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Identifying emerging topics in the peer-reviewed literature to facilitate curriculum renewal and development

Andrew James Amos[1] · Kyungmi Lee[2] · Tarun Sen Gupta[1] · Bunmi S. Malau-Aduli[1]

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Abstract
This article reports a bibliometric analysis of emerging topics in the psychiatric literature indexed in the MEDLINE database as a technique for renewal of clinical training curricula. Summary data of English-language articles indexed in the MEDLINE database between 1971-2018 were downloaded. Emerging topics in nine demi-decades between 1972-1976 and 2012-2016 were identified by the incremental incidence of individual Medical Subject Headings (MeSH) compared with previous years. Co-word analysis was used to investigate and visualise the relationships between emerging topics in each demi-decade. Summaries of 18 million articles annotated with psychiatric/psychological MeSH were retrieved and used to identify emerging topics. Peaks in the number of articles annotated by the top 20 emerging topics in 9 demi-decades coincided with release of the third and fourth editions of the Diagnostic and Statistical Manual which codifies psychiatric diagnoses. Themes emerging from network visualisations of the most common emerging MeSH in each demi-decade were consistent with movements in psychiatric/psychological theory and practice since the 1970s, including the recent focus on psychological and social factors implicated in suicide and suicide prevention. The identification of emerging topics within the published medical literature is a viable technique for use in curriculum renewal projects as a counterweight to biases driven by expert judgement. While indices like MEDLINE make the published literature an appealing initial step in building an empirical basis for curriculum development, it also demonstrates the potential value of less public and less structured data, such as health service electronic medical records.

Keywords Trends in life science · Emerging topics · MeSH · PubMed · Curriculum development · Medical education

Introduction

Modern clinical training curricula seek to promote excellent patient care by helping junior health workers acquire and maintain effective and up-to-date skills, knowledge, and attitudes. While there are well-established and systematic approaches to clinical curriculum development, due to the enormous, rapidly growing amount of health research, and the complex, unbounded, and rapidly changing nature of health work, these approaches rely heavily on expert judgement (Harden, 2001; Thomas et al., 2015b). Unfortunately, the unconscious biases of health experts are now recognised to have had negative effects across many areas of health care. The most prominent example may be the exclusion of female patients from medical trials on the incorrect assumption that they would show the same patterns of illness and treatment response as male patients, leading to many years of suboptimal treatment of cardiovascular disease in women (The Lancet, 2019). Our own work has examined how the unconscious biases of experts may contribute to the underrepresentation of minority groups in specialist medical training (Amos et al., 2021; Roberts et al., 2018).

Existing curriculum development approaches attempt to reduce bias almost exclusively by expert consensus, using methods such as the Delphi technique, which assumes that a synthesis of the beliefs of a diverse group of stakeholders will be less subjective than the beliefs of any individual stakeholder (Thomas et al., 2015a). While the peer reviewed literature has long been the most objective source of evidence about health, illness, and treatment, only recently has the emergence of data mining techniques made it possible

✉ Andrew James Amos
Andrew.Amos@jcu.edu.au

[1] College of Medicine & Dentistry, James Cook University, Townsville, Australia

[2] College of Science and Engineering, James Cook University, Cairns, Australia

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to extract high-level objective evidence about the nature, structure, and relative importance covering all aspects of health care from large databases such as hospital admissions, medication prescriptions, and health outcomes (Brunn et al., 2020). The current article describes an effort to apply data mining techniques to databases describing the peer reviewed medical literature to provide objective evidence suitable for use in curriculum development to help reduce the unconscious biases which are likely to arise from expert judgement.

Curriculum development and expert bias

Although frameworks such as those developed by Harden (Harden, 2001) and Kern (Thomas et al., 2015a) highlight the need for periodic revision of medical education curricula to add the most important recent innovations and remove outdated information, there is no standard method to identify which of the many changes in clinical knowledge should be considered, or how to judge the relative importance of different areas of practice (Benson et al., 2019). As a result, other than expert consensus, there are no standard methods for identifying or correcting biases in health curricula. Existing approaches either do not address curricula content selection at all (Swanwick et al., 2018), or focus on topic- or process-specific questions, such as describing how a small group of experts in a local training program might refine their expertise with reference to models of learning (Kulasegaram et al., 2018) or feedback from stakeholders (Benson et al., 2019). Rather than using empirical evidence to identify or reduce systemic sources of bias, research has focused on mechanisms leading to bias in individual stakeholders (Risberg et al., 2009), or proposed that there is an ethical imperative to reform clinical education, without exploring how reform can be achieved, or how it would improve training or patient outcomes (Braun & Saunders, 2017). Even research which explicitly analyses the biases inherent in expert-driven curricula makes limited use of empirical evidence to identify gaps in coverage or over-represented material (D'Eon & Crawford, 2005). Compared with the narrow focus of these methods, efforts to identify and correct expert bias using data mining can rely on objective evidence drawn from large databases that cover all areas of health and health care.

Bibliometric analysis

Among many other applications, data mining techniques have been used to identify high-level patterns in science such as the most active areas of scientific research (Zitt et al., 2019). Scientometrics, which analyses quantitative features of science, such as the size, growth, and relationships between different forms of scientific knowledge, makes heavy use of data mining. Within scientometrics, bibliometrics focuses on the quantitative features of scientific communication such as peer-reviewed publications, including network maps that visualise underlying implicit knowledge structures (van Raan, 2019).

