Tracing Trends in Educational Measurement : A Longitudinal Analysis of Research Journals

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[Introduction]

This study examines the historical progression of research trends in educational measurement, providing an era-specific overview to help new researchers understand the field's evolution. Text mining, the core methodology for this analysis, has demonstrated versatile across various domains, making it invaluable For instance, text mining has been used to examine public discourse on policies (Gyódi et al., 2023; Ngai & Lee, 2016; Sun et al., 2020) and to track shifts in consumer sentiment and preferences through product reviews (Mostafa, 2013; Zhu et al., 2022; Feng et al., 2017).Recently, text mining has been widely applied in educational research, offering valuable insights into learning analytics, assessments, and teaching behavior. For example, Buenaño-Fernandez et al. (2020) used text mining to analyze open-ended responses in teacher self-assessment, applying topic modeling to identify recurring themes in university teaching. Choi et al. (2019) applied topic modeling to educational assessments to explore the spread of pedagogical strategies within major evaluations. Gencoglu et al. (2022) analyzed student perceptions of teaching behavior with big data and topic modeling, demonstrating how machine-based insights can supplement traditional evaluations. Some studies have used topic modeling to analyze trends in specific educational subfields, such as English Language Teaching (Ibna Seraj et al., 2024), early childhood education (Methlagl et al., 2024), and competency-based education (Paek et al., 2021), each demonstrating how topic modeling can uncover distinctive trends and themes within specialized areas.

Other studies have taken a longitudinal approach to examine shifts in educational research over time. Wang, Bowers, and Fikis (2016) conducted a five-decade analysis of educational leadership literature, employing probabilistic topic modeling to trace the evolution of key themes. Chen, Zou, and Xie (2022) conducted a decade-long bibliometric analysis using structural topic modeling, identifying nuanced trends in learning analytics. Yun (2020) used topic modeling to explore changes in physics education research, examining shifts in areas such as pedagogical content, assessment, and problem-solving. These studies underscore the value of topic modeling for understanding long-term developments across various educational fields.

These applications underscore the flexibility and utility of text mining and topic modeling in tracking educational research trends across multiple contexts and timeframes. Building on these foundations, this study categorizes educational measurement research into five distinct eras: behaviorism and early assessment (1960-1980), cognitive and learner-centered approaches (1980-1990), social constructivism and educational technology integration (2000-2010), personalized learning and big data analytics (2010-2020), and the recent focus on online education innovations post-pandemic (2020-present). This longitudinal approach aims to provide a comprehensive overview of shifts in educational measurement, though the completeness of the findings may be limited by data availability, particularly for early publications.

[Methodology]

1. **Data Collection and Preprocessing**

   1) Journal Selection: the following journals are considered as primary sources: Educational and Psychological Measurement, Psychometrika, Applied Psychological Measurement, Journal of Educational Measurement, and Applied Measurement in Education. These journals were chosen for their relevance to educational measurement, high impact within the field, and long publication histories, which support a longitudinal study. They provide a broad scope of theoretical and practical research, covering psychometric advances, educational assessment, and practical applications. Additionally, their accessible archives facilitate consistent data collection across eras, ensuring a comprehensive analysis of trends in educational measurement.

   2) Era Classification: The study segments journals into five eras: 1960-1980 (Behaviorism and early education theories), 1980-1990 (Cognitive theories and the spread of educational assessment), 2000-2010 (Social constructivism and ICT integration), 2010-2020 (Personalized learning and big data analytics), 2020-presen (Online learning and post-pandemic educational innovation)

   3) Tokenization and Filtering: All journal titles, abstracts were preprocessed to facilitate keyword extraction and trend analysis. This included removing punctuation, URLs, and stop words (expanded to include common terms like "research" or "effect" that contribute little meaningful insight in this context). Each document was then tokenized and lemmatized for consistent word representation.

2. **Keyword Extraction**

   1) n-gram Analysis: For each era, 2-gram combinations were extracted from abstracts to capture significant word pairs, which help reveal more specific topic trends. Keywords were then identified based on the most frequently occurring 2-grams, highlighting dominant themes and specific research focuses within each era.

   2) TF-IDF (Term Frequency-Inverse Document Frequency): This metric was applied to determine each term's significance within an era relative to the entire dataset. Terms with high TF-IDF scores in specific eras were identified as potential keywords, reflecting unique research emphases.

3. **Keyword Clustering**

   1) Clustering Method Selection: The optimal number of clusters for each era was identified using the Elbow Method. Then, K-means or K-medoids clustering was applied to group similar research themes, with each cluster representing a distinct focus within educational measurement during the era.

   2) Keyword Representatives: Each cluster's keywords were analyzed to determine dominant terms, helping characterize the primary research areas of each period.

4. **Topic Modeling with LDA and NMF**

   Latent Dirichlet Allocation (LDA) and Non-Negative Matrix Factorization (NMF) were used to identify underlying topics within each cluster. By exploring these models, we could uncover specific sub-themes within the larger clusters, clarifying nuanced research interests that emerged within each period.

5. **Cluster Evolution Analysis**

   For trend visualization, a heatmap visualizing keyword prominence over time will illustrate the temporal shifts in research focus. Changes in cluster sizes across eras indicate growth or decline in specific areas, providing a quantitative perspective on educational measurement's evolution.

This study demonstrates how educational measurement research has evolved in response to broader societal changes, technological advancements, and policy shifts.

