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Measuring fintech development through composite indices: A text-mining-based review of fintech index studies

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Abstract

Fintech has become one of the most dynamic and rapidly expanding domains in financial innovation, profoundly transforming the way financial products and services are designed, delivered, and consumed. To evaluate the level of fintech development across countries, regions, and markets, it is essential to construct a comprehensive and data-driven metric - a Fintech Index - that enables comparative assessment and evidence-based policy formulation. This study provides a systematic literature review of research that has contributed to the conceptualization and construction of fintech index. By applying a text mining approach to Scopus database on fintech-related publications, we employ automated techniques to extract, classify, and synthesize key themes, methodological approaches, and index dimensions. The review framework integrates several stages of data mining—data collection, cleaning, and transformation—combined with natural language processing (NLP) and topic modeling (LDA) to identify dominant research clusters and emerging topics in the fintech index literature. Our findings reveal that most existing studies focus on three core dimensions: fintech development indicators, adoption indicators and financial inclusion indicators. Existing studies show that Fintech contributes to industry growth, innovation, green finance, sustainability, and entrepreneurial development by reducing financial constraints and improving resource mobilization. Fintech adoption is mainly driven by perceived usefulness, trust, institutional support, social influence, and facilitating conditions. Meanwhile, Fintech inclusion expands access to digital financial services, supports poverty reduction, and promotes inclusive economic growth. This paper contributes both a methodological framework for text-mining–based literature reviews and a conceptual synthesis that advances understanding of how fintech indices are defined, structured, and operationalized in global research.

Keywords: Composite indices, Fintech index, NLP, Systematic literature review, Text analytics, Text mining, Topic modeling.

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1. Introduction

The rapid development of financial technology (Fintech) has profoundly transformed the global financial services industry, reshaping how individuals and firms' access, deliver, and manage financial activities. Innovations such as digital payments, blockchain solutions, and algorithmic lending have accelerated financial inclusion and expanded the digital financial ecosystem [1]. This growth has also stimulated a substantial increase in academic research, spanning topics including regulatory frameworks, Fintech adoption behavior, technological infrastructures, and socio-economic impacts [2]. As the Fintech knowledge base expands, there is a pressing need for systematic approaches to synthesize existing evidence, identify research patterns, and guide future inquiry. Systematic literature reviews (SLRs) traditionally serve as rigorous methods for consolidating knowledge and avoiding redundancy in research [3]. However, conventional review approaches face several limitations, particularly time constraints, selection biases, information overload, and uneven article quality. Narrative reviews may lack methodological transparency, while scoping and rapid reviews often sacrifice depth or reliability for breadth and speed [4, 5]. Meanwhile, the emergence of Big Data significantly expands available knowledge sources beyond academic publications to include web-based platforms, social networks, and digital repositories. This environment renders manual review processes increasingly insufficient [6]. Text Mining (TM) provides a powerful solution to these challenges. As an AI-driven approach combining natural language processing and machine learning, TM enables efficient extraction, transformation, and pattern recognition within large document collections [7, 8]. Integrating TM into SLRs can reduce human bias, enhance scalability, and uncover deeper thematic structures within research fields [9]. Such capabilities are especially relevant for analyzing Fintech research, where the rapidly evolving knowledge landscape requires timely and data-driven synthesis. Within the Fintech domain, numerous frameworks and indicators have been developed to measure Fintech development, financial inclusion, and technology adoption across countries and industries [10-12]. However, existing studies often examine these indicators in isolation, focusing on one aspect of Fintech performance rather than capturing the broader ecosystem. The absence of a comprehensive and standardized review of Fintech index research limits comparative assessments and policy-relevant insights [13]. A systematic, data-driven approach is therefore required to consolidate fragmented knowledge and expose current trends and gaps.

This study addresses this gap by applying TM techniques, combined with structural topic modeling, to synthesize academic research on Fintech Indexes. Using a curated dataset of published articles from Scopus databases, we identify key thematic clusters, analyze intellectual developments, and forecast emerging research directions. The findings aim to contribute both methodological innovations to review practices and conceptual clarity to Fintech measurement research.

The remainder of the paper is structured as follows. Section 2 describes the data collection process and research methodology, including TM and topic modeling procedures used to systematically review related research. Section 3 presents the research results from the literature review and text-mining analysis. It reports publication trends by year and journal, describes keywords and themes, and identifies major topic clusters related to fintech development, fintech adoption, and financial inclusion indices. This section also summarizes common methodologies for constructing fintech index using enterprise survey data and social media data. Section 4 concludes with implications for research, practice, and policy.

2. Data Collection and Research Methodology

This section outlines our study approach with six phases: Data Collecting, Text pre-processing, Text Classification, Topic Modeling, Topic Analysis, and Trend Discovery analysis to investigate Fintech Index containing hundreds of research studies. Figure 1 represents the six phases of this investigation. At data collection phase, we accessed Scopus database and query by term ("Fintech Index" OR 'Fintech Indicator" OR 'Fintech Indices") consisting of full-text journal articles, technical reports, preprints, books, and other documents. Then, we collected each paper's title, abstract, authors, keywords, journal, and publication date from main databases. Our database includes a short overview of Fintech Index research articles that address diverse themes. We chose to evaluate titles, abstracts, and keywords rather than full-text papers since the title, abstract, and keywords provide detailed information and highlight crucial results [14, 15]. In this phase, we extracted 227 research publications from the query results including titles, abstracts, keywords, public years, authors, journals. We also found that Science Direct, Springer Link were the database sources that had the most articles on the topic of "Fintech Index/Indicator/Indices". *Text pre-processing* prepares unstructured text for analysis by removing

noise and standardizing linguistic elements [16]. This process improves feature extraction quality and enhances the performance of later algorithms [17]. The workflow includes:

- Step 1. Expand Contraction: Contractions are shortened versions of words, such as "world's for would is." These phrases are used to abbreviate text but are not useful for text analysis. A dictionary of contractions has been established and mapped to enlarged versions utilizing regular expressions for improved outcomes [18].
- Step 2: Remove punctuation: Punctuation is important for English grammar but does not make a difference in text analysis. As a result, all punctuation and special characters from the text have been removed [18].
- Step 3: Lowercase: Natural language processing models can distinguish between terms such as "Fintech" and "Fintech".

