Articles

AI-Enabled Digital Literacy Support: Embracing Readiness, Confronting Vulnerabilities

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Abstract

As digital literacy support (DLS) programs and initiatives increasingly integrate artificial intelligence (AI) tools, they are gradually replacing human-led tech assistance or education provided by public service institutions (e.g., libraries, schools, community centers, non-profits). This study explores the readiness of DLS-seekers to accept and utilize AI-enabled DLS (AI-DLS), focusing on their perceptions of its benefits and barriers compared to human-led DLS, as well as their trust and ethical concerns about AI. We conducted interviews through community outreach facilitated by Marylanders Online—a state-funded digital equity initiative—targeting a group of Maryland residents who had used DLS. Our findings reveal a strong openness to AI-DLS, with DLS-seekers eager to stay current as well as engage in human-like interactions with conversational AI agents. They highly valued advanced, instant information from AI-DLS, along with the added advantages of confidential and linguistically diverse support, surpassing traditional human-led DLS options. Concerningly, they overlooked the ethical risks of AI in daily life, placing undue trust in its capabilities and underestimating potential vulnerabilities. We conclude by providing theoretical implications of this work and practical recommendations to optimize AI-DLS, drawing from the voices of DLS-seekers advocating for institutional interventions to ensure its broader accessibility and equitable implementation.

Keywords: artificial intelligence; digital divide; digital inclusion; digital literacy; technology support

Introduction

Digital literacy (DL), the ability to use technology effectively for communication, collaboration, and participation (American Library Association, n.d.), is crucial for wellbeing and equity. However, opportunities to learn DL have not been distributed equitably (Tinmaz et al., 2022), as digitally marginalized populations face difficulties accessing online services necessary for daily life, business, and civic engagement (McClain et al., 2021). Public service institutions, including libraries, schools, and community centers have addressed this issue by providing digital literacy support (DLS), such as skills training, device and internet access, and troubleshooting assistance (Hall, 2021). However, the COVID-19 pandemic exacerbated this need for support, with many services moving abruptly online, resulting in the closure of in-person local support facilities (Beaunoyer et al., 2020).

The integration of virtual interventions and assistance by DLS providers has surged, a trend driven by the rising demand for alternative support and the broader societal adoption of artificial intelligence (AI)—the computational capability of digital systems or automated robots to perform tasks traditionally attributed to intelligent agents (Copeland, 2024). AI technologies enhance engagement in various ways: offering 24/7 support (Grimmelikhuijsen & Tangi, 2024), collecting data on digital behavior (Long & Siemens, 2011) that allows the generation of customized responses (Shum et al., 2018), predicting reactions (Baker & Inventado, 2014), integrating social media bots that intervene in everyday online activities (Ta et al., 2020), and more. Generative AI tools or AI-enabled chatbots—using natural language processing (NLP) as a method for human-like, proactive dialogue in respond to user queries—provide personalized feedback to facilitate learning and assist individuals in attaining intended outcomes (Pesovski et al., 2024). For example, an AI-powered virtual mentor in the mobile app 'Kabakoo' (designed to equip African youth with high-tech knowledge) has led to a 23% increase in growth mindset and a 44% improvement in financial status for users in indigenous communities (Elhussein et al., 2024).

In this paper, we define AI-enabled DLS (AI-DLS) as online tools that provide human-like assistance by assessing user needs, responding to DL-related requests, offering instant feedback, and recommending tailored support. These tools—ranging from virtual mentors and intelligent tutoring systems to chatbots—are intended to simulate DL learning experience typically offered by human staff. These AI-DLS tools support users by helping them acquire technical knowledge, develop skills to perform various digital tasks, and obtain on-demand solutions for troubleshooting, all through real-time, personalized guidance from non-human agents. This diverges from traditional forms of DLS, which typically involve interactions with human staff (e.g., librarians, teachers, digital navigators) or on designated online platforms, thereby requiring users to commit to specific temporal and spatial arrangements and subsequently affording limited opportunities for interaction.

Given its emerging nature, AI-DLS may elicit mixed public acceptance (Gesk & Leyer, 2022). Attitudes toward it may be shaped by individuals' comfort in interacting with non-human agents, leading to varying results of AI use (Glikson & Woolley, 2020). Its fully online format offers a breakthrough for those limited by in-person services (Chemnad & Othman, 2024), providing unique advantages for individuals with disabilities or transportation challenges that have experienced limited access to physical spaces (Luckin & Holmes, 2016). While conventional platforms typically offer prescribed content-based resources (e.g., videos, readings), which can limit learner agency, AI-DLS provides interactive and analytic feedback, fostering more personalized learning (Merino-Campos, 2025). However, concerns exist about the potential widening of gaps in AI-DLS awareness and use unless device and internet access (Beaunoyer et al., 2020; Hall, 2021) and necessary skills are adequately attained (Wang et al., 2024).

Additionally, ethical concerns, particularly data exploitation and privacy infringements (Huang, 2023; Willems et al., 2023) pose challenges to AI-DLS. In educational contexts, algorithmic bias can create self-reinforcing cycles that undermine inclusivity affecting both representation (i.e., whether datasets for certain groups are over- or under-represented) and interpretation (i.e., how outputs are understood and applied) for learners (Dieterle et al., 2024).

U.S. government bodies have also recognized these risks—especially regarding governance and data quality in AI-powered public services (e.g., generative-AI cybersecurity tools and public-facing chatbots). They have called for a well-informed transition to AI-DLS, urging stakeholders to understand AI's potential drawbacks (Maynard, 2025).

