Implications for Extension

Transforming Cooperative Extension with Artificial Intelligence: A Scoping Review of Education, Programming, Outreach, and Evaluation

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Abstract

This scoping review examined 20 studies published between 2016 and 2026 to investigate the integration of artificial intelligence (AI) in Cooperative Extension education, programming, outreach, and evaluation. Findings were categorized into program delivery, needs assessment, data analytics, and educational outreach and informed a proposed AI-Enhanced Cooperative Extension Programming Model. Results indicate that AI can enhance Extension programming through personalized instruction, data-informed decision-making, improved resource efficiency, and broader educational outreach. These findings suggest AI can expand Extension's reach and effectiveness by supporting educators in delivering more efficient, scalable, and impactful programs nationwide.

Introduction

Cooperative Extension functions as a vital conduit for translating research-based findings into practical community solutions, facilitating educational initiatives that contribute to the betterment of individuals, families, and communities. However, rapid technological advancement and evolving societal dynamics are fundamentally reshaping how communities access information, engage in learning, and respond to emerging challenges (Varsha et al., 2025). Digital technologies, with artificial intelligence (AI) at the forefront, are exerting a growing influence on educational delivery (Matar, 2025). This paradigm shift is characterized by the provision of personalized learning pathways, greater access to informational resources, and the facilitation of data-informed strategies for program enhancement. These changes introduce both opportunities and challenges for Cooperative Extension systems nationwide. While traditional in-person outreach models remain foundational, they may limit engagement with geographically dispersed, time-constrained, or underserved populations (Brown et al., 2024). At the same time, persistent digital inequities, varying levels of technological literacy, and growing complexity in community needs require more adaptive and scalable approaches (Anderson et al., 2025). Within this context, AI-driven tools present a promising pathway to enhance Extension programming through automated needs assessments, customized educational content, and real-time feedback mechanisms that improve both reach and effectiveness (Saini, 2025).

Across the broader educational literature, AI is regularly presented as a means to enhance efficiency, facilitate personalized learning tailored to individual requirements, and support data-informed decision-making. AI technologies are widely used to support adaptive learning system tools to modify content, automate administrative tasks, and provide immediate feedback to learners, ultimately enhancing engagement and knowledge retention (Sajja et al., 2025; Martín-García et al., 2022). Within Extension, these capabilities hold a particular promise for strengthening program planning, targeting resources, and evaluating outcomes in more responsive and evidence-based ways.

The integration of AI into educational systems is supported by established theoretical frameworks. The Technology Acceptance Model (TAM) suggests that individuals' willingness to adopt new technologies is influenced by perceived usefulness and ease of use (Davis et al.,2024). The AI-Augmented Learning Theory emphasizes AI's role as a supportive tool that enhances rather than replaces educators by enabling personalized instruction, identifying learning gaps, and improving instructional effectiveness (Ortony et al., 2022). Together, these frameworks provide a foundation for understanding both the adoption and pedagogical application of AI within the Cooperative Extension system.

Despite the abundance of studies concerning AI's role in education and agriculture, key deficiencies are apparent (Tzachor et al., 2022). Much of the current research has concentrated on formal education, precision agriculture, or individual case studies. More comprehensive analysis of AI implementation within Cooperative Extension programs such as Family and Consumer Sciences is still needed. Furthermore, research points more to AI's advantages, and less attention to its effects on fair access, level of educators' preparation, and the specific outreach focus of Extension programs. This gap limits practitioners' and decision-makers' ability to adopt and scale AI-driven innovations (Mensah and Swortzel, 2026).

Importantly, the adoption of AI within Cooperative Extension reflects a continuation of its longstanding commitment to innovation in educational delivery (Saini, 2025). Historical integration of technologies such as radio and television broadcasting demonstrate Extension's capacity to adapt while maintaining its core mission of community engagement and knowledge dissemination (Hu et al., 2022). However, AI introduces new considerations related to ethics, data privacy, and digital equity. Thoughtful implementation is essential to ensure that AI enhances rather than exacerbates existing disparities in access to information and resources (High et al., 2025). Overall, the literature suggests that AI has significant potential to strengthen Cooperative Extension programming by enabling more personalized, scalable, and data-informed approaches. Though, this potential requires careful attention to educator capacity, infrastructure, and equitable access.

