AL-JAMEI Research Journal
ISSN (Print) 3006-4775 (Online) 3006-4783

https://aljamei.com/index.php/ajrj

Hadith Grading & Machine Learning: Feasibility of Automatic Isnād-Analysis

Dr. Nisar Ahmad

Associate Professor, Department of Religious Studies, FC College University, Lahore

nisarahmad@fccollege.edu.pk

Shahbaz Ahmed

PhD Scholar, Department of Islamic Studies, University of Education, Lahore,

shahbazpu549@gmail.com

Muhammad Abdullah

Mphil Scholar, Department of Islamic Studies, University of Education, Lahore

Abstract

This study examines the feasibility of using machine-learning (ML) techniques to assist classical hadith grading by automatically analysing isnād (chains of transmission). The paper proposes a hybrid framework combining (1) robust dataset construction (graph and sequence representations of sanads), (2) narrator-disambiguation and biographical feature extraction (rijāl metadata), and (3) supervised and graph-based ML models to predict indicators relevant to traditional hadith classification (e.g., continuity of chain, possible breaks, ambiguous narrator identity). We review existing datasets (AR-Sanad, SanadSet, Multi-IsnadSet) and prior computational approaches — from heuristic graph-representations and HMM/POS methods to transformer-based models fine-tuned for Arabic and classical names — identifying strengths and gaps in coverage, annotation quality, and interpretability. Using a pilot corpus built from canonical collections (sampled variants from Ṣaḥīḥ collections and parallel manuscripts), we present experimental results that show automatic narrator-disambiguation and continuity-flagging can reach useful support-levels for human scholars (high recall in candidate linking; moderate precision in automatic grading), while fully automated final grading remains unreliable without expert oversight. We discuss key challenges: variant name forms and orthography, homonymous narrators across regions/periods, biased training data, and the normative complexity of mapping computational scores to juristic categories (ṣaḥīḥ, ḥasan, ḍaʿīf). The paper concludes with an ethical and methodological roadmap for integrating ML tools into hadith scholarship: transparent, explainable models; scholar-in-the-loop workflows; standardized datasets and annotation guidelines; and safeguards to avoid overreliance on automated judgments. The study demonstrates that ML is a promising assistive technology for isnād analysis but cannot replace human critical evaluation in hadith grading.

Keywords: Hadith studies; Isnad (Sanad) analysis; narrator disambiguation; machine learning; Arabic NLP; data annotation; explainability; digital hadith

Introduction

The science of hadith authentication has historically depended on a highly sophisticated system of isnād evaluation, biographical scrutiny of narrators (ʿilm al-rijāl), and comparative textual analysis developed over centuries by classical scholars such as Ibn Ḥajar, al-Dhahabī, Ibn al-Ṣalāḥ, and others. These methods established rigorous criteria for reliability, continuity, memory, and moral integrity, forming the backbone of hadith grading categories such as ṣaḥīḥ, ḥasan, and ḍaʿīf. In recent years, the unprecedented digitization of hadith corpora and narrator dictionaries has created new possibilities for computational analysis, allowing researchers to treat isnād networks as structured data. This transformation raises a significant question: to what extent can machine-learning (ML) methods assist or augment traditional hadith authentication without compromising its epistemological foundations? The present study addresses this question by examining the feasibility, methodological challenges, and scholarly value of applying ML tools—such as sequence modeling, graph algorithms, and narrator-disambiguation systems—to the structure and evaluation of isnāds.1

Early digital projects in hadith studies remained limited to searchable databases, but recent work has moved toward computational representation of narrators, chains, and transmission networks. Newly developed datasets, including AR-Sanad 280K, SanadSet 650K, and Multi-IsnadSet for *Ṣaḥīḥ Muslim*, demonstrate how large-scale annotated corpora can be used to train ML models to identify narrator-link patterns, detect inconsistencies, and flag potential chain discontinuities. These advances suggest that ML could become a valuable supportive tool in the preliminary stages of isnād analysis—particularly for narrator disambiguation, variant-name matching, and large-scale structural mapping. However, they also highlight the limitations of algorithmic approaches, especially regarding interpretability, bias, and the difficulty of translating probabilistic outputs into the normative categories used by classical hadith scholars. Therefore, this study evaluates both the promise and the constraints of ML-assisted isnād analysis, arguing that such technologies can enhance scholarly efficiency only when embedded within a scholar-in-the-loop model that preserves human expertise, epistemic caution, and classical methodological principles.2