The uses of network maps in bibliometric analysis are rapidly evolving, but can be usefully summarised in terms of goals, data sources, and techniques. At a general level, bibliometrics uses network maps to understand and explain the structure and relationships of diverse phenomena such as research communities and domains of knowledge (Boyack & Klavans, 2019). For example, network maps have been used to visualise concrete instantiations of the scientific research paradigms proposed by Kuhn to understand the influence of social dynamics on scientific activity (Chen, 2003; Kuhn, 1962). While data mining techniques work on any structured or unstructured data set, bibliometric analyses often use structured databases containing summaries of published peer review literature because of their technical advantages, including reduced computational load and increased interpretability. Despite requiring commercial licenses for large-scale access, Web of Science (WoS) and Scopus are the two most prominent scientific research indexes because of the detailed information they collect across all or most scientific research and related materials. MEDLINE is frequently used for the analysis of published medical literature because it is free to use, well structured, and extensively used by clinicians (Boyack & Klavans, 2019).

The bibliometric techniques used to map scientific constructs involve four main steps: extracting data from primary sources (e.g. collating search results from a database such as MEDLINE); calculating similarities between entities (for example, how similar is the research output of two researchers, or two universities); clustering (essentially grouping relatively similar entities together and separating relatively different entities); and visualisation (converting abstract information into meaningful visual patterns) (Boyack & Klavans, 2019). Four main alternatives are used to generate the linkages constituting bibliometric networks: co-citation, co-word, co-author, and bibliographic coupling. Co-citation analyses link entities by the number of times they have both been cited by a third entity (paradigmatically two peer reviewed articles both cited by a third article). Co-word analyses link entities by the frequency with which they use the same words (for example, two articles which use a large number of the same words in their title and abstracts are linked in this way). Co-author analyses examine networks of authors or other actors who have been authors on the same articles. Finally, bibliographic coupling networks link publications if they both cite a third publication (the reciprocal of co-citation analysis) (Moral-Munoz et al., 2019).

Emerging topics

Recently, bibliometric researchers have developed techniques for analysing the large sets of published articles indexed in databases such as MEDLINE to identify the most active areas of research and debate, described by one set of authors as emerging topics (Ohniwa & Hibino, 2019; Ohniwa et al., 2010; Wang et al., 2018). While it cannot replace expert judgement in the curriculum management process, automated identification of emerging topics has the potential to mitigate existing biases by providing a more objective and rapid basis for identifying the topics to be considered for inclusion in training curricula. In addition to the phrase "emerging topics", researchers in this area have described many alternative techniques using diverse terms including "emerging trends" (Chen, 2006), "research fronts" (Åström, 2007; Persson, 1994), "scientific revolutions" (de Langhe, 2017), and "innovation" (Vernon et al., 2021), among others.

There does not appear to be a dominant paradigm for the investigation of what we will describe as emerging topics hereafter. The literature reports the use of co-word analyses (Persson, 1994; Wang et al., 2018), co-citation analyses (Åström, 2007; Chen, 2006), and bespoke quantitative analyses of dynamic changes in publication patterns over time (Ohniwa & Hibino, 2019; Ohniwa et al., 2010). Bibliographic coupling and co-author analyses seem less often used to identify emerging topics, which for the former may be due to the time lag before two articles can acquire a common citing source.

MEDLINE and medical subject headings

MEDLINE is the most accessible large index of peer-reviewed medical literature. It records the title, abstract, and authors of every article published in almost all well-established peer-reviewed medical journals for more than a century, alongside a wealth of other information. The National Library of Medicine (NLM), which maintains MEDLINE, also annotates every indexed article with Medical Subject Headings (MeSH) that classify the patients, area of specialty, research methods, and other characteristics. Ohniwa et al. used these MeSH to identify emerging topics across the whole of medicine by calculating which MeSH were starting to be used much more often than in previous years, which they described as the increment rate (Ohniwa & Hibino, 2019; Ohniwa et al., 2010).

The MeSH used to describe the topics addressed by each article indexed in the MEDLINE database are an example of a controlled vocabulary. Demotic languages such as English are uncontrolled in the sense that while there are formal frameworks such as dictionaries and grammatical guidelines which suggest meaning and structure, for most purposes the rules are not enforced. Controlled vocabularies, by contrast, establish precise meanings and specific rules for use. The meanings and usage of MeSH are established and maintained by the NLM using a combination of semi-automated bibliometric analyses interpreted and applied by human experts (with primary expertise in classification rather than necessarily in medical knowledge domains) (Mork et al., 2013). This is an ideal model for developing techniques by which bibliometric analyses might support curriculum development by human experts, as it demonstrates the complementary abilities of computers, which can rapidly analyse, organise, and present summaries of enormous sets of data; and humans, who are much better at disambiguating specific usages of polysemous words, identifying exceptions, making attributions regarding relative importance, and contextualising research, for example by understanding of social context.

Bibliometric analysis and curriculum development

Our research was designed to explore how bibliometric data mining techniques might be used to support curriculum development and maintenance by identifying emerging topics from the published medical literature in a way that would be independent of the biases of individual experts. While it is likely that the published literature itself contains biases, as a primary source of evidence about medical knowledge and practice it is difficult to conceive of a more complete and less biased source of evidence. In addition, unlike the biases associated with individual experts, it is possible for the biases within the published literature to be systematically identified and addressed. In the absence of a gold standard method for the identification of emerging topics within peer-reviewed literature, we selected the model used by Ohniwa and Hibino (2019) as the most intuitively understandable, and the most widely accessible due to its use of the publicly available MEDLINE database rather than the more comprehensive but less specific and commercially restricted WoS and Scopus databases.