Purpose

This study examines the role of artificial intelligence (AI) in enhancing Cooperative Extension education, programming, outreach and evaluation. The research examines how AI can improve data-driven decision-making, program delivery, and evaluation in Extension systems. The objective is to learn how to integrate AI tools into Extension programming, to enhance community engagement, and extend the reach and effectiveness of research-based education, to improve the impact of Extension services.

Method

This study conducted between September 2025 and February 2026, employed a scoping review method to examine the breadth and nature of existing research on integrating artificial intelligence (AI) in Cooperative Extension programming. Scoping reviews allowed for a comprehensive mapping of literature, identifying gaps, and setting the stage for future research. A systematic search was conducted across three academic databases: Scopus, ERIC, and JSTOR, supplemented by relevant gray literature, including Extension fact sheets and reports. Search strings included combinations of keywords using Boolean operators - *artificial intelligence, machine learning (ML), Cooperative Extension,* *community education, Extension programming, digital learning, and technology integration.*

The initial search yielded 2,532 records. After the removal of duplicates (n = 713), automated exclusions (n = 389), and non-relevant records (n = 709), 721 records remained for screening. Title and abstract screening resulted in the exclusion of 619 records, leaving 102 reports sought for retrieval. Of these, 52 reports could not be retrieved, resulting in 50 full-text reports assessed for eligibility. Of the 50 reports assessed for eligibility, 30 were excluded for the following reasons: non-relevant outcomes (n = 11), no relation to Extension (n = 5), no empirical evidence (n = 7), insufficient full-text information for eligibility assessment (n = 4), and language barrier (n = 3).

The remaining 20 studies met the final inclusion criteria and were included in the scoping review (See Figure 1: PRISMA Flow Diagram). Inclusion criteria required studies to: (1) address AI or digital technologies within educational or Extension-related contexts; (2) include applications relevant to community-based or nonformal education; and (3) be published in peer-reviewed journals between 2016 and 2026. Exclusion criteria removed studies unrelated to educational programming, lacking empirical evidence, or without accessible full text. These 20 eligible studies comprised the final scoping review dataset and were included in the thematic analysis. The characteristics of the included studies, including study focus, population or setting, methodology, AI application, key findings, and relevance to Extension or community-based education, were summarized (See Table 1: Characteristics of the 20 Studies Included in the Scoping Review). Findings from the included studies were examined to identify recurring themes, evidence-based applications, and examples of AI integration relevant to Extension education, programming, outreach, and evaluation.

Data extraction and coding were conducted for each included study based on key variables, including application area, reported outcomes, and relevance to Extension programming. Four thematic categories emerged from the analysis (See Table 2: Thematic Distribution of Studies Included in the Scoping Review). **AI in educational delivery** encompassed personalized instruction, adaptive learning, automated feedback, learner support, workforce preparation, and AI-enhanced educational experiences (Cao & Phongsatha, 2025; Dai, 2025; Delgadillo & Clouse, 2025; Ezenwa, 2025; Feng et al., 2025; High et al., 2025; Jin et al., 2024; Khairulanwar & Jamaludin, 2025; Kohli, 2025; Li et al., 2025; Mensah & Swortzel, 2026; Sajja et al., 2025; Salhab & Aboushi, 2025; Tan et al., 2026; Zhu, 2025). **Data-driven decision-making** included predictive analytics, environmental monitoring, program planning and evaluation, agricultural decision support, and identification of learner or community needs (Cao & Phongsatha, 2025; Costa et al., 2024; Dong et al., 2022; Feng et al., 2025; Gangwani, 2024; Jin et al., 2024; Mallya et al., 2023; Mohanty et al., 2016; Sajja et al., 2025; Tan et al., 2026; Zhu, 2025).

Outreach and engagement reflected AI applications that expanded access, personalized advisory services, strengthened communication, and engaged rural or underserved populations (Dong et al., 2022; Ezenwa, 2025; Feng et al., 2025; High et al., 2025; Li et al., 2025; Mensah & Swortzel, 2026; Tan et al., 2026). **Challenges and ethical considerations** included concerns related to AI literacy, privacy, data security, bias, accuracy, equitable access, infrastructure, overreliance, intellectual property, trust, and human oversight (Dai, 2025; Delgadillo & Clouse, 2025; Ezenwa, 2025; Gangwani, 2024; Khairulanwar & Jamaludin, 2025; Kohli, 2025; Li et al., 2025; Mensah & Swortzel, 2026; Mohanty et al., 2016; Salhab & Aboushi, 2025).