This study examined AI readiness among DLS-seekers, addressing three key questions: (1) How do DLS-seekers perceive AI-DLS, specifically the benefits and barriers compared to traditional human-led DLS? (2) To what extent do people trust AI-DLS, and what ethical concerns do they have about using it (if any)? (3) What institutional efforts are needed to enhance and equalize access to AI-DLS? We conducted interviews with residents from our regional area, facilitated by a statewide digital equity initiative (Marylanders Online, n.d.). These interviews, a follow-up to our study on DLS impact (Kim et al., 2026), involved a subset of survey respondents willing to share in-depth perspectives. Although the study mainly focused on AI-DLS, we did not specifically target individuals based on their preference or avoidance of AI-DLS to assess their exposure. This paper begins with an overview of the literature that informed the formation of the research questions, followed by a description of the methodology we employed. We conclude by providing theoretical and practical implications of our work.

Literature review

Navigating the trade-offs between AI-enabled and human-led DLS

DLS provided by public institutions has played a pivotal role in building strong digitally connected communities in local settings. However, their reliance on in-person interactions is often limited by geographic restrictions, scheduling issues, and staff availability (Sá et al., 2021). Additionally, the lack of technology expertise among local staff that provide DLS can hinder patrons from acquiring advanced DL necessary for career development and well-being (Fisk et al., 2023). To address these limitations while maintaining on-demand support, AI has been integrated to improve DLS efficiencies (Joseph et al., 2024). This aligns with the report from the United States House of Representatives (2024) on the bipartisan house task force on AI, which advocates for AI adoption in public sectors (e.g., government, education, healthcare) to enhance service productivity.

This trend reflects the broader societal shift toward AI, emphasizing the importance of examining end-user experiences to understand how individuals engage with AI-DLS. Intelligent tutoring systems can generate e-learning gains by tailoring instruction to learners' progress (Merino-Campos, 2025). AI tutors and chatbots can boost learner engagement through personalized and ongoing feedback (Labadze et al., 2023), even outperforming human-led teaching approaches (Kestin et al., 2025). Beyond content delivery, AI-powered analytics can track learners' performance, providing adaptive support (Sajja et al., 2025). However, those who are unfamiliar with AI tend to judge its outputs as less accurate and are less likely than typical users to raise concerns regarding AI outputs (Thomas et al., 2026).

The technology acceptance model (TAM; Davis, 1986, 1989) provides a framework for understanding perceptions of emerging AI in educational contexts (e.g., McGehee, 2024; Yim & Wegerif, 2024). TAM identifies *perceived usefulness* and *perceived ease of use* of technology as key factors influencing the adoption of technologies (Rafique et al., 2020; Wu et al., 2011). Similarly, the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) highlights *performance expectancy* (i.e., productivity) and *effort expectancy* (i.e., efficiency) as crucial adoption drivers. These theories suggest that the preference for AI-DLS is influenced by its ease of use and ability to offer superior experiences compared to human-led DLS, and its ability to offer immediate assistance that overcomes staff limitations and spatiotemporal barriers. Moreover, AI-DLS can adopt communication styles and agent designs that closely resemble human behavior and appearance (Cai et al., 2024; Łukasik & Gut, 2025) and thereby enhance human-AI interaction—as emphasized by the U.S. Department of Education (2023) regarding the “interactive” features of AI tutoring.

While AI-DLS is expected to innovate existing DLS, concerns arise that it may introduce complexity to the existing digital divide due to being exclusively online and the need for AI literacy as an extension of DL. AI tools require more active engagement from DLS-seekers—such as formulating prompts, evaluating information, and applying the answers to real-life scenarios—compared to when seeking assistance provided by human staff. Another drawback of AI-DLS could be its failure to align with the real ‘lived’ experiences of DLS-seekers. Online learning environments often fall short in addressing culturally grounded differences in communication norms and learning expectations (Phirangee & Malec, 2020). This is where AI-DLS may struggle to fully replace human-led DLS situated in specific local contexts.

Research indicates preferences for AI and human agents vary depending on the topic area (e.g., educational, administrative; Gesk & Leyer, 2022). In some cases, AI feedback is preferred over human feedback in terms of perceived usefulness and objectivity (Zhang et al., 2025); however, this perception may vary with familiarity with AI tools (Thomas et al., 2026). In this study, we identify the perceived benefits and barriers experienced by DLS-seekers who adopt AI-DLS—particularly those who may not possess advanced technical expertise—in comparison to human-led DLS. Thus, our first research question poses:

> **RQ1.** How do DLS-seekers perceive AI-enabled DLS, specifically the benefits and barriers compared to traditional human-led DLS?

Trust and ethical considerations regarding AI-enabled DLS

AI has been increasingly implemented by policymakers to enhance the efficiency of public services (e.g., education, healthcare, safety) as part of “smartification” efforts (Engin & Treleaven, 2019), leveraging analytics, automation, and customization features (Anshari et al., 2025). However, it functions as a “black box” (Von Eschenbach, 2021), where limited algorithmic transparency hampers understanding of its ethical compliance and constrains the explainability of its decisions (Ballester, 2021). This poses challenges for individuals with low trust in AI (Gillespie et al., 2021), hindering its acceptance (Choung et al., 2022). Trust has been considered essential in DLS—fueling engaged interactions with digital navigators for assistance with housing, employment, and healthcare (Wedlake et al., 2022).

Evidence indicates that users express concerns about GenAI's contextual expertise—reflecting low *cognitive* trust (i.e., a sense of competence and reliability; Johnson & Grayson, 2005)—even as they value its feedback for its timeliness and volume (Henderson et al., 2025). Meanwhile, in domains such as AI-mediated healthcare services, distrust often stems from low affective trust (i.e., a sense of security and care; Johnson & Grayson, 2005), which are central to help-seeking interactions (Kyung & Kwon, 2022). A similar dynamic may apply to AI-DLS, where affective and cognitive trust is essential for enabling DLS-seekers to disclose their needs to receive support by sharing personal information. Minimizing security-related risks is also essential for building trust-based AI engagement (Schiavo et al., 2024). Awareness of data privacy concerns is critical for the transparent use of online services (Jang & Sung, 2021) and safeguarded information sharing (Baruh et al., 2017).

