prominent in LIS research, they noted that experimental methods appeared to be rapidly increasing in use. For instance, Chu (2015) examined shifts in methods from 2001to 2010 in three major LIS journals (i.e., *J. Doc.*, *JASIST*, and *LISR*). The top-five methods were identified, with the list order unique for each journal (theoretical approach was top method for *J. Doc.*, experimental method for *JASIST*, and content analysis for *LISR*).

Chu and Ke (2017) utilized the data set from Chu (2015), with greater emphasis on the history and usage of each method in discussion of the literature. Noruzi (2017) analyzed research methods used in "hot papers," which refer to papers that have been cited at a significantly quicker rate than the average paper. These "hot" LIS papers tended to utilize bibliometric methods and/or reviews of timely topics. Ullah and Ameen (2018) performed a meta-analysis of prior reviews of methods in LIS, which revealed that survey (a category which includes questionnaire, interviews, and focus groups as data collection methods) was the most common method, with an incidence of 33% across the reviews. Other methods, which have been found to be more prevalent in recent reviews, are less common in the overall data set Ullah and Ameen (2018) identified. For instance, while studies such as Åström (2007) and Chu (2015) indicated a growing number of bibliometrics studies, Ullah and Ameen (2018) found that historically bibliometrics had averaged only 5% of methods identified in these types of studies.

2 | METHODS

This study analyzed the selected article samples by the author-supplied titles, keywords, and abstracts to explore the evolution and distribution of research topics and data collection methods over three equidistant periods of time: 2006, 2012, and 2018. These three years were selected based on the last year of data collection for the Tuomaala et al. (2014) being 2005 (so 2006 as a start date picks up where that study leaves off) and 2018 being the last full year before data collection for this study began in the fall of 2019. Six years may not be the most standard gap, but it does allow us to closely capture major shifts at three equidistant points, without leaving a gap between the last year of the Tuomaala study and the first year of this one. This selection of those three years also has several benefits relative to social and technological change relevant to LIS research. For instance, social media really emerged in the period between 2006 and 2012, smartphones or mobile devices became popular in the early years of the 2010s, and the 2016 Presidential election in the United States brought the topics of "fake news" and information literacy to the public's attention. The selection of only three years (rather than all years from 2006 to 2018) is a matter of practicality (the data set would be too large to analyze manually) and is consistent with the Järvelin studies, which also sampled three years (for instance, 1965, 1985, and 2005 in the 2014 Tuomaala study).

The type of systematic analysis approach employed in this study has been applied to disciplinary evaluation in LIS, such as studies of LIS evolution from 1971 to 2015 (Onyancha, 2018), research subjects in LIS from 1995 to 2014 (Chang et al., 2015), and research foci among information science institutions in China (Chen, Xiao, Hu, & Zhao, 2015). However, those studies often failed to closely adopt the methods of the Järvelin studies in terms of applying equivalent or appropriate sampling techniques, size of data sets, and the systematic analysis approach. Many of these studies examined one particular element of LIS research, or a small data set of journals (like *JASIST*, *LISR*, and *J. Doc.*).

The data for this study comprises all scholarly articles ($n = 3{,}422$) published in a set of 31 journals (see Appendix) in the years of 2006, 2012, and 2018. The inclusion criteria of journal selection included: the data set of Tuomaala study, top LIS journals ranked by the 2019 Journal Citation Reports (JCR) of the Social Sciences Citation Index (SSCI), and consecutive publications across the three datapoints (2006, 2012, and 2018). Bibliographic data for these articles, including keywords and abstracts and links to full text retrieved from relevant LIS databases such as *Web of Science*, *Library and Information Science Source*, *Library Information Science & Technology Abstracts*, *ACM Digital Library*, and *ScienceDirect* were imported to Endnote—a citation management software. Each data entry was validated for inclusion by excluding non-research articles (e.g., book reviews, editorials), publications in a wrong year (e.g., online-first date), and content in a non-English language (i.e., title, keywords, and abstract). After manually retrieving and filling in the missed Endnote data fields (i.e., title, keywords, and abstract), the researchers exported the bibliographic data to a Microsoft Excel file for further analysis.

To analyze the articles, the researchers adopted the coding schemes of the Tuomaala study. The full list of topics and methods codes are displayed in Table 1 below. Each research topic and method is paired with definitions and/or examples to illustrate the criteria by which the researchers coded the data in this study. Additionally, the LIS research topics (which are meant to closely resemble those of the Tuomaala study) were broken down into subtopic for a more precise analysis of emerging themes.

Table 2 shows the subtopics developed for this study. Subtopics do not necessarily align directly with any main topics, but rather can transcend across several topic