To enhance reliability, two independent reviewers conducted the screening and coding, with discrepancies resolved through consensus and oversight from a third reviewer. This reconciliation method provided a transparent and replicable framework for future research seeking to build upon these findings. This study was exempt from human subject review. It uses no direct human participant data, and all sources are cited appropriately to maintain academic integrity and respect intellectual property rights.

Findings

The scoping review found AI consistently associated with three primary outcomes across Cooperative Extension and related educational settings: enhanced engagement, improved efficiency in program delivery, and increased precision in targeting community needs. Across the 20 studies reviewed, AI applications most frequently supported personalized learning environments, automated data analysis, and expanded outreach capabilities. AI-driven tools enable Extension professionals to shift from generalized programming toward data-informed, audience-specific interventions - increasing both relevance and effectiveness.

For example, a national 4-H initiative reported survey findings showing a 64% increase in youth valuing AI skills for future careers, attributed to hands-on learning experiences and industry partnerships (National 4-H Council, 2024). Similarly, precision agriculture applications reported a 15% increase in crop yields, driven by AI-assisted analysis of soil and weather data (Gangwani, 2024). AI-enabled interventions in community health outreach led to 30% increase in health knowledge retention, particularly among underserved populations (Feng et al., 2025). These findings collectively suggest that AI is most impactful when applied to real-time adaptation, large-scale data processing, and individualized engagement strategies. Its effectiveness is contingent upon intentional design, educator preparedness, and equitable meaning infrastructure. (See Table 3: Potential Applications for Artificial Intelligence in Cooperative Extension).

The literature also highlights a need for broader implementation and longitudinal evaluation. Cross-study synthesis identified recurring challenges, including digital literacy gaps, unequal access to technology, and ethical concerns related to data privacy and algorithmic bias (See Table 4: Opportunities and Challenges of AI Integration in Cooperative Extension). Overall, the findings demonstrate that AI holds significant potential to transform Cooperative Extension programming, particularly when integrated as a tool for augmenting rather than replacing educator expertise and community-centered approaches (See Table 5: Examples of AI Tools).

Implications for Extension

AI Supported Needs Assessment and Program Design

AI-Supported needs assessment and program design technologies can significantly improve needs assessment processes by enabling Cooperative Extension professionals to analyze community data more efficiently and identify emerging trends (Manobharathi, 2024). Machine learning (ML) tools can process large datasets, survey responses, demographic data, and community feedback, to help educators design programs reflecting local needs. Integrating AI into program planning allows Cooperative Extension professionals to identify underserved populations and tailor programming accordingly. By combining AI analytics with traditional participatory methods such as focus groups and community advisory boards, Cooperative Extension systems can create more responsive and culturally relevant programming.

AI helps Expand Outreach and Engagement

AI has the potential to transform Cooperative Extension outreach strategies by enabling personalized communication and adaptive learning experiences. AI-powered tools can help educators deliver customized educational materials, automate routine communication tasks, and provide learners with immediate feedback (Manoj et al., 2024). These technologies can also support multi-channel engagement strategies, including online learning platforms, digital messaging tools, and adaptive training modules (Anderson et al., 2025). These approaches can increase participation rates and improve accessibility for individuals who may face barriers to attending traditional in-person programming.

AI Supported Interventions

Limitations in AI supported interventions include addressing structural barriers and digital inequity. While AI offers promising opportunities for innovation in Cooperative Extension interventions, structural barriers may limit participation. Communities withlimited internet access, low digital literacy, or limited technological infrastructure may be at risk of exclusion from AI-enabled programming (Ezenwa, 2025). To ensure equitable implementation, Cooperative Extension systems should invest in digital literacy education, technology access initiatives, and inclusive program design strategies (Mensah & Swortzel, 2026). Addressing the digital divide ensures that AI supported Cooperative Extension's mission serve all communities equitably.