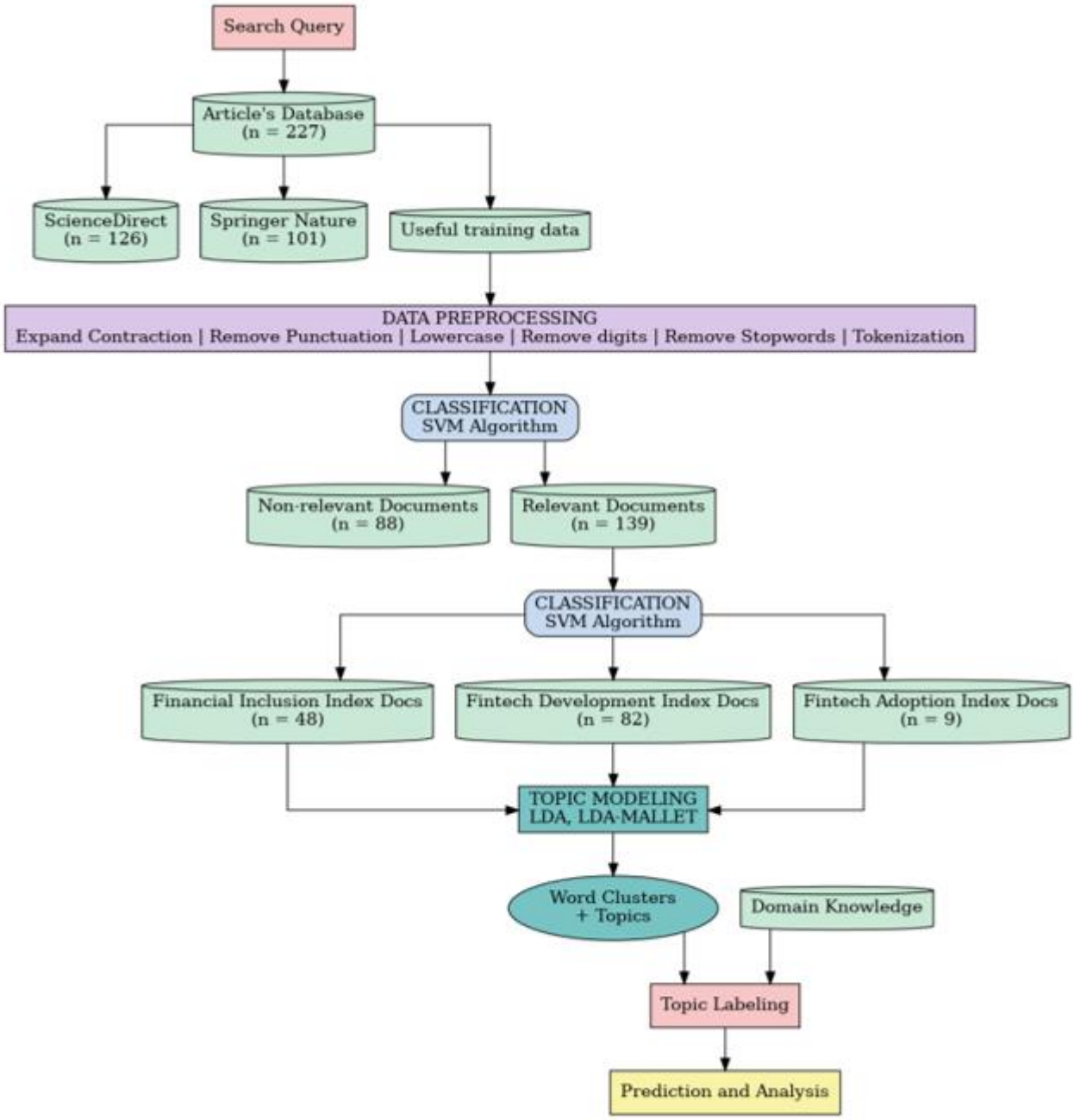

Figure 1.
Research framework.

- Step 4: Remove stopwords: Stop words are considered common words in English grammar, so they were removed for better search performance.
- Step 5: Lemmatization: It is the process of stemming the words to their original state (Ex, best for good, etc.). The goal is to return to the base of a given word. After multiple tests, the spaCy library has been chosen as it gives the most accurate results [18].
- Step 6: Tokenization: A text document consists of a set of sentences; the tokenization process breaks the document into parts of words called tokens.

Through these steps, the text corpus is transformed into a structured dataset consisting of normalized, meaningful tokens.

Text classification assigns documents to categories based on extracted linguistic features. In traditional approaches, classification requires manually engineered representations such as bag-of-words or TF-IDF. These representations are then processed by machine learning algorithms such as Support Vector Machines (SVM) or logistic regression. The accuracy of classification depends heavily on the quality of feature extraction. Because manual feature engineering may overlook semantic nuances, classification performance is often constrained. Nevertheless, classification helps group documents according to conceptual similarity, forming a foundation for deeper thematic analysis.

Topic modeling identifies latent thematic structures within the corpus. Latent Dirichlet Allocation (LDA) is employed to infer topics as clusters of words that frequently co-occur across documents [19]. The process consists of:

- Input Preparation: The pre-processed corpus is used as model input.
- LDA Execution and Topic Visualization: The model extracts candidate topics and visualizes them to aid interpretation.
- Coherence Evaluation with LDA-Mallet: Multiple topic numbers (k = 2 to 9) are tested, and coherence scores are compared to selecting the optimal model.
- Final Visualization and Interpretation: The selected topic model is examined to generate meaningful thematic labels.

Topic modeling reveals dominant themes, emerging research patterns, and conceptual gaps, enabling a comprehensive understanding of the intellectual landscape.

3. Literature review of Fintech Index Research

3.1. Word and Theme Descriptive Analysis

From 2020 to 2024, there is a significant increase in research publications on the Fintech Index. Out of the total 227 research articles identified, only 12 were published prior to 2021. The remaining 215 articles were published between 2021 and March 2024. Notably, by the midpoint of 2024, the number of articles related to the "Fintech Index" keyword has already reached nearly 85.71% (on source Scopus) of the total number published in 2023. This rapid growth suggests a potential surge in quantitative Fintech research in the near future, likely driven by groundbreaking developments and widespread adoption across various industries. Furthermore, the data from 2021-2022 and 2022-2023 indicates a growing interest in novel Fintech models following the COVID-19 pandemic and the subsequent socio-economic shifts related to recovery and development. This trend suggests an exponential rise in the use of experimental methods to assess the level of development and popularity of Fintech solutions.

Figure 2.
Word cloud of top 50 frequent terms in keywords of the relevant research articles.

