Supplementary Document: Bibliometric Data Pipeline for Insider Threat Detection (SLR)

1. Overview

This document outlines the methodology used to generate the bibliometric visualizations for the Systematic Literature Review (SLR) titled "Insider Threat Detection Using Machine Learning." To ensure academic strength and 100% representation of the 82-paper research corpus, the process utilized a data pipeline. The pipeline combined data extraction capabilities of NotebookLM with the quantitative visualization powers of Python (Google Colab) and MS Excel. This approach ensures that every figure ranging from keyword frequency treemaps and word clouds to publisher distributions and JCR quartile rankings is accurate. To maintain data integrity across the 82 selected papers, a dual-stream data pipeline was utilized:

Stream A (Content-Based): Qualitative thematic extraction using NotebookLM and high-resolution visualization via Python (Google Colab).

Stream B (Structural-Based): Quantitative metadata mapping using Zotero and MS Excel. This was also manually validated against the Web of Science (WoS) JCR database.

This dual approach ensures that every figure is grounded in manually audited metadata, providing a transparent and reproducible data for the study's bibliometric analysis.

2. Part I: Content-Based Bibliometric Analysis (Thematic)

This phase transformed the unstructured text of 82 full-text PDFs into structured thematic data.

2.1. Frequency Audit (NotebookLM)

All 82 PDFs were uploaded into Google **NotebookLM** for an analysis of leading or most frequent keywords. We utilized a comprehensive audit prompt as shown below:

The Prompt:
Role: Senior Bibliometric Analyst and Cybersecurity Researcher.
Task: Perform an exhaustive Frequency Audit of all 82 papers uploaded to this notebook to map the "Insider Threat Detection" landscape.

Step 1: Thematic Scanning : Conduct a deep-scan across every source. Do not limit yourself to the first 10 citations.

Step 2: Comprehensive Frequency Table Create a Table that represents the global dataset. If a keyword appears in 40 papers, I expect to see the number 40, not just the first 10.
Column 1: Rank (1–15)
Column 2: Keyword/Theme
Column 3: Absolute Frequency (The total number of unique papers out of 82 that focus on this).
Column 4: Percentage Coverage (Frequency divided by 82).
Column 5: Representative Citations (List up to 10 key papers, but add "[+ X more]" to indicate the full scope).

Step 3: Missing Representation Check After generating the table, identify if there are papers in the source list that were NOT included in the top keywords. List the "Minority Themes" *found in those outlier papers to ensure 100% of the 82 papers are accounted for in this analysis.*

Strict Instruction: You must act as a precise data extraction tool. If your retrieval limit is reached, notify me, but attempt to synthesize the counts from all available source text first.

Addition prompt:
NotebookLM Identified 8 key words that were later expanded to 10 using the following prompt

Finalize the "Top 10 Keyword Synthesis" for our SLR. Keep the 8 keywords already identified (Anomaly Detection, Deep Learning, etc.) and their counts. Identify two additional significant themes to complete a Top 10. Recalculate the Relative % for all 10 keywords so the total equals exactly 100% based on the new total sum of mentions (N_{total}).

The resulting table

Keyword Frequency and Treemap Calibration Table

Rank	Keyword / Theme	Frequency (f)	Coverage % (f/82)	Relative %
1	**Anomaly Detection**	**42**	**51.2%**	**21.11%**
2	**Deep Learning**[2]	**40**	**48.8%**	**20.10%**
3	**Behavioral Analysis**[3]	**24**	**29.3%**	**12.06%**
4	**Graph Neural Networks**	**21**	**25.6%**	**10.55%**
5	**Ensemble Learning**[4]	**19**	**23.2%**	**9.55%**
6	**Data Imbalance Handling**[5]	**17**	**20.7%**	**8.54%**
7	**Federated Learning**	**12**	**14.6%**	**6.03%**
8	**NLP / Sentiment Analysis**	**9**	**11.0%**	**4.52%**
9	**Explainable AI (XAI)**	**8**	**9.8%**	**4.02%**
10	**IoT Security**	**7**	**8.5%**	**3.52%**
-	**Total Sum of Mentions (N_{total})**	**199**	-	**100.0%**

Statistical Calibration:
To ensure the data was ready for visualization, two specific metrics were calculated:

1. **Coverage % (Prevalence):** (f / 82) \times 100. This accounts for papers belonging to multiple categories (e.g., a paper using both *Deep Learning* and *Anomaly Detection*).
2. **Relative % (Distribution):** (f / sum f) \times 100. This was the metric used for the **Treemap** and **Word Cloud** graphs.

