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From Digital Competence Gaps to AI-Enabled Inclusive Learning: A Learner-Centered Framework for Persons with Disabilities in Mongolia

Daariimaa Chuluunbaatar
Ph.D. Candidate, School of Management
Mongolian University of Science and Technology
Ulaanbaatar, Mongolia
chdaariimaa@must.edu.mn

***Abstract*—Artificial intelligence can widen access to learning, but it can also reproduce digital and accessibility gaps when systems are built for an assumed average user. This design study asks which learner needs should shape an inclusive AI-enabled learning environment in Mongolia and how those needs can be translated into an auditable architecture. The empirical base is a mixed-method study of 158 adult (16-35 years old) with vision impairments (n=67), hearing impairments (n=47), and speech impairments (n=44) in Ulaanbaatar. It combined a questionnaire, observation, focus-group inquiry, a five-area DigComp assessment, and an accessibility review of 85 websites and five mobile applications. Aggregate results show that smartphones were the main device for 53%-67% of the three groups, while mean digital-competence scores remained between 2.20 and 2.54 on a four-point scale. Independent participation in online learning ranged from 29% to 49%; average accessibility was 41% for visual access, 47% for hearing access, and 29% across the evaluated mobile applications. Using a design-science process, these findings were converted into requirements for a mobile-first, offline-capable, WCAG 2.2 AA learning environment. The proposed framework combines a consent-based learner model, DigComp 3.0 learning paths, multimodal content transformation, bounded generative AI over approved sources, accessible interaction, human support, and privacy-aware learning analytics. The contribution is a traceable link between disability-specific evidence and a responsible learner-centered AI architecture.**

Keywords— AI in education, accessibility, digital competence, inclusive education, persons with disabilities

I. INTRODUCTION

Equal access to education is a right rather than an optional feature of educational technology. Article 24 of the United Nations Convention on the Rights of Persons with Disabilities requires an inclusive education system and reasonable accommodation across the life course [1]. In the current AI transition, this obligation extends beyond access to a device: learners must be able to perceive content, express knowledge, understand automated assistance, and retain agency over decisions and data. UNESCO therefore calls for human-centered, rights-based AI that expands learning opportunities without deepening inequalities affecting persons with disabilities and other marginalized groups [2].

Generative AI (GenAI) can explain difficult material, reorganize information, create alternative representations, and provide support outside scheduled teaching hours. These affordances are valuable for learners who encounter inaccessible interfaces or require flexible pacing. Yet performance gains do not automatically indicate learning. The OECD cautions that general-purpose GenAI may enable task completion without durable learning when it replaces cognitive effort, while purpose-built tools guided by pedagogy can strengthen learning and learner agency [3]. For inclusive systems, the central question is therefore not whether AI can generate content, but whether it can support meaningful learning under explicit accessibility, pedagogical, and governance constraints. Mongolia presents a high-value context for this problem. Its dispersed population and rapid expansion of digital public services make mobile and remote learning strategically important. A 2025 Mongolian study found that teachers recognize inclusive education and digital transformation but still face weak access to suitable tools and limited methodological capacity for accessible digital teaching [4]. National and United Nations initiatives likewise identify inclusive digital literacy as a priority for underserved communities [5]. However, there remains little empirical work translating the digital practices of Mongolian persons with disabilities into an AI-enabled learning architecture.

This paper addresses that gap through two research questions: RQ1, which observed digital-competence and accessibility barriers should determine the design requirements of an inclusive learning environment? RQ2, how can those requirements be translated into a learner-centered AI architecture that preserves human oversight and can be evaluated in practice? The paper contributes (1) a descriptive baseline across three disability groups; (2) a needs-to-design traceability model; and (3) an updated architecture aligned

with WCAG 2.2, DigComp 3.0, Universal Design for Learning (UDL) 3.0, and current responsible-AI guidance.

II. Realted work and design foundations

A. Accessibility, Competence, and Learner Agency

The original accessibility audit used WCAG 2.0; the proposed system updates the target to WCAG 2.2 AA. WCAG 2.2 organizes accessibility around perceivable, operable, understandable, and robust content and adds criteria relevant to touch targets, focus visibility, consistent help, and accessible authentication [6]. Conformance is necessary but insufficient: an interface may pass technical checks while the instructional sequence remains cognitively inaccessible or poorly matched to a learner's goals.