Figure 2 illustrates the most used keywords in chosen publications are “Fintech”, “financial”, “risk”, “bank”, “index”, “inclusion”, “ecosystem”, “covid”, “green", "technology” and “develop”. The terms emphasize Fintech's importance in areas such as financial inclusion, risk management, and market efficiency. This is study on how Fintech might address difficulties and enhance existing financial systems. The high occurrence of "financial" and "technology" further emphasizes the critical intersection of finance and innovation within this sector. Additionally, terms like "bank," "development," and "risk" highlight the evolving challenges and opportunities that fintech presents to traditional banking institutions and the broader financial landscape. These keywords collectively reflect the importance of understanding how fintech can drive development and manage risks in an increasingly digital world.

3.2. Correlated Topic Modeling

A comparative coherence analysis between LDA and LDA-Mallet was conducted to determine the optimal number of topics for each Fintech Index theme. Specifically, the LDA-Mallet model was run with the number of topics ranging from 2 to 9, and the topic coherence scores were compared to identify the most appropriate topic structure. The coherence scores of the LDA-Mallet model were compared across different numbers of topics, ranging from 2 to 9, for three major themes: *Fintech Development Index, Fintech Adoption Index, and Financial Inclusion Index.*

Table 1.
Coherence score table by themes using LDA-Mallet.

Theme	2 Topics	3 Topics	4 Topics	5 Topics	6 Topics	7 Topics	8 Topics	9 Topics
Fintech Development Index	0.2667	0.3354	*0.3773*	0.3246	0.3386	0.375	0.3113	0.3649
Fintech Adoption Index	0.2756	0.3906	0.422	0.3997	0.4468	0.4401	*0.4771*	0.4588
Financial Inclusion Index	0.2698	0.2484	0.2514	*0.3512*	0.3339	0.3316	0.2923	0.3395

Based on the coherence score results, the optimal number of topics varies across the three themes. For the Fintech Development Index, the highest coherence score is achieved with 4 topics at 0.3773, closely followed by 7 topics at 0.3750. For the Fintech Adoption Index, the optimal number is 8 topics, with the highest coherence score of 0.4771. For the Financial Inclusion Index, the best topic structure is obtained with 5 topics, reaching a coherence score of 0.3512. These results suggest that LDA-Mallet provides different optimal topic structures for each Fintech Index theme, reflecting the diversity and complexity of the underlying literature.

Then, we provide an in-depth analysis of the topic modeling results for the Fintech Development Index, Fintech Adoption Index and Fintech Inclusion Index. It examines number of extracted topics by interpreting their frequently used terms, FREX-based keywords, expected topic prevalence, and representative studies.

The analysis further explains how each topic reflects a distinct dimension of fintech development, fintech adoption and fintech inclusion. Figure 3 plots the semantic coherence and topic exclusivity scores for each topic, and it is evident that all the topics are distantly placed on the plot, which confirms that topics are distinct and the terms which are frequent in a topic are not co-occurring in other topics. STM also features estimating correlation among the topics where a positive correlation with a value of more than 0.5 shows that the topics are not exclusive, and many documents equally represent two topics. The correlation values less than 0.3 represent no matching of concepts among the topics and the corresponding documents [20].

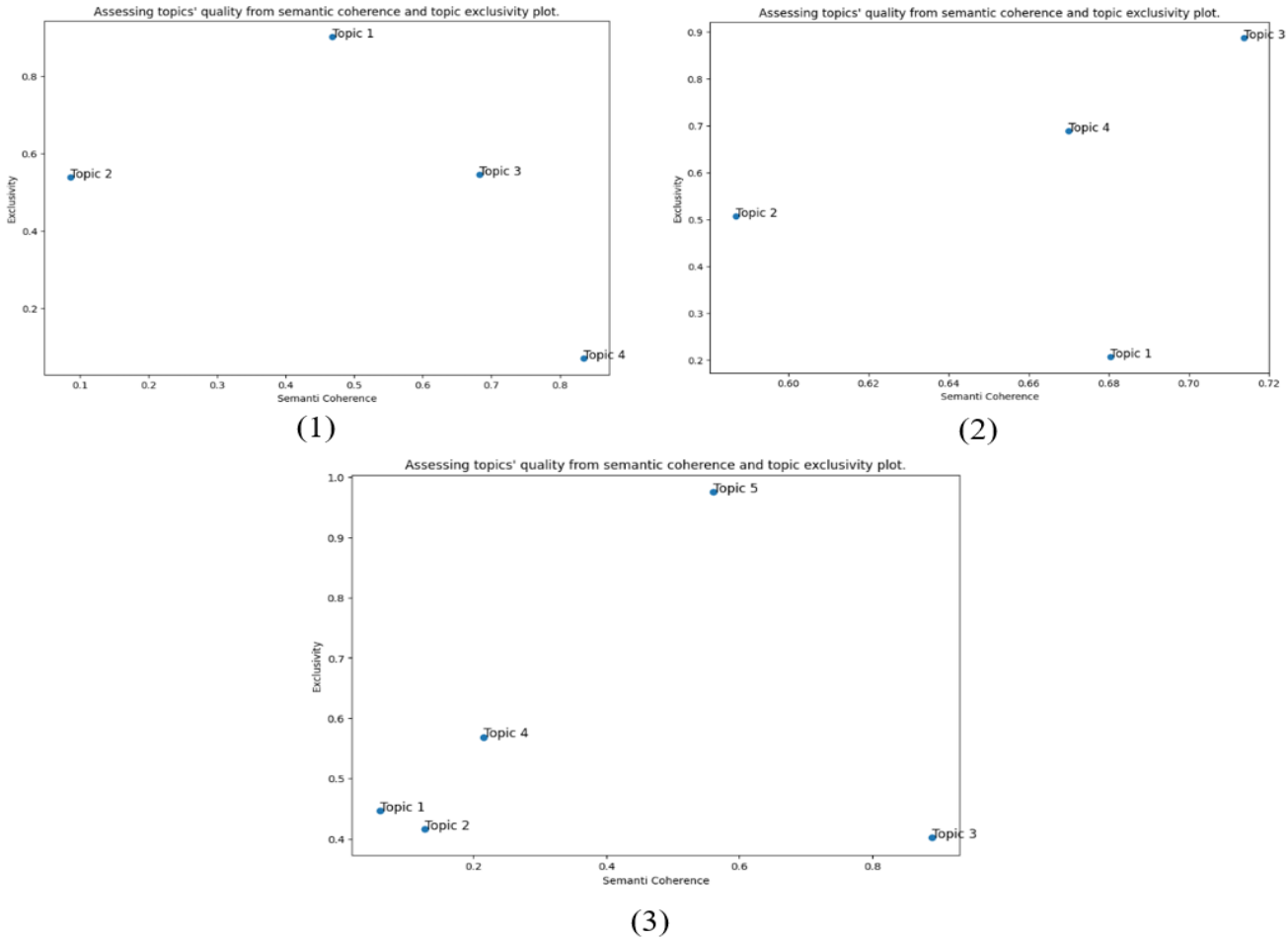

Figure 3.
Assessing topics' quality from semantic coherence and topic exclusivity plot of (1) Fintech Development Index (2) Fintech Adoption Index. (3) Fintech Inclusion Index