We expected that the pattern of emerging topics in psychiatry and psychology would be influenced by the release of new editions of the Diagnostic and Statistical Manual of Mental Disorders (DSM) in 1980, 1994, and 2013 (American Psychiatric Association, 1980, 1994, 2013) due to the significant research required to revise this handbook of psychiatric diagnosis. We hypothesized that applying the methods described by Ohniwa et al (2010) to the published psychiatric literature would generate an evidence base that could be used to guide psychiatric curriculum development independent of expert judgement. Our aim was to describe the emerging topics in the psychiatric literature since 1972, 8 years before the third edition of the DSM in 1980, to show

how they could be integrated into the curriculum development framework and examine the potential of data mining other sources for curriculum development and renewal.

Materials and methods

Datasets

While Web of Science and Scopus are the most complete and most commonly used datasets for bibliometric analyses, we selected the MEDLINE database for our research, for two main reasons. MEDLINE is a well-structured database maintained by the US-based NLM that covers a large corpus (defined as a set of documents) of the scientific research most relevant to our study, with an established controlled vocabulary constructed by human experts aided by automated bibliometric data analysis (Mork et al., 2013). Perhaps more importantly, as we intended to develop a technique able to be used for curriculum development across all settings, MEDLINE is publicly available, while WoS and Scopus require commercial licenses for access to the level of data required for the type of analysis developed here.

We downloaded the complete MEDLINE (https://www.nlm.nih.gov/databases/download/pubmed_medline.html) and MeSH (https://www.nlm.nih.gov/databases/download/mesh.html) databases on 01.01.21. Although we planned to look at the years 1972 – 2016, calculation of the increment statistic described below requires one year of leading and two years of lagging data. After selecting articles published in English between 1971 and 2018, summary data about 18,072,356 articles described by 29,640 medical subject headings (MeSH) were included in the analyses. Each article is labelled ("annotated" in the bibliometric literature) with a variable number of MeSH, where each MeSH represents a medical subject that is present in the article. For example, an article about the treatment of bipolar affective disorder with the medication lithium would be annotated with MeSH for "Bipolar disorder" and "Lithium" as well as others specifying the type of clinical trial, the population, and so on. Following Ohniwa et al., we extracted only unique MeSH tags and excluded terms unrelated to research topics (excluding the top 2 levels of the MeSH tree and MeSH terms under categories M, N, V, and Z) (Ohniwa & Hibino, 2019; Ohniwa et al., 2010). The MeSH hierarchy groups all psychiatry and psychology terms under a common branch – all psychiatry and psychology MeSH have codes beginning with the letter F. To consider only articles with psychiatric content, we excluded all indexed articles which did not contain at least one F-coded MeSH. Of the 29,640 MeSH there were 1123 unique MeSH under the "Psychiatry and Psychology" main heading beginning with the letter F included in our study.

Emerging topics

Following Ohniwa et al., the equation for the increment rate (I) of MeSH term α in year β was:

$$I_{\alpha \text{ in } \beta} = X_{\alpha \text{ in } \beta} / Y_{\alpha \text{ in } \beta}$$

where $X_{\alpha \text{ in } \beta}$ total appearances of α in years $\beta+1$ and $\beta+2$
and $Y_{\alpha \text{ in } \beta}$ total appearances of α in years β -1, β, $\beta+1$ and $\beta+2$

Emerging topics were defined as MeSH in the top 5% of $I_{\alpha \text{ in } \beta}$ of each year β (Ohniwa et al., 2010).

The increment rate I can be thought of as a ratio comparing the number of appearances of a MeSH in two consecutive years with its appearances in those years plus the two previous years. An emerging topic will have a small number of appearances in the two prior years compared with the two subsequent years, leading to a relatively large I close to 1.0. This will also force the I of previously emerging topics that have reached a plateau towards 0.5. The context for emerging topics was examined using the accumulation of articles annotated with all psychiatry/psychology MeSH over the period of study and the number of articles annotated with emerging topics alone.

Co-word analysis

Co-word analysis measures how similar the information content of individual documents within a corpus is to other documents by how many words with similar meanings co-occur in each document. It relies upon the assumption that the words used in each document represent ideas important in understanding scientific background, methodology, or evidentiary claims, and that co-occurrence of the same words in different documents means that they address the same ideas (Callon et al., 1983). Our co-word analysis was performed using the MeSH annotating each article (considered as words within a controlled vocabulary), rather than the plain text words of the titles, abstracts, or document bodies. First, we created a list of emerging topics comprising the MeSH with the top 5% of I rates in each year. From this list of MeSHs, the 20 that appeared most frequently in each five-year period (demi-decade) were selected and analysed with the statistical package R (R Core Team, 2020) to discover the extent to which they annotated the same articles. To simplify the visualisations, only MeSH contained in the top 20 were represented by vertices, and only the top 5% most common co-word occurrences were shown as edges.

Application of emerging topics to psychiatric curricula

To illustrate how the emerging topics may be applied to curriculum development, we analysed the most recent World Psychiatric Association curriculum published in 2002 (World Psychiatric Association, 2002) with reference to the top 5 keywords in each of the three demi-decades.

Results and discussion

Emerging topic analysis

At the time of extraction the MEDLINE database indexed close to 30 million articles of which around 18 million were annotated with at least one MeSH indicating a link with psychiatry/psychology (Fig. 1). Figure 2 shows the number of articles annotated with emerging topics alone, per period. Consistent with our expectation, Fig. 2 shows emerging topic peaks associated in time with publication of different editions of the DSM, discussed below. Putative emerging topics in psychiatry are represented by Table 1, which shows the top 20 most frequently appearing emerging topics in each period. While it might be expected that each topic would only appear once on the list of emerging topics, with a period of rapidly increasing frequency of use followed by a plateau, a small number appeared on two or three separate occasions, indicating a number of peaks followed by regression. This might be the result of the same topic appearing at different times associated with different innovations (for example, a single medication being associated with different conditions), or peaks and troughs of interest in the same topic (for example, a treatment with initial promise being discontinued due to side effects, but later revisited when the side effects can be managed). Table 2 shows which MeSH appeared as emerging topics in more than one period.

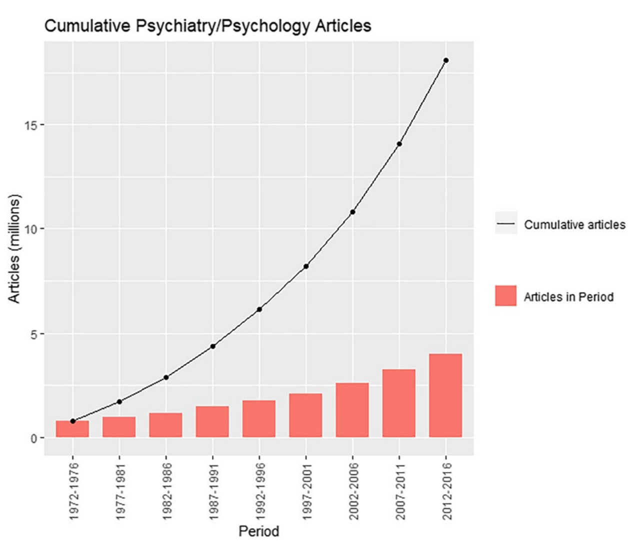

Fig. 1 Cumulative articles annotated with psychiatry/psychology MeSH (1972–2016)

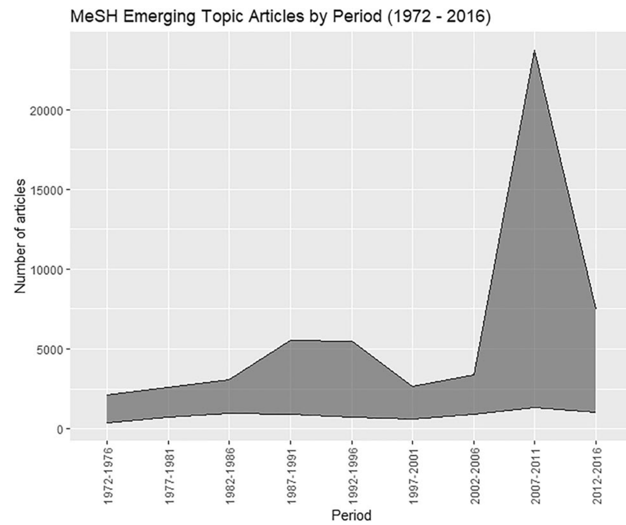

Fig. 2 Number of articles annotated with emerging topics per period

A separate network showing the number of annotated articles for each emerging topic and the strength of relationship between each keyword is reported for each demi-decade between 1972 and 2016 (Fig. 3). The size of each node represents the number of articles containing each emerging topic MeSH, while the thickness of the line between each pair of nodes represents how frequently different MeSH appeared in the same articles. This illustrates how the identified emerging topics in some demi-decades are arranged around one core concept, such as the “Family” node for 1972–1976, while other demi-decades feature a number of relatively disconnected sub-networks, such as 1977–81 with distinct clusters around “Bipolar disorder”, “Cerebral dominance”, and “Physician–patient relations”.

Table 3 shows examples of how emerging topics could be used to identify areas of the WPA curriculum and how the WPA syllabus could be reviewed with reference to the latest literature. For example, emerging topic activity annotated with the “Personality Inventory” MeSH would trigger attention to the WPA curriculum items “Didactic Curriculum” and “Syllabus”.

The bibliometric approach proved able to condense the information contained in the indexed summaries of more than 18 million published medical articles and extract useful information about the most cited emerging topics across four decades. Figure 2 shows two peaks of emerging topics associated with the top 20 MeSH in a period, with a doubling of activity between 1987 – 1996, and an order of magnitude increase between 2007 – 2011. We speculate that these periods were associated with a concentration of

Table 1 Top 20 most frequently appearing emerging topics in each demi-decade

1972–1976		1977–1981		1982–1986		1987–1991		1992–1996		1997–2001		2002–2006		2007–2011		2011–2016	
Family	2123	Physician–Patient Relations	2605	Attitude of Health Personnel	3056	Attention	5530	Health Knowledge, Attitudes, Practice	5511	Cues	2666	Personality Inventory	3386	Neuropsychological Tests	23688	Animal Distribution	7496
Discrimination Learning	1248	Dominance, Cerebral	2288	Adaptation, Psychological	2950	Arousal	4948	Patient Satisfaction	5296	Cooperative Behavior	2385	Recognition, Psychology	2727	Psychiatric Status Rating Scales	14147	Cognitive Dysfunction	5633
Nurse-Patient Relations	1062	Patient Compliance	1829	Arousal	2305	Psychiatric Status Rating Scales	4072	Personality Assessment	3352	Task Performance and Analysis	2043	Social Perception	2671	Risk Reduction Behavior	3590	Sedentary Behavior	4502
Consumer Behavior	967	Discrimination Learning	1816	Attention	2221	Neuropsychological Tests	3390	Internal–External Control	2722	Erectile Dysfunction	1573	Memory, Short-Term	2507	Medication Adherence	3416	Consensus	3745
Judgment	863	Bipolar Disorder	1502	Homosexuality	2160	Mental Recall	2874	Mental Health Services	1620	Depressive Disorder, Major	1498	Psychophysics	2496	Speech	3068	Social Stigma	3685
Chemotaxis	857	Pattern Recognition, Visual	1268	Alzheimer Disease	1974	Personality Development	2471	Suicide, Assisted	1216	Disclosure	1417	Empathy	2345	Interview, Psychological	3056	Opioid-Related Disorders	3295
Psychometrics	836	Arousal	1244	Psychomotor Performance	1904	Discrimination Learning	2289	Empathy	1141	Personal Autonomy	1299	Siblings	1939	Psychological Tests	2980	Thinking	3284
Identification, Psychological	684	Psychiatric Status Rating Scales	1200	Mental Recall	1802	Orientation	2266	Cues	1126	Mental Processes	1244	Association Learning	1664	Child Behavior	2778	Suicidal Ideation	3230
Mental Health Services	663	Mental Recall	1124	Learning	1660	Personality Tests	1929	Social Perception	1075	Cocaine-Related Disorders	1225	Narration	1640	Uncertainty	2710	Tobacco Use Disorder	2973
Dominance, Cerebral	645	Dementia	1103	Consumer Behavior	1586	Problem Solving	1908	Group Processes	1047	Nurse's Role	1176	Trust	1461	Social Identification	2534	Autism Spectrum Disorder	2835
Stereotyped Behavior	636	Depressive Disorder	998	Nurse-Patient Relations	1497	Personality Inventory	1890	Parenting	963	Psychological Theory	1057	Interdisciplinary Communication	1444	Executive Function	2282	Resilience, Psychological	2367
Schizophrenic Psychology	624	Affective Symptoms	998	Suicide	1475	Leadership	1445	Erectile Dysfunction	905	Judgment	1035	Inhibition, Psychological	1401	Consensus	1796	Burnout, Professional	2287
Learning Disabilities	582	Learning Disabilities	980	Physician's Role	1449	Internal–External Control	1428	Homosexuality, Male	902	Self Efficacy	930	Risk Reduction Behavior	1309	Language Tests	1644	Bullying	2032
Attitude to Death	573	Speech Perception	958	Vision, Ocular	1269	Cognition Disorders	1349	Psychology, Child	884	Social Identification	827	Concept Formation	1295	Arthralgia	1560	Marijuana Smoking	1667
Self-Assessment	568	Social Responsibility	954	Orientation	1263	Health Behavior	1327	Pain Threshold	830	Tobacco Use Disorder	795	Comprehension	1191	Efficiency	1555	Gambling	1594
Goals	507	Life Change Events	848	Fear	1187	Health Knowledge, Attitudes, Practice	1313	Self-Assessment	779	Problem-Based Learning	724	Esthetics	1133	Child Development Disorders, Pervasive	1526	Mindfulness	1357
Efficiency	479	Sleep Stages	833	Neurocognitive Disorders	1177	Patient Participation	1113	Maze Learning	775	Peer Review, Research	694	Achievement	1046	Impulsive Behavior	1526	Touch Perception	1299
Psychophysics	465	Discrimination, Psychological	825	Confidentiality	1149	Language	1106	Nuclear Family	748	Inhibition, Psychological	684	Uncertainty	977	Ergonomics	1453	Bisexuality	1275
Individuality	417	Job Satisfaction	824	Anorexia Nervosa	951	Individuality	1014	Achievement	744	Facial Expression	656	Intention	974	Psycholinguistics	1419	Racism	1136
Object Attachment	392	Psychometrics	745	Job Satisfaction	951	Substance Abuse, Intravenous	927	AIDS Dementia Complex	729	Dementia, Vascular	629	Language Tests	892	Sexuality	1326	Spatial Memory	1053

activity triggered by the creation and publication of two editions of the Diagnostic and Statistical Manual (DSM; 4^{th} and 5^{th} editions in 1994 and 2013, respectively (American Psychiatric Association, 1994, 2013)). This interpretation is supported by the presence of MeSH "Psychiatric Status Rating Scales" and "Neuropsychological Tests" in the top 5 most annotated lists of both periods. "Psychiatric Status Rating Scales" was also in the top 10 most annotated list for the period 1977–1981, overlapping the publication of the 3^{rd} Edition of the DSM in 1980 (American Psychiatric Association, 1980).

Several patterns emerge from visualisations of the most annotated emerging topics and their relationships in each period (Fig. 3). Over all periods there was a greater than expected tendency for all 20 top emerging topics to form relatively coherent networks. The second of the nine periods had four separate clusters of activity (1977–1981), with five periods having two clusters (including three with one dominant and one relatively minor cluster) and three completely connected networks (1972–6, 1987–1991, and 2002–2006).