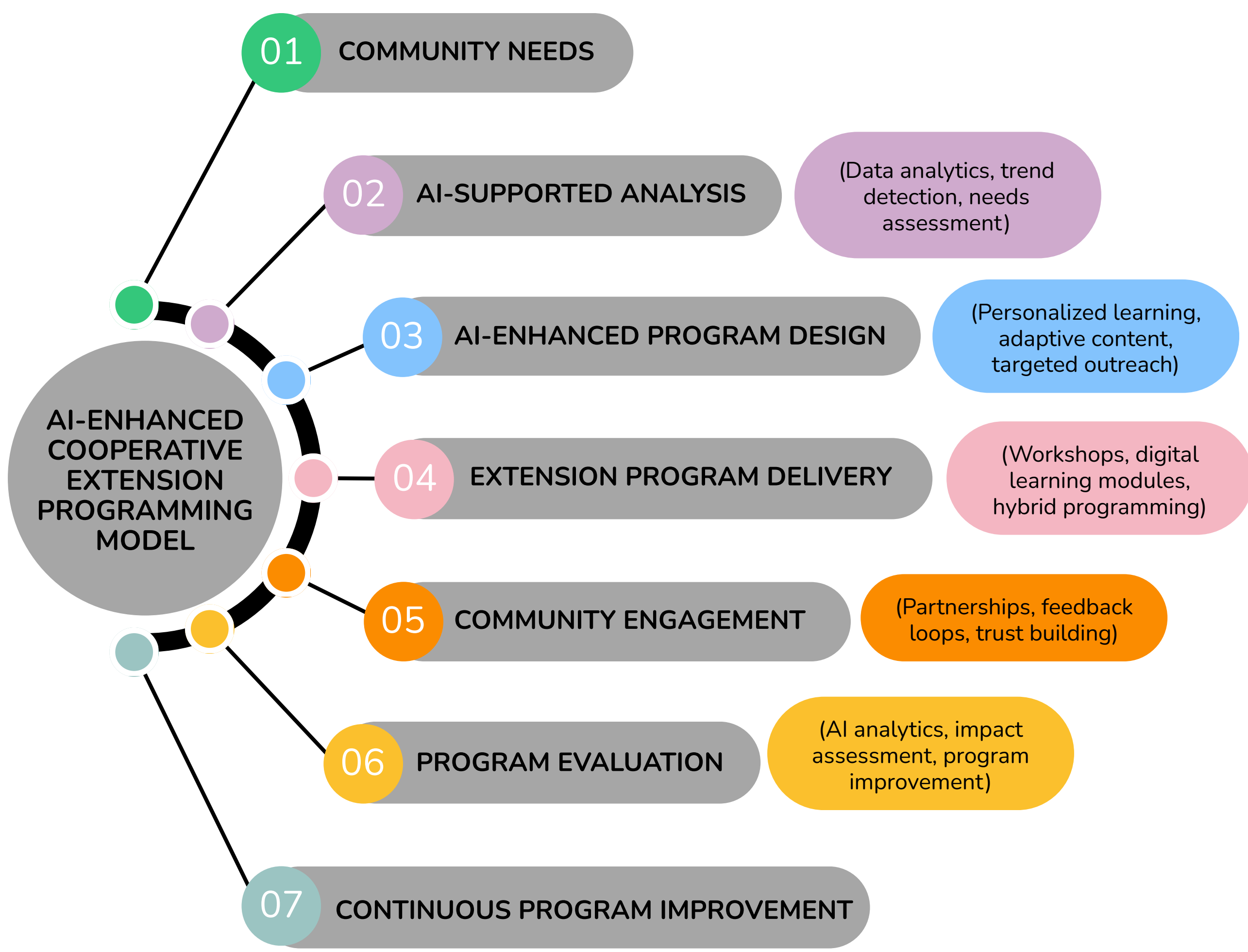
Professional Development and Workforce Capacity. Educators should develop proficiency in AI literacy, data ethics, and digital instructional design. Training programs that introduce Cooperative Extension professionals to AI tools and applications can enhance workforce capacity and support innovative programming (Keerthi et al., 2025). Early efforts across Cooperative Extension systems suggest that developing AI literacy among educators may lead to increased efficiency and improved program outcomes.

Discussion

This study provides compelling evidence that artificial intelligence (AI) has the potential to enhance Cooperative Extension programming by improving precision, scalability, and responsiveness in educational delivery. The literature supports AI as a tool that enables Extension professionals to move beyond traditional, one-size-fits-all approaches toward data-informed and learnercentered programming. This study identified AI's role in strengthening needs assessment and program targeting. By leveraging predictive analytics and real-time data processing, Extension systems can identify emerging community needs and tailor interventions more accurately accordingly (Raj et al., 2025). These findings expand existing literature by illustrating how AI can operationalize these principles at scale. For Extension educators, this represents a shift toward more strategic program planning that maximizes resource efficiency and program impact.

