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ARTIFICIAL INTELLIGENCE – DRIVEN PERSONALIZATION: SYSTEMATIC REVIEW OF FEATURE INFLUENCE ON JAWI LITERACY MODEL FOR DYSLEXIA

Syamilah Saliman[1]*, Hafiza Abas[2], Zilal Saari[3]

[1]Faculty of Artificial Intelligence, Universiti Teknologi Malaysia (UTM), Malaysia
Email: syamilah92@graduate.utm.my
ORCID: https://orcid.org/0009-0006-1927-3924
[2]Faculty of Artificial Intelligence, Universiti Teknologi Malaysia (UTM), Malaysia
Email: hafiza.kl@utm.my
ORCID: https://orcid.org/0000-0003-0137-3127
[3]Faculty of Social Sciences and Humanities, Universiti Teknologi Malaysia (UTM), Malaysia
Email: zilal@utm.my
ORCID: https://orcid.org/0009-0007-0776-4854
*Corresponding Author

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Abstract:

The effectiveness of personalized educational technology is important for students with complex orthographic processing disorders. Considering the unique challenges posed by the Jawi script among dyslexic students, the objective of this research is to identify the artificial intelligence (AI) features that influence the development of personalized model for Jawi literacy among dyslexic students. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, a Systematic Literature Review (SLR) was conducted using advanced search strategies across Scopus and Web of Science (WoS) databases. A total of 23 published papers were included. From these, 21 categories of grouped codes which were synthesized into five analytical themes reflecting the development of personalized models: Data Processing and Input Features, Core AI Architecture and Models, Adaptation and Personalization, Interface and Presentation, and Feedback, Fluency and Assessment. This research identifies five themes of AI features demonstrates for intervention development, concluding that successful personalization relies on the synergistic integration of multimodal feature extraction and cognitive load mitigation techniques. The findings demonstrate significant practical implications for educators, developers and policymakers aiming to advances the inclusive educational technology through a shift from standardized digital tools toward neurodiverse centric design. Thus, it moves beyond to create a more responsive literacy environment for dyslexic students.

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Keyword:

Artificial Intelligence; Dyslexia; Jawi; Personalized Learning

Introduction

Rapidly advancing integration of Artificial Intelligence (AI) into educational technology offers diverse opportunities to address specific learning challenges through highly adaptive and personalized instruction. Personalized learning is defined as the dynamic adjustment of instructional content, pace and sequencing based on student needs and performance data. Dyslexia is defined as a difficulty with phonological processing which involves accessing and manipulating the basic sound units of literacy language (Shaywitz & Shaywitz, 2017). This impairment severely affects the development of literacy language skills. It is widely recognized that early intervention plays a critical role in mitigating its long-term effects on academic achievement. The gap in literacy ability between dyslexic students and their typically developing peers emerges as early as the first grade and frequently persists into adolescence (Ferrer et al., 2015). This persistent pattern underscores the importance of early targeted and personalized structured literacy programs implemented since primary school.

In contexts where literacy development involves non-Latin scripts such as Jawi, the challenges may be further increase. Jawi is an Arabic derived script adapted for the Malay language and its distinct orthographic features are able to create additional cognitive and perceptual demands for dyslexic students. Thus, the development for personalized literacy support becomes more interesting. Despite the inherent complexity of the Jawi script, a significant gap remains in the development of personalized literacy models that effectively integrate AI with the unique cognitive and multimodal requirements of dyslexic learners. Although general literacy tools are available, it is still insufficiently addressed to the specific orthographic challenges of Jawi and the unique needs of neurodiverse learners (Coluzzi, 2022; Saliman et al., 2024). This limitation creates a significant gap in the availability of instructional technology tailored for dyslexic students. Furthermore, most current adaptive systems are optimized for Latin-based alphabets, which does not account for the high perceptual and orthographic demands of Jawi (Al-Dawsari & Alghabban, 2025). This lack in AI features underscores the necessity for models that specifically bridge the gap between machine learning capabilities and the phonological processing deficits associated with Jawi literacy (Iyer et al., 2023; Ishaq et al., 2021).