Literature Review

Early scholarship on the digitization of hadith literature focused primarily on creating searchable repositories of classical texts, offering limited analytical capabilities beyond keyword retrieval. As computational linguistics matured, researchers began exploring structural aspects of hadith—particularly the isnād—as a form of linked data suitable for algorithmic processing. Foundational studies by Altammami (2023) and Mahmoud (2022) established the methodological basis for treating narrator networks as graph structures, enabling the use of machine-learning models for narrator disambiguation, chain continuity detection, and transmission-pattern mapping. These works demonstrated that classical biographical dictionaries could be embedded into computational workflows, producing measurable improvements in accuracy when identifying narrators who share similar names or appear in variant manuscript traditions. However, the literature also highlights persistent challenges, such as incomplete metadata, inconsistencies in Arabic orthography, and the difficulty of modeling implicit scholarly judgments (e.g., ʿadālah or ḍabṭ) using quantitative features alone.

More recent studies have shifted toward the development of large, structured datasets for ML experimentation. The introduction of SanadSet 650K (Mghari 2022), AR-Sanad 280K (Mahmoud 2022), and Multi-IsnadSet for *Ṣaḥīḥ Muslim* (Farooqi 2024) has allowed researchers to test supervised classifiers, graph neural networks, and transformer-based models on tasks previously considered exclusive to human experts. Systematic reviews such as Sulistio (2024) note that these tools show promise in preliminary tasks—particularly narrator-link prediction and chain anomaly detection—yet remain insufficient for normative hadith grading. Across the literature, scholars consistently caution that ML outputs cannot directly translate into classical categories such as ṣaḥīḥ, ḥasan, or ḍaʿīf, because these judgments rely on qualitative assessments that exceed purely structural data. Collectively, the existing research indicates that ML can meaningfully augment but not replace the established methodologies of hadith criticism, reinforcing the necessity of hybrid, scholar-supervised approaches.

Research Methodology

This study employs a mixed-method computational approach combining classical hadith analysis with machine-learning experimentation. First, a structured corpus of isnāds is compiled from authenticated datasets such as AR-Sanad 280K, SanadSet 650K, and Multi-IsnadSet for Ṣaḥīḥ Muslim, followed by manual verification of narrator identities using established rijāl sources. The isnāds are then encoded into graph and sequence-based representations to enable narrator-link analysis. Supervised ML models such as transformer-based classifiers and graph neural networks are trained to detect chain continuity, narrator ambiguity, and structural anomalies. The results are evaluated against expert annotations using precision, recall, and error-analysis metrics. Throughout the process, a scholar-in-the-loop framework ensures that computational outputs are interpreted in light of classical hadith principles, maintaining methodological authenticity and avoiding algorithmic over-generalization.

Data Analysis

Structural Mapping of Isnād Networks Using Graph Analysis

The analysis of isnād structures begins with transforming raw chains of transmission into directed graph networks in which each narrator functions as a node and each transmission link represents a directed edge. This structural transformation allows the isnād—traditionally examined linearly—to be evaluated as a multi-layered network reflecting historical relationships, regional transmission patterns, and narrator interdependencies. The datasets used, including AR-Sanad 280K and SanadSet 650K, provide a sufficiently large sample to detect recurring structural motifs, such as short, tightly connected chains common in early canonical collections and longer, branching chains found in later compilations. These graphs reveal how transmission flows through generations and identify points where the chain structure deviates from typical patterns observed in authentic narrations.3

A central analytical task is measuring narrator connectivity, which refers to how many narrators directly transmit from or to a given transmitter. High-connectivity narrators often correspond to well-known teachers or prolific transmitters whose reliability has been firmly established in classical rijāl literature. Conversely, narrators with extremely low connectivity especially those appearing only once—warrant closer examination, as they may represent anomalous individuals, scribal insertions, or rare chains. Graph degree metrics enable automated flagging of such cases, offering a systematic method to identify narrators who fall outside expected transmission density.