The findings also highlight AI's capacity to enhance educational effectiveness through personalization. Adaptive learning systems and AI-supported instructional tools enable educators to customized content and feedback, resulting in increased engagement and knowledge retention (Keerthi et al., 2025). This supports AI-Augmented Learning Theory of complementing rather than replacing educator expertise (See Figure 2: *AI Enhanced Cooperative Extension Conceptual Programming Model)*. The AI-Enhanced Cooperative Extension Programming Model (Figure 2) provides a conceptual framework for strategically

Figure 2: AI-Enhanced Cooperative Extension Programming Model illustrating how artificial intelligence can enhance needs assessment, program design, outreach, and evaluation.



integrating artificial intelligence across the Extension programming process. Rather than positioning AI as a stand-alone technology or replacement for Extension professionals, the model illustrates how AI-supported tools can be incorporated into established program planning, delivery, engagement, and evaluation practices. The model is cyclical and improvement-oriented, emphasizing that effective AI integration begins with identified community needs and ultimately supports continuous program improvement.

The model begins with **community needs**, reinforcing the principle that Extension programming should remain responsive to the priorities, challenges, and lived experiences of the populations served. AI integration is therefore not technology-driven; instead, technology is introduced in response to an identified educational or community need. This starting point is critical because it positions community priorities, rather than the capabilities of AI, as the foundation for program development.

The second component, **AI-supported analysis**, demonstrates how data analytics, trend detection, and needs assessment can assist Extension professionals in interpreting community data and identifying emerging needs. For example, AI tools could support the analysis of pre-program surveys, open-ended responses, demographic trends, or recurring questions from community members. These insights may help educators identify patterns that would otherwise require extensive manual review. However, professional judgment remains essential when interpreting AI-generated findings and determining their relevance to local contexts.

Insights from the analysis phase inform AI-enhanced program design. At this stage, AI may support personalized learning, adaptive content, and targeted outreach. Extension professionals could use identified audience needs to modify examples, adjust the complexity of educational materials, or develop differentiated learning resources for specific audiences. For example, pre-program assessment data may indicate that one group requires foundational budgeting instruction while another is ready to explore credit management or investment concepts. AI-supported design allows content to be more responsive while maintaining educator oversight and research-based standards.

The Extension program delivery component translates program design into practice through workshops, digital learning modules, and hybrid programming. This component recognizes that AI integration can occur across multiple delivery formats and should complement, rather than displace, Extension's educational and relational functions. AI-enhanced resources may provide additional learning support, generate practice scenarios, or facilitate individualized feedback; however, Extension professionals remain responsible for instructional quality, accessibility, accuracy, and audience appropriateness.

Community engagement serves as a critical connection between program delivery and evaluation. Partnerships, feedback loops, and trust-building ensure that community voices remain present throughout the AI integration process. This component is particularly important because the successful adoption of AI-supported programming may be influenced by digital access, AI literacy, privacy concerns, and community trust. Ongoing engagement provides Extension professionals with opportunities to identify unintended barriers, gather participant feedback, and determine whether AI-supported strategies are meeting community expectations.

The program evaluation component uses AI analytics, impact assessment, and program improvement processes to examine program effectiveness. AI may assist educators in analyzing quantitative and qualitative evaluation data, identifying trends in participant outcomes, and synthesizing large volumes of feedback. For instance, AI could help categorize open-ended evaluation responses to identify common themes related to participant satisfaction, knowledge gains, or implementation challenges. These findings should be reviewed and interpreted by Extension professionals to ensure that evaluation conclusions are accurate, ethical, and contextually appropriate.

Finally, evaluation findings contribute to **continuous program improvement**. This component reinforces the cyclical nature of the model. Evaluation results and community feedback are used to refine future needs assessments, AI-supported analyses, program designs, and delivery strategies. Therefore, AI integration is presented as an iterative process rather than a one-time technology adoption decision. As community needs, technological capabilities, and organizational readiness evolve, Extension professionals can continually assess and modify how AI is used within programming.

Collectively, the six interconnected components form a cohesive strategy for AI integration in Cooperative Extension. The model positions community needs as the starting point, AI as a supportive analytical and instructional resource, Extension professionals as the human decision-makers, and continuous improvement as the intended outcome. In this way, the framework provides Extension professionals with a practical pathway for moving from general interest in AI toward intentional, responsible, and community-centered implementation. Varsha et al. (2025) posit that integrating AI into program delivery may improve learning outcomes while allowing Extension professionals to devote greater attention to relationship-building and community engagement. However, realizing these benefits requires Extension systems to address significant barriers to equitable and responsible AI adoption.