3.3. Fintech Development Index

FD1. Financial Technology in Entrepreneurial Ecosystems and Industry Growth

Fintech has a significant impact across industries, including big data, green finance, and entrepreneurial ecosystems. Zhang, et al. [21] show that fintech helps reduce financial constraints and supports the growth of the big data industry, especially when fintech development reaches a higher threshold. Cheng, et al. [22] demonstrate that fintech promotes green finance by enhancing green technology innovation, optimizing energy structures, and reducing carbon emissions, although its effects vary across regions. At the entrepreneurial level, Alaassar, et al. [23] highlight how interactions among actors in Singapore's fintech ecosystem support venture success by enabling opportunity identification and resource mobilization. Together, these studies show fintech's role in driving industry growth, sustainability, and entrepreneurial innovation.

FD2. Fintech's Impact on Commercial Bank Loan Risk

Recent studies have explored the multifaceted impacts of financial technology (fintech) on operational risk and loan risk within Chinese commercial banks. Cheng and Qu [24] find that fintech significantly reduces operational risk, particularly through artificial intelligence, with state-owned banks benefiting the most. Their analysis shows that a one-unit increase in the fintech index corresponds to a notable decrease in operational risk. In contrast, You, et al. [25] reveals a complex, nonlinear relationship between fintech and loan risk, highlighting a U-shaped effect that underscores the crucial role of risk management in the evolving financial landscape. This study emphasizes the need for comprehensive data to draw definitive conclusions. Geng, et al. [26] further contributes to this discourse by identifying both positive and negative effects of fintech on bank stability, noting that while fintech can enhance risk control, it may also lead to increased noninterest activities that jeopardize stability. Together, these findings illustrate the dual nature of fintech's influence on risk dynamics in China's rapidly evolving financial sector.

FD3. Fintech's Role in Market Performance and ESG

Recent studies have highlighted the significant role of fintech in enhancing market performance and addressing ESG considerations. Dehghani, et al. [27] developed a patent quality index for fintech, demonstrating that high-quality patents are positively associated with firm earnings, thereby boosting market competitiveness. In parallel, Najaf and Najaf [28] explored the relationship between carbon emissions and market performance, finding that fintech firms, with their lower emissions, outperform traditional financial firms, underscoring their commitment to environmental stewardship. Additionally, Najaf and Najaf [28] examined corporate governance issues within fintech firms, noting challenges such as

CEO duality and a lack of anti-misconduct policies, which can undermine shareholder rights and market stability. Collectively, these insights underscore fintech's pivotal role in driving market performance while promoting sustainable practices in the financial sector.

FD4. Assessing Fintech's Environmental Sustainability

The growth of fintech companies in Lithuania is driven by multiple factors, including technological advancements and economic efficiency. Taujanskaitė and Kuizinaitė [29] highlight the main determinants influencing the number of fintech firms and forecast several development scenarios for the sector. They emphasize the need for thorough analysis of scientific investigations and correlation-regression assessments to identify ten key factors affecting fintech growth. Additionally, Popova [30] examines the economic basis for fintech services, demonstrating that fintech companies can provide efficient digital banking solutions, thus bridging gaps in economic justification for smart city initiatives. Furthermore Wu, et al. [31] discuss fintech's role in sustainability, revealing that it significantly reduces carbon emissions intensity, particularly in urban areas, and contributes to the optimization of industrial structures. Collectively, these studies underscore the interplay between innovation, economic efficiency, and environmental sustainability as pivotal drivers of fintech growth in Lithuania.

Figure 4 illustrates the trends in four distinct topics related to the Fintech Development Index. Notably, Topic 1, titled "Financial Technology in Entrepreneurial Ecosystems and Industry Growth," shows a marked upward trend, indicating a significant increase in relevance and interest over time. This suggests that fintech is increasingly recognized as a crucial driver of entrepreneurship and economic development [32].

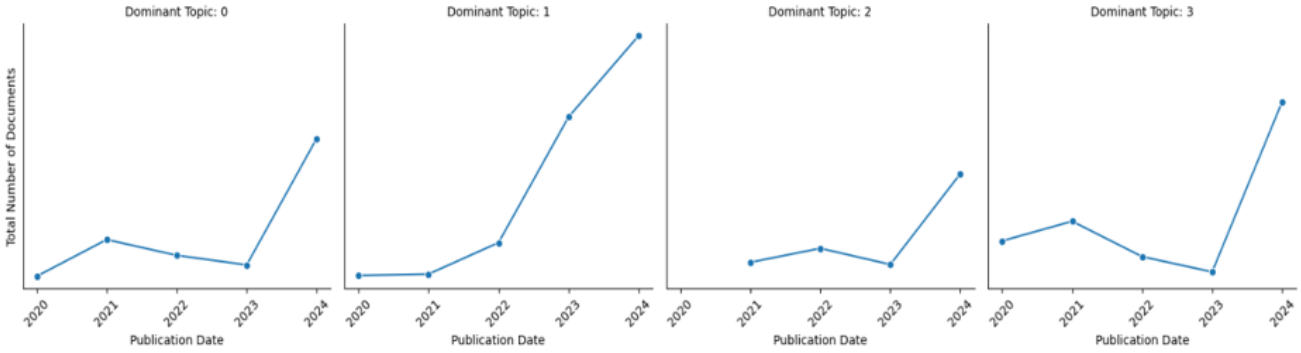

Figure 4.
Topical trends based on expected topic proportions of Fintech Development Index.

In contrast, the remaining three topics exhibit slower growth rates. While these topics remain important, their slower trajectory suggests that they may be emerging areas of interest rather than the rapidly expanding focus observed in Topic 1. This differential growth in topic relevance highlights the dynamic nature of fintech discussions, with entrepreneurial applications currently taking precedence in research and industry focus. The analysis further explains how each topic reflects a distinct dimension of fintech development, ranging from entrepreneurial ecosystems and industry growth to commercial bank risk, market performance, ESG issues, and environmental sustainability. In addition, topical trend analysis is used to assess how research attention toward each topic has evolved over time, while semantic coherence and topic exclusivity are employed to evaluate the quality, distinctiveness, and interpretability of the identified topics.