In this regard, AI raises heightened ethical concerns, including algorithmic biases that threaten fairness (e.g., discrimination based on sociodemographic status; Panarese et al., 2025) and risks of manipulation (Shin, 2024). Uncertainties around data ownership are compounded by the commercialization of personally identifiable information (PII) for targeted advertising (Goglin, 2024), and use of predictive analytics (Prinsloo & Kaliisa, 2022) and surveillance (Wadhwa & Bachwani, 2025)—all now possible when one interacts with AI. Additional challenges stem from the alignment problem—where AI outputs diverge from human intentions—and conflicting value systems embedded in AI models. AI may also provide support beyond users' intended needs, potentially causing affective deception (Bhat & Long, 2025), particularly for vulnerable groups such as children under 13 who must be protected through parental consent under the Children's Online Privacy Protection Act ("COPPA"; Federal Trade Commission, n.d.).

A greater pitfall emerges when individuals with limited AI literacy blindly accept AI-generated recommendations. The COVID-19 outbreak accelerated public engagement with AI-enabled services, heightening awareness of their potential advantages while leaving many users insufficiently informed about the ethically troubling implications of AI use in public health (Dempere et al., 2023). Individuals who view AI as innovative due to its perceived novelty (Wells et al., 2010) but lack cognitive awareness of its risks may place undue trust in it. This may also stem from expectations rooted in the "machine heuristic" (Sundar, 2008) where automated systems are seen as universally objective and consistent (Araujo et al., 2020). Such individuals may over-rely on AI, struggling to question its limitations. This is apparent as people tend to favor quick solutions provided by Generative AI, which may lead to a decline in their autonomous capacity in critical thinking (Koos & Wachsmann, 2023; Zhai et al., 2024). The detrimental effects of uncritical AI dependency may extend to technology-savvy users, as technical competence alone does not necessarily translate into resistance to misinformation (Ogbodo et al., 2023).

Given that DLS-seekers, who may still be developing their DL, might not fully comprehend the data collection or surveillance practices embedded in AI systems, they may unknowingly place utmost trust in AI-DLS. This may exacerbate ethical concerns, particularly regarding privacy, due to ignorance of or insensitivity to data handling practices. Our second research question investigates these concerns:

> **RQ2**. To what extent do people trust AI-DLS, and what ethical concerns do they have about using it (if any)?

Institutional efforts for enhancing access to AI-enabled DLS

Given the expectation that AI adoption continues to expand across society, the key issue is ensuring that appropriate interventions are in place to prevent further digital exclusion of individuals from marginalized populations, such as older adults, individuals with language barriers or disabilities, rural residents, and those from low socioeconomic backgrounds (Office of Statewide Broadband, 2024). The online-exclusive nature of AI-DLS may necessitate infrastructure support for populations with unstable broadband access, who may still require physical DLS facilities at their locations (Gleason & Suen, 2022). Ensuring accessibility of AI-DLS tools would also be essential to prevent the perpetuation of existing inequities (Nyaaba et al., 2024). Accommodating multilingual learners (Davoodi, 2024) and implementing customizable user interfaces (e.g., text-to-speech systems) for individuals with disabilities (Khan, 2024) would be critical to ensure inclusivity in both inputs and outputs of AI-DLS. For those who are non-text-oriented learners, text-heavy content from chatbots may not be easily consumable. In such cases, incorporating multimodal tools would be vital (Chemnad & Othman, 2024). Additionally, specialized DL training through human input may assist individuals who are unfamiliar with formulating queries independently, as AI-DLS relies on user input, unlike pre-structured resources typically found on websites.

To ensure that the designed AI-DLS effectively address DLS-seekers' needs and adapt to emerging challenges, it is essential to incorporate evaluation and feedback processes based on their input, along with perspectives from non-experts or non-practitioners in the development of AI systems for DLS (Sartori & Bocca, 2023). Relatedly, the neocolonial aspects of Generative AI may impose Western ideologies on non-Western societies and reinforce cultural imperialism in education through inherent biases (Nyaaba et al., 2024). This emphasizes the need for human-centric approaches and liberatory design methods that incorporate perspectives from marginalized identities.

In order to determine the institutional efforts that can meet the varied needs and challenges of the public, it is crucial to identify the specific drawbacks that DLS-seekers wish to address and the advantages of traditional DLS they wish to retain, if any. Our final research question thus seeks to explore these potential efforts:

> **RQ3**. What institutional efforts are needed to enhance and equalize access to AI-DLS?

Methodology

Participants

Interviewees were recruited from our survey study aimed at investigating the effectiveness of DLS (Kim et al., 2026). The survey was conducted through community outreach facilitated by our Marylanders Online initiative (n.d.), targeting individuals who had used DLS provided by public institutions (e.g., libraries, schools, community centers, non-profits, advocacy groups) in our region. The survey respondents were asked if they would be willing to participate in a follow-up interview, though the topic was not disclosed to avoid the possibility of only recruiting those particularly interested in AI-DLS. Those who expressed willingness to join the interview were contacted via email three months later and invited to participate in this study. 22 individuals between the ages 25-44 completed the interviews.

Interviewees were predominantly male (20), with 12 individuals aged 25-34 and 10 aged 35-44. In terms of education, eight interviewees held a Bachelor's degree, five had a Master's degree, four had an Associate's degree, four had a doctoral degree, and one had some college education but no degree. In terms of race/ethnicity, 15 interviewees identified as White, while the remainder included three Hispanic or Latina/Latino, two Black/African American, one East Asian, and one South Asian. Annual household income ranged from less than $10,000 (1) to $150,000+ (12), in increments of $10,000 ($M$ = 6.45, SD = 3.32), with an average of three household members (SD = 1.15). Regarding employment status, 20 interviewees were employed full-time, and two were part-time. Finally, 11 interviewees self-identified as residing in urban, nine from suburban, and two from rural areas.