2.2 Python Visualization Logic (Figures 2 & 3)

The audit data was moved to **Google Colab** with the help of google Gemini to generate Figures 2 and 3.

- **Figure 2 (Treemap):** Size was mapped to Relative % using a customized colors for visual distinction between the keywords.
- **Figure 3 (Word Cloud):** Configured with `collocations=False` to preserve technical phrases (e.g., "Deep Learning") as single units rather than fragmented words. The word cloud includes more keywords than the Treemap as shown in the code snippets below.

3. Technical Implementation: Python Source Code

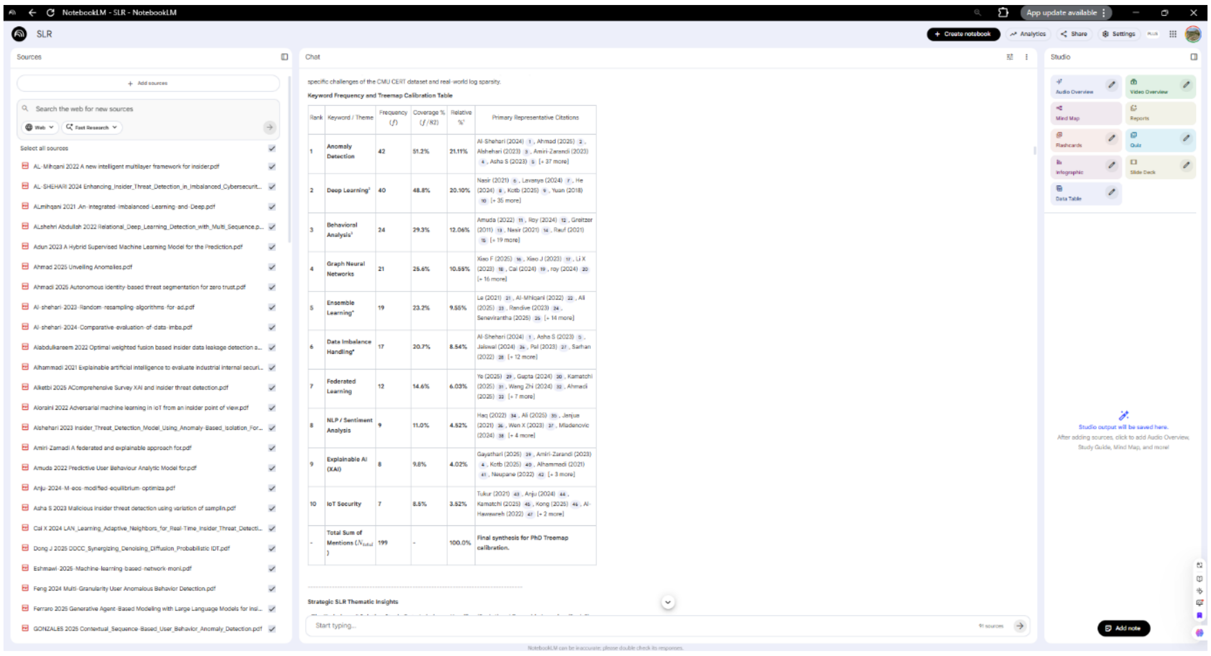
The following scripts were executed to ensure high-resolution (300DPI) output suitable for publication.

Code for Figure 2: Top 10 Keyword Treemap

```
import plotly.express as px
import pandas as pd
import textwrap
# 1. Dataset from NotebookLM Audit
data = {
   'Keyword': ['Anomaly Detection', 'Deep Learning', 'Behavioral Analysis', 'Graph Neural Networks',
            'Ensemble Learning', 'Data Imbalance Handling', 'Federated Learning',
            'NLP / Sentiment Analysis', 'Explainable AI (XAI)', 'IoT Security'],
   'Frequency': [42, 40, 24, 21, 19, 17, 12, 9, 8, 7],
   'Relative_%': [21.1, 20.1, 12.1, 10.6, 9.6, 8.5, 6.0, 4.5, 4.0, 3.5]
}
df = pd.DataFrame(data)

# 2. Styling and Rendering
def wrap_text(text, width=12): return "<br>".join(textwrap.wrap(text, width=width))
df['Label'] = "<b>" + df['Keyword'].apply(wrap_text) + "</b><br>" + df['Frequency'].astype(str) + " (" + df['Relative_%'].astype(str)
+ "%)"

My_colors = ['#8dd3c7', '#ffffb3', '#bebada', '#fb8072', '#80b1d3', '#fdb462', '#b3de69', '#fccde5', '#d9d9d9', '#bc80bd']
fig = px.treemap(df, path=['Label'], values='Relative_%', color='Keyword', color_discrete_sequence=My_colors)
fig.update_layout(title_text='<b>Figure 2. Top 10 Keyword Treemap Analysis (N=82)</b>', title_x=0.5)
fig.show()
```