This Systematic Literature Review (SLR) is focused on synthesizing the extant knowledge to define the necessary architectural components of such an advanced system. The objective of this study is to identify the AI features that influence the development of personalized models for Jawi literacy among dyslexic students. By conducting a systematic literature review of relevant research published between 2015 and 2025, this study reviews the AI capabilities to address the unique phonological challenges of the Jawi literacy among dyslexic students. The

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findings demonstrate significant practical implications for educators, developers and policymakers aiming to create inclusive Jawi learning environments. This research contributes a framework that serves as a practical guide by mapping specific AI features, such as adaptive sequencing and generative font modification, directly to the unique orthographic hurdles of the Jawi script. By addressing the high cognitive load and phonological deficits associated with Jawi, this study advances inclusive educational technology through a shift from standardized digital tools toward neurodiverse centric design. These findings inform future personalized AI models by demonstrating how machine learning must integrate multisensory feedback loops and comorbidity aware adaptation. Ultimately, this approach moves beyond simple automation to create a more responsive literacy environment for dyslexic students.

Methodology

Method

Following PRISMA guidelines, a systematic literature review was conducted across Web of Science and Scopus, resulting in 23 relevant studies that were coded into 21 categories and synthesized into five analytical themes. The review across these databases was implemented based on predefined inclusion and exclusion criteria that strictly filtered the literature for relevance to AI features and personalized Jawi literacy for dyslexic students.

Review And Synthesis Protocol

The SLR encompasses four key stages that are specifically outlined by the PRISMA 2020 framework: Identification, Screening, Eligibility and Included. These systematic phases were critical in enabling the authors to comprehensively track the retrieval, organization and ultimate synthesis of the findings. The protocol ensured a transparent documentation of the evidence selection process, build up in a significant set of articles for subsequent analysis. The data extracted from these included papers was subjected to thematic synthesis to structure the evidence for the AI features and the influence on the development of personalized model for Jawi literacy among dyslexic students.

Identification

During identification phases, the keywords are identified and sought related terms through dictionaries, thesaurus, encyclopedias and previous research as shown in Table 1. To achieve the need for a systematic review of this field, Petticrew and Roberts (2008) suggest using the PICOC (Population, Intervention, Comparison, Outcome and Context) criteria to frame the research question. To perform a comprehensive search and locate the relevant research papers, this review was conducted on the following two electronic publisher databases which are Web of Science and Scopus. Once all pertinent phrases have been selected, search strings for the databases Web of Science and Scopus (Table 1) have been produced. As part of the current research effort, 66 specific research papers are successfully retrieved during the first phase of the systematic review approach from both databases.

As an addition, regarding to snowballing method by Wohlin (2014), this research broadened by checking the reference lists (backward snowballing) and citation (forward snowballing) of the articles that were already included. 10 specific publications successfully found during this identification phase. The search string in Table 1 below is used to search articles in Web of Science and Scopus.

Table 1: Search Strings

Database	Search Strings
Web Of Science	("Artificial Intelligence" OR "Machine Learning") AND (Features OR Elements OR Components OR Factors OR Aspects OR Characteristics OR Attributes) AND (Personalization OR Personalized OR "Personalized Learning") AND (Dyslexia OR Dyslexic) Access Date: October 2025
Scopus	TITLE-ABS-KEY (("Artificial Intelligence" OR "Machine Learning") AND (Features OR Elements OR Components OR Factors OR Aspects OR Characteristics OR Attributes) AND (Personalization OR Personalized OR "Personalized Learning") AND Dyslexia) AND (EXCLUDE (DOCTYPE , "Cr") OR EXCLUDE (DOCTYPE , "Re")) Access Date: October 2025