3.3.1. Fintech Adoption Index

FA1. Fintech Adoption through Digital Innovation and Financial Inclusion (FA1)

The interconnectedness of digital innovation, fintech development, and financial inclusion is a growing area of interest in the modern financial landscape. Rizvi, et al. [32] emphasize the strong association between innovation, digital adoption, and fintech, particularly highlighting the bidirectional relationship between digital adoption and innovation, though fintech's linkage is less pronounced when control variables are considered. Meanwhile, Dianty and Faturohman [33] explore fintech lending adoption in Indonesia, identifying key factors such as perceived usefulness, trust, and government support as drivers of increased adoption. Their findings suggest that fintech lending could significantly contribute to financial inclusion, which in turn may enhance both national and global economic efficiency. Together, these studies illustrate the multifaceted role that innovation and digital integration play in advancing fintech adoption and economic development.

FA2. Fintech Adoption and Rural Economic Growth ***(FA2)***

The role of fintech in promoting rural entrepreneurship and economic development has been gaining attention, particularly in regions with lower urbanization. Studies indicate that fintech positively influences rural household entrepreneurship by alleviating credit constraints and fostering formal financial relationships, especially in less developed regions [34]. Furthermore, fintech adoption has been shown to enhance rural household income by creating non-agricultural employment opportunities and improving property income, particularly through the effective operation of rural

enterprises [35]. These findings highlight the transformative potential of fintech in narrowing the urban-rural income gap and driving rural revitalization.

FA3. AI and Fintech Adoption: Behavioral Drivers and Industry Challenges

Artificial intelligence (AI) and fintech services are revolutionizing the financial industry, with both technological and behavioral factors influencing their adoption. Research in the banking sector highlights that AI is increasingly being integrated to enhance productivity and customer services, though challenges such as high implementation costs, skills gaps, and regulatory concerns hinder full-scale adoption [36]. Additionally, consumer behavior studies reveal that performance expectancy, effort expectancy, social influence, and facilitating conditions are key drivers of fintech adoption, with educational segmentation playing a moderating role in Pakistan's banking context [37]. These insights underscore the need for financial institutions to address both technological and behavioral factors to foster widespread adoption.

FA4. Fintech Adoption and Its Effects on Bank Liquidity and Profitability

The rapid adoption of financial technology (fintech) poses significant implications for traditional banking systems, particularly regarding liquidity creation and profitability. A study focusing on sixteen African countries found that while early fintech adoption does not threaten bank profitability, it begins to negatively impact profitability beyond certain thresholds, indicating that excessive fintech integration can harm traditional banks [38]. Similarly, an analysis of top U.S. banks revealed a consistent negative relationship between fintech adoption and bank liquidity creation, emphasizing that even during crises like the COVID-19 pandemic, the transformative influence of fintech disrupts fundamental banking functions [39]. These findings suggest that while fintech presents opportunities, careful management of its adoption is essential to mitigate risks to traditional banking operations.

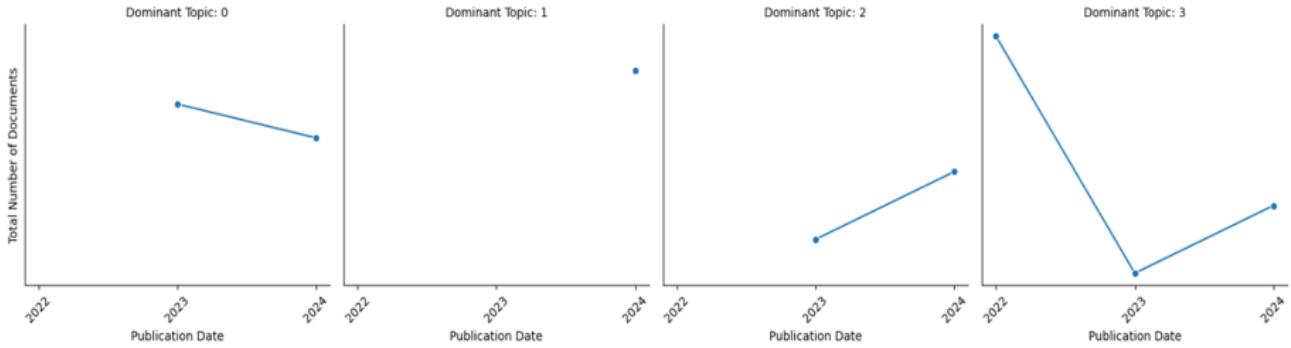

Figure 5.
Topical trends based on expected topic proportions of Fintech Adoption Index.

Figure 5 illustrates subject trends based on predicted topic proportions in the Fintech Adoption Index. Notably, Topic 1, "Fintech Adoption through Digital Innovation and Financial Inclusion," shows a delayed emergence, with only a few publications appearing in 2024. This suggests that while this area is gaining traction, it has not yet reached the same level of attention as other topics. In contrast, topic 3, "AI and Fintech Adoption: Behavioral Drivers and Industry Challenges," initially boasts the highest number of publications. However, it experiences a sharp decline in 2023 before rebounding in 2024. This fluctuation may indicate that while interest in this topic is strong, it faced challenges that temporarily hindered research output.

The other two topics exhibit more stable trends. This stability reflects ongoing interest in understanding the implications of fintech adoption across different sectors, with each topic contributing valuable insights into how fintech impacts economic growth and banking dynamics. Overall, these trends underscore the evolving nature of fintech research, highlighting both the rising areas of interest and the fluctuations in publication output across various themes.

3.3.2. Financial Inclusion Index

FI1. Fintech's Impact on Financial Inclusion and Sustainability Development

Fintech plays a pivotal role in enhancing financial inclusion and promoting sustainable economic growth. It has been identified as a key driver in expanding investment opportunities and increasing participation rates among savers and lenders, thereby supporting sustainable development goals [40]. Additionally, the relationship between the fintech environment and sustainable finance indicators demonstrates that favorable conditions for fintech development can significantly contribute to achieving these goals [41]. The positive impact of fintech on sustainable finance further underscores its potential to facilitate the transition to a lower carbon economy and drive inclusive financial practices (Nguyen et al., 2023). These insights highlight the integral role of fintech in advancing financial inclusion while fostering sustainable growth.