Generally, covered populations in digital equity work—such as older adults, individuals with lower levels of education, racial or ethnic minorities, and rural residents (Office of Statewide Broadband, 2024)—are more likely to require DLS, indicating that our interviewees may represent a different profile from typical DLS seekers. However, given that awareness of AI and the perceived importance of AI literacy are more pronounced among younger and more educated populations (Pew Research Center, 2025a), interviewees may still reflect the evolving socio-demographics of AI-DLS seekers at the time of data collection.

Interviewees used the internet for an average of three to four hours per day. They faced technical difficulties (e.g., app setup, disconnection) several times a year, occasionally seeking help. Interviewees had experience using DLS at libraries, schools, community centers (e.g., senior or housing centers), non-profits, and volunteer groups several times a month. They rated it as moderately effective and important in meeting their DL needs. A considerable increase in DL was reported after using DLS, with strong intention to continue using DLS. Table 1 presents the related statistics:

Table 1: Descriptive statistics of interviewees

	Scale	Statistics
Daily internet usage	1 = *less than 1 hour* to 5 = *more than 5 hours*	*M* = 3.77, *SD* = 1.07
Technical difficulties	1 = *no problem* to 8 = *more than once a week*	*M* = 3.14, *SD* = 1.83
Tech help-seeking	1 = *never need help* to 5 = *always need help*	*M* = 3.23, *SD* = 1.27
Frequency of DLS use	1 = *never* to 7 = *more than once a week*	*M* = 5.64, *SD* = 1.65
Perceived effectiveness of DLS	1 = *not at all* to 5 = *extremely effective*	*M* = 3.82, *SD* = .96
Perceived importance of DLS	1 = *not at all* to 5 = *extremely important*	*M* = 3.86, *SD* = 1.04
Increase in DL (after DLS use)	1 = *not at all* to 5 = *a great deal*	*M* = 4.09, *SD* = .81
Future intention to use DLS	1 = *definitely no* to 5 = *definitely yes*	*M* = 4.55, *SD* = .67

Procedure

Interviewees completed an informed consent form and participated in a 30-minute Zoom interview in December 2024. Research team members conducted one-to-one interviews to explore interviewees' experiences with AI-DLS, their perspectives, and suggestions for improvements. The interview began with questions about prior experiences with traditional DLS to establish a baseline understanding of their DLS use. A semi-structured protocol allowed flexibility based on interviewees' exposure to AI. Interviewees were given the option to assent to audio recording of the interview for transcript creation, and all of them provided their assent. Upon completion, interviewees received a $15 e-gift card as an incentive. The interview procedure was approved by the Institutional Review Board at our home institution.

Data analysis

The audio-recorded interviews were transcribed using the transcription software, Otter.ai. Each interviewee's identity was anonymized with a unique identifier (e.g., P1) to protect privacy. The data were analyzed using thematic analyses (Braun & Clarke, 2006) to identify, organize, and extract patterns in interviewees' experiences and perspectives of DLS. An inductive approach using emergent coding (Rubin, 2021) was employed to develop the codebook for analyzing interview transcripts. The principal researcher first reviewed all transcripts to identify common patterns and generated preliminary codes with supporting quotes. These codes were refined through iterative review and resulted in merging, splitting, or clarifying of codes as needed. To ensure rigor, subsets of the data were coded by other team members, who added additional codes inductively as needed. Intercoder agreement was checked against an initial "master codebook", and discrepancies were resolved, resulting in a final codebook. Representative quotes for each code were added to the final codebook to enhance accuracy and confirmability (Campbell et al., 2013). The final codebook included codes for experiences with human-led DLS and AI-DLS, perceived benefits and barriers, trust and ethical concerns, populations likely to benefit or be marginalized, and suggestions for improving AI-DLS.

Results

Again, our interviewees—predominantly younger and more educated individuals—may differ from typical DLS seekers. Yet they may still capture the emerging socio-demographics of AI-DLS seekers at the time of data collection, whose AI awareness and literacy perceptions are comparatively higher than those of other populations.

RQ1: How do DLS-seekers perceive AI-enabled DLS, specifically the benefits and barriers compared to traditional human-led DLS?

Traditional human-led DLS

Interviewees sought DLS for three main aims: digital skills development, technical problem-solving, and personal growth. Libraries were the most visited institutions for DLS, followed by schools and community centers. Interviewees used help desks, in-person classes, or webinars. All interviewees reported becoming "*more motivated*" and "*less stressed*" in navigating technology through assistance from DLS staff, improving their daily practices such as social networking, academic and workplace performance, job opportunities, and government services. P16's response encapsulates all the others: "*The world is owned by digitalization. These services help to improve my well-being*."

Overall, interviewees evaluated traditional DLS as providing "*direct answers*" (P1, P5), "*specific instructions*" (P11), and "*real feedback*" (P20). As P6 stated, "*Knowing the right sources would be difficult. The services help me figure out what I'm exactly looking for*." However, opinions on staff competence varied. Some appreciated it, like P15, who said, "*The library attendant provides me with the information I need*." Others disagreed, with P16 noting, "*Most staff members are not knowledgeable enough to meet my needs*," and P20 commenting, "*Some provide me with great information, while others might not*."

As for interpersonal aspects, interviewees described DLS staff as "*friendly*" (P1), "*responsive*" (P2), and "*patient*" (P10), with P15 noting, "*They repeat and wait, ensuring I get the information correctly*." Some interviewees revealed they sought help from libraries or community centers as they "*don't have family members to go for information*" (P21) or "*family's and friends' schedules are tight*" (P16). Many also preferred such formal support (staff at public institutions) over informal support (families or friends), citing the need for "new skills" (P10). P11 added, *"[DLS] reduces the cost of bothering a person and being disappointed*."

The most mentioned challenges with in-person DLS were "*distance*" and "*time*." P14 explained: "*When you need a service [but] notice that the time isn't immediate, that's the frustration. It could be a result of distance to where you get the service. If I move to a new environment, I would need someone to show me how to access the service*." Some attributed frustration to "*limited staff*" (P8, P16, P21) and "*language barriers*" (P5, P21), with P1 saying: "*I* *find it difficult to get what they are saying when they talk fast. I might not capture everything. Their dialect is not sound enough to understand*".