Screening

During screening process, it involved the following procedures: 1) removing the duplicated research papers; 2) removing the studies that unsatisfied the inclusion rules; 3) reading the full research papers again and removing the research papers that unsatisfied the inclusion rules (see Table 2). This phase involves the inspection of potentially relevant research materials to identify content aligning with predefined research questions. Commonly employed criteria during screening include the selection of research items centred on AI features that influence the development of a personalized model for Jawi literacy among dyslexic students. This stage also requires eliminating any duplicate research papers from the initially retrieved list. The initial screening phase excluded 20 research papers while the subsequent phase assessed 43 research papers and 10 research papers from snowballing method based on distinct exclusion and inclusion criteria outlined in Table 2. Materials not included in the most recent research were considered. It also includes the exclusion from the current research of publications in the form of systematic review, review, meta-analysis and meta-synthesis. Additionally, the review focused exclusively on English-language publications, and it is essential to emphasize that the strategy concentrated solely on the period from year of 2015 to 2025 only.

Table 2: Selection Criterion

Criterion	Inclusion	Exclusion
Language	English	Non - English
Timeline	2015 - 2025	< 2015
Literature Type	Journal (Article)	Review, In Press, Conference
Publication Stage	Final	In Press

Eligibility

For the third step, known as eligibility, a total of 43 research papers and 10 research papers from snowballing method have been prepared. All papers' titles and key content were thoroughly reviewed at this stage to ensure that the inclusion requirements were fulfilled and fit into the present research with the current research aims. Thus, some of research papers were omitted because they were due to the out of research field, title not significant and abstract not related to the field of research. Finally, only 13 research papers and 10 research papers from snowballing method are available for review (Figure 1).

Included

Selected research papers are also considered available in full text. Finally, 23 research papers were found to be relevant to this research. The collection of research papers ended on October 2025. The 23 research papers were selected based on the inclusion criteria then were evaluated using the following three quality assessment criteria (Table 3). To assess the quality of the papers selected in this research, each paper was evaluated by using the criteria from these quality assessment questions (QA) adopted from (Ishaq et al., 2021):

Table 3: Quality Assessment Checklist

Question Number	**Question**	**Answer**
QA1	Does the paper elaborate about the AI features that influence the development of a personalized model for Jawi literacy among dyslexic students?	i. **Y** (yes), the study elaborated about the AI features related in detail. ii. **P** (partly), the AI features related in is not clearly elaborated in detail in the paper. **N** (no), the study did not elaborate about the AI features related in detail at all.
QA2	Does the methodology clearly state?	i. **Y** (yes), it described clearly the method of research. ii. **P** (partly), it mentioned the method, but did not explain in detail **N** (no), it did not explain the method.
QA3	Is the paper the paper elaborates results and discussion in details?	i. **Y** (yes), it has 4 or more papers with literature reviews that cover related topics in the paper. ii. **P** (partly), there are 1 to 3 papers with literature reviews that cover related topics. **N** (no), there are no literature reviews covered about related topics of the paper at all.

Source: Ishaq et al. (2021)
The scoring procedure: Y = 1, P = 0.5, N = 0.

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The evaluation procedure is documented using Microsoft Excel with indicators marked as Yes (Y), Partly (P) or No (N) for each quality assessment criterion. Based on this method, the selected research papers scored between seven and nine out of nine items which is indicating an overall fair quality. The results suggest that the included studies met a reasonable standard of methodological rigor suitable for inclusion in the review.

Data Analysis

The 23 papers were analysed using the thematic synthesis approach proposed by Thomas and Harden (2008). This approach was selected because the purpose of the review was not only to collate findings but to develop a higher-order conceptual understanding of how AI features contribute to personalized learning for dyslexic students particularly within the context of Jawi literacy. Thematic synthesis is well-suited to reviews that seek to generate analytical constructs that extend beyond the descriptive content of the included studies.