Digital competence provides the learning dimension. The original DigComp framework defined five areas—information, communication and collaboration, content creation, safety, and problem solving [7]. DigComp 3.0 retains this overall structure, revises proficiency levels, and integrates AI competence across all 21 competences, including critical evaluation, digital rights, safety, and human-centered problem solving [8]. Thus, accessibility support and AI literacy should be taught together rather than implemented as separate add-ons.

UDL 3.0 complements these standards by emphasizing multiple means of engagement, representation, and action or expression, with learner agency as the goal [9]. In the proposed framework, personalization does not mean silently deciding what a learner can do. It means offering understandable choices, alternative formats, adjustable scaffolding, and a path toward greater autonomy.

B. GenAI and Learners with Disabilities

A 2025 study of students with disabilities in higher education found that GenAI was used for clarification, writing support, and planning, but participants also reported concerns about accuracy, academic integrity, and cost [10]. A subsequent affordance study identified explainability, expressibility, and plannability as benefits, while hallucination, loss of voice, and uncertainty about permissible use remained important gaps [11]. These findings argue for tools that expose sources, preserve the learner's own expression, and clearly distinguish coaching from answer generation.

Systematic reviews reach a similar conclusion. Wang et al. found that GenAI in special education was used mainly as a pedagogical assistant, but the evidence base remained geographically concentrated and statistically inconclusive, with ethical, competence, and technical concerns [12]. A 2026 review of 88 records reported growing activity but continuing gaps in disability-inclusive design and evaluation [13]. A higher-education review similarly emphasized accessibility opportunities alongside bias, privacy, reliability, and uneven access [14]. These studies rarely address low-resource, Mongolian language, mobile-first settings; the present work contributes a context-specific requirements baseline rather than claiming a universally transferable solution.

III. Methodology

A. Design-Science Approach

The study follows design-science research, in which understanding is developed by constructing an artifact that addresses an identified problem [15]. The process was organized as problem identification, requirement derivation, artifact design, and specification of evaluation criteria, consistent with the iterative method of Peffers et al. [16]. The artifact in this paper is an architecture and its traceability to empirical needs; implementation and outcome evaluation are future phases.

B. Empirical Evidence Base

The evidence base was collected in Ulaanbaatar between 2024 and 2025. The target population was 8,409 persons with visual, hearing, or speech-related disabilities. With a 95% confidence level, 0.08 margin of error, and a 5% allowance for non-sampling error, the planned sample was 158. The realized sample included 67 persons with visual disabilities, 47 with hearing disabilities, and 44 with speech-related disabilities.

The mixed-method design combined questionnaire responses, direct observation of digital tasks, and focus-group inquiry. Digital competence was self-rated from 1 (cannot perform/unknown) to 4 (can perform fully) across the five DigComp areas; observation was used to check whether reported skills were demonstrated. The accessibility of 85 frequently used educational websites and five mobile applications was assessed using WCAG 2.0 criteria.

C. Requirement Derivation

Requirements were derived in three passes. First, each quantitative or qualitative barrier was expressed as a user need. Second, each need was mapped to a pedagogical, accessibility, technical, or governance response. Third, the responses were checked against WCAG 2.2 AA, DigComp 3.0, UDL 3.0, UNESCO's AI competency framework for students [17], and human-centered GenAI guidance [18]. An AI feature was retained only when it supported a stated learning need and could include a non-AI fallback or human escalation path.

IV. Empirical findings and design requirements

A. Device Access and Digital Competence

Smartphone use was substantial but not universal: 59% of participants with visual disabilities, 53% with hearing disabilities, and 67% with speech-related disabilities reported using a smartphone. Feature-phone use remained 32%, 39%, and 29%, respectively, while 4%-9% reported no phone. Consequently, smartphone ownership cannot be treated as equivalent to uninterrupted broadband, a modern device, or an accessible application.

Mean scores across the five DigComp areas were 2.34 for the visual group, 2.54 for the hearing group, and 2.20 for the speech group. All were below 3 on the four-point scale. Figure 1 shows different profiles rather than one common deficit. Communication and collaboration was highest for the hearing group (2.8) but lowest for the speech group (1.9). Problem solving was comparatively strong across groups (2.6-2.7), while safety remained modest (2.1-2.3). A learner-centered system should therefore diagnose dimensions separately and avoid assigning a global ability label based on disability type.