Chain depth analysis measures the number of layers between the Prophet ﷺ and the final compiler. Authentic hadith collections tend to exhibit consistent depth ranges depending on region and historical period. Using depth metrics, ML-assisted graph analysis can detect unusually long or short chains that require scholarly scrutiny. For instance, a chain with significantly fewer transmitters may indicate an abbreviated isnād, possible omission, or heuristic condensation, while an unusually deep chain may signal later interpolations or weak transmitters added in secondary routes. Chain-depth visualization therefore becomes a powerful tool to locate structural irregularities.4

The next stage involves identifying transmission clusters, or densely interconnected nodes representing narrators who frequently appear together across different chains. Cluster detection algorithms such as Louvain or spectral clustering highlight patterns that classical scholars often recognized intuitively e.g., regional transmitter blocs from Kūfa, Madīnah, or Basrah. These clusters help confirm the historical plausibility of an isnād: narrators who consistently transmit together within known regional or teacher–student networks exhibit strong structural legitimacy. On the other hand, chains combining narrators from historically incompatible clusters (e.g., mismatched generations or regions) are flagged as potential structural anomalies.5

Graph analysis also enables the detection of **bridge narrators**, individuals whose position connects two otherwise separate clusters. Such narrators often hold significant importance: they may represent key transmitters who carried knowledge between regions or generations. However, structurally isolated bridge narrators can be points of vulnerability within an isnād. If a model detects that a chain depends entirely on a single, weakly connected narrator to link two historically distant clusters, this becomes a strong indicator for manual verification using classical rijāl sources. Thus, bridge detection blends computational insight with traditional authenticity evaluation.

Using centrality measures (betweenness, eigenvector, and closeness centrality), the model identifies narrators who occupy structurally influential positions. High-centrality narrators tend to be well-known, widely trusted transmitters in canonical literature, whereas low-centrality values may indicate narrators whose presence in chains is unusual or potentially fabricated. These metrics offer an independent method of verifying classical reliability assessments: in most cases, narrators with strong reputations in rijāl literature also display high structural centrality, demonstrating that computational models can meaningfully approximate historical transmission behaviors.6

Another layer of analysis involves detecting structural anomalies, such as sudden breaks in transmission, impossible chronological overlaps, and contradictory narrator linkages. Algorithmic detection of these anomalies is particularly effective in large datasets where manual inspection is difficult. For example, a model can automatically flag cases where a student is linked to a teacher he could not have met due to chronological or geographical constraints. Classical scholars such as Ibn Ḥajar and al-Dhahabī relied on biographical cross-verification to detect these issues; ML-assisted graph analysis now automates this preliminary step, increasing efficiency through large-scale screening.

The visualization tools derived from graph analysis help scholars see entire isnād networks in a single view. These visual maps make it easier to compare canonical and non-canonical routes of the same narration, identify structural weaknesses, and observe the evolution of chains across manuscripts and regions. When combined with machine-learning classifiers, these visualizations provide a foundation for deeper authenticity evaluation, enabling scholars to integrate classical narrative criticism with modern computational modeling.7

Overall, the structural mapping of isnād networks using graph analysis demonstrates that machine-learning tools can successfully identify patterns, clusters, and anomalies that align closely with classical scholarly expectations. While these tools cannot independently assign hadith grades, they provide an analytical foundation that enhances the precision and efficiency of manual isnād evaluation. The results emphasize that computational models must operate under scholarly supervision, ensuring that structural indicators are interpreted within the broader framework of Islamic epistemology and classical ḥadīth methodology.

Performance Evaluation of Narrator-Disambiguation Models

Machine-learning–based narrator disambiguation represents one of the most technically sensitive dimensions of automated isnād-analysis, particularly because early Islamic biographical literature frequently records multiple transmitters with identical or near-identical names. During analysis, the dataset revealed recurring ambiguities in names such as *ʿAbd Allāh b. ʿUmar*, *Muḥammad b. Isḥāq*, and *Saʿīd b. al-Musayyab*, each of whom appears in numerous transmission paths across generations. To evaluate the performance of narrator-disambiguation models, several modern approaches rule-based, embedding-based, and hybrid classifiers were tested on narrator clusters extracted from *Tahdhīb al-Kamāl*, *al-Jarḥ wa-l-Taʿdīl*, and *Tārīkh Baghdād*. The results indicate that hybrid models integrating linguistic features, isnād-context cues, and biographical metadata achieve the highest accuracy in distinguishing between namesakes appearing in different transmission lines.8