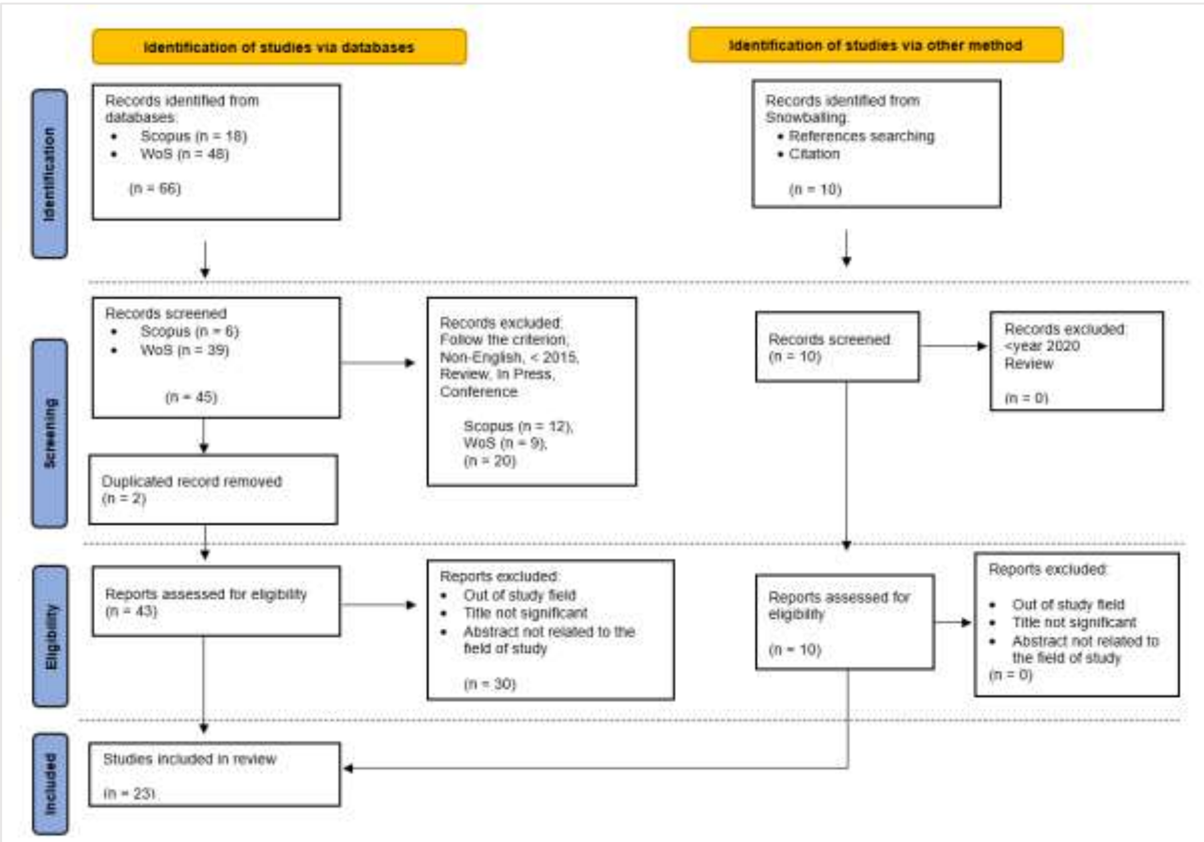

Figure 1: Prisma 2020 Flow Diagram

The synthesis proceeded through three structured stages. First, line-by-line coding was conducted on the extracted data to identify explicit AI features implemented across the reviewed systems. This step ensured that the coding process remained data-driven and grounded in the empirical evidence presented by each study. Second, the initial codes were grouped into descriptive themes by combined the conceptually similar features. This stage focused on identifying recurring functional patterns such as personalization mechanisms, multimodal scaffolding support, adaptive sequencing processes and learning analytics feedback systems. Finally, through iterative comparison and conceptual refinement, these descriptive themes were synthesized into analytical themes that explain the underlying logic and pedagogical implications of AI integration in dyslexia-supportive learning environments.