Persistent digital inequities, including limited broadband connectivity, inadequate access to digital devices, and varying levels of digital and AI literacy, may disproportionately exclude rural, low-income, and other underserved communities from AI-supported programming. Extension organizations can help mitigate these barriers by integrating digital literacy and AI readiness into their programs, providing non-AI and low-technology participation options, expanding access to shared technology resources, and leveraging community partnerships to strengthen digital access, as demonstrated by the University of Maryland Extension's Marylanders Online program.

At the organizational level, developing scalable digital infrastructure and adopting AI tools that can be adapted across programs and delivery formats may support more sustainable implementation while reducing resource disparities among Extension units. In addition to access concerns, data privacy, algorithmic bias, and the ethical use of AI require clear organizational guidelines, transparent data practices, human oversight, and accountability measures. Addressing these challenges proactively is essential to ensure that AI strengthens, rather than widens, existing inequities and that its integration remains aligned with Extension's commitment to accessible, research-based, and community-centered education.

Conclusion

The implications of AI for Cooperative Extension are substantial and require a strategic, responsible, and community-centered approach to implementation. First, Extension systems must prioritize workforce capacity building to strengthen AI literacy and readiness among Extension educators. Second, organizations should invest in scalable infrastructure and strategic partnerships that support the sustainable integration of AI tools into program planning, delivery, and evaluation. Third, Extension systems must prioritize inclusive design, accessibility, and ethical oversight to ensure that AI-supported innovations do not magnify existing digital inequities or create new barriers to participation.

The AI-Enhanced Cooperative Extension Programming Model presented in this study provides a conceptual and practice-oriented framework for guiding this integration. The model connects community needs, AI-supported analysis, AI-enhanced program design, Extension program delivery, community engagement, program evaluation, and continuous program improvement in a cohesive and iterative process. By positioning community needs as the starting point and continuous improvement as an ongoing outcome, the model emphasizes that AI adoption should not be driven by technology alone. Rather, AI should function as a supportive resource embedded within established Extension programming processes, with Extension professionals maintaining human judgment, ethical oversight, and responsibility for program decisions. The model provides a practical pathway for moving Extension systems from general exploration of AI toward intentional and responsive implementation.

Future research should examine the model's application through longitudinal and large-scale evaluations of AI-supported programming within Cooperative Extension to assess sustained outcomes and impacts. Research is also needed to explore its implementation across diverse Extension program areas, including family and consumer sciences, youth development, agriculture, and community health, as well as across rural, urban, and digitally underserved communities. Empirical testing and refinement of the proposed model could further identify organizational readiness factors, implementation barriers, ethical considerations, and scalable practices that influence successful AI integration.

AI offers significant opportunities for Cooperative Extension systems to enhance their reach, relevance, and effectiveness in an increasingly complex and digital world. When implemented thoughtfully, ethically, and responsibly, AI can strengthen Extension's capacity to deliver research-based education, improve community programming outcomes and impacts, and uphold its commitment to equitable and accessible outreach. The AI-Enhanced Cooperative Extension Programming Model offers a strategic foundation for this work by ensuring that technology supports, not replaces the community relationships, professional expertise, and public-service mission at the core of Cooperative Extension.

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Tables

Table 1. Characteristics of the 20 Studies Included in the Scoping Review.