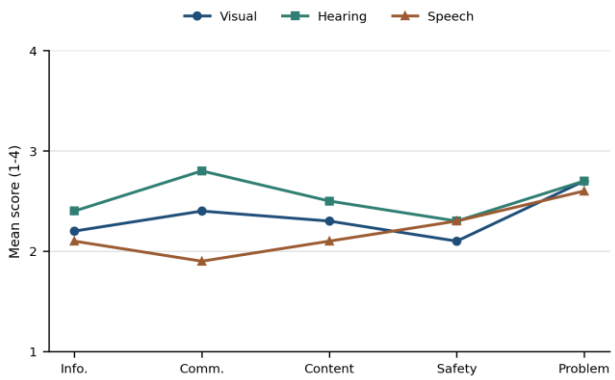


Fig 1. DigComp profiles by disability group (1-4 scale)

B. Accessibility and Learning Participation

Average access to information was 41% for participants with visual disabilities and 47% for those with hearing disabilities. Across the five evaluated mobile applications, the mean result was 29%. Participants described missing screen-reader support, inaccessible changing menus, limited instructions, and absent sign-language explanation.

Prior independent participation in online learning was reported by 29% of the visual group, 41% of the hearing group, and 49% of the speech group. The gap between device availability and independent learning indicates that access must include onboarding, task sequencing, accessible help, and opportunities to practise. Table I converts the strongest empirical findings into system responses.

TABLE I. EVIDENCE-TO-DESIGN TRACEABILITY

Observed evidence	Derived requirement and design response
Smartphone use: 53%-67%; some feature-phone or no-phone use.	Mobile-first, low-bandwidth delivery; downloadable micro-lessons; resumable offline sync; alternative support channel.
Mean DigComp: 2.20-2.54/4 with different skill profiles.	Five-area diagnostic; competence-level goals; adaptive scaffolding based on demonstrated mastery, not disability label.
Independent online learning: 29%-49%.	Stepwise onboarding, worked examples, accessible help, practice-feedback cycles, and human escalation.
Visual access 41%; screen-reader and menu barriers.	Semantic navigation, keyboard/touch access, scalable text, alt text, TTS, focus management, and WCAG 2.2 AA testing.
Hearing access 47%; instructions and sign-language media missing.	Captions and transcripts by default; visual alerts; verified Mongolian Sign Language media; asynchronous text support.
Speech-group communication score 1.9/4.	Multiple expression modes: text, icons, upload, AAC-compatible input, optional STT/TTS, and extra response time.
Mobile apps averaged 29% accessibility.	Automated plus user-based accessibility tests in every release; accessible fallback for AI failure.

V. PROPOSED AI-ENABLED LEARNER-CENTERED FRAMEWORK

A. Architecture and Learning Loop

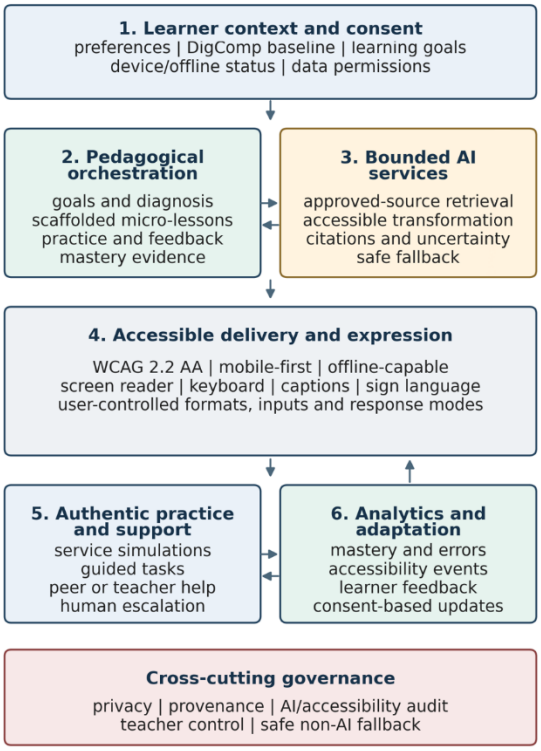


Fig 2. Needs-driven architecture for inclusive AI-enabled learning

Figure 2 presents a six-stage learning loop with governance spanning every stage. The learner begins with an accessible choice-and-consent process that records preferred formats, input methods, goals, baseline competences, device constraints, and offline status. Disability category may inform options, but it does not determine difficulty, pace, or allowed activities. The learner can inspect and revise the profile.

The pedagogical orchestrator converts a DigComp 3.0 goal into short lessons, guided practice, feedback, retrieval, and mastery checks. It uses explicit rules authored by educators. Analytics may recommend the next activity, but advancement is determined by transparent mastery evidence and learner choice. This prevents personalization from becoming an opaque ability track.

