatial analysis of 91,142 members of the 45 and up study in Sydney, Australia. *International Journal of Environmental Research and Public Health, 15*(2), https://doi.org/10.3390/ijerph15020275.

McHugh, M. L. (2012). Interrater reliability: The kappa statistic. *Biochemia Medica, 22*(3), 276–282.

McInerny, G. J., Chen, M., Freeman, R., Gavaghan, D., Meyer, M., Rowland, F., ... Hortal,

J. (2014). Information visualisation for science and policy: Engaging users and avoiding bias. *Trends in Ecology & Evolution, 29*(3), 148–157.

Metraux, S., Brusilovskiy, E., Prvu-Bettger, J. A., Irene Wong, Y. L., & Salzer, M. S. (2012). Geographic access to and availability of community resources for persons diagnosed with severe mental illness in Philadelphia, USA. *Health & Place, 18*(3), 621–629. https://doi.org/10.1016/j.healthplace.2011.12.011.

Moraga, P. (2017). SpatialEpiApp: A Shiny web application for the analysis of spatial and spatio-temporal disease data. *Spatial and Spatio-Temporal Epidemiology, 23*, 47–57.

Moreno, B., Garcia-Alonso, C. R., Hernandez, M. A. N., Torres-Gonzalez, F., & Salvador-Carulla, L. (2008). Spatial analysis to identify hotspots of prevalence of schizophrenia. *Social Psychiatry and Psychiatric Epidemiology, 43*(10), 782–791. https://doi.org/10.1007/s00127-008-0368-3.

Moriarty, D. G., Zack, M. M., Holt, J. B., Chapman, D. P., & Safran, M. A. (2009). Geographic patterns of frequent mental distress US adults, 1993–2001 and 2003–2006. *American Journal of Preventive Medicine, 36*(6), 497–505. https://doi.org/10.1016/j.amepre.2009.01.038.

Moscone, F., & Knapp, M. (2005). Exploring the spatial pattern of mental health expenditure. *The Journal of Mental Health Policy and Economics, 8*(4), 205–217.

Moscone, F., Knapp, M., & Tosetti, E. (2007). Mental health expenditure in England: A spatial panel approach. *Journal of Health Economics, 26*(4), 842–864. https://doi.org/10.1016/j.jhealeco.2006.12.008.

Munzner, T. (2014). *Visualization analysis and design.* AK Peters/CRC Press.

Ngui, A. N., Apparicio, P., Fleury, M.-J., Lesage, A., Grégoire, J.-P., Moisan, J., ... Vanasse, A. (2013). Spatio-temporal clustering of the incidence of schizophrenia in Quebec, Canada from 2004 to 2007. *Spatial and Spatio-Temporal Epidemiology, 6*, 37–47.

Ngui, A. N., Apparicio, P., Moltchanova, E., & Vasiliadis, H. M. (2014). Spatial analysis of suicide mortality in Quebec: Spatial clustering and area factor correlates. *Psychiatry Research, 220*(1–2), 20–30. https://doi.org/10.1016/j.psychres.2014.07.033.

Okoro, C. A., McKnight-Eily, L. R., Strine, T. W., Crews, J. E., Holt, J. B., & Balluz, L. S. (2011). State and local area estimates of depression and anxiety among adults with disabilities in 2006. *Disability and Health Journal, 4*(2), 78–90. https://doi.org/10.1016/j.dhjo.2010.05.001.

Ola, O., & Sedig, K. (2016). Beyond simple charts: Design of visualizations for big health data. *Online Journal of Public Health Informatics, 8*(3).

Pantazos, K., Lauesen, S., & Vatrapu, R. (2013). *End-user development of information visualization. Paper Presented at the International Symposium on End User Development*.

Pedersen, P. B., & Lilleeng, S. (2000). Resource distribution in mental health services: Changes in geographic location and use of personnel in Norwegian mental health services 1979–1994. *The Journal of Mental Health Policy and Economics, 3*(1), 45–53.