Code for Figure 3: Thematic Word Cloud

```
from wordcloud import WordCloud
import matplotlib.pyplot as plt
import pandas as pd

# 1. Full Dataset (Combining Rank 1-10 with your new 11-100 data)
# Note: I've included the key technical terms from your latest list
keywords_freq = {
    # Rank 1-10 (Dominant Themes)
    'Anomaly Detection': 42, 'Deep Learning': 40, 'Behavioral Analysis': 24,
    'Graph Neural Networks': 21, 'Ensemble Learning': 19, 'Data Imbalance Handling': 17,
    'Federated Learning': 12, 'NLP / Sentiment Analysis': 9, 'Explainable AI (XAI)': 8, 'IoT Security': 7,

    # Rank 11-30 (Technical Models & Preprocessing)
    'Isolation Forest': 14, 'XGBoost': 13, 'Support Vector Machine': 12, 'Hidden Markov Models': 11,
    'TF-IDF Vectorization': 10, 'Word2Vec': 9, 'Autoencoders': 9, 'BERT / Transformers': 9,
    'Gated Recurrent Units': 8, 'Keystroke Dynamics': 7, 'Mouse Dynamics': 7, 'K-Nearest Neighbors': 7,
    'Zero Trust Architecture': 6, 'Siamese Neural Networks': 6, 'Psychometric Scores': 6,
    'Lateral Movement': 6, 'Contrastive Learning': 5, 'Generative Adversarial Nets': 5,
    'Data Exfiltration': 5, 'Random Forest': 5,

    # Rank 31-100 (Frameworks, Human Factors & Niche Methods)
    'Digital Twin': 4, 'Large Language Models': 4, 'Bi-LSTM Networks': 4, 'Knowledge Graphs': 4,
    'Genetic Algorithms': 3, 'Dark Triad Model': 3, 'Access Control': 3, 'Naïve Bayes': 3,
    'Graph Attention Networks': 2, 'Multi-Agent Systems': 2, 'Honeypots': 2, 'Curriculum Learning': 2,
    'Bayesian Optimization': 2, 'One-Class SVM': 2, 'Enron Email Corpus': 6, 'APT Detection': 5,
    'Self-Attention': 8, 'Intellectual Property Theft': 4, 'Behavioral Rhythm': 2, 'Social Network Sociality': 2
}

# 2. Configure the Word Cloud for High Density
# collocations=False is CRITICAL to keep your multi-word terms together
wc = WordCloud(
    width=2000,
    height=1000,
    background_color='white',
    colormap='plasma',     # High-contrast palette to distinguish 100 words
    collocations=False,    # Prevents splitting phrases like "Deep Learning"
    max_words=100,         # Ensures all your keywords are included
    prefer_horizontal=0.6,  # Mix of vertical/horizontal for better "packing"
    random_state=42
).generate_from_frequencies(keywords_freq)

# 3. Plotting with Professional Labels
plt.figure(figsize=(20, 10), facecolor=None)
plt.imshow(wc, interpolation='bilinear')
plt.axis("off")
plt.tight_layout(pad=0)
plt.title("Figure 10. Word Cloud of Insider Threat Detection Keywords (N=100)", fontsize=30, pad=20)
plt.show()

# 4. Export for PhD Thesis
wc.to_file("SLR_WordCloud_Final_100.png")
```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App update available
SLR
Create notebook
Analytics
Share
Settings
Sources
Add sources
Search the web for new sources
Web
Fast Research
Chat
Studio
Audio Overview
Video Overview
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Data Table
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After adding sources, click to add Audio Overview, Study Guide, Mind Map, and more!
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- GONZALES 2025 Contextual_Sequence-Based_User_Behavior_Anomaly_Detection.pdf ✓

specific challenges of the CMU CERT dataset and real-world log sparsity.