FI2. The Role of Fintech in Poverty Alleviation

The relationship between fintech adoption and poverty alleviation has garnered increasing attention, particularly in the Sub-Saharan Africa (SSA) region. A study highlights that improvements in fintech can initially lead to a decrease in

extreme poverty rates; however, a threshold of 35 points must be reached for continued benefits in poverty reduction [42]. Similarly, research on China demonstrates that enhancements in fintech, coupled with effective policies, can significantly promote poverty reduction, illustrating the intricate dynamics between trade policy uncertainty, natural resource development, and fintech [43]. Furthermore, the impact of fintech on energy consumption and emissions adds another layer, indicating a complex interplay that can influence sustainable development goals, particularly those aimed at reducing poverty [44]. Together, these findings underscore the crucial role of fintech in fostering inclusive economic growth and addressing poverty challenges globally.

FI3. Fintech's Impact on Financial Inclusion in Developing Countries

The rise of financial technology (fintech) is significantly reshaping the financial landscape, particularly in developing countries. A case study in Lithuania highlights that the interaction between the banking sector and fintech companies is marked by collaboration rather than disruption, emphasizing the importance of qualitative assessments to understand this relationship [45]. In broader terms, fintech innovations, particularly mobile money, have the potential to enhance financial inclusion in regions such as Africa, where two-thirds of adults remain unbanked [46]. Moreover, research across Latin America, Africa, and Asia underscores the high potential for fintech investment in developing countries, driven by mobile payment systems, although challenges and risks persist [47]. Together, these findings illustrate fintech's crucial role in advancing financial inclusion and addressing economic disparities in developing regions.

FI4. Fintech's Role in Financial Development and Digitalization in Europe

The transformative influence of fintech on financial development across European Union countries is a significant area of research. A study by Lavrinenko, et al. [48] identifies a positive linear relationship between the global fintech index and financial markets, highlighting how fintech contributes to market depth and efficiency. Furthermore, the research indicates that while fintech enhances certain aspects of financial institutions, it negatively correlates with financial institutions' access, suggesting varying impacts across different financial dimensions. In the context of shadow banking, Feng, et al. [49] reveal that fintech may reduce entrusted loans among non-financial firms, particularly in regions with specific lender characteristics, indicating a nuanced relationship between fintech development and traditional banking activities. Lastly, Pakhnenko, et al. [50] propose a digital financial services index to evaluate the digitalization of financial services in European countries, further underscoring the diverse levels of fintech integration across the region. Together, these findings illuminate the multifaceted role of fintech in advancing financial development and digitalization within Europe.

FI5. The Role of Fintech and Digital Capital in Financial Inclusion

In the evolving landscape of finance, the interplay between corporate social responsibility (CSR) and fintech is crucial for banking stability. A study focusing on the MENAT region finds that fintech significantly moderates the relationship between CSR and banks' financial stability, enhancing stability particularly at higher quantiles [51]. Additionally, research exploring new technologies post-pandemic indicates that regression analysis can quantify the innovative developments in the financial sector, highlighting the importance of integrating innovative strategies for sustainable growth [52]. Furthermore, the role of digital social capital in enhancing financial inclusion for SMEs underscores the need for digital engagement to strengthen the impact of fintech on financial accessibility [53]. Together, these findings illustrate that fintech and digital capital are pivotal in advancing financial inclusion and stability across various sectors.

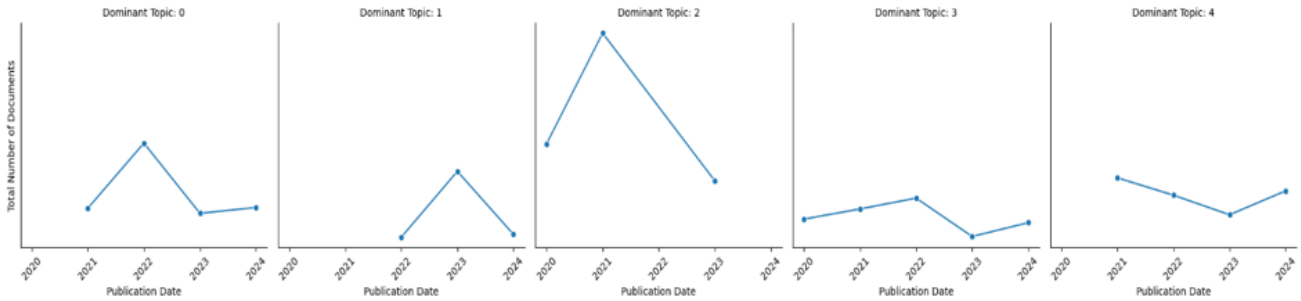

Figure 6.
Topical trends based on expected topic proportions of Financial Inclusion Index.

Figure 6 illustrates the topical trends based on expected topic proportions within the Financial Inclusion Index, featuring five distinct topics. Each topic—ranging from "Fintech's Impact on Financial Inclusion and Sustainability Development" to "The Role of Fintech and Digital Capital in Financial Inclusion" exhibits a relatively balanced number of publications.

Despite this overall parity, the publication counts for these topics display erratic fluctuations over time. Such variability suggests that while interest in fintech's role in enhancing financial inclusion remains consistent, it is influenced by various external factors, such as shifts in policy, technological advancements, or emerging challenges in the financial landscape.

The fluctuations may also indicate periods of heightened focus on specific aspects of fintech and financial inclusion, reflecting the dynamic nature of research in this field. Overall, the trends highlight a sustained interest across multiple facets of fintech's impact on financial inclusion, even as specific topics experience ups and downs in research activity.

3.4. Fintech Index Construction Methodology

The construction of a Fintech Index aims to translate diverse observed variables into a unified composite measure that enables meaningful comparison across entities, sectors, and time periods. Following the composite-indicator frameworks proposed by the OECD [54] and the JRC Handbook [55] this process typically unfolds through five sequential stages: *indicator selection, data preprocessing and normalization, weighting, aggregation,* and *validation with sensitivity testing.* However, methodological practices differ substantially depending on the data regime. When indicators originate from structured enterprise or survey instruments, the focus lies in ensuring conceptual validity, measurement reliability, and behavioral interpretability. Conversely, when derived from unstructured textual or social-media data, the emphasis shifts to large-scale signal extraction, normalization, and information-based weighting. The following subsections review each regime, summarizing key methods, formulas, and trade-offs in FinTech index construction.