Peters, M. D., Godfrey, C. M., Khalil, H., McInerney, P., Parker, D., & Soares, C. B. (2015). Guidance for conducting systematic scoping reviews. *International Journal of Evidence-based Healthcare, 13*(3), 141–146.

Peters, M., Godfrey, C., McInerney, P., Soares, C., Khalil, H., & Parker, D. (2015). *The Joanna Briggs institute reviewers' manual 2015: Methodology for JBI scoping reviews.* The Joanna Briggs Institute.

Qi, X., Hu, W. B., Page, A., & Tong, S. L. (2012). Spatial clusters of suicide in Australia. *BMC Psychiatry, 12*. https://doi.org/10.1186/1471-244x-12-86.

Raja, S., Wood, S. K., de Menil, V., & Mannarath, S. C. (2010). Mapping mental health finances in Ghana, Uganda, Sri Lanka, India and lao PDR. *International Journal of Mental Health Systems, 4*, 11. https://doi.org/10.1186/1752-4458-4-11.

Robinson, I. (2016). *Data visualisation: Contributions to evidence-based decision-making*Retrieved 3 October, 2018, fromhttps://www.scidev.net/filemanager/root/site_assets/leanring_reports/data_visualisation_learning_report_scidevnet.pdf.

Rodero-Cosano, M. L., Salinas-Perez, J. A., Gonzalez-Caballero, J. L., Garcia-Alonso, C. R., Lagares-Franco, C., & Salvador-Carulla, L. (2016). A multi-level analysis of the relationship between spatial clusters of outpatient-treated depression, risk factors and mental health service planning in Catalonia (Spain). *Journal of Affective Disorders, 201*, 42–49. https://doi.org/10.1016/j.jad.2016.04.024.

Ronzio, C. R., Guagliardo, M. F., & Persaud, N. (2006). Disparity in location of urban mental service providers. *The American Journal of Orthopsychiatry, 76*(1), 37–43. https://doi.org/10.1037/0002-9432.76.1.37.

Ruppert, T. (2018). *Visual analytics to support evidence-based decision making.* Technische Universität.

Salinas-Perez, J. A., Garcia-Alonso, C. R., Molina-Parrilla, C., Jorda-Sampietro, E., & Salvador-Carulla, L. (2012). Identification and location of hot and cold spots of treated prevalence of depression in Catalonia (Spain). *International Journal of Health Geographics, 11*, 36. https://doi.org/10.1186/1476-072x-11-36.

Salinas-Pérez, J. A., Rodero-Cosano, M. L., García-Alonso, C. R., & Salvador-Carulla, L. (2015). Applying an evolutionary algorithm for the analysis of mental disorders in macro-urban areas: The case of Barcelona. *Spatial Economic Analysis, 10*(3), 270–288.

Salvador-Carulla, L., Salinas-Pérez, J. A., Martín, M., Grané, M.-s., Gibert, K., Roca, M., ... Bulbena, A. (2010). A preliminary taxonomy and a standard knowledge base for mental-health system indicators in Spain. *International Journal of Mental Health Systems, 4*(1), 29.

Salvador-Carulla, L., Haro, J. M., & Ayuso-Mateos, J. L. (2006). A framework for evidence-based mental health care and policy. *Acta Psychiatrica Scandinavica, 114*, 5–11.

Sopan, A., Noh, A. S.-I., Karol, S., Rosenfeld, P., Lee, G., & Shneiderman, B. (2012). Community Health Map: A geospatial and multivariate data visualization tool for public health datasets. *Government Information Quarterly, 29*(2), 223–234.

Spiegelhalter, D., Pearson, M., & Short, I. (2011). Visualizing uncertainty about the future. *Science, 333*(6048), 1393–1400.

Stahler, G. J., Mennis, J., Cotlar, R., & Baron, D. A. (2009). The influence of neighborhood environment on treatment continuity and rehospitalization in dually diagnosed patients discharged from acute inpatient care. *The American Journal of Psychiatry, 166*(11), 1258–1268. https://doi.org/10.1176/appi.ajp.2009.08111667.

Strum, R., Ringel, J. S., & Andreyeva, T. (2003). Geographic disparities in children's mental health care. *Pediatrics, 112*(4), E308–E315. https://doi.org/10.1542/peds.112.4.e308.

Stulz, N., Pichler, E. M., Kawohl, W., & Hepp, U. (2018). The gravitational force of mental health services: Distance decay effects in a rural Swiss service area. *BMC Health Services Research, 18*(1), 81. https://doi.org/10.1186/s12913-018-2888-1.

Takahashi, K., Tachimori, H., Kan, C., Nishi, D., Okumura, Y., Kato, N., ... Takeshima, T. (2017). Spatial analysis for regional behavior of patients with mental disorders in Japan. *Psychiatry and Clinical Neurosciences, 71*(4), 254–261. https://doi.org/10.1111/pcn.12488.

Tate, L. (2018). *An overview of GIS history.* Retrieved 18 October, 2018, fromhttps://www.geospatialworld.net/blogs/overview-of-gis-history.

Thornicroft, G., Ruggeri, M., & Goldberg, D. (2013). *Improving mental health care: The global challenge.* John Wiley & Sons.

Tibaldi, G., Munizza, C., Pasian, S., Johnson, S., Salvador-Carulla, L., Zucchi, S., ... Pinciaroli, L. (2005). Indicators predicting use of mental health services in Piedmont, Italy. *The Journal of Mental Health Policy and Economics, 8*(2), 95–106.

Torres-Jiménez, M., García-Alonso, C. R., Salvador-Carulla, L., & Fernández-Rodríguez, V. (2015). Evaluation of system efficiency using the Monte Carlo DEA: The case of small health areas. *European Journal of Operational Research, 242*(2), 525–535.

Tory, M., & Moller, T. (2004). *Rethinking visualization: A high-level taxonomy. Paper Presented at the IEEE Symposium on Information Visualization*.

Trani, J. F., Ballard, E., Bakhshi, P., & Hovmand, P. (2016). Community based system dynamic as an approach for understanding and acting on messy problems: A case study for global mental health intervention in Afghanistan. *Conflict and Health, 10*. https://doi.org/10.1186/s13031-016-0089-2.

Vazquez-Polo, F. J., Negrin, M., Cabases, J. M., Sanchez, E., Haro, J. M., & Salvador-Carulla, L. (2005). An analysis of the costs of treating schizophrenia in Spain: A hierarchical Bayesian approach. *The Journal of Mental Health Policy and Economics, 8*(3), 153–165.

Walker, S. C., Hurvitz, P. M., Leith, J., Rodriguez, F. I., & Endler, G. C. (2016). Evidence-based program service deserts: A geographic information systems (GIS) approach to identifying service gaps for state-level implementation planning. *Administration and Policy in Mental Health, 43*(6), 850–860. https://doi.org/10.1007/s10488-016-0743-4.

Wong, Y. L. I., & Stanhope, V. (2009). Conceptualizing community: A comparison of neighborhood characteristics of supportive housing for persons with psychiatric and developmental disabilities. *Social Science & Medicine, 68*(8), 1376–1387. https://doi.org/10.1016/j.socscimed.2009.01.046.

Wu, Y. T., Fratiglioni, L., Matthews, F. E., Lobo, A., Breteler, M. M., Skoog, I., ... Brayne, C. (2016). Dementia in western Europe: Epidemiological evidence and implications for policy making. *The Lancet Neurology, 15*(1), 116–124. https://doi.org/10.1016/s1474-4422(15)00092-7.