Thematic synthesis process enabled the review to move beyond specific features toward generating perception specifically on how certain AI functionalities support student's profiling, individualized content sequencing and differentiated feedback strategies. The resulting framework highlights the core AI feature clusters that consistently contribute to effective personalization and cognitive scaffolding in dyslexia-oriented educational technologies, thereby informing the conceptual design of a personalized Jawi literacy support model.

Research Findings

To answer the research question addressed, all findings were analysed and summarized in these sections. Table 4 below represents the summary of research papers findings from journals based on the criteria related to AI features that influence the development of a personalized model for Jawi literacy among dyslexic students.

Abstracts were first searched and then a full text review was conducted to ensure that the studies met the inclusion and exclusion criteria and that data could be extracted on the sources or papers, AI features identified, variables addressed such as personalization strategy, Jawi literacy focus or availability in dyslexia learning and the research purpose (Table 4).

Table 4: AI Features Research Papers Findings

No.	Authors	AI Features Used	Variables	Study Purpose
1	Alsobhi, A., Khan, N., & Rahanu, H. (2015)	Learner profiling; rule-based adaptation; presentation-layer adjustments (font, spacing); sequencing	Dyslexia type; learning style; UI adaptivity	Adaptive presentation and sequencing improved comprehension and reduced frustration.
2	Alsobhi, A. Y., & Alyoubi, K. H. (2019)	Adaptation algorithms; learner subtype matching; personalized pathways	Learner profile; task difficulty; adaptation rules	Subtype-based personalization enhances engagement and comprehension.
3	Hamid, S. S. A., Admodisastro, N., & Kamaruddin, A. (2018)	ML engagement prediction; adaptive pacing; task selection	Engagement score; accuracy; time-on-task	ML detects disengagement and supports adaptive pacing to sustain practice.
4	Hamid, S. S. A., Admodisastro, N., & Kamaruddin, A. (2015)	Multisensory cues; interface simplification; rule-based scaffolding	Recognition accuracy; interaction; motivation	Visual and audio cues improve recognition and reduce cognitive load.

5	Srivastava, B., & Haider, M. T. U. (2020)	Adaptive sequencing of learning objects; rule-based personalization	Performance score; sequencing rules; completion time	Personalized sequencing improves accuracy and learning efficiency.
6	Zingoni, A., Taborri, J., & Calabrò, G. (2024)	ML classification; recommender for learning strategies; personalization engine	Cognitive features; recommended strategies; outcomes	Recommendations increase strategy fit and learner confidence.
7	Iliska, D., & Gudonienė, D. (2025)	Design-level personalization principles; ongoing customization; accessibility features	Accessibility metrics; learner feedback; long-term use	Sustainability requires usability and ongoing personalization.
8	Hany, N., Sherif, R., Emad, K., Emad, A., Elsayed, M., & Abdelrahman, H. (2024)	Adaptive tutoring engine; reinforcement-based progression; multisensory lessons	Speech feedback; adaptive difficulty; progress scores	Adaptive tutor enhanced fluency and motivation.
9	Popa, V., Morelli, A., Di Maio, C., Dini, L., Cosci, C., & Perri, E. F. (2025)	Adaptive audio; voice cloning; engagement analytics	Audio pace; voice selection; comprehension scores	Adaptive audiobook increases attention and comprehension.
10	Guo, J. V., Francis, P. A., & Tan, G. (2023)	Sensor-based handwriting analysis; real-time corrective feedback; practice adaptation	Stroke data; correction feedback; progression rate	Real-time handwriting feedback improves orthographic fluency.
11	Praveena, K. N., Mahalakshmi, R., Manjunath, C., & Dakhole, D. K. (2024)	Hybrid AI personalization; multimodal assistive tools; comorbidity-aware adaptation	Learner profile; engagement; adaptive pathways	Multimodal adaptation benefits learners with comorbid conditions.
12	Yildiz, M., Keskin, H. K., Oyucu, S., Hartman, D. K., Temur, M., & Aydogmus, M. (2025)	Automated fluency scoring; speech analysis; assessment-driven personalization	Fluency score; classification accuracy; speech metrics	AI fluency scoring comparable to human assessment; useful for personalization input.

13	Salim, R., Zamri, A. N. M., & Mahamarowi, N. H. (2024)	Difficulty adjustment; motivational analytics	Game progress; error rates; motivation indicators	Gamification with adaptive difficulty improves performance and consistency.
14	Iyer, L. S., Chakraborty, T., Reddy, K. N., Jyothish, K., & Krishnaswami, M. (2023)	Overview of AI-assisted models; taxonomy of assistive strategies (NLP, CV, ITS)	Model types; intervention components	Provides taxonomy and conceptual overview; useful for mapping AI feature space.
15	Gilbert, B., Stubblefield, J., Qualls, J., Huang, X., Pait, A., Yanowitz, K., & Washington, T. (2023)	Image analysis for font evaluation; generative font modification; readability optimization	Font features; readability metrics; reader performance	AI can generate font modifications that improve readability for dyslexic readers.
16	Alqahtani, N. D., Alzahrani, B., & Ramzan, M. S. (2023)	CNN-based handwriting image analysis; hybrid classifiers; feature extraction (stroke, spacing)	Image features; classification accuracy	Handwriting-based hybrid AI can classify dyslexia with reasonable accuracy.
17	Spoon, K., Siek, K., Crandall, D., & Fillmore, M. (2019)	Discussion of neural network detection pipelines; ethical considerations	Detection pipeline components; ethical risk factors	Highlights feasibility and ethical concerns of automated detection; cautions against deployment without safeguards.
18	Spoon, K., Crandall, D., & Siek, K. (2019)	Neural network architectures for handwriting detection; feature engineering notes	Model architecture; dataset descriptions	Prototype neural models show proof-of-concept for handwriting-based detection.
19	Banumathi, K., Sudha Sadasivam, G., Banu Rekha, B., Shahana, N., & Vaishnavi, K. (2023)	Language-specific feature extraction for Tamil; speech/handwriting ML pipelines	Language-specific features; classifier outputs	Screening methods can be adapted to non-English scripts; localization necessary.

20	Žabkar, J., Urankar, T., Javornik, K., & Košak Babuder, M. (2023)	Readability assessment integration; ML fluency modeling	Readability scores; fluency outputs	ML models on readability metrics can distinguish fluency differences between dyslexic and typical readers.
21	Hussein, A. (2024)	Deep learning classifiers on student datasets; feature selection	Selected features; model performance	Deep learning can classify dyslexia; emphasizes feature and dataset importance.
22	Aldehim, G. (2024)	CNN benchmarking for handwriting analysis; comparative model evaluation	Architecture variants; benchmark performance	Provides benchmarking and recommendations for CNN-based handwriting detection.
23	Jincy, J., & Jose, P. S. H. (2024)	Exploratory ML studies; small-sample feature engineering	Feature types; pilot outcomes	Highlights challenges with small datasets and need for robust feature engineering.

Across the 23 research papers as shown in Table 4 above, a diverse range of AI features was applied to contribute evidence relevant to personalized model design. Adaptive and rule-based personalization was emphasized in Alsobhi et al. (2015), and Alsobhi and Alyoubi (2019) that tailoring presentation and sequencing based on learner profiles which improves comprehension and engagement. AI-driven adaptive support was further developed by Hamid et al. (2015, 2018), Srivastava and Haider (2020) and Zingoni et al. (2024) through multisensory cues, adaptive pacing and recommender-based strategy selection. Researches such as Iliska and Gudonienė (2025), and Praveena et al. (2024) highlighted the importance of long-term usability, accessibility and multimodal adaptation. More advanced systems including the reinforcement-based tutor by Hany et al. (2024) and adaptive audio technologies by Popa et al. (2025) demonstrated the improvements in fluency, comprehension and motivation. AI-supported handwriting and fluency assessment were explored in works by Guo et al. (2023), Yildiz et al. (2025) and Gilbert et al. (2023), who applied real-time corrective feedback, automated fluency scoring and generative font optimization. Detection-oriented research by Alqahtani et al. (2023), Hussein (2024), Aldehim (2024) and Spoon et al. (2019) employed CNNs, hybrid classifiers and neural pipelines to classify dyslexia and examine ethical concerns of automated detection.