B. Accessibility and Learning Participation

AI is used as a constrained assistant rather than an autonomous teacher. A retrieval layer limits factual explanations to an approved Mongolian-language learning corpus and returns source links. Generative services may simplify text, propose examples, draft alt text, create practice questions, or transform material into caption, transcript, TTS, or STT workflows. High-impact outputs—assessment decisions, sign-language learning media, safety advice, and claims affecting public-service eligibility—require human verification. When confidence or source coverage is inadequate, the system must say so and offer the original content or human help.

The interface implements multiple means of representation and expression. Visual access includes semantic structure, screen-reader labels, logical focus, high

contrast, scalable text, descriptive alternatives, and keyboard or switch-compatible operation. Hearing access includes captions, transcripts, visual alerts, and verified Mongolian Sign Language recordings. Speech-related access includes text and symbol-based responses, AAC-compatible input, asynchronous participation, and optional speech conversion. Learners can disable any AI conversion and compare transformed content with the source.

C. Offline Operation, Authentic Tasks, and Support

Requirements were derived in three passes. First, each quantitative or qualitative barrier was expressed as a user need. Second, each need was mapped to a pedagogical, accessibility, technical, or governance response. Third, the responses were checked against WCAG 2.2 AA, DigComp 3.0, UDL 3.0, UNESCO's AI competency framework for students [17], and human-centered GenAI guidance [18]. An AI feature was retained only when it supported a stated learning need and could include a non-AI fallback or human escalation path.

D. Analytics, Privacy, and Human Oversight

The analytics layer collects only data required for learner feedback and service improvement: mastery attempts, error patterns, accessibility events, sync status, and optional self-reported effort or trust. Accessibility telemetry must not be used to infer a medical diagnosis. Learners should see what is collected, correct profile data, and withdraw optional permissions without losing core access. Educators receive interpretable indicators and can override recommendations.

Governance includes data minimization, role-based access, content provenance, audit logs, bias and accessibility tests, incident reporting, and documented non-AI fallback. Automated WCAG checks are paired with testing by persons from the three target groups because conformance tools cannot determine whether instructions, captions, or transformed explanations are educationally meaningful.

VI. Discussion

A. Contribution and Implications

The primary contribution is traceability. The framework does not begin with an available chatbot and search for a use case; it begins with observed barriers and retains only AI functions that answer a documented need. Device data justify offline-first delivery. DigComp profiles justify dimension-specific diagnosis. Accessibility findings justify multimodal delivery and release-level testing. Learning-participation rates justify onboarding, scaffolding, and human support. This chain makes design assumptions reviewable by learners, educators, developers, and policy makers.

The framework also links accessibility with AI competence. DigComp 3.0 treats AI literacy, source evaluation, rights, safety, and problem solving as cross-cutting competences [8]. A learner should therefore not only receive an AI-generated simplification, but learn how to compare it with a source, recognize uncertainty, protect personal data, and decide when human advice is necessary. This approach responds to the risk that GenAI improves immediate performance while weakening independent learning [3].

For Mongolian higher education and lifelong-learning providers, implementation should proceed through participatory co-design. Persons with visual, hearing, and speech-related disabilities should serve as paid design partners, not only test participants. Educators require training in accessible content, AI limitations, and alternative assessment. Procurement criteria should require WCAG 2.2 AA evidence, offline behavior, Mongolian-language quality, exportable learner data, and transparent AI controls.

B. Evaluation Plan

A prototype should be evaluated in three stages. First, technical verification should combine automated checks with expert and user-based WCAG 2.2 audits, including screen-reader, keyboard, caption, contrast, authentication, and offline-recovery tasks. Second, a formative co-design study should measure task completion, errors, time, perceived effort, trust, and explanation usefulness across the three groups. Third, a longer quasi-experimental or randomized pilot should test pre/post DigComp 3.0 outcomes, retention without AI assistance, learner agency, participation, and accessibility incidents. AI quality measures should include source coverage, unsupported-claim rate, harmful or biased output, and successful human escalation.

VII. Conclusion

This paper translated evidence from 158 Mongolian adults with visual, hearing, and speech-related disabilities into a learner-centered AI-enabled learning framework. The findings show meaningful smartphone access alongside moderate digital competence, low independent online-learning participation, and substantial web and mobile accessibility gaps. The proposed response combines mobile-first offline delivery, accessible multimodal interaction, DigComp 3.0 learning paths, bounded GenAI over approved sources, authentic practice, human support, and privacy-aware analytics. The next step is participatory prototyping and rigorous evaluation. AI should be judged not by how much content it generates, but by whether learners can access, understand, question, and ultimately perform important digital tasks with greater autonomy.

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