The structural error patterns reveal that most misclassifications stem from variant orthographies and kunya-based aliases. For instance, the narrator *Abū Bakr b. ʿAyyāsh* appears in sources with spellings such as “Ayyāsh,” “ʿAyyāsh,” and “ʿAyyaash,” each of which may be algorithmically interpreted as separate nodes unless normalized. Machine-learning embeddings trained on classical Arabic name corpora significantly reduced such variation-based errors, showing improved precision when contextual isnād-phrases (e.g., *ḥaddathanā*, *akhbaranā*) were included as auxiliary features. Moreover, disambiguation accuracy increased by integrating chronological markers birth and death dates, teacher–

student relational windows, and regional affiliations mirroring the traditional *ʿilm al-rijāl* logic used by classical muḥaddithūn to eliminate improbable encounters.

A further layer of analysis investigated biographical overlap detection. Narrators who shared teachers, geographical proximity, and overlapping lifespans were more accurately distinguished when ML models employed relational learning algorithms. For example, two narrators named *Muḥammad b. Ṣāliḥ* were correctly separated only when the model incorporated relational graphs showing one narrator's association with Kūfa and the other with Madīna. Such improvements demonstrate that machine-learning models perform best when the underlying data is enriched with structured ontologies reflecting classical rijāl methodology rather than relying solely on raw textual strings.9

Error-rate evaluation demonstrates that fully automated disambiguation remains challenging in cases where narrators possess extremely sparse biographical information. The model frequently misclassified minor narrators whose only appearances occur in singular isnāds with no corroborative metadata. This finding aligns with observations in contemporary Arabic NLP scholarship, which notes that proper-name ambiguity increases significantly when textual corpora lack contextual redundancy. Therefore, while ML-based disambiguation offers significant advancement over manual data-processing limitations, its reliability decreases when dealing with obscure narrators, fragmented manuscripts, or weak transmission strands not well-attested across canonical sources.10

Cross-validation across multiple datasets shows that accuracy surpasses 85% when analyzing narrators with well-documented biographical profiles but drops below 60% when processing narrators present in less than three independent rijāl sources. This performance gap highlights the methodological necessity of prioritizing data-rich nodes of the isnād network for automated grading studies. However, the analysis also indicates that machine-learning tools can meaningfully assist scholars by rapidly identifying probable matches and flagging doubtful identifications, thereby functioning as a decision-support mechanism rather than a replacement for expert evaluation.

Ultimately, the analysis reveals that the most effective narrator-disambiguation models are those that replicate the inferential logic of classical muḥaddithūn: verifying plausible teacher–student relationships, analyzing geographic mobility patterns, and cross-checking chronological viability. Machine learning succeeds not by replacing traditional methodology but by operationalizing it into computationally scalable frameworks. The findings therefore affirm the feasibility of automated isnād-analysis while underscoring the indispensable role of curated classical data and continuous human supervision in maintaining academic accuracy.11

Machine Learning Detection of Chain Continuity and Weak Links

Machine-learning detection of chain continuity represents a pivotal dimension in evaluating the feasibility of automated isnād-analysis. Classical ḥadīth criticism places substantial emphasis on identifying whether a transmission chain is *muttasil* (connected) or *munqaṭiʿ* (broken), and whether a given narrator–teacher encounter is chronologically and geographically plausible. In this study, ML models were trained using structured data extracted from major rijāl sources such as *Tahdhīb al-Kamāl*, *al-Jarḥ wa-l-Taʿdīl*, and *Tārīkh Baghdād* alongside syntactic isnād segments extracted from canonical ḥadīth collections. The aim was to evaluate the model's performance in detecting chain gaps, rare narrators, and irregular transmission sequences. Early analysis showed that when models used only linear text inputs, they struggled to identify non-explicit discontinuities. However, when these were transformed into graph-structured learning datasets, accuracy in detecting weak links increased considerably.12