3.4.1. Index Construction Methods for Enterprise Survey Data

Enterprise survey data provides one of the most direct empirical foundations for constructing Fintech indices that assess readiness, adoption, and innovation capability at the firm, sectoral, or national level. Unlike administrative records or text-mined data—which mainly capture observable market outcomes or public sentiment—survey-based approaches focus on the organizational and behavioral dimensions of Fintech transformation. They reveal how firms and consumers perceive, internalize, and implement digital-financial innovations within specific institutional contexts. This tradition aligns closely with the OECD–JRC composite-indicator framework [54, 55] where each latent construct (e.g., *digital infrastructure, Fintech adoption, innovation capability, or regulatory support*) is conceptualized as a multidimensional domain measured through several observable indicators. By operationalizing perceptions and internal processes, survey-based indices extend beyond performance metrics to capture the underlying capacity and readiness that enable Fintech development.

- *Instrument Design and Construct Validation*. Survey instruments are typically organized around four conceptual pillars: (1) digital and IT infrastructure, (2) organisational capability and human capital, (3) Fintech adoption and usage intensity, and (4) Institutional or regulatory support. Items within each pillar are usually measured on Likert-type scales (e.g., 1 = strongly disagree to 5 = strongly agree), converting qualitative perceptions into quasi-interval data amenable to statistical modeling. To ensure construct validity, most studies employ a psychometric validation pipeline comprising Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) before any index aggregation occurs. For example, Durak, et al. [56] developed a multi-dimensional *Fintech Adoption Scale* using EFA/CFA, achieving strong fit indices (RMSEA < 0.08; CFI > 0.90) and internal consistency (Cronbach's $\alpha > 0.70$). Similarly, Tarawneh, et al. [44] validated a structural path from Fintech knowledge to adoption intention via PLS-SEM, demonstrating that reliable constructs enhance the interpretive power of subsequent indices. Through this process, measurement error is minimized, and conceptual coherence is maintained, ensuring that each survey indicator truly reflects an underlying dimension of Fintech readiness or capability.
- *Data preprocessing and normalization*. Once constructions are validated, indicator data are standardized to enable comparability across firms, regions, or time periods. The z-score transformation remains the standard normalization approach:

$$z_{ik} = \frac{x_{ik} - \bar{x}_k}{s_k} \quad (1)$$

  where $x_{ik}$is the raw value for the indicator k of entity i, $\bar{x}_k$the mean, and $s_k$the standard deviation. When distributions are skewed, logarithmic transformation or winsorization is applied before scaling, particularly in financial-inclusion and enterprise-readiness studies. This process ensures proportional representation of each indicator.
- *Weighting.* The determination of weights (w_k) remains central to index construction. Three broad paradigms dominate the Fintech index literature:
- Equal weighting – transparent and easily replicable baseline.
- Expert-based weighting – employing Saaty's Analytic Hierarchy Process (AHP) [57] or Delphi approaches where experts assign relative importance to indicators.
- Data-driven weighting – using Principal Component Analysis (PCA), Factor Analysis, or PLS-SEM to derive objective weights from statistical variance.

A notable example is Zheng, et al. [58] who designed a two-stage PCA-based *Fintech Inclusion Index* across 40 developing economies (2011–2021), reducing subjective bias and enhancing cross-country comparability. Similarly, Zhang, et al. [21] combined Coefficient of Variation (CV) and AHP to construct a *Regional Fintech Indicator (RFI)* for 31 Chinese provinces, where CV captured statistical dispersion and AHP represented conceptual priorities—Application (53.9%), Industry (29.7%), and Environment (16.4%).

- *Aggregation.* Once normalized scores $S_{ik}$and weights $w_k$are obtained, the composite index can be aggregated through either a linear or geometric function:

$$FI_i = \sum_k w_k S_{ik} \ (2), \text{ or } FI_i = \prod_k S_{ik}^{w_k} \ (3)$$

as recommended in the OECD Handbook on Constructing Composite Indicators [54]. The linear form assumes full substitutability among dimensions, whereas the geometric mean is preferred when the underlying components are complementary or non-compensatory. These formulations are widely adopted in Fintech index studies [21, 58, 59].

- *Validation and sensitivity analysis.* Validation ensures that the constructed index is both statistically and conceptually sound. Internal validation involves reliability and convergence checks using Cronbach's α, Composite Reliability (CR), and Average Variance Extracted (AVE):

$$CR = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum \theta_i} \quad (4),$$

$$AVE = \frac{\sum \lambda_i^2}{\sum \lambda_i^2 + \sum \theta_i} \quad (5)$$

where $\lambda_i$are factor loadings and $\theta_i$error variances. Thresholds of CR > 0.70 and AVE > 0.50 indicate satisfactory convergence [60]. External validation tests correlations between FI scores and independent indicators (e.g., productivity, digital payments, financial inclusion) through OLS or GMM regressions. Sensitivity analyses-comparing equal, PCA, and AHP weight schemes-further confirm index robustness.

In short, survey-based Fintech indices emphasize conceptual validity, internal coherence, and behavioral interpretability, offering depth but limited scalability due to data-collection constraints.

3.4.2. Index Construction Methods for Social Media or Textual Data

Indices derived from digital-trace sources such as search volumes, social media mentions, or text-mined documents represent a distinct methodological strand in Fintech measurement.

Rather than relying on structured responses, these approaches extract continuous, real-time signals that reflect public attention, discourse, and sentiment surrounding fintech innovation.

Within the composite-indicator framework, the methodological emphasis shifts from psychometric validation toward signal extraction, scale harmonization, and information-based weighting, enabling unstructured textual data to be transformed into coherent quantitative measures of Fintech activity.

- *Indicator selection and feature engineering.* In this context, observable proxies such as keyword search frequencies, topic model weights, sentiment scores, or Fintech-related patent counts are employed as indicators of Fintech development and diffusion.
  For instance, Zhang, et al. [21] constructed a *Regional Fintech Indicator (RFI)* for 31 Chinese provinces using Baidu search frequencies of 48 Fintech-related keywords, supplemented by administrative variables grouped under three conceptual pillars: *Application*, *Industry*, and *Environment.* This feature-engineering process converts dispersed digital signals into structured components representing thematic dimensions of Fintech discourse.
- *Data preprocessing and normalization.* Because digital-trace data frequently exhibit heavy-tailed or highly skewed distributions, normalization is essential for comparability across entities and time. A commonly applied transformation is the log–min–max mapping [21] expressed as:

$$d_{ijk} = \frac{\log(x_{ijk}) - \log(x_{min})}{\log(x_{max}) - \log(x_{min})} \times 100 \quad (6)$$