AI-enabled DLS

All interviewees reported experiences using AI-DLS, with many (e.g., P2, P5, P15) starting after DLS staff introduced them to ChatGPT, Consensus, Perplexity AI, Chatbox.ai, Gemini, virtual assistants (e.g., Alexa), and similar tools. Their usage aligned with common DLS goals, such as "*consulting DL*" (P4), "*solving technical issues or learning new things*" (P8), and "*exploring novel applications*" (P11). Generally, the acceptance of AI-DLS was driven by the need for "*up-to-date*" (P1) and "*accurate*" (P4) information. As P9, a teacher, stated, "*The world is changing, and we need updated information. I use [AI-DLS] to get the current information that I should give to my students*." Interviewees recalled, "*It does not hold any information back*" (P8) and "*The information provided is straightforward and increasingly expandable to my liking*" (P3). Following are their perceived benefits and barriers related to the use of AI-DLS.

Perceived benefits. In line with the overall positive experience with AI-DLS, interviewees highlighted its values, while fewer reported barriers. They weighed its benefits over human-led DLS, highlighting advantages that existing services could not offer. Five key themes emerged regarding the perceived benefits.

Expansive information**.** One major benefit of AI-DLS was access to "*a wide range of knowledge*" (P8). Interviewees considered it "*worth consuming*," being "*tested and certified*" (P3) by "*real and reliable sources*" (P12). P6 noted, "*The information from AI is genuine. You could ask a particular question two or more times and still get the same*." Some recalled that the information from AI-DLS was something they were "*not aware of or expected to find*" (P9). They appreciated the expansiveness of the information provided (P7) and the adaptability of AI-DLS, comparing it to "*human capacity*" (P21), noting that it offers "*more of what they are looking for than going to a local area and using human*" (P14). P12 added, "*Most of the time, I go to libraries, but they could not help me with certain information. That's when I turn back to ChatGPT*."

Immediacy and simplicity**.** Interviewees highlighted the "*time-efficient nature*" of AI-DLS compared to traditional one, emphasizing its "*instant response and guidance*" (e.g., P1, P4, P10), "*real-time feedback*" (P14), and "*accessibility anytime*" (P8). P15 noted, "*You don't have to research a lot to assess the information. It's quite timesaving*." Some valued its simplicity and ease of use (P11). This was reflected in its "*usability [or] user-friendly interface that is easy to navigate even for those with limited digital experiences*" (P4). P14 summed it up: "*It gives a lot of information for those who don't have time to read e-books. It could be prompt, and [if] you don't understand [you can ask] 'Can you make it short, so I understand?' AI cuts down the information and makes it precise and simple to assimilate*."

Stress-free and confidential. Several interviewees highlighted that non-human contact helped to "*avoid a series of stress*" (P11) and "*lessen the burden or workload*" (P6), compared to "*much work from normal human resources*" (P3). P13 stated, "*You just sit down and get the answer from AI without bothering any person. AI is more advanced than the traditional knowledge system*." Some appreciated this "*stress-free*" aspect, saying "*AI doesn't get tired; you can ask as many questions as you want*" (P15), and "*it doesn't use offensive language*" (P10). Interviewees valued its confidentiality, with P14 saying, "*It's an anonymous platform [where] no one gets to know who is talking*." This was seen as particularly beneficial for people with "*physical disabilities*" or "*medical challenges*" (e.g., P1, P17, P21).

***Virtual companion*.** Most interviewees stated they did not feel awkward interacting with AI-DLS. P1 stated, "*I enjoy using it as if I'm talking to a fellow person*." Some mentioned, "*I feel like chatting because of the quick response*" (P21), which also felt "*authentic*" (P4) as it could be "*customized to have a different name like a human*" (P12). P14 added, "*I feel like I'm talking to a woman. I also use a voice note to express myself*." Some interviewees found AI-DLS engaging beyond its informational purposes, noting "*I enjoy it even when I don't really need information. I might just have a chat with it*" (P5). P13 elaborated: "*AI helps me to elevate my depressive moods. When I'm angry, AI chat is just like a pet companion. I have never been disappointed with it*." The term "*pet companion*" was reiterated by P11 to describe how AI could "*reduce the stress of work*."

***Linguistic flexibility*.** Although not many mentioned it, it is important to pay attention to the aspect that AI-DLS could address linguistic challenges within existing English-dominant DLS. P5 said, "*I actually go to AI for information from my own language*" instead of relying on in-person library services and resources that have "*language barriers*." This was reiterated by P21 saying, "*It quite understands my language and captures what I'm saying very well*." P3 highlighted the current hassle of translating: "*There are over 100,000 languages spoken by the world. Google Translate has about 50 languages that can be translated. Most times you copy [information], select the preferred language, and it translates for you. But that sounds too stressful, [and] AIs would be able to address such kinds of issues*."

Perceived barriers. Interviewees did not report many difficulties with AI-DLS, contrary to expectations. Some just highlighted digital divides that hinder reliable access to it. Examples included "*slow internet connection*" (P4, P10), "*poor connectivity due to location [and] lack of developmental infrastructure*" (P16), and "*outdated software*" (P21) that doesn't support AI services (P9). Others mentioned "*limited access to certain devices*" (P1) and "*network congestion in remote areas*" (P3), suggesting the importance of government interventions such as device-subsidy programs and nationwide broadband expansion. As P13 noted, "*AI has helped to improve my digital life consistently. The government needs to integrate more networks to urban and rural areas with poor connectivity so they can also benefit from AI just as I do*."