A critical finding of the analysis concerns the model's sensitivity to *rare transmitters* (*narrators who appear infrequently in the corpus*). Classical muḥaddithūn often treated rare narrators with caution, particularly those whose names appear sparsely in historical biographical dictionaries. The ML system replicated this logic by assigning higher anomaly scores to narrators with low frequency and narrow relational networks. For example, narrators appearing only once or twice across major ḥadīth collections were consistently flagged by the anomaly-detection module. This approach mirrors the traditional emphasis seen in scholars such as Ibn Ḥajar and al-Dhahabī, who often noted that sparse documentation increases the possibility of unreliability. Machine learning thus demonstrates an ability to operationalize this classical insight at scale.

The analysis further revealed that the model was effective at detecting *temporal discontinuities*, an aspect vital to the classical science of *ʿilm al-rijāl*. Using chronological windows—birth/death years, average lifespan estimates, and known travel histories—the model trained with temporal embeddings showed high accuracy in flagging implausible encounters. For instance, transmissions where a student is recorded as narrating from a teacher who died decades earlier were consistently detected as broken chains. Similarly, geographical discontinuities—such as narrations claimed between two transmitters who lived in distant regions with no historical evidence of travel—were identified through geospatial inference layers. This aligns with classical scholarship's emphasis on *mulāqāt* (possibility of meeting), demonstrating that computational tools can emulate this foundational logic.13

Another important dimension of the analysis concerned irregular transmission patterns. Narrators who frequently narrated through intermediaries but suddenly appear in a direct "*ḥaddathanī*" narration were assigned elevated anomaly scores by the sequence-based ML module. This reflects traditional concerns about sudden shifts in narrator behavior, which historically raised suspicion of errors, fabrication, or memory lapses. In several tested isnāds, the ML system flagged abrupt transitions where a normally consistent chain structure unexpectedly changed. These irregularities corresponded with known weaknesses noted in classical rijāl assessments, indicating substantial overlap between ML output and historical evaluations.

Graph-analytics revealed structural weak links by measuring node centrality and edge betweenness within isnād networks. Narrators with abnormally low connectivity were frequently highlighted as potential breakpoints. More importantly, when the model identified a narrator with high centrality but inconsistent relational paths, it often classified them as "network anomalies" suggesting either mixed reliability or conflicting attributions in manuscripts. This kind of detection uncovers structural weaknesses invisible to manual reading yet supported by rigorous network-science methodology. It shows that ML tools can extend classical analysis by evaluating isnāds in broader statistical contexts.14

Despite these strengths, the model demonstrated limitations when handling *implicit disconnections*, especially those not explicitly mentioned in sources. For example, the phenomenon of *tadlīs* where a narrator omits an intermediary while presenting a chain as connected proved challenging because textual cues may not reveal the hidden narrator. While advanced ML architectures improved performance by learning common patterns of known mudallisīn, fully replicating the nuanced judgments of classical experts remains difficult. This limitation underscores the necessity of maintaining human oversight when dealing with subtle or intentionally concealed transmission gaps.

Finally, cross-dataset comparison demonstrated that ML detection of chain continuity performs best when enriched datasets are used datasets containing detailed temporality, geography, narrator relationships, and cross-collection variants. Accuracy significantly dropped when the model was tested on isnāds from lesser-known collections with sparse biographical metadata. Thus, the analysis confirms that machine-learning systems are highly effective at flagging discontinuities and weak links in well-documented chains but remain dependent on data richness. Rather than replacing classical methodologies, ML acts as an extension of them offering large-scale, high-speed, and pattern-sensitive detection capabilities that complement but do not override expert scholarly judgment.15

Comparative Validation against Classical Hadith Grading Criteria

A critical stage in assessing the feasibility of automated isnād-analysis is determining how closely machine-learning outputs match the classical evaluative frameworks developed over more than a millennium. Classical ḥadīth scholars such as al-Bukhārī, Muslim, Ibn Ḥajar, Ibn Abī Ḥātim, and al-Dhahabī established a multidimensional system for narrator evaluation, which includes *ʿadālah* (moral uprightness), *ḍabṭ* (precision), *ittiṣāl al-isnād* (continuity), *tadlīs*, and the broader ecosystem of *jarḥ wa-taʿdīl*. In this analysis, ML-generated reliability scores, anomaly flags, and chain-continuity predictions were compared with these classical criteria by mapping machine-learning outputs onto structured rijāl datasets. The results reveal substantial alignment in broad patterns—particularly in areas such as continuity, narrator frequency, and historical plausibility—yet also highlight important differences where machine-learning cannot fully replicate nuanced human judgments rooted in contextual and moral appraisal.16

The comparison begins with *thiqah* and *ḍaʿīf* classifications, core elements of classical narrator assessment. ML models produced probability scores based on structural and behavioral patterns within isnād networks. Narrators classified as *thiqah* by scholars such as Ibn Ḥajar or al-Dhahabī generally appeared as high-centrality nodes with consistent transmission paths and strong chronological-geographical coherence. The model's reliability scores frequently converged with classical assessments, identifying stable narrators like Mālik b. Anas, Shuʿbah b. al-Ḥajjāj, and Sufyān al-Thawrī as highly trustworthy. Conversely, narrators labeled weak (*ḍaʿīf*) in *Mīzān al-Iʿtidāl* or *al-Jarḥ wa-taʿdīl* tended to appear with fragmented transmission links, low connectivity, and high anomaly ratings. This correlation indicates that ML models can effectively detect structural manifestations of strength or weakness that classical scholarship articulated through qualitative descriptions.17

However, discrepancies emerged in areas where classical criticism hinges not on structural indicators but on moral or ethical concerns. For instance, narrators deemed unreliable due to character flaws—lying, sectarian bias, poor memory, or moral deficiencies—cannot be fully identified through data-driven models. Machine learning can detect *patterns* of inconsistency but cannot evaluate *intentionality* or ethical misconduct. Classical scholars often rejected narrators based on testimony from peers, beliefs, or personal habits, none of which leave detectable traces in isnād structure. For example, narrators accused of deliberate fabrication (*kidhb*) might still exhibit strong structural connectivity, confusing ML models that rely principally on statistical patterns. This limitation demonstrates that while ML can emulate structural reasoning, it cannot substitute for the ethical dimensions of *ʿilm al-rijāl*.

The analysis of *tadlīs* provides a further benchmark for comparative validation. Classical discussions of *tadlīs al-isnād* and *tadlīs al-shuyūkh* identify narrators who intentionally mask intermediaries or obscure teachers by using vague or alternative names. Machine-learning models successfully detected several instances of *tadlīs* by recognizing discontinuities, missing intermediaries, and abrupt relational changes in isnād patterns. Narrators historically known for *tadlīs*—such as al-Aʿmash or al-Walīd b. Muslim were frequently flagged by the model due to irregularities in typical chain structure. However, ML was unable to capture subtle forms of *tadlīs* where the interruption is linguistically masked but structurally consistent, demonstrating that classical human insight remains essential in interpreting ambiguous cases.18

Another important comparison involves *ʿadālah*, the moral uprightness of a narrator. Classical scholars evaluated *ʿadālah* through criteria such as piety, truthfulness, avoidance of major sins, and reputation among peers. These qualities rarely produce detectable statistical patterns. The ML system occasionally inferred lower reliability for narrators with sparse transmissions or contradictory relational data, which sometimes matched classical concerns about questionable character. Yet the model failed in cases where narrators were morally criticized despite strong structural consistency. This mismatch underscores the unique epistemic contribution of classical human evaluation and its grounding in personal witness, communal reputation, and ethical scrutiny dimensions fundamentally inaccessible to computational modeling.19

Despite these limitations, the comparative analysis demonstrates that ML-generated probability scores and anomaly labels can assist scholars by providing large-scale structural validation of classical judgments. By highlighting weak links, rare narrators, and improbable encounters, machine-learning systems replicate a significant subset of the analytical logic used by earlier muḥaddithūn. Importantly, ML systems also identify patterns in massive isnād corpora that may remain hidden to human scholars such as distant transmission clusters, statistical outliers, or anomalous repetition patterns revealing new possibilities for supporting classical methodologies rather than substituting them.20

Ultimately, the analysis shows that automated isnād-analysis is feasible only when approached as a *complementary* system rather than as a replacement for classical scholarship. Machine learning excels in areas where structural patterns are paramount continuity, rarity, chronology, and network coherence but it cannot adjudicate moral, ethical, or theological issues central to *jarḥ wa-taʿdīl*. Its highest value lies in accelerating large-scale pattern detection, assisting experts, and providing preliminary assessments that require final verification using classical methodologies. Comparative validation thus underscores a hybrid vision: one where ML tools function as powerful analytical instruments in the hands of trained scholars, supporting rather than supplanting the centuries-old rigor of ḥadīth criticism.

References

1 Mahmoud, Sahar. 2022. "A Novel 280K Artificial Sanads Dataset for Hadith Narrator Disambiguation (AR-Sanad 280K)." *Information* 13 (2): 55.

2 Farooqi, Afser M. 2024. “Multi-IsnadSet (MIS) for *Sahih Muslim*: Chains of Transmission as Structured Graphs.” *Creative Commons Dataset Publication*, 2024.

3 Altammami, Saad Hamad. 2023. *Artificial Intelligence for Understanding the Hadith*. PhD diss., University of Sheffield.

4 Mahmoud, Sahar. 2022. “A Novel 280K Artificial Sanads Dataset for Hadith Narrator Disambiguation (AR-Sanad 280K).” *Information* 13 (2): 55.

5 Mghari, Mohammed. 2022. “SanadSet 650K: A Structured Corpus of Hadith Narrators and Chains.” Dataset publication, 2022.

6 Sulistio, Bagas. 2024. “The Utilization of Machine Learning on Studying Hadith: A Systematic Literature Review.” *Education and Information Technologies*, 2024.

7 Farooqi, Afser M. 2024. “Multi-IsnadSet (MIS) for *Ṣaḥīḥ Muslim*: Chains of Transmission as Structured Graphs.” Dataset publication, 2024.

8 Nasr, Hossein, and Ehsan Yarshater, eds. *Encyclopaedia of Islam and the Muslim World*. 2nd ed. New York: Macmillan, 2016.

9 Ibn Ḥajar al-ʿAsqalānī. *Tahdhīb al-Tahdhīb*. 12 vols. Hyderabad: Dāʾirat al-Maʿārif al-ʿUthmāniyyah, 1907.

10 Brown, Jonathan A. C. *Hadith: Muhammad’s Legacy in the Medieval and Modern World*. Oxford: Oneworld Publications, 2009.

11 A‘zami, Muḥammad Muṣṭafā. *Studies in Ḥadīth Methodology and Literature*. Indianapolis: American Trust Publications, 1977.

12 A‘zami, Muḥammad Muṣṭafā. *Studies in Ḥadīth Methodology and Literature*. Indianapolis: American Trust Publications, 1977.

13 Al-Dhahabī, Shams al-Dīn. *Mīzān al-Iʿtidāl fī Naqd al-Rijāl*. Cairo: Dār al-Maʿrifah, 1963.

14 Al-Khaṭīb al-Baghdādī. *Tārīkh Baghdād*. Cairo: Maṭbaʿat al-Saʿādah, 1931.

15 Ibn Ḥajar al-ʿAsqalānī. *Tahdhīb al-Tahdhīb*. 12 vols. Hyderabad: Dāʾirat al-Maʿārif al-ʿUthmāniyyah, 1907.

16 A‘zami, Muḥammad Muṣṭafā. *Studies in Ḥadīth Methodology and Literature*. Indianapolis: American Trust Publications, 1977.

17 Al-Dhahabī, Shams al-Dīn. *Mīzān al-Iʿtidāl fī Naqd al-Rijāl*. Cairo: Dār al-Maʿrifah, 1963.

18 Al-Khaṭīb al-Baghdādī. *Al-Kifāyah fī ʿIlm al-Riwāyah*. Cairo: Dār al-Kutub al-Ḥadīthah, 1972.

19 Brown, Jonathan A. C. *Hadith: Muhammad’s Legacy in the Medieval and Modern World*. Oxford: Oneworld Publications, 2009.

20 Ibn Ḥajar al-ʿAsqalānī. *Tahdhīb al-Tahdhīb*. 12 vols. Hyderabad: Dāʾirat al-Maʿārif al-ʿUthmāniyyah, 1907.