[Directions for Future Research]

Future work could expand this trend analysis on a global scale by including non-English publications and international journals. Utilizing OCR (Optical Character Recognition) technology to process older, scanned publications with non-digitized text would further enrich the dataset, allowing for a more comprehensive and diverse analysis.

The ultimate goal is to develop an open-source website where new researchers can interactively explore these trends. This platform will visualize the evolution of the field across key eras, making it easier for newcomers to educational measurement to grasp foundational shifts and contemporary trends. By offering a structured historical overview, the site will serve as a valuable resource for scholars and educators, bridging the gap between established research foundations and emerging developments in the field.

[References]

Buenaño-Fernandez, D., González, M., Gil, D., & Luján-Mora, S. (2020). Text mining of open-ended questions in self-assessment of university teachers: An LDA topic modeling approach. *IEEE Access, 8*, 35318-35330. https://doi.org/10.1109/ACCESS.2020.2974983

Chen, X., Zou, D., & Xie, H. (2022). A decade of learning analytics: Structural topic modeling based bibliometric analysis. *Education and Information Technologies, 27*, 10517–10561. https://doi.org/10.1007/s10639-022-11046-z

Choi, H. J., Kwak, M., Kim, S., Xiong, J., Cohen, A. S., & Bottge, B. A. (2019). An application of a topic model to two educational assessments. In M. Wiberg, S. Culpepper, R. Janssen, J. González, & D. Molenaar (Eds.), *Quantitative Psychology. IMPS 2017*. Springer Proceedings in Mathematics & Statistics (Vol. 265). Springer, Cham. https://doi.org/10.1007/978-3-030-01310-3_38

Feng, Z., Jianxin, R. J., Xi, J. Y., & Baiying, L. (2017). Augmenting feature model through customer preference mining by hybrid sentiment analysis. *Expert Systems with Applications, 82*, 248-260. https://doi.org/10.1016/j.eswa.2017.07.021

Gencoglu, B., Helms-Lorenz, M., Maulana, R., Jansen, E. P. W. A., & Gencoglu, O. (2022). Machine and expert judgments of student perceptions of teaching behavior in secondary education: Added value of topic modeling with big data. *Computers & Education, 104682*. https://doi.org/10.1016/j.compedu.2022.104682

Gyódi, K., Nawaro, Ł., & Paliński, M. (2023). Informing policy with text mining: Technological change and social challenges. *Quality & Quantity, 57*, 933–954. https://doi.org/10.1007/s11135-022-01378-w

He, J., Rubinstein, B. I. P., Bailey, J., Zhang, R., Milligan, S., & Chan, J. (2016). MOOCs meet measurement theory: A topic-modeling approach. *Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence (AAAI-16)*, 1195-1201. https://doi.org/10.1609/aaai.v30i1.10151

Ibna Seraj, P. M., Klimova, B., & Khan, R. (2024). Visualizing research trends in English Language Teaching (ELT) from 2013 to 2022: A bibliometric analysis. *Sage Open, 14*(2). https://doi.org/10.1177/21582440241251998

Lee, H., Kwak, J., & Song, M. (2015). Coherence analysis of research and education using topic modeling. *Scientometrics, 102*, 1119–1137. https://doi.org/10.1007/s11192-014-1453-x

Lemay, D. J., Baek, C., & Doleck, T. (2021). Comparison of learning analytics and educational data mining: A topic modeling approach. *Computers and Education: Artificial Intelligence, 2*, 100016. https://doi.org/10.1016/j.caeai.2021.100016

Methlagl, M., Taslimi, N. J., & Rudloff, C. (2024). Exploring research topics and trends in early childhood education using structural topic modeling. *SN Social Sciences, 4*(183). https://doi.org/10.1007/s43545-024-00982-x

Mostafa, M. M. (2013). More than words: Social networks' text mining for consumer brand sentiments. *Expert Systems with Applications, 40*(10), 4241-4251. https://doi.org/10.1016/j.eswa.2013.01.019

Ngai, E. W. T., & Lee, P. T. Y. (2016). A review of the literature on applications of text mining in policy making. *PACIS 2016 Proceedings*, 343. http://aisel.aisnet.org/pacis2016/343

Paek, S., Um, T., & Kim, N. (2021). Exploring latent topics and international research trends in competency-based education using topic modeling. *Education Sciences, 11*(6), 303. https://doi.org/10.3390/educsci11060303

Sun, Y., Wang, Z., Zhang, B., Zhao, W., Xu, F., Liu, J., & Wang, B. (2020). Residents' sentiments towards electricity price policy: Evidence from text mining in social media. *Resources, Conservation and Recycling, 160*, 104903. https://doi.org/10.1016/j.resconrec.2020.104903

Waheeb, S. A., Khan, N. A., & Shang, X. (2022). Topic modeling and sentiment analysis of online education in the COVID-19 era using social networks based datasets. *Electronics, 11*(5), 715. https://doi.org/10.3390/electronics11050715

Wang, Y., Bowers, A. J., & Fikis, D. J. (2016). Automated text data mining analysis of five decades of educational leadership research literature: Probabilistic topic modeling of EAQ articles from 1965 to 2014. *Educational Administration Quarterly, 53*(2). https://doi.org/10.1177/0013161X16660585

Yun, E. (2020). Review of trends in physics education research using topic modeling. *Journal of Baltic Science Education, 19*(3), 388-400.

Zhu, B., Guo, D., & Ren, L. (2022). Consumer preference analysis based on text comments and ratings: A multi-attribute decision-making perspective. *Information & Management, 59*(6), 103626. https://doi.org/10.1016/j.im.2022.103626