Author/Year	Purpose	Population/Setting	Methodology	AI Application	Key findings	Extension/ Community Relevance
Cao & Phongsatha (2025)	Evaluate effects of AI-driven blended learning on Business English performance and student engagement.	472 undergraduates in China; 240 AI-blended instruction and 232 conventional instruction.	Quasi-experimental pretest-posttest control-group design.	FLIT AI platform providing automated feedback, speech recognition, personalized analytics, and blended learning activities.	AI group significantly improved reading, listening, writing, and speaking and showed greater cognitive and behavioral engagement than controls.	Supports Extension blended/online education through personalized instruction, automated feedback, learner engagement, and scalable educational delivery.
Costa et al. (2024)	Determine effective machine learning (ML) approaches for estimating key water-quality parameters in an experimental watershed.	Experimental watershed with monitored water-quality and environmental data.	Quantitative predictive modeling comparing multiple ML techniques with cross-validation and hyperparameter optimization.	ML models for predicting biochemical oxygen demand (BOD), nitrate, and phosphate concentrations.	ML showed potential to estimate important water-quality parameters and support monitoring where conventional sampling is resource intensive.	Supports Extension water-quality education, nutrient-management programming, watershed monitoring, and data-informed conservation decisions.
Dai (2025)	Examine why engineering students choose to use or not use Generative AI (GenAI) during design activities.	403 undergraduate students in a large engineering design course.	Natural experiment examining students' voluntary GenAI use/non-use during engineering design projects.	GPT-4 powered chatbot for brainstorming, idea generation, addressing knowledge gaps, facilitating instructor/TA discussions, and optimizing design solutions.	59.8% substantially used GenAI; adopters used it for ideation, problem solving, and design optimization. Non-adopters cited output limitations, poor task fit, inadequate prompting skills, and unclear learning benefits.	Supports Extension/4-H STEM education through AI-assisted problem solving, design thinking, creativity, workforce preparation, and AI literacy; emphasizes training and evidence-based AI integration.
Delgadillo & Clouse (2025)	Examine financial literacy teachers' attitudes, AI adoption, and perceived barriers.	High school financial literacy teachers across 42 U.S. states; 152 complete responses.	Quantitative cross-sectional survey.	AI/Large language models (LLMs) for financial education, personalized learning, instructional materials, and student learning activities.	Teachers viewed AI positively, but adoption was limited; 63% cited lack of training, 66% ethical guidance, and 79% student overreliance as concerns.	Supports Extension financial education through AI-enhanced instruction while emphasizing professional development, ethical guidance, critical thinking, and responsible AI use.
Dong et al. (2022)	Develop a deep-learning approach integrating physical and social sensor data for predictive watershed flood monitoring.	Multiple flood-prone watersheds using flood sensors and community 3-1-1 reports.	Quantitative predictive modeling using multivariate time-series data and deep learning.	Deep learning integrating physical flood sensors with crowdsourced/social 3-1-1 reporting data.	Combining physical and social sensor information increased data availability and improved predictive flood monitoring across watersheds.	Supports Extension/ community disaster preparedness, flood-risk education, community reporting, emergency communication, and data-informed resilience planning.
Ezenwa (2025)	Examine how AI can expand access to finance, healthcare, and education in underserved communities.	Underserved rural and urban communities, including students, health workers, entrepreneurs, and community members.	Mixed methods: surveys, focus groups, interviews, and literature review.	AI credit scoring, diagnostic tools, predictive analytics, adaptive learning, and digital education.	AI expanded financial access, supported faster healthcare decisions, and improved STEM learning; barriers included digital access, bias, privacy, and low digital literacy.	Supports Extension use of AI for community education, digital literacy, health outreach, financial education, and equitable access in underserved communities.
Feng et al. (2025)	Examine AI applications, challenges, and future directions	Older adults with chronic diseases, including rural and	Systematic review	Machine learning, natural language processing (NLP), computer vision,	AI supports personalized care, health education, remote monitoring, medication	Supports AI-assisted health education and remote outreach to improve access and

Table 1. Characteristics of the 20 Studies Included in the Scoping Review Continued.

	in chronic disease management.	underserved populations.		telemedicine, and AI health education tools.	management, and decision-making; barriers include privacy, access, and user acceptance.	health literacy in rural and underserved communities.
Gangwani (2024)	Examine AI applications for improving crop yield and resource efficiency.	Agricultural production and precision farming settings.	Review/analysis	Predictive analytics, smart irrigation, pest/disease detection, precision fertilization, and robotic harvesting.	AI improved yield prediction accuracy by 15%, reduced water use up to 30%, and reduced fertilizer use by 20%, while supporting efficiency and sustainability.	Supports Extension education on precision agriculture, AI literacy, resource management, and technology adoption among farmers.
High et al. (2025)	Examine the potential and limitations of AI-enabled agricultural advisory systems for supporting learning, knowledge exchange, and innovation among smallholder farmers.	Farmer.Chat users across India, Kenya, Nigeria, and Ethiopia, with primary qualitative analysis focused on Kenya; platform data included 15,000+ users and 300,000+ queries.	Mixed-methods case study using platform analytics, focus groups, interviews, usability testing, phone surveys, shadowing, and conversational logs.	Farmer.Chat, a generative AI agricultural advisory platform using LLMs and retrieval-augmented generation (RAG) