

A survey of OMOP CDM-compatible visualization tools & what the community may do to support tool development and adoption

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Background

Data visualization generates a visual representation of data that enables data exploration and data analytics to gain new information or insights as well as explains such insights to the intended audience. In the healthcare settings, there are over 50 visualization tools published in peer-reviewed journals, as reviewed in existing papers.^{1, 2} One main obstacle of adopting these tools in new environments or institutions is the vast differences in data source models. The standardization of data models, such as OMOP CDM and HL7 FHIR, considerably eases the adoption of visualization and analytics tools. This survey aims to characterize OMOP CDM-compatible visualization tools and identify opportunities for new visualization tools with OMOP CDM support.

Methods

We systematically reviewed the literature with the following eligibility criteria: (1) the visualization tool or system was created to use OMOP CDM as its main data source, (2) written in English, and (3) original peer-reviewed work. Search terms were grouped into two categories: (1) visualization, which consisted of three terms: *information visualization*, *visual analytics*, and *dashboard*, (2) data model, which consisted of two terms: *OMOP CDM* and *OHDSI*. Within each group, the keywords were combined using “OR” logic. Then, two keyword groups were combined using “AND” logic. Searches were conducted in PubMed and Scopus in May 2022.

Results

Our searches yielded 80 articles (PubMed n = 10 and Scopus n = 70). We removed 6 duplicates. The 74 remaining records were assessed for eligibility with 7 records retained for further classification. The included articles cited 3 relevant publications that were not already included, and one additional article was added manually. Thus, there are 11 records for qualitative analysis. The screening process is summarized as a PRISMA flow diagram³ in **Figure 1**.

The included publications are summarized in **Table 1**. The tools were grouped by their sources (standard OHDSI tools or non-OHDSI tools) and the applicable scope of usage of the tools. A broad scope is recognized by the generalizability of a given tool to all or most datasets in OMOP CDM, while a tool with a limited scope supports only some datasets or scenarios, namely certain fields of medicine. Detailed summaries of the tools are reported in **Table 2**.

Most of the reviewed tools provide open-source libraries that are generalizable to other research and connectable to databases with data in the OMOP CDM format. These 3 features (open-source,

generalizability, and database connection) are crucial for tool adoption by other users. Conversely, lacking any of the 3 features limits the applicability of the tools to other use cases.

Only two included publications report evaluation studies of the visualization tools.

Our searches were limited to articles that specifically mentioned visualization work. It is probable that there are other visualization methods compatible with OMOP CDM that leverage visualization libraries in R or Python, for example.

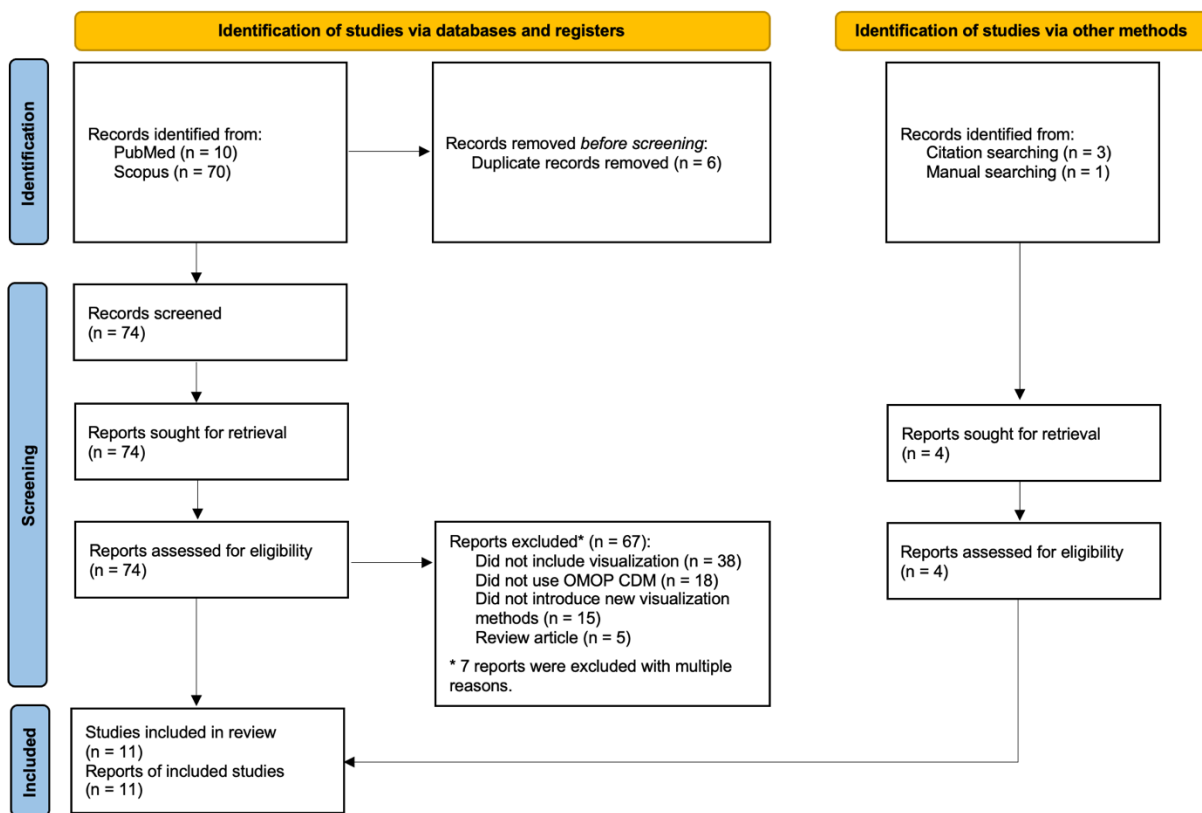


Figure 1: PRISMA flow diagram.

Table 1: Statistical summary of all included publications. (n = 11)

| | | n | % |
|------------------------------------|----------------------|----------|----------|
| Source | PubMed ^a | 5 | 45 |
| | Scopus | 2 | 18 |
| | Citation network | 3 | 27 |
| | Manual | 1 | 9 |
| Publication year | 2022 | 1 | 9 |
| | 2021 | 5 | 45 |
| | 2020 | 2 | 18 |
| | 2019 | 1 | 9 |
| | 2016 | 2 | 18 |
| Study location | North America | 7 | 64 |
| | Europe | 4 | 36 |
| Target audience | Academicians | 10 | 91 |
| | Healthcare providers | 2 | 18 |
| Data source in OMOP CDM | Database connections | 10 | 91 |
| | Static files | 1 | 9 |
| | Undefined | 1 | 9 |
| Visualization type | Data analysis tool | 5 | 45 |
| | Data quality tool | 3 | 27 |
| | Data query tool | 2 | 18 |
| | Dashboard | 2 | 18 |
| Programming language | R | 7 | 64 |
| | Java | 3 | 27 |
| | JavaScript | 3 | 27 |
| | Python | 2 | 18 |
| Evaluation of visualization | Structured interview | 1 | 9 |
| | User feedback | 1 | 9 |
| | Not reported | 9 | 82 |

^a Publications indexed in both PubMed and Scopus count as PubMed in the source.

Table 2: Classification of all included publications. (in chronological order)

| | Publication year | Summary | Target audience | Data source in OMOP CDM | Visualization type | Programming language |
|--|------------------|--|---------------------------------------|---------------------------------------|--|----------------------|
| OHDSI tools with a broad scope of usage (n = 4) | | | | | | |
| Huser <i>et al.</i> 4 | 2016 | OHDSI Achilles with evaluation by structured interviews | Academicians | Database connections | Data quality tool | R |
| Hripcsak <i>et al.</i> 5 | 2016 | Sunburst plot that is later integrated in OHDSI Atlas | Academicians | Database connections | Data analysis tool | JavaScript |
| Dixon <i>et al.</i> 6 | 2020 | Extensions to OHDSI Atlas | Academicians | Database connections | Data quality tool | Java; JavaScript |
| Blacketer <i>et al.</i> 7 | 2021 | OHDSI Data Quality Dashboard | Academicians | Database connections | Data quality tool | R |
| Non-OHDSI tools with a broad scope of usage (n = 4) | | | | | | |
| Glicksberg <i>et al.</i> 8 | 2019 | PatientExploreR visualizing patient timeline | Academicians | Database connections | Data analysis tool; Data query tool | R |
| Callahan <i>et al.</i> 9 | 2021 | Advanced Cohort Engine (ACE), a scalable time-aware data query application | Academicians | Database connections; Static files | Data query tool | Java; Python; R |
| Boudis <i>et al.</i> 10 | 2021 | Sankey diagram visualizing clinical pathways | Academicians | Database connections | Data analysis tool | R; JavaScript |
| Kunnapuu <i>et al.</i> 11 | 2022 | Trajectories detecting disease comorbidity trajectories | Academicians | Database connections | Data analysis tool | R |
| Non-OHDSI tools with a limited scope of usage (n = 3) | | | | | | |
| Felmeister <i>et al.</i> 12 | 2020 | Visualization for pediatric brain cancer research with evaluation by user feedback | Academicians | Database connections | Data analysis tool | Python |
| Lamer <i>et al.</i> 13 | 2021 | Anesthesia dashboard | Academicians; Healthcare providers | Database connections | Dashboard | R |
| Zoch <i>et al.</i> 14 | 2021 | Dashboard of rare disease patients | Healthcare providers | Undefined | Dashboard | Java |

Conclusion

We observed a considerable growth in the number of publications describing new tools in the last 2 years (2021 and 2022), which coincides with the increase in the number of publications from the OHDSI community in the recent years. Further visualization tools leveraging OMOP CDM could be introduced to address other visual analytics scenarios, such as machine learning-incorporated visualization and longitudinal exploratory analyses, that will benefit observational research. Finally, we offer suggestions for the community to support further tool development and adoption:

1. curate existing OMOP CDM-compatible visualization tools in addition to the current list on OHDSI Software Tools webpage (<https://www.ohdsi.org/software-tools>) or as an additional page on the OHDSI Community Dashboard (<http://dash.ohdsi.org>),
2. support new tool development and the refitting of existing tools to support OMOP CDM by preparing additional guidelines and best practices that promote open-source, generalizability, and database connection features, and
3. encourage more visualization evaluation studies and publications of the tools.

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