  where x_{ijk}denotes the raw value for entity *i*, indicator *j*, and year *k*.
  This transformation rescales observations to the [0, 100] interval, compresses outliers, and preserves relative distances—an effective technique when combining diverse information sources such as search intensity, media frequency, or text-based sentiment.
- *Weighting.* Weight determination in text-based indices often combines objective statistical measures with expert judgment to balance empirical variability and conceptual relevance.
  Objective weights are commonly derived via the Coefficient of Variation, defined as

$$CV_k = \sigma_k / \bar{x}_k \quad (7)$$

  where $\sigma_k$is the standard deviation and $\bar{x}_k$ is the mean of indicator *k*. In the *RFI* of Zhang, et al. [21] indicator-level weights w_k^{CV}were computed using the CV method, while higher-level pillar weights $\alpha_j$were elicited through the Analytic Hierarchy Process (AHP).
  This two-tiered structure yielded the following relative importance: *Application* = 53.9 %, *Industry* = 29.7 %, *Environment* = 16.4 %. Such hybrid schemes enhance transparency by anchoring expert-based conceptual hierarchies in data-driven dispersion metrics.
- *Aggregation.* The final composite Fintech indicator is obtained through hierarchical aggregation, as formulated by Zhang, et al. [21]

$$RFI_i = \sum_j \alpha_j \left(\sum_k w_k^{CV} d_{ijk} \right) \quad (8)$$

  where $w_k^{CV}$are Coefficient-of-Variation-based sub-indicator weights and $\alpha_j$are AHP-derived pillar weights (*Application = 53.9 %, Industry = 29.7 %, Environment = 16.4 %*).
  This two-level structure preserves transparency and allows decomposition of contributions across pillars.
- *Validation and robustness.* Validation for digital indices typically involves external benchmarking rather than psychometric testing. For example, RFI scores are correlated with outcomes such as financial disintermediation, online credit growth, or bank efficiency in panel regressions. Robustness checks often test alternative weighting

methods (CV, entropy, equal) or re-normalization procedures. While these models excel in capturing dynamic, large-scale patterns of Fintech diffusion, they are inherently limited in interpretability and concept validity compared with survey-based counterparts.

Table 2 provides a comparative insight into the construction of the Fintech index for different types of data. The comparison suggests that the construction of a Fintech index should be data-sensitive: survey-based approaches are more appropriate for capturing latent constructs such as adoption, perception, and readiness, whereas textual or digital-trace-based approaches are better suited to measuring observable Fintech activity, public attention, and market dynamics.

Table 2.
Comparative construction of the Fintech index for different types of data.

Stage	Enterprise/Survey Data	Social-Media/Textual Data
Indicator selection	Theory-driven constructs validated via EFA/CFA/SEM	Engineered features from text/search streams + administrative metrics
Normalization	z-score, percentile, log/winsorize where needed	Log-min-max mapping $d = \frac{\log x - \log x_{\min}}{\log x_{\max} - \log x_{\min}} \times 100$
Weighting	Equal / AHP / PCA-derived	Hybrid CV + AHP (indicator-level CV; pillar-AHP)
Aggregation	Linear or geometric combinations of sub-indices	Hierarchical linear aggregation (sub-indices → overall)
Validation	Internal (α, CR, AVE, CFA) + external (OLS/GMM)	External only (panel regressions, robustness checks)

4. Conclusion

In this paper, we propose a novel approach that integrates text-processing techniques into each stage of the SLR methodology. The process began with data collection, where URL based retrieval enabled us to identify 227 publications and relevant information on Fintech Index studies. To expand the search beyond manually selected keywords, text-mining techniques were used to extract keywords and synonyms from the collected papers. The data were then pre-processed through lowercase conversion, tokenization, stop-word removal, and stemming/lemmatization to prepare them for further analysis. Using content-based clustering, the study efficiently organized a large body of literature and identified the most important research clusters. In the final stage, NLP-based text classification was applied to categorize collected papers into 2 groups: Relevant documents (including papers on **f**intech development, adoption and inclusion) **and** non-relevant documents**.** TF-IDF was used to assess term importance, while SVM supported document classification. Topic modelling techniques, including LDA and LDA-Mallet, further revealed latent themes and trends in Fintech literature.

The reviewed literature identifies three main groups of Fintech-related indices: Fintech Development, Fintech Adoption, and Fintech Inclusion. Although the total number of studies remains relatively limited, publication trends indicate growing academic interest in Fintech index construction. The Fintech Development Index focuses on Fintech's contribution to industry growth, innovation, green finance, entrepreneurial ecosystems, and sustainability. Existing studies show that Fintech can reduce financial constraints, support technological innovation, optimize energy structures, and facilitate entrepreneurial opportunity identification and resource mobilization. In banking, however, Fintech has mixed effects: it may reduce operational risk and improve risk control, but it can also increase loan risk or threaten bank stability without proper governance. The Fintech Adoption Index emphasizes the role of digital innovation, financial inclusion, consumer behavior, and institutional readiness in shaping adoption. Key drivers include perceived usefulness, trust, government support, performance expectancy, effort expectancy, social influence, and facilitating conditions. Fintech adoption also supports rural entrepreneurship and household income, though excessive adoption may challenge traditional banks' liquidity and profitability. The Financial Inclusion Index highlights Fintech's role in expanding access to financial services, promoting sustainable finance, reducing poverty, and supporting inclusive economic growth, especially through mobile money, digital financial services, and collaboration with traditional financial institutions.

The paper also provides a comparative overview of how Fintech indices are constructed using different types of data, particularly enterprise/survey data and social media/textual data. The comparison highlights key methodological differences across five main stages: indicator selection, normalization, weighting, aggregation, and validation. While enterprise- or survey-based indices are typically grounded in theory-driven constructs and validated through statistical techniques such as EFA, CFA, or SEM, indices based on social-media and textual data rely more heavily on engineered indicators derived from text, search behavior, and administrative data. We also show that normalization, weighting, and validation strategies vary according to data characteristics, with textual-data-based indices often requiring log-based transformations and external validation through econometric models.

While these findings provide a foundation for further exploration and indicator development, limitations exist. The current study encountered accessibility challenges and limitations in available techniques for extracting and analyzing detailed index models from the full text of articles. Future research in this area could potentially enhance the SLR methodology by incorporating more sophisticated techniques for comprehensive data retrieval and analysis. This would allow for the inclusion of a broader range of Fintech index studies, ultimately contributing to the widespread dissemination of knowledge and attracting further research efforts to advance the field of Fintech as a whole.

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