Dominant themes of each period are outlined in Table 4.

Table 4 shows that the themes emerging out of this analysis are consistent with the trends observable during the periods reviewed. Our primary interest is how this information can be used in the curriculum development process. To illustrate how this might work, we have used the curriculum of the World Psychiatric Association, published in 2002, and indicated how the results of each period since then might have been used to identify areas of the curriculum and syllabus which would require reconciliation with the emerging literature. We have taken examples both from the didactic curriculum (essentially an overview at an abstract level of the domains of knowledge, skills, and attitudes required for competent psychiatric practice) and the syllabi (the specific learning experiences planned to acquire the features outlined in the curriculum (World Psychiatric Association, 2002).

In the most recent period, attention to emerging topics in the published psychiatric/psychological literature would have alerted a curriculum development project to the growing importance of social phenomena, stigma, vulnerable populations including minorities, and complex determinants such as bullying and professional burnout, in the effort to address suicide and parasuicidal symptoms including suicidal ideation. In addition to the counterbalance to biases which may influence expert-driven curriculum development, an empirical approach like the current one has the advantage of being directly linked with the published literature. Using Web of Science, a topic search for "social stigma" and "suicidal ideation" sorted by times cited in the years 2012–2016 returns an article on mechanisms of risk for depression and suicidal ideation among LGB youth which could be used in the curriculum development process (Baams et al., 2015).

The techniques described here cannot replace expert judgement in curriculum development but can be used by experts involved in curriculum development to identify topics to be considered for inclusion. The model used to create MeSH by the NLM shows how the information provided by data mining techniques can be integrated into a system where human experts use the outputs of data mining techniques in combination with expert judgement to achieve better outcomes than would have been achieved by either expert or technique alone (Mork et al., 2013). Another useful model of how these techniques could be integrated into curriculum development is provided by Chen and Song (2019). These authors used co-word analysis to explore

Table 2 Top 20 emerging topics appearing in more than one demi-decade

Frequency	Emerging topic	
Appears three times	Arousal	
	Discrimination Learning	
	Mental Recall	
	Psychiatric Status Rating Scales	
Appears twice	Achievement	Mental Health Services
	Attention	Language Tests
	Consensus	Learning Disabilities
	Consumer Behavior	Neuropsychological Tests
	Cues	Nurse-Patient Relations
	Dominance, Cerebral	Orientation
	Efficiency	Personality Inventory
	Empathy	Psychometrics
	Erectile Dysfunction	Psychophysics
	Health Knowledge, Attitudes, Practice	Risk Reduction Behavior
	Individuality	Self-Assessment
	Inhibition, Psychological	Social Identification
	Internal–External Control	Social Perception
	Job Satisfaction	Tobacco Use Disorder
	Judgment	Uncertainty

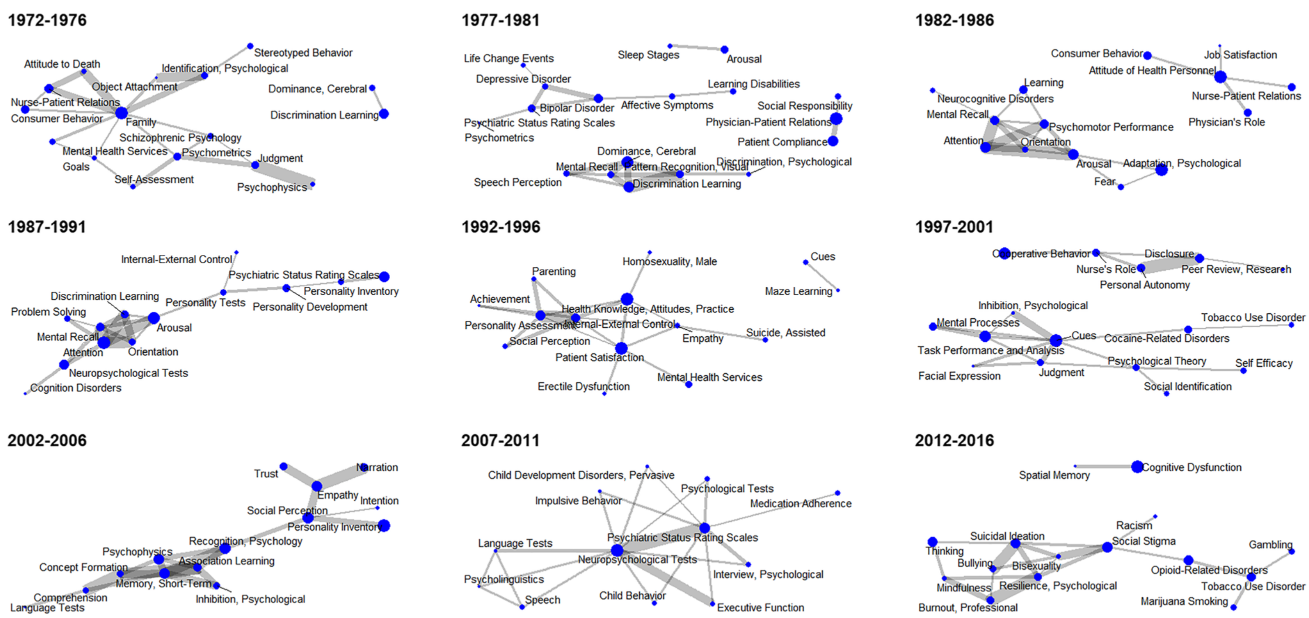

Fig. 3 Emerging topic networks (1972 – 2016)

how systematic reviews can optimally leverage bibliometric techniques to avoid missing relevant research, and to compare the effectiveness of alternative search strategies in returning relevant and specific results. They describe the seminal work of Swanson, who is recognised as an early pioneer of literature-based discovery (LBD) for his work linking Raynaud's phenomenon to a potential treatment purely by a systematic approach to the examination of the relevant literature, rather than by empirical investigation (Swanson, 1993). Their approach would be particularly useful for the curriculum development process by making it very easy to trace the pathways of scientific development across years and citations.

Complementary datasets

The information contained in the published literature is not the only large set of independent empirical evidence that would be useful for the curriculum development process with judicious bibliometric analysis. Although we have started with indexed literature due to its public availability and highly structured format, there is a wealth of other

Table 3 Cues for curriculum/syllabus renewal based on emerging topics

Period	Top 5 Keywords in Period	Curriculum/syllabus review
2002–2006	Personality Inventory Recognition, Psychology Social Perception Memory, Short-Term Psychophysics	Didactic curriculum (WPA p9-10) • Human growth and development • Basic knowledge – classification Syllabus (WPA 54 +) • Growth and development • Diagnostic instruments
2007–2011	Neuropsychological Tests Psychiatric Status Rating Scales Risk Reduction Behavior Medication Adherence Speech	Didactic curriculum • Neurosciences • Adult psychopathology Syllabus • Neurology/Neuropsychiatry • Psychopharmacology
2012–2016	Animal Distribution Cognitive Dysfunction Sedentary Behavior Consensus Social Stigma	Didactic curriculum • Neurosciences and biological risk factors • Geriatric/old age psychopathology Syllabus • Psychiatric rehabilitation • Sexual/gender issues

Table 4 Themes emerging in each period

Period	Keywords Curriculum/syllabus review
1972–76	The most common MeSH was Family, forming a nexus between psychological MeSH including Object Attachment, service-oriented terms like Nurse-Patient Relations and Consumer Behavior, and a clinical subnetwork comprising Goals, Psychometrics, and Self-Assessment. This combination of emerging topics reflects two transitions occurring at the time: from a more biological model of psychiatry focused on severe mental illnesses like schizophrenia to a more bio-psycho-social approach including more prevalent conditions like anxiety and depression; and from a psychoanalytic tradition (Object Attachment) towards psychological approaches (Psychology, Psychometrics, and Self-Assessment)
1977–81	The only period with four disconnected clusters shows the influence of the DSM-III published in 1980, with a cluster dominated by formulation of the mood disorder category comprising Psychiatric Status Rating Scales, Psychometrics, Bipolar Disorder, and Depressive Disorder. There is a neuroscience cluster including Discrimination Learning, Psychological Discrimination, Mental Recall, and Visual Pattern Recognition. Finally, there are two smaller clusters with a biological group linking arousal and Sleep Stages, and a clinical services group containing Social Responsibility, Physician–Patient Relations, and Patient Compliance
1982–86	The larger of two clusters shows the growing importance of neuropsychology (as distinct from neuroscience) linking cognitive processes like Attention, Mental Recall, Orientation, and Learning, through Arousal to Fear and Adaptation. A smaller group associated with health workforce issues centred on Attitude of Health Personnel radiating out to Nurse-Patient Relations, Physician's Role, Consumer Behavior, and Job Satisfaction
1987–91	A completely connected network driven by preparations for the DSM-IV published in 1994 continues the dominance of neuropsychological processes with a central axis of Attention and Arousal closely associated with Problem Solving, Orientation, and Cognition Disorders, and a more distant grouping associated with the diagnostic and epidemiological work underlying the DSM-IVs nosology including Psychiatric Status Rating Scales, Personality Tests, and Personality Development
1992–96	One of the two peaks of emerging topic activity possibly associated with the DSM-IV, this period is dominated by an axis linking Patient Satisfaction and Health Knowledge, Attitudes, Practice, consistent with the growing importance of community based psychiatric care and the recovery movement. The appearance of Assisted Suicide and previously less investigated phenomena including Erectile Dysfunction and Male Homosexuality indicate the growing breadth of the bio-psycho-social model first detectable in the mid-to-late 1970s
1997–2001	Two reasonable sized clusters in this period indicate the growing sophistication and importance of cognitive models, with the most important keyword, Cues, repeated from the previous period but now representing both the largest group of articles, and forming the central part of the dominant network focused on explaining complex clinical conditions such as Cocaine-Related Disorders and Tobacco Use Disorder as the result of cognitive processes such as Psychological Inhibition, Judgment, and Social Identification/Self Efficacy. The smaller cluster is more focused on service characteristics including Nurse's Role, Personal Autonomy, and Disclosure
2002–2006	Another of the unitary networks, with two semi-networks each focused on one of the two largest nodes. One side of the network, grouped around the largest keyword (Recognition, Psychology), appears to reflect another stage in the development of psychological theories including Psychophysics, Association Learning, Concept Formation, and Comprehension Tests/Language Tests. On the other side, the second and third largest keywords, Social Perception and Personality Inventory are linked with more therapeutic concepts used in psychotherapy including Trust, Empathy, Intention, and Narration
2007–2011	The final unitary network is centred on another axis probably driven by the development of the DSM-V, with the two largest nodes being Neuropsychological Tests and Psychiatric Status Rating Scales. Arrayed around these nodes are smaller groupings including largely unconnected assessment-oriented features such as Psychological Interview, Executive Function, and Child Behavior, and a verbal process cluster comprising Language Tests, Psycholinguistics, and Speech
2012–2016	The most recent network is unusual in that the keyword with the greatest number of articles in the period (Cognitive Dysfunction) is relatively unconnected to most of the other nodes, forming a small cluster with Spatial Memory. The rest of the nodes are closely linked around a set of concepts which show the growing importance of social factors in psychiatric/psychological theory and practice, with one end of an axis – Suicidal Ideation, linked with Bullying, Bisexuality, Psychological Resilience, and Mindfulness; connected via the other end of the axis – Social Stigma, with specific risk factors including Racism, and a substance abuse subnetwork including Opioid Related Disorders, Tobacco Use Disorder, Gambling, and Marijuana Smoking

data that could be used to address biases. Complementary to the theoretical and experimental evidence contained in the literature, electronic medical records contain a wealth of detailed information about what is actually done in practice across all medical and allied health disciplines. Government and other public entities including medical licensing bodies, pharmaceutical organisations, and health services record a great deal of data about diverse variables including prescribing practices, economic indicators, epidemiological factors, and patient behaviours like engagement, adherence, and changing demands. Morbidity and mortality registers track the most common and most serious causes of negative outcomes associated with health care. A curriculum informed by systematic mining of all available sources of information could reduce expert-driven biases and constantly calibrate educational experiences to match the real-world importance of the constantly changing features of medical practice.

Complementary methods

Our research focused on a single method chosen for ease of interpretation and public access to data. It has been proposed that alternative bibliometric techniques such as co-citation, co-word, co-author, and bibliographic coupling, reveal different characteristics of scientific knowledge, and we are still in the early stages of determining which methods are most suited to which tasks (Boyack & Klavans, 2019). An ideal combination of techniques for the purposes of curriculum development might chain the technique reported in this paper with that reported by Chen and Song (2019). Such a combination could use the Increment rate statistic to identify emerging topics, and Chen & Song's cascading citation expansion to outline the development of strands of scientific knowledge from seminal articles to the most important recent publications (Chen & Song, 2019). Li et al (2022) report a co-word analysis that demonstrates how these techniques can be used to understand the thematic evolution of the concept of psychological distance across four distinct periods, from infancy, through exploration and growth, to the outbreak to more general dissemination (Li et al., 2022).

Use of the MeSH controlled vocabulary rather than co-word analysis of free text has the potential disadvantage that there is likely to be a delay between the reporting of new ideas, methods, or conclusions in the literature, and their incorporation into the vocabulary. Co-word analysis of the free-text of published articles' title, abstract, or body, may be the method with the potential for the earliest identification of emerging topics, although as noted the polysemous nature of free-text can make this type of analysis difficult to interpret.

Limitations and future research

In addition to issues noted in the discussion above, the research reported here displays the limitations of exploratory research. Identifying emerging topics by the Increment statistic is a first step towards a framework that uses objective evidence to reduce biases in curriculum development. It is encouraging that the emerging topics identified are consistent with our knowledge of the psychiatric and psychological domains and appear to show the anticipated effect of the publication of different editions of the DSM. However, confidence in the validity of the information would be improved by empirical evidence that it can be effectively integrated with expert judgement. We are developing an experimental paradigm that will present the emerging topics to a group of psychiatrists engaged in continuous professional development to confirm the novelty of the knowledge identified, and to calibrate the most useful form for the presentation of the information for use in curriculum development. Further research would be required to estimate or measure the impact of this information on biases exhibited by experts during curriculum development and related activities.

The other main limitations of the paper are related to choices regarding methods and materials. As discussed in the text, we have chosen the Increment statistic over other potential methods for identifying emerging topics such as citation analysis; the MEDLINE database over larger databases such as Scopus or Web of Science; and the MeSH controlled vocabulary rather than free text. These choices have the advantages of a database focused on relevant clinical research; open access to data; and the ability to identify emerging topics without having to wait for citation paths to become evident. As there are likely to be countervailing advantages to other materials and methods, if it can be demonstrated that integrating evidence about emerging topics in curriculum development processes can reduce expert bias, it may prove useful to compare the choices we have made with the alternatives. For example, the coverage of a larger set of literature provided by Web of Science or Scopus might prove better at identifying and addressing gaps in the coverage of medical curricula.

Conclusions

We have argued that data mining techniques used in bibliometrics may be valuable for reducing biases implicit in expert-driven medical curriculum development by identifying the most important emerging topics independent of expert biases. We have shown that a network analysis based on the Increment rate statistic computed from MeSH annotations of the medical literature can identify the most active emerging topics in psychiatry and psychology, suggest which components of a psychiatric curriculum and syllabus to review, and identify specific articles upon which to base the review. This is the only current alternative to expert judgement for the identification of topics to be considered during curriculum development. While the published literature is a natural first target for the application of data mining techniques to curriculum development due to its large, structured, and freely available data set, other less accessible sources would provide objective data about the relative importance of a wide range of the knowledge, skills, and attitudes needed for an up-to-date curriculum.

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Declarations

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