Zhang, J., Wang, W., Tan, Z., Wu, Q., Xiao, W., Shang, L., ... Miao, D. (2014). Spatial analysis of schizotypal personality traits in Chinese male youths: Evidence from a GIS-based analysis of Sichuan. *International Journal of Mental Health Systems, 8*(1), 3. https://doi.org/10.1186/1752-4458-8-3.

Zhang, W., Li, X., Lin, Y., Zhang, X., Qu, Z., Wang, X., ... Tian, D. (2013). Pathways to psychiatric care in urban north China: A general hospital based study. *International Journal of Mental Health Systems, 7*(1), 22. https://doi.org/10.1186/1752-4458-7-22.

Zulian, G., Donisi, V., Secco, G., Pertile, R., Tansella, M., & Amaddeo, F. (2011). How are caseload and service utilisation of psychiatric services influenced by distance? A geographical approach to the study of community-based mental health services. *Social Psychiatry and Psychiatric Epidemiology, 46*(9), 881–891. https://doi.org/10.1007/s00127-010-0257-4.

Younjin Chung (YC): a postdoctoral research fellow at the Centre for Mental Health Research (CMHR) at the Research School of Population Health (RSPH), Australian National University (ANU). She is working as a health systems engineering researcher in the Visual and Decision Analytics (VIDEA) Lab. Her research originated in computer science has focused on information visualisation, machine learning, artificial intelligence and data mining for visual analytics, and this has been applied to mental health research in developing decision support and visualisation tools for evidence-informed policy planning.

Nasser Bagheri (NB): a senior research fellow at the CMHR at the RSPH, ANU, recipient of an Australian Research Council DECRA Fellowship and leads a spatial epidemiology team and co-leads the VIDEA lab. His research has focused on chronic disease risk assessment, particularly, cardiovascular disease, diabetes, mental health and dementia with a particular interest in spatial variation and quantifying the impact of modifiable risk factors including lifestyle and built environment on chronic disease. He has recently developed his interest in mental healthcare systems engineering.

Jose A. Salinas-Perez (JS): an associate professor at the Department of Quantitative Methods at the Universidad Loyola Andalucía. He is a health geographer with training in Geographic Information Systems and urban and regional planning. His research focus on health geography, demographics, health indicators, epidemiology and health service research. He is also interested in decision support systems in health, including tools such as cartography, geo-statistics and technical efficiency. He is also a visiting academic at the CMHR in ANU.

Kayla Smurthwaite (KS): a PhD student in spatial epidemiology at the Department of Health Services Research and Policy at the RSPH, ANU. Her project is centred on understanding the geographical variation of Chronic Obstructive Pulmonary Disease hospital admissions in NSW, Australia.

Erin Walsh (EW): a postdoctoral research fellow at the Centre for Research on Ageing, Health and Wellbeing at the RSPH, ANU. Her research focused on the strengths and weaknesses of text messaging (SMS) as a tool for self-report psychological research. Alongside research, she works as a scientific illustrator, offering assistance with stimuli preparation, data visualisation, and figure preparation for scholarly publication or engaging the general public with science.

MaryAnne Furst (MF): a PhD student in service research at the CMHR at the RSPH, ANU. Her research assesses and compares availability, capacity, and variability of mental health care services in areas across Australia to support health policy and planning.

Sebastian Rosenberg (SR): a research fellow at the CMHR at the RSPH, ANU. He also hold a position as a senior lecturer at the Brain and Mind Centre at the University of Sydney and works privately as a consultant in the area of mental health. He is currently researching new tools in accountability for mental health, attempting to assess system performance and whether what is being done for people is actually helping.

Luis Salvador-Carulla (LS): a professor and the head of the CMHR at the RSPH, ANU leading the VIDEA Lab. His research has been focused in developing decision support systems in health and social policy, including tools for analysis of technical efficiency and benchmarking, indicators for health policy analysis, priority setting in mental health and in disability, and Integrated Atlases of Mental Health. He received the Leon Eisenberg Award of the Harvard Medical School in 2012 for his contributions in the field of developmental disorders.