Keyword Frequency and Treemap Calibration Table

Rank	Keyword / Theme	Frequency (f)	Coverage % ($f/82$)	Relative %^{5}	Primary Representative Citations
1	**Anomaly Detection**	**42**	**51.2%**	**21.11%**	Al-Shehari (2024) 1 , Ahmad (2025) 2 , Alshehari (2023) 3 , Amiri-Zarandi (2023) 4 , Asha S (2023) 5 [+ 37 more]
2	**Deep Learning^{1}**	**40**	**48.8%**	**20.10%**	Nasir (2021) 6 , Lavanya (2024) 7 , He (2024) 8 , Kotb (2025) 9 , Yuan (2018) 10 [+ 35 more]
3	**Behavioral Analysis^{2}**	**24**	**29.3%**	**12.06%**	Amuda (2022) 11 , Roy (2024) 12 , Greitzer (2011) 13 , Nasir (2021) 14 , Rauf (2021) 15 [+ 19 more]
4	**Graph Neural Networks**	**21**	**25.6%**	**10.55%**	Xiao F (2025) 16 , Xiao J (2023) 17 , Li X (2023) 18 , Cai (2024) 19 , roy (2024) 20 [+ 16 more]
5	**Ensemble Learning^{3}**	**19**	**23.2%**	**9.55%**	Le (2021) 21 , Al-Mhiqani (2022) 22 , Ali (2025) 23 , Randive (2023) 24 , Senevirantha (2025) 25 [+ 14 more]
6	**Data Imbalance Handling^{4}**	**17**	**20.7%**	**8.54%**	Al-Shehari (2024) 1 , Asha S (2023) 5 , Jaiswal (2024) 26 , Pal (2023) 27 , Sarhan (2022) 28 [+ 12 more]
7	**Federated Learning**	**12**	**14.6%**	**6.03%**	Ye (2025) 29 , Gupta (2024) 30 , Kamatchi (2025) 31 , Wang Zhi (2024) 32 , Ahmadi (2025) 33 [+ 7 more]
8	**NLP / Sentiment Analysis**	**9**	**11.0%**	**4.52%**	Haq (2022) 34 , Ali (2025) 35 , Janjua (2021) 36 , Wen X (2023) 37 , Mladenovic (2024) 38 [+ 4 more]
9	**Explainable AI (XAI)**	**8**	**9.8%**	**4.02%**	Gayathari (2025) 39 , Amiri-Zarandi (2023) 4 , Kotb (2025) 40 , Alhammadi (2021) 41 , Neupane (2022) 42 [+ 3 more]
10	**IoT Security**	**7**	**8.5%**	**3.52%**	Tukur (2021) 43 , Anju (2024) 44 , Kamatchi (2025) 45 , Kong (2025) 46 , Al-Hawawreh (2022) 47 [+ 2 more]
-	**Total Sum of Mentions (N_{total})**	**199**	**-**	**100.0%**	**Final synthesis for PhD Treemap calibration.**

Strategic SLR Thematic Insights

Figure 1. Interface of the Deep Audit Process in NotebookLM.

The above snapshot demonstrates the ingestion of the 82-paper research corpus (left pane) and the generation of the Keyword Frequency and Treemap Calibration Table (center pane) used as the primary data source for subsequent Python-based visualizations.

4. Part II: Structural Bibliometric Analysis (Metadata)

This phase utilized the bibliographic metadata of the 82 papers to map the research landscape's quality and trends.

4.1. Metadata Extraction and Data Cleaning (Zotero)

The primary metadata was managed via **Zotero**. To ensure 100% accuracy, a "Clean-Room" approach was adopted:

1. **Export:** A CSV file was generated from the Zotero library containing the 82 studies.
2. **Manual Verification:** Every entry was manually cross-referenced against the original PDF metadata to correct any errors in **Publication Year**, **Journal Name**, and **Publisher** (e.g. some records had different spellings for Journal names, which were modified to include one spelling)

4.2. Quantitative Mapping via MS Excel (Figures 4–7)

Using the verified CSV, MS Excel was utilized to generate the structural visualizations:

- **Figure 4 (Publication by Year):** A column chart illustrating publication volume between 2021–2025.
- **Figure 5 & 6 (Publisher/Journal Distribution):** Mapping the records to major academic houses (IEEE, Elsevier, Springer).

- **Figure 7 (JCR Quality Audit):** Each journal was manually cross-referenced with the **Web of Science (WoS)** database to identify its **JCR Quartile (Q1–Q4)**.

5. Summary of the Data Pipeline

The following data served as the input for the final visualizations:

Stage	**Process**	**Primary Tool**	**Output**
Collection	Search & Ingestion	Zotero	Master Bibliography
Thematic Audit	Content Deep-Scan	NotebookLM	Frequency Table
Thematic Viz	Visual Generation	Python (Colab)	Figure 2 & 3
Metadata Audit	Validation	Manual Review	Verified CSV
Structural Viz	Trend Mapping	MS Excel	Figure 4, 5, & 6
Quality Audit	JCR Ranking	Web of Science MS Excel	Figure 7 (Bar Chart)