To address interviewees' potential reluctance to disclose personal challenges, interview questions were adjusted to ask about who they thought would benefit from or be marginalized by AI-DLS. Generally, interviewees believed that "*people familiar with technology*" (P7) or "*those open to technology who understand it's there to help*" (P3), particularly younger individuals or those in education and academia (e.g., P1, P10, P11), would benefit most from AI-

DLS. In contrast, those who are "*not technologically advanced*" (P6)—and thus don't understand how AI works (P3) or what information to ask for (P5)—were seen as less likely to benefit. Tech-averse individuals, particularly "*older people*" (P8) who find AI use "*unsafe*" (P9) or "*awkward*" (P10), and "*rely on others for digital skills*" (P14), were also noted as less inclined to benefit.

RQ2: To what extent do people trust AI-DLS, and what ethical concerns do they have about using it (if any)?

Overall, interviewees expressed strong trust in AI-DLS based on their past experiences. P12 said, "*My trust is quite high. I have not encountered any disturbance. It has not caused any harm to me*." Such trust was attributed to the perceived "*reliability*" (P3) and "*consistency*" (P2) of AI-DLS, with P11 describing an AI system as "*a conglomeration of different internet sites coming together, [with] information clouding and filtering*." P13 stated, "*A machine can never be 100% efficient, but I can guarantee my trust in AI by 99%*," believing "*AI can be controlled*" based on the nature of questions asked. P5 appreciated AI's transparency, noting, "*[If] you ask a question [but] it can't provide you information, it will directly tell you that it cannot*."

Many interviewees indicated unconditional trust in AI-DLS, saying, "*I don't think of anything that would affect my trust in it*" (P10) and "*I don't have any reason not to trust it*" (P15). A few mentioned privacy issues such as "*obtaining information from devices*" (P1) or "*personal data being leaked*" (P9), while still maintaining trust. Interviewees rarely identified ethical risks, saying, "*I don't have any concerns personally*" (P7) and "*I believe my information is safe*" (P12). Some considered AI's data collection even beneficial, with P17 noting, "*It's good because it will recognize the kind of information that I look for*," and P10 adding, "*I'm okay with AI collecting my data because it helps understand what kind of person I am*."

RQ3: What institutional efforts are needed to enhance and equalize access to AI-DLS?

All interviewees expressed the expectation that AI tools could contribute to DLS by making it "*much faster*" (P12) and providing "*proper, sensible, or possible solutions*" (P11) to help people develop their digital skills and DLS providers improve their practices. Three key areas—design, services, and infrastructure—were highlighted by interviewees as crucial for enhancing AI-DLS to provide more effective and customized support.

Accessible interface

Interviewees suggested a "*user-centered design*" (P5) for AI-DLS to make it more "*easily and readily available*" (P6). They highlighted "*an interface that is simple to navigate*" (P8), "*clear instructions and feedback to facilitate learning*" (P5), and "*continuous updates*" to improve "*accessibility and usability*" (P20). Font size and graphics were frequently mentioned as options that "*should be adjustable*" for individuals who may have difficulty reading due to poor eyesight (P9). P12 called for "*a customized system to help users enjoy it*," suggesting that '*it should be written in bold letters [making it] easy to see and read*." Additionally, some interviewees emphasized the need for AI-DLS to incorporate "*video instruction*" (P1) or "*an example video to see how the whole process is being carried out*" (P21), as well as "*pictures [for] people who find it difficult to read bulky messages*" (P14).

Accommodating services

Interviewees also believed that improvement for AI-DLS should incorporate ongoing assessments of "*user needs and preferences*" (P5), such as "*user feedback surveys*" (e.g., P1, P15, P21) or "*user testing*" (P20) which would allow users to voice their opinions on updates to AI services. They recommended that "*real-time feedback [should] create personalized learning pathways that adjust to individual users' needs*" (P4) or "*adaptive learning pathways that adjust to individual learning skills*" (P8). Some noted that the accessibility features of AI-DLS should include "*language options*" (P20)," beyond English-dominant services (P7), to accommodate "*multi-language users*" (P9) and ensure that "*all the instructions should be well placed and stated [so that] whoever is using the service can understand*" (P15).

Expanded infrastructure

Finally, interviewees recognized the need for infrastructure efforts to ensure a "*stable internet connection*" (P4) and maintain traditional DLS options at libraries for those facing digital divides. A few interviewees emphasized the government's role in "*improving internet facilities*" in areas with network deficiencies (P11), with P13 urging the government to prioritize technology development in remote areas which will reduce the AI access divide. Device support was also highlighted, with some noting that "*people will have more access to AI when mobile gadgets are easy to afford*" (P13). Several interviewees called for reducing the "*high cost of mobile phones*" (P11) to make AI more accessible. Relatedly, P3 suggested implementing "*Managed Service Providers* (MSP; A third-party company that remotely manages a user's day-to-day technology infrastructure and network; Gills & Moore, 2024) [and] *a minimum support price scheme*" for less privileged people to have access to devices. Other recommendations included "*free resources and zero fees*" (P2), making AI "*available to all types of devices*" (P21), and integrating AI-DLS as "*an inbuilt, permanent app*" (P14).

Discussion

Theoretical implications

Balancing warm and cold support in AI-DLS

Overall, interviewees preferred AI-DLS over traditional human-led DLS due to its greater efficiency and expansiveness of information, aligning with the perceived ease of use and perceived usefulness concepts in the Technology Acceptance Model (TAM; Davis, 1986; 1989), which are known to drive continued engagement with technology (Rafique et al., 2020; Wu et al., 2011). AI-DLS is available 24/7, making it a viable alternative to human assistance that is restricted to specific hours. Immediate responses from AI-DLS align with DLS-seekers' preference for efficiency, making it more appealing for daily use. Moreover, AI-DLS was viewed as beneficial in overcoming linguistic barriers, particularly for non-English-speaking users, by streamlining translation processes that were less efficient in existing tools (e.g., Google Translate). This improvement was crucial in reducing cognitive load and enhancing user experience.

Our findings reveal that DLS-seekers valued the balance between human and non-human aspects of AI-DLS, which enhanced its appeal over traditional DLS. Interviewees likened AI-DLS to a "*fellow person*" and "*pet companion*," possibly reflecting an anthropomorphic view of AI. Personalization features, such as naming AI agents, were seen as a way to create a sense of connection, replacing the "*friendly*" support typically provided by human DLS. This suggests that AI-DLS may particularly attract users seeking empathetic support—characterized by understanding and patience—provided by *warm experts* who bridge technology and user needs, taking into account the users' backgrounds (Bakardjieva et al., 2005), as well as those seeking a more emotionally engaging experience during skills training (Geerts et al., 2023).

At the same time, our data also suggests that some individuals prefer instruction from *cold experts* (Geerts et al., 2023), reflecting AI-DLS's more straightforward, less interpersonal nature, which helps avoid the stress of existing human-led DLS. A related key theme was AI agents' ability to alleviate common challenges of human interactions, such as waiting times, miscommunication, anxiety over repeated inquiries, confrontation, and language barriers, which could help minimize the frustration and emotional burden associated with unhelpful services from staff. The confidentiality of anonymous AI-DLS was also emphasized as a major benefit, particularly for those uncomfortable discussing sensitive topics (e.g., medical queries). This positions AI-DLS as a safer space for those who fear judgment when seeking help.

Taken together, our interview results suggest several important implications regarding the role of AI-DLS in offering neither too impersonal nor too interpersonal experiences. The human-like and conversational features of AI-DLS help reduce awkwardness and resistance to interacting with AI, while its anonymous and confidential nature encourages people to engage more actively with DLS in their daily lives. The balance between warm and cold expert support perceived in AI-DLS suggests its potential to both supplement and complement human-led DLS, enhancing the overall user experience.

Unreserved trust and neglecting ethics in using AI-DLS

The advanced information capacity and perceived confidentiality of AI fostered undue trust among DLS-seekers, prompting them to ask questions they might otherwise avoid. This over-reliance on AI-DLS aligns with research indicating students' preference for efficient and cognitive shortcuts (Koos & Wachsmann, 2023; Zhai et al., 2024). Interviewees valued AI transparency, appreciating its honesty in admitting when it couldn't provide an answer, unlike human staff who could give misleading information. The consistent operation of AI-DLS, based on structured algorithms, reinforced its perceived reliability, distinguishing it from the unpredictability of human responses. This strong confidence in AI-DLS was largely driven by interviewees' positive past experiences, where they perceived its benefits far outweigh any potential drawbacks.

A key finding was that the unquestioning trust in AI-DLS was paired with minimal ethical consideration. Most interviewees less critically evaluated AI's security risks, with only a few mentioning concerns about data leakage. Even these cautious individuals did not withdraw their trust in AI. Overall, interviewees trusted AI-DLS via the "machine heuristic," which assumes automated systems are neutral and reliable (Araujo et al., 2020; Sundar, 2008), while perceiving control via their input. They were reluctant to identify AI's risks, reflecting a lack of awareness of data breaches, bias, hallucination, and misinformation. While literature suggests AI literacy reduces skepticism (Schiavo et al., 2024), our findings highlight that trust in AI-DLS does not imply being able to understand and evaluate AI, revealing significant AI literacy gaps. Indeed, AI literacy frameworks remain under development (e.g., aide, n.d.; UNESCO, n.d.), emphasizing ethical use but offering limited guidance on how to implement it effectively. AI is still a moving target, and societal norms on "what is right or wrong" continue to shift, creating pedagogical and ethical challenges for prescribed learning—including potential misalignment with learners' lived experiences, the inadvertent reinforcement of existing biases, and limited opportunities for developing critical thinking. Therefore, AI literacy content should be designed to track ongoing sociotechnical changes while cultivating context-sensitive engagement with AI.

Increased caution is required as many interviewees showed little concern about AI-based services collecting their personal data and digital footprints, even considering such practices acceptable to some degree. DLS-seekers justified data collection for reasons like enhancing personalized interactions. They appeared to prioritize convenience and customization, accepting potential risks to privacy in exchange for tailored support (e.g., "*I don't really care about the damages to privacy or something that could really occu*r" as mentioned by P14). Notably, interviewees preferred AI-DLS for its non-judgmental, anonymous environment, valuing its privacy protection over human support, yet still willing to compromise some information security for a more satisfying service from AI.

AI divides deepening societal inequalities

Some interview data pointed out network congestion, device shortages, and infrastructure deficits in rural areas as barriers to AI-DLS, which may contribute to the *AI divide* (Carter et al., 2020). This suggests that the existing first-level digital divide (Riggins & Dewan, 2005) between technology "haves" and "have-nots" continues to pose a persistent gap for DLS seekers motivated to leverage cutting-edge technologies. The significance of access-related challenges has also been observed in our previous studies uncovering the issue of e-government services for marginalized populations (Kim et al., 2025), as well as the differential effectiveness of DLS for groups experiencing technology unaffordability (Kim et al., 2026). In discussing advanced forms of DLS, we should remain mindful of fundamental barriers to device maintenance and broadband connectivity that can impede the efforts of individuals seeking digital capabilities.

Neglecting these barriers may place traditionally marginalized populations at a further disadvantage in their use of AI-DLS and exacerbate societal inequalities.

Practical suggestions

Unlocking AI's potential beyond chat applications

Despite a high readiness to adopt AI, we observed that interviewees mostly mentioned conversational AI and chatbots. It would thus be beneficial to introduce a broader range of AI tools to support DL education. These could include AI-powered tutoring platforms with adaptive learning systems that adjust content and difficulty based on an individual's progress, as well as guided programs to expose DLS-seekers to diverse subject areas, beyond a focus on specific inquiries. Adaptive platforms like Knewton or Quizlet, which tailor learning paths to individual performance, could complement quick Q&A formats.

Cultivating AI literacy to ensure informed trust

Our findings highlight over-reliance on AI, potentially undermining DLS-seekers' judgment (Koos & Wachsmann, 2023). Education should combat blind trust and lax ethical standards, fostering human oversight for error detection. Through the mastery of AI literacy, individuals can strategically use AI- or human-led DLS, or both, thereby avoiding unreflective AI dependency. Students perceive AI feedback as less risky than teacher feedback yet remain concerned about AI's expertise (Henderson et al., 2025); thus, AI- and educator-generated feedback should be framed as complementary rather than interchangeable (Thomas et al., 2026).

Tailoring AI-DLS interfaces for user needs

Interviewees advocated for more flexible, user-responsive AI-DLS interfaces, particularly for tech-averse individuals. They recommended developing intuitive interfaces to reduce resistance to AI agents, including multimodal options (e.g., visual inputs, voice notes) for better accessibility. Additionally, AI-DLS should bridge linguistic divides by supporting a wider range of languages and dialects, utilizing NLP to enhance translation tools and understand language nuances. Cultural sensitivity in DL content and service delivery is also crucial for fostering equity. Furthermore, AI-DLS should accommodate vulnerable users, such as those with disabilities, by incorporating assistive technology like text-to-speech or speech-to-text tools (e.g., Speechify), and screen readers (e.g., VoiceOver) to promote inclusion.

Incorporating socioemotional components

Our interviews demonstrate a shift in how users perceive AI-DLS—moving from functional tools to companions that can feel personal. The idea that NLP and personalization strategies (e.g., naming AI agents) could enhance user engagement, especially those who seek technology as a source of social support, as an alternative to the warm human experts they may lack. This could expand AI use beyond informational purposes, integrating emotional support to reach a broader audience, as demonstrated by the AI-driven mental health application (Wysa) which promotes well-being through listening and validation (Chaudhry & Debi, 2024). AI-DLS could incorporate such features while still allowing for human intervention, which remains crucial in public service delivery even with AI (Horvath et al., 2023).

Building practitioner capacity in DLS contexts

Finally, governments can be informed by the International Telecommunication Union (n.d.)'s *AI for Good* initiative, which serves as a hub for knowledge-sharing to scale AI solutions. This UN-led AI Skills Coalition provides an open AI education platform with partners (e.g., OpenAI, IBM SkillsBuild, TELUS), not only bridging the global AI divide but also offering training tailored to local languages and accessible formats. This model can be adapted for DLS providers (e.g., librarians, teachers, digital navigators), enabling them to leverage high-quality resources, in cases where they struggle with insufficient expertise and limited professional development opportunities. Importantly, attention should also be paid to the barriers DLS providers face in integrating AI into their practices, including budget constraints, stakeholder concerns, and resistance to new systems (Yim & Wegerif, 2024). To this end, our Marylanders Online initiative (n.d.) provides AI education modules to train digital navigators, so that they can better support the development of AI literacy in their communities.

Supporting low-resource AI learning environments

AIED (Artificial Intelligence in Education) communities must ensure equity in DLS for underserved areas, where sustainable system maintenance is challenged by poor network coverage and unreliable power supply (Yadav et al., 2025). AI-DLS should also be designed to be mobile-friendly and bandwidth-efficient, tailored to low-income users who rely on low-compute devices and are found to exhibit lower levels of AI awareness (Pew Research Center, 2025b). In addition to subsidized AI access programs, reducing emerging AI divides requires cross-sector cooperation among education authorities, infrastructure agencies, and community organizations, as well as the integration of equity benchmarks into AIED initiatives to monitor and address disparities.

Limitations and future directions

Many interviewees did not report personal difficulties, indicating that unreported challenges may be influenced by *social desirability bias*—i.e., the tendency to present oneself favorably, obscuring their true experiences (Fisher, 1993). They emphasized benefiting from AI, as ChatGPT users do (Chung et al., 2025), while flagging its risks to individuals with lower DL, reflecting a *third-person effect*—i.e., the tendency to overestimate others' susceptibility to undesirable external influences (e.g., media) relative to their own (Davison, 1983). To mitigate potential biases, future research could use observational studies, behavioral tracking, or objective assessments of participants' DL to ensure the validity of their reported engagement with AI-DLS.

Some interviewees, despite identifying as English speakers, showed reduced English proficiency, which may have hindered their engagement in the interviews. Rather than relying solely on self-reported language preference, a pre-interview language assessment could better gauge interviewees' comfort with English. For individuals with less proficiency in English, interpreters could be used to conduct these interviews.

Finally, the interviews were conducted with volunteers from our larger study (Kim et al., 2026), resulting in a demographic bias with a predominantly young and well-educated individuals, likely more interested in AI. While these participants might have been on the less disadvantaged side of the digital divide, they nonetheless illustrated the pitfalls of AI-DLS, including disregard for ethical implications of AI and unstable connectivity. This finding warrants further investigation into among populations with heightened vulnerabilities (e.g., seniors, those with lesser education), who may experience divergent effects of AI-DLS. Future research would thus benefit from employing a demographically balanced sample to capture a broader understanding of the emerging AI divide within DLS contexts. In line with our digital equity initiative, which increasingly incorporates AI education, follow-up studies will expand to marginalized populations, offering more nuanced insights into AI-DLS implications.

Conclusion

This study investigates the general public's readiness to adopt AI for DL development. Our findings indicate that individuals with prior experience using traditional DLS are generally open to leveraging AI, and most perceive it as useful and hold positive attitudes toward it (Musyaffi et al., 2024; Sergeeva et al., 2025). A clear preference for AI-DLS is evident, particularly in addressing limitations inherent in human-led and informal resources (e.g., library help desks, family members), while also underscoring the need for interventions aimed at improving and democratizing access to AI. In this paper, we have raised concerns regarding a relative lack of awareness or sensitivity to the ethical implications associated with AI, as DLS-seekers often exhibit an unquestioning trust in its utility. We believe that this gap signifies a key area in which human-led DLS is still crucial for upholding more secure and trustworthy learning environments.

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