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Designing AI-Supported Adaptive English Literacy Learning for Post-Disaster Education Recovery: A Simulation-Based Development Study

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Abstract

Post-disaster education is frequently disrupted not only by learning loss but also by unstable connectivity, limited devices, temporary learning spaces, and uneven access to teachers. This study aimed to design and conduct an initial simulation-based evaluation of an AI-supported adaptive English literacy learning model for primary-school education recovery. A Design and Development Research approach was employed. Needs were synthesized from secondary sources, policy documents, and recent research on education in emergencies, adaptive learning, and artificial intelligence in language education. The resulting dual-context model combines learner conditions (diagnostic performance, learning gap, pace, and progress) with disaster learning-environment conditions (connectivity, device availability, and learning access). A lightweight web prototype, Sahabat Belajar Adaptif, was developed to operationalize the model through learner profiling, diagnostic assessment, explainable rule-based recommendations, teacher review, adaptive learning content, formative assessment, and progress monitoring. Scenario-based simulation was organized across three recovery levels—Intensive, Guided, and Independent—and three access conditions—Connected, Limited Connectivity, and No Connectivity. The simulations showed that academic parameters consistently determined recovery level and content difficulty, while access parameters determined delivery mode through digital, semi-digital/offline, or manual learning pathways. The teacher-in-the-loop mechanism enabled recommendations to be accepted, modified, or overridden, preserving pedagogical control. Functional simulation also confirmed that the prototype could represent the full assessment–recommendation–learning–evaluation–readaptation cycle. The study contributes a context-sensitive model for adaptive English literacy learning in disrupted educational settings. Because the present evaluation relies on secondary data and synthetic scenarios rather than direct learner-effectiveness testing, future research should validate the model with teachers and primary-school learners in disaster-affected settings.

Keywords: *adaptive English literacy, artificial intelligence, post-disaster education, personalized learning, education recovery*

Introduction

Disasters can interrupt schooling through damaged infrastructure, displacement, reduced teacher availability, temporary learning spaces, and interruptions in access to learning materials. In such situations, educational continuity is not simply a matter of

moving conventional instruction to an online platform. Education in emergencies requires flexible arrangements that protect continuity, respond to heterogeneous learner needs, and remain workable when technology access is unstable (Burde et al., 2017). For primary-school learners, these disruptions may be particularly consequential because foundational literacy development depends on regular exposure to texts, guided practice, feedback, and opportunities to build vocabulary and comprehension over time.

Digital technologies and artificial intelligence (AI) provide new possibilities for making learning more responsive. AI-supported educational systems can use learner data to provide differentiated content, feedback, and recommendations, while adaptive learning environments can dynamically adjust learning pathways according to learner performance (Chen et al., 2020; Hwang et al., 2020). A systematic review of adaptive and personalized technology-enhanced learning also indicates growing attention to learner modelling, differentiated pathways, and data-informed recommendation mechanisms (Xie et al., 2019). These developments are relevant to language learning because English literacy involves cumulative skills—such as vocabulary, sentence comprehension, reading comprehension, identifying main ideas, and interpreting short texts—that may require different levels of scaffolding for different learners.

In English language education, technology-enhanced learning has increasingly been used to support interaction, feedback, learner autonomy, and differentiated practice (Shadiev & Yang, 2020). Recent work has also shown that AI can support language teaching through conversational assistance, immediate feedback, content generation, and individualized practice, although teacher mediation remains important for pedagogical accuracy and responsible use (Kohnke et al., 2023). Within DEIKTIS itself, Farlina et al. (2024) reported that AI-supported tools could improve English learning engagement and performance, while Aisyah et al. (2024) showed the potential of technology-mediated activities to support English comprehension and participation. These studies confirm the relevance of AI and digital tools to the journal's language-learning domain.

However, most adaptive or AI-supported language-learning studies assume relatively stable access to devices, connectivity, and learning environments. The design problem becomes different in disaster-affected settings. A learner may need intensive English literacy support but have only intermittent internet access; another learner may have stronger literacy performance but no dependable device. A system that adapts only to academic performance may therefore provide recommendations that are pedagogically appropriate but operationally unusable. The key gap addressed in this study is the absence of a simple adaptive language-learning model that simultaneously considers what the learner needs and under what post-disaster access conditions learning can realistically occur.