Meanwhile additional contributions included Banumathi et al. (2023) on language-specific feature extraction, Žabkar et al. (2023) on ML readability modeling, Salim et al. (2024) on adaptive difficulty, Iyer et al. (2023) on AI taxonomy and Jincy and Jose (2024) on small-sample feature engineering. Collectively these research papers demonstrate that AI features such as adaptive personalization, multimodal analytics, ML-based assessment and deep-learning classification form a robust foundation for designing a personalized Jawi literacy model tailored to dyslexic students.

Identify The AI Features

The identification of AI features represents the initial stage of analysing on how artificial intelligence has been applied to support dyslexic learners across existing research. Thus, a comprehensive set of AI features was identified. These features capture the AI applications from machine learning based detection and adaptive feedback systems to multimodal support tools and personalized content delivery methods.

Identifying the AI feature set forms of foundation for the subsequent thematic analysis, which it enables the diverse of AI capabilities into coherent themes that inform the design of a personalized model for Jawi literacy among dyslexic students. Detailed methods for thematic synthesis by Thomas and Harden (2008) form of three stages which are Line-By-Line Coding, Initial Code Grouped and Developing the Analytical Themes.

Step 1: Line-By-Line Coding

In the first stage of thematic synthesis, all 23 research papers were analysed line by line to identify specific AI features that support dyslexic learners. This detailed analysing process generated a comprehensive set of AI Feature Identification that reflect how different AI methods, models and adaptive mechanisms were coded across the reviewed research.

Step 2: Initial Code Grouped

The analysis of AI features code and the category of grouped code across the selected research papers led to the development of descriptive themes that illustrate how personalization for dyslexic students is being operationalized. The categorization is achieved by identifying the constant comparison of grouped AI Features Codes.

Step 3: Developing Analytical Themes

The provided Table 5 below is important for ensuring the scope of the investigation by segmenting the complex domain into five analytical themes.

Table 5: AI Features Analytical Theme

No.	Theme	Categories of Grouped Code	Key Features	Description
1	Data Processing & Input Features	Characteristics; Detection; Feature; Feature Engineering; Handwriting	Feature Extraction, Language-Specific ML Pipelines, CNN Benchmarking, Speech Analysis, Sensor-Based Handwriting Analysis.	Focuses on how the system captures, processes and extracts relevant information specific to Jawi literacy challenges (like handwriting and speech) from the student.

2	Core AI Architecture & Models	Engines; Model; Neural Network	Personalization Engine, Hybrid AI Personalization, Deep Learning Classifiers, Neural Network Architectures, ML Fluency Modelling.	Focuses on the machine learning backbone, algorithms and computational tools used to build the predictive and functional components of the personalization engine.
3	Adaptation & Personalizati on	Adaptation; Behaviours; Learning; Patterns; Personalizati on; Sequencing	Rule-Based Adaptation, Adaptive Sequencing, Motivational Analytics, Task Selection, Comorbidity-Aware Adaptation.	Addresses the core function of the system: using analysed data to make dynamic, rule-based, or model-driven decisions to adjust the learning path and content.
4	Interface & Presentation	Cognitive Strain; Font; Presentation Elements	Generative Font Modification, Readability Optimization, Presentation-Layer Adjustments, Image Analysis for Font Evaluation.	Concerns the front-end user experience, particularly how content is delivered and modified to reduce cognitive load and enhance accessibility for dyslexic students.
5	Feedback, Fluency & Assessment	Enhanced; Fluency; Reading; Scoring	Automated Fluency Scoring, Readability Assessment Integration, Multisensory Lessons, Reinforcement-Based Progression, Adaptive Tutoring Engine.	Focuses on mechanisms for measuring performance (especially fluency), providing corrective feedback, and enhancing sensory learning.

Theme 1: Data Acquisition and Feature Extraction

The first theme encompasses the initial stage of system operation which are data acquisition and feature extraction. For a Jawi literacy model tailored to dyslexic students, this requires specialized mechanisms to accurately capture and quantify nonstandard inputs such as dysgraphia in handwriting or inconsistent vocalization to translating them into usable digital features. The influence of AI features such as Feature Extraction, detailed Handwriting analysis and the deployment of Language-Specific ML Pipelines is important to ensure the system accurately constructs a detailed profile of a dyslexic student's specific Jawi challenges. Also, by moving beyond generalized models to extract the orthographic and phonetic significations essential for Jawi script analysis, this theme identifies the foundational of data integrity required to drive a personalized model for Jawi literacy among dyslexic students.

Theme 2: Architectural Backbone and Computational Core

Next, the second theme represents the computational core or architectural backbone of the personalized system. It includes advanced tools and structural features responsible for pattern recognition, complex prediction and functional service delivery such as Engines, Neural

Networks and Hybrid AI Personalization designs. The AI features within this theme are essential as they give direction to the ultimate intelligence and processing capacity of the system. For a personalization model, the architecture determines the ability to effectively manage the high-dimensional data characteristic of dyslexia, performing complex nonlinear classifications such as differentiating Jawi character misidentification caused by visual tracking deficits versus phonological errors. The use of Deep Learning Classifiers serves as the engine that transforms raw dyslexic student's data into a tailored Jawi literacy experience.

Theme 3: Dynamic Educational Personalization

Meanwhile, the third theme represents as the primary mechanism for achieving the system's core objective: dynamic educational personalization. It covers how the AI leverages processed data to create a personalized learning experience through components related to Adaptation, Sequencing, Behaviors and Patterns analysis. These AI features regulate the flow, difficulty and content delivery of the instructional modules. For a Jawi model, this translates to dynamically modifying reading difficulty, providing immediate behavior-based feedback and applying Comorbidity-Aware Adaptation to fine-tune lesson progression. By centralizing Adaptive Sequencing and Rule-Based Adaptation, this theme directly executes the personalized aspect of the model by aligning the Jawi curriculum with the dyslexic student's developmental pace.

Theme 4: Accessibility and Cognitive Strain Mitigation

The fourth theme focuses on the student-facing output of the system, prioritizing accessibility and the reducing the cognitive strain. It includes AI features related to Font manipulation and the management of Presentation Elements such as character spacing, line height and contrast ratios. For dyslexic Jawi students, visual presentation is important because the connection of Jawi script can significantly increase their common reading difficulties. Consequently, AI features such as Generative Font Modification and Readability Optimization ensure the Jawi characters are displayed in a format that minimizes demand on the visual processing system. This theme bridges the gap between the system's internal logic and the user's sensory needs to ensure that the personalized Jawi content remains decodable and accessible.

Theme 5: Performance Evaluation and Continuous Enhancement

The fifth theme identifies the continuous systemic loop of performance evaluation, corrective feedback and enhancement. It incorporates AI features categorized under Scoring, Fluency modeling and the delivery of Enhanced learning experiences such as Multisensory Lessons. The influence of this theme rests on its capacity for system validation and iterative improvement. AI features such as Automated Fluency Scoring and Readability Assessment Integration enhances the performances of real-time model to validate the effectiveness of current personalization strategy. Through these assessment-to-action loops, the model ensures that Jawi literacy development is continuously guided by accurate and timely performance data.

Conclusion

The thematic analysis identifies five themes for critical AI features for developing a personalized model for Jawi literacy among dyslexic students. By bridging the gap between technical architecture and pedagogical accessibility, these five themes identify a comprehensive ecosystem for Jawi literacy. This integration ensures that the multi-faceted difficulties of Jawi literacy are not just addressed personalized, but are managed through a cohesive, AI-driven model tailored to the specific needs of dyslexic students.

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