To address this gap, the study proposes a dual-context adaptive model implemented in a lightweight web prototype named Sahabat Belajar Adaptif. The model treats AI as explainable pedagogical decision support rather than an autonomous teacher. It combines learner-condition data with disaster learning-environment data and maps them to three delivery pathways: digital, semi-digital/offline, and manual learning. The study asks two questions: (1) How can learner and post-disaster access conditions be integrated into an AI-supported adaptive English literacy model? and (2) Can the resulting logic be represented consistently through scenario-based simulation and a functional web prototype? The objective is to design the model and provide initial proof-of-concept evidence through secondary-data synthesis and synthetic scenario testing. The novelty lies in dual-context adaptation, teacher-in-the-loop control, and multi-mode delivery designed specifically for educational continuity under disrupted access.

Method

This study used Design and Development Research (DDR) because the research objective was to produce and examine an educational model and its functional representation rather than to estimate a population effect. The development cycle comprised four connected activities: needs synthesis, conceptual modelling, prototype development, and simulation-based evaluation. The design remained aligned with the original research plan to develop an adaptive interactive learning system for post-disaster education recovery supported by AI.

The needs-analysis phase used secondary data rather than a full primary field survey. Sources included peer-reviewed studies on education in emergencies, AI in education, adaptive and personalized learning, technology-enhanced language learning, and recent language-learning studies relevant to AI-supported instruction. Policy and institutional documents relevant to post-disaster educational continuity were also used as contextual materials. The synthesis focused on identifying recurring constraints and translating them into system requirements. These requirements were organized into two categories: learner conditions and disaster learning-environment conditions.

For the article-level implementation, English literacy was selected as the learning domain to ensure a direct fit with language-education scholarship. The prototype represents five illustrative learning areas: basic vocabulary, simple sentences, reading comprehension, identifying main ideas, and interpreting short texts. These modules function as proof-of-concept content; the model itself remains extensible to other learning domains.

The conceptual model was designed as a dual-context decision structure. Learner-condition inputs include diagnostic score, topic-level difficulty, learning pace, prior activity, and formative performance. Disaster-context inputs include connectivity, device availability, and learning access. A lightweight hybrid adaptive engine combines rule-based classification with configurable thresholds. Three recovery levels are represented: Intensive Recovery, Guided Recovery, and Independent Recovery. The default simulation thresholds were below 50, 50–75, and above 75, respectively. These values are model parameters for simulation and are not presented as clinically or psychometrically validated cut-off scores.

Access conditions were classified as Connected, Limited Connectivity, and No Connectivity. Connected conditions route learners to digital adaptive learning; Limited Connectivity routes them to semi-digital/offline resources; and No Connectivity routes them to manual or printable learning packs. The recommendation layer generates a recovery level, content difficulty, learning mode, suggested activity, duration, and a short explanation. The teacher-in-the-loop layer allows a teacher to Accept, Modify, or Override the recommendation.

Scenario-based evaluation used a synthetic matrix that crossed the three recovery levels with the three access conditions, resulting in nine core learner-context scenarios. Additional transition cases were used to test re-adaptation after formative assessment. The evaluation did not attempt to estimate learning effectiveness; instead, it examined logical consistency: whether changes in learner performance changed pedagogical level, whether changes in access conditions changed delivery mode, and whether teacher review remained available before recommendation enactment.

The model was implemented in the web prototype Sahabat Belajar Adaptif using a lightweight PHP-native and relational-database architecture. The prototype includes a public landing page, registration and role-based authentication, student, teacher, and administrator/researcher dashboards, learner and context profiles, diagnostic assessment, adaptive recommendation, teacher review, learning content, formative assessment, progress monitoring, research analytics, and data export. Functional checks were carried out by executing simulated user flows across the main modules. The prototype was subsequently deployed online as a functional proof of concept.

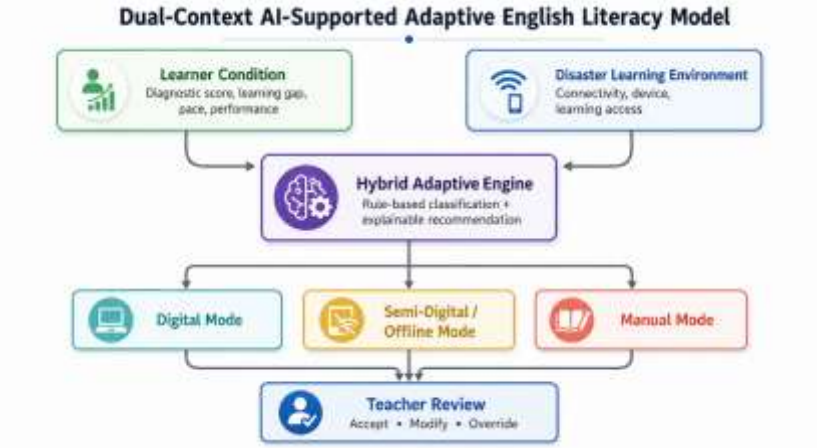


Figure 1. Dual-context AI-supported adaptive English literacy model

Results

Post-disaster learning requirements

The secondary-data synthesis produced a requirement structure in which educational adaptation had to respond to both learner heterogeneity and access constraints. Four recurrent design needs were translated into prototype functions: personalization for different literacy levels, low-bandwidth access, printable/manual continuity, and teacher oversight of automated recommendations.

Table 1. Post-disaster learning requirements and corresponding system responses

Observed condition	Learning requirement	System response
Different literacy performance	Differentiated content and difficulty	Recovery-level classification and adaptive content
Stable connectivity and device access	Interactive digital learning	Digital Adaptive Learning
Intermittent/limited connectivity	Lightweight and downloadable resources	Semi-Digital/Offline Learning
No dependable connectivity/device	Learning continuity without continuous technology	Manual/Printable Learning Pack
Need for pedagogical accountability	Teacher control over AI output	Accept, Modify, or Override recommendation

Dual-context adaptive logic

The resulting model separates pedagogical level from delivery feasibility. Academic and learning-performance variables determine the recovery level and content difficulty, while access variables determine how the recommended content should be delivered. This separation allows the same learner to retain a pedagogically appropriate level even when the delivery mode changes because of connectivity or device constraints.

Table 2. Representative outputs from scenario-based simulation

Simulated case	Diagnostic/learning state	Access condition	System output
S1	Score 42; substantial support need	Limited Connectivity	Intensive Recovery; beginner content; semi-digital mode
S2	Score 68; moderate support need	Connected	Guided Recovery; intermediate content; digital mode
S3	Score 84; stronger independent performance	No Connectivity	Independent Recovery; enrichment content; manual mode
S4	Score 45; support need unchanged	Connected	Intensive Recovery retained; delivery changed to digital
S5	Score 45; support need unchanged	No Connectivity	Intensive Recovery retained; delivery changed to manual

Adaptive feedback and teacher control

Transition simulations showed that recovery levels could change after formative assessment. In one illustrative case, an initial score of 44 placed the learner in Intensive Recovery; a subsequent formative score of 82 triggered a progression recommendation to Guided Recovery. When the simulated formative result remained low, the model retained Intensive Recovery and recommended remedial activity. Before any recommendation became the active learning pathway, the teacher interface retained the options to accept, modify, or override the system output.



Figure 2. Adaptive feedback loop represented in the Sahabat Belajar Adaptif model

Prototype implementation and functional simulation

The conceptual model was implemented as the web-based Sahabat Belajar Adaptif prototype. The system was structured around three authenticated roles—student, teacher, and administrator/researcher—while public users could access an informational landing page and registration workflow. The learner flow connected profiling, diagnostic assessment, adaptive recommendation, learning content, formative assessment, and progress monitoring. The teacher flow emphasized recommendation review and learner monitoring, whereas the administrator/researcher flow supported configuration, content management, aggregated analytics, and research-oriented data export.

Table 3. Functional simulation of the main prototype components

Core function	Simulation-based check	Result
Landing page and registration	Public access and account creation flow	Functioned as intended
Role-based authentication	Student, teacher, and admin access separation	Functioned as intended
Learner/context profiling	Learner and access variables recorded	Functioned as intended
Diagnostic assessment	Score available to adaptive logic	Functioned as intended
Adaptive recommendation	Level, mode, content, and rationale generated	Functioned as intended
Teacher review	Accept/Modify/Override available	Functioned as intended
Learning and formative assessment	Recommended content and follow-up assessment linked	Functioned as intended
Progress and analytics	Learning progress represented for monitoring	Functioned as intended

The prototype was deployed online at https://sahabatbelajar.infinityfreeapp.com/ as a functional proof of concept. The online deployment was used to demonstrate that the conceptual architecture could be represented in an operational web environment without requiring a complex AI stack or constant access to paid generative-AI services.

Prototype dashboard visualization

To make the prototype output more explicit, the article also documents the main interface components of the Sahabat Belajar Adaptif web system. The visual documentation is important because the prototype is not only a conceptual artifact but also a functional proof of concept that demonstrates how the dual-context model is translated into an operational interface. The figures below are organized around the main user flows: public access, student learning, teacher review, research analytics, and progress monitoring.

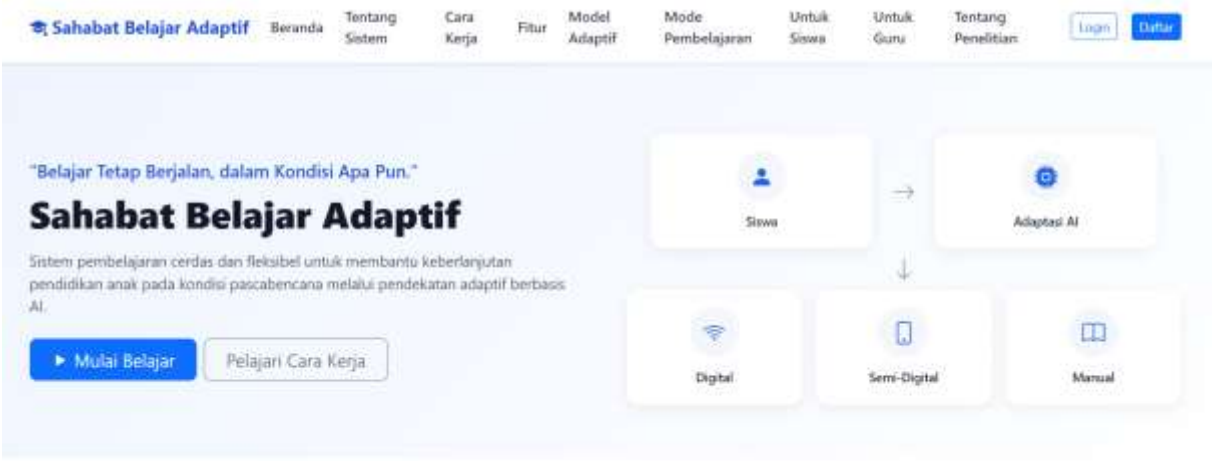


Figure 3. Landing page of the Sahabat Belajar Adaptif prototype

Figure 3 presents the landing page of the prototype. This page functions as the public entry point and communicates the identity of the system, its purpose, and the adaptive-learning workflow before users register or log in. The landing-page design is significant because it positions the system not simply as a technical dashboard but as an educational support platform for post-disaster learning continuity. In the context of the present study,

the landing page also acts as evidence that the prototype was designed for real user interaction rather than remaining a backend-only concept.

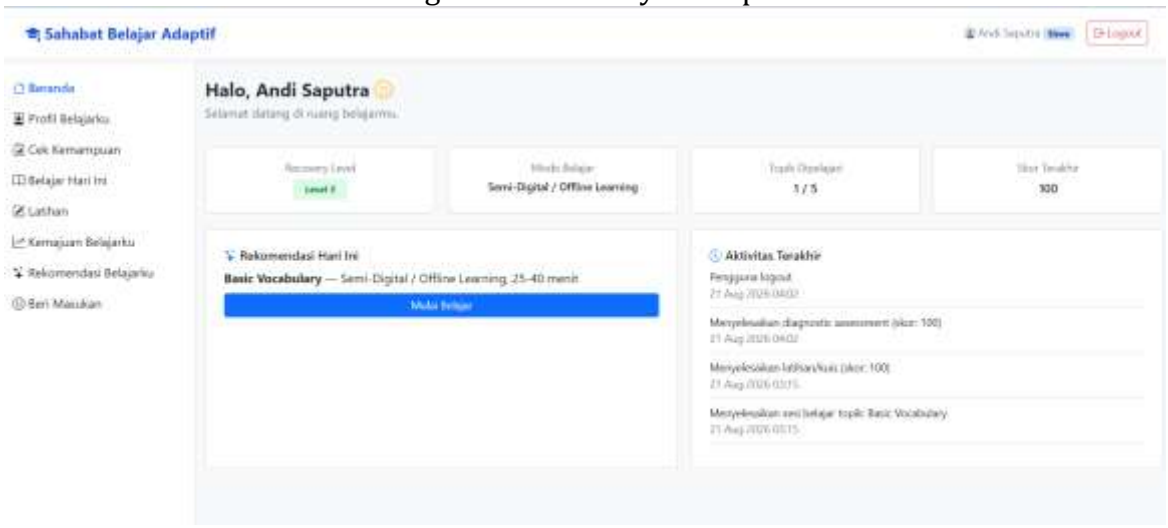


Figure 4. Student dashboard and adaptive learning pathway

Figure 4 illustrates the student dashboard. This interface is intended to display the learner profile, recovery level, recommended learning mode, daily learning tasks, and access to diagnostic and formative assessments. From a research perspective, the student dashboard operationalizes learner-condition adaptation because it turns the outputs of the adaptive model into learner-facing activities. The interface embodies the principle that students with different performance profiles receive different content pathways, difficulty levels, and follow-up actions.

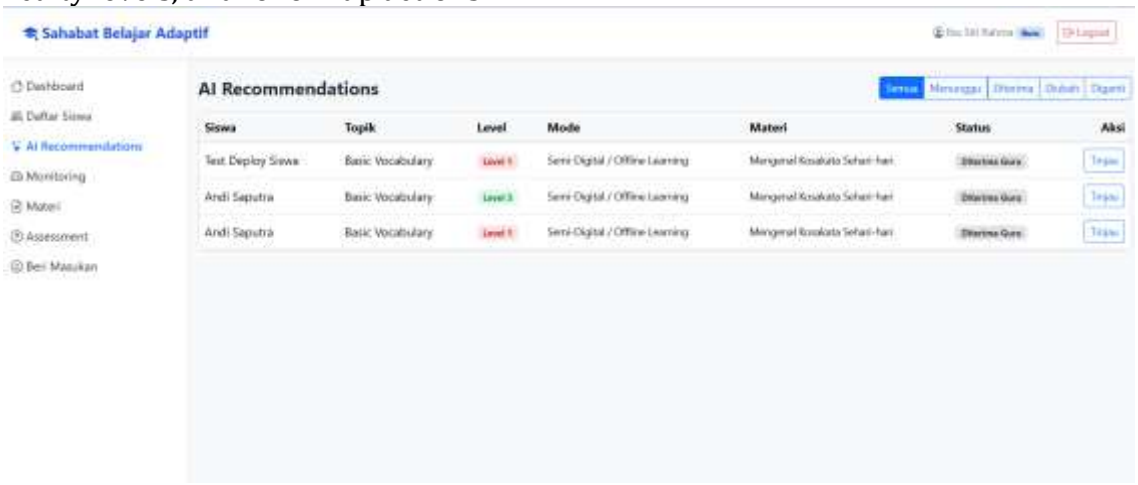


Figure 5. Teacher dashboard and AI recommendation review

Figure 5 shows the teacher dashboard. The key role of this interface is to maintain the teacher-in-the-loop principle. Through this page, teachers can inspect student profiles, review AI-generated recommendations, and decide whether to Accept, Modify, or Override them. This is a crucial design feature because the study deliberately frames AI as a pedagogical decision-support tool rather than an autonomous replacement for teacher judgment. Therefore, the teacher dashboard is not merely administrative; it is the interface where human pedagogical control is preserved.

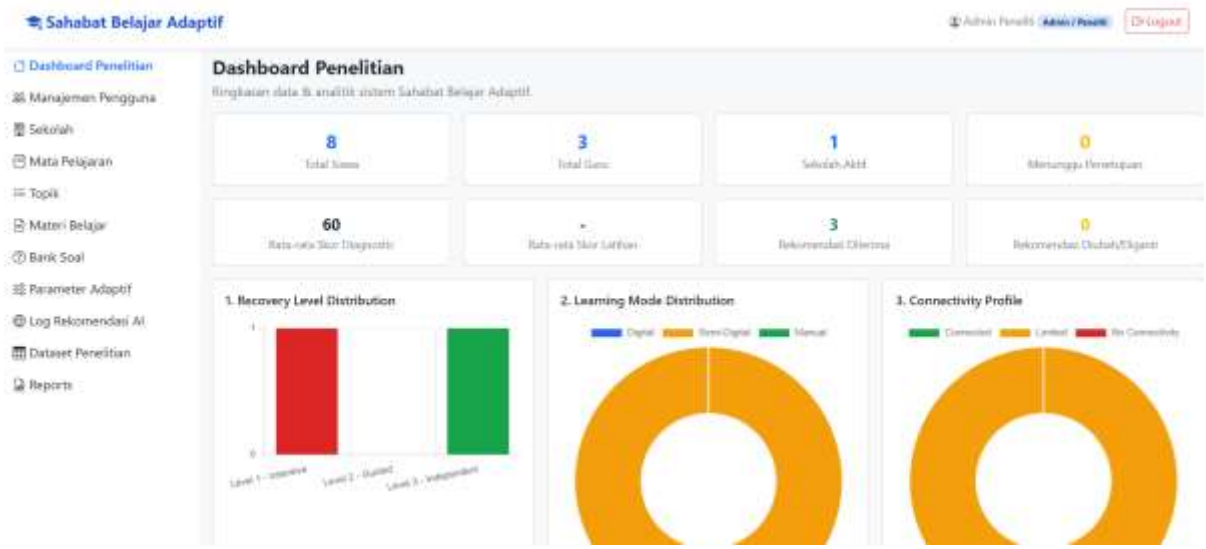


Figure 6. Admin/research dashboard and prototype analytics

Figure 6 presents the administrator or research dashboard. This visual component is relevant to the study because it aggregates prototype-level information such as user distribution, recovery-level categories, connectivity conditions, recommendation logs, and system usage patterns. In addition to management functions, this dashboard provides the basis for research analytics. It transforms the prototype into a data-generating environment that can support later empirical validation, reporting, and refinement of the adaptive model.

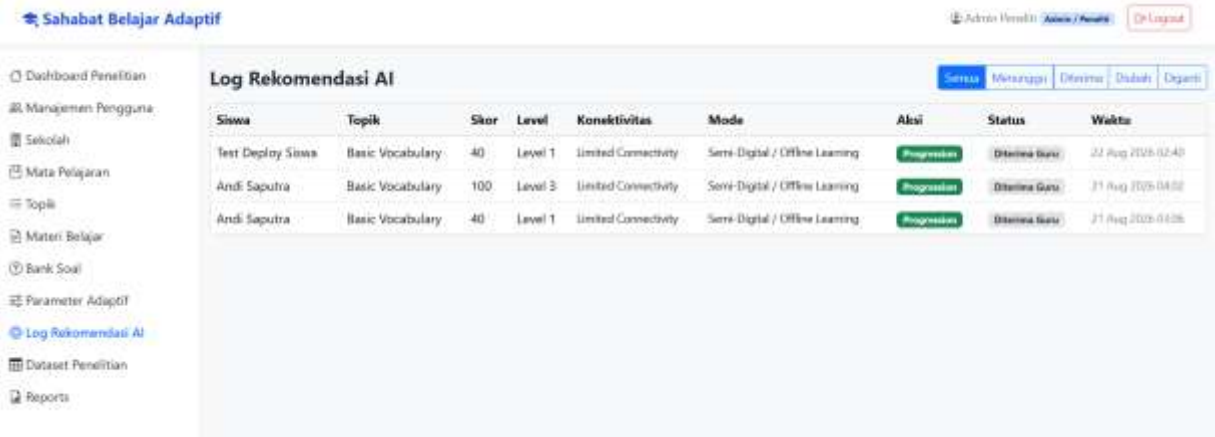


Figure 7. Learning progress and recommendation interface

Figure 7 focuses on the learning-progress and recommendation interface. This page is intended to show how assessment outcomes are translated into updated recommendations and level transitions. It represents the adaptive feedback loop of the model—Assess, Recommend, Learn, Evaluate, and Adapt. The visual importance of this interface lies in its capacity to demonstrate that the prototype is not static. Instead, it continuously responds to learner performance by updating recommendations and suggesting remedial or progression actions.

Taken together, the interface visuals show that the prototype output of this study is not limited to abstract modelling. The system includes concrete user-facing components that correspond to the conceptual structure reported earlier: learner profiling, contextual adaptation, AI recommendation, teacher review, and progress monitoring. These visuals therefore strengthen the claim that Sahabat Belajar Adaptif has reached the level of a deployable prototype suitable for further expert validation and user testing.

Discussion

The main contribution of this study is the separation and subsequent integration of two adaptation problems that are often treated independently. Adaptive-learning research typically emphasizes learner modelling, content sequencing, and performance-responsive recommendations (Xie et al., 2019), whereas education-in-emergencies research emphasizes continuity, access, protection, and contextual feasibility (Burde et al., 2017). The proposed model connects these two concerns. A learner's academic need determines what level of English literacy support is appropriate, while the disaster learning environment determines how that support can realistically be delivered.

This dual-context logic extends common interpretations of AI-supported personalization. AI in education is frequently described in terms of prediction, automated feedback, learner modelling, and tailored instruction (Chen et al., 2020; Hwang et al., 2020). Those functions remain important, but a post-disaster system must also avoid making recommendations that presume stable internet or device access. The simulation results demonstrate why this distinction matters: the same low-performing learner can remain in Intensive Recovery while moving between digital, semi-digital, and manual modes as access conditions change. Adaptation is therefore not only pedagogical but also infrastructural.

The study also reinforces the value of technology in English-language learning while placing stronger emphasis on contextual constraints. Prior DEIKTIS studies have reported positive uses of AI-supported or technology-mediated tools in English learning (Aisyah et al., 2024; Farlina et al., 2024). Related research on technology-enhanced language learning highlights opportunities for interaction, feedback, and learner engagement (Shadiev & Yang, 2020). The present model does not challenge those findings; instead, it adds a design condition: technology-enhanced English learning should preserve a viable learning pathway when access to that technology is reduced or temporarily unavailable.

A second contribution is the teacher-in-the-loop design. Recent AI tools can produce language-learning explanations, examples, and feedback quickly, but they can also generate inappropriate, inaccurate, or poorly contextualized responses. Language-learning scholarship therefore increasingly emphasizes the need for teacher mediation and critical use of AI (Kohnke et al., 2023). In Sahabat Belajar Adaptif, AI recommendations are explicitly reviewable. The teacher can accept, modify, or override them, and the system records the resulting decision. This positions AI as pedagogical decision support and preserves professional judgement as the final instructional control.

A third contribution concerns model simplicity. The prototype deliberately avoids complex black-box machine learning. A configurable rule-based mechanism was chosen because the present research is at proof-of-concept level and because explainability is important in educational settings. Hwang et al. (2020) note that AI in education should be designed from educational needs rather than from technological capability alone. For this study, the important question is not whether the system uses a sophisticated algorithm, but whether its recommendations are transparent, pedagogically interpretable, and responsive to changing conditions.

The English literacy framing is especially relevant for early recovery because literacy activities can be structured in short, progressive units and distributed through multiple media. Vocabulary tasks, simple sentence comprehension, short reading passages, and main-idea activities can be represented digitally, downloaded for intermittent access, or printed for manual use. This makes language-learning content suitable for testing the model's multi-mode delivery logic. At the same time, the study does

not claim that the prototype improves English achievement because no direct learner-effectiveness trial was conducted in this phase.

The limitations of the study are therefore important. The needs analysis relied on secondary sources, and the initial evaluation relied on synthetic scenarios and functional simulation. The recovery thresholds were configurable design parameters rather than validated proficiency cut-offs. No causal learning-outcome claim can be inferred from the current results. In addition, the online prototype demonstrates operational feasibility but not scalability under real disaster conditions. Future studies should involve expert review, teacher usability testing, and controlled or quasi-experimental implementation with primary-school learners in disaster-affected settings. Such research should also examine whether adaptation improves literacy outcomes, engagement, and continuity compared with non-adaptive alternatives.

Conclusion

This study developed a dual-context AI-supported adaptive English literacy learning model for post-disaster education recovery and represented it through the Sahabat Belajar Adaptif web prototype. The model integrates learner conditions with disaster learning-environment conditions, allowing academic need and delivery feasibility to be treated as related but distinct adaptation decisions. Simulation showed that learner-performance variables consistently determined recovery level and content difficulty, while connectivity and device conditions determined digital, semi-digital/offline, or manual delivery. The teacher-in-the-loop mechanism preserved pedagogical control through Accept, Modify, and Override decisions, and the adaptive feedback loop enabled progression or remedial recommendations following formative assessment. These results provide proof-of-concept evidence that an adaptive language-learning model can remain meaningful under variable access conditions without relying on a complex black-box AI architecture. The primary limitation is that the evidence is based on secondary-data synthesis and synthetic scenarios rather than direct learner-effectiveness testing. Future research should conduct expert validation and field-based evaluation with teachers and primary-school learners, test English literacy outcomes, examine usability and acceptability, and refine adaptive thresholds using empirical performance data. The model contributes to language-education research by connecting personalized English literacy support with the practical requirements of educational continuity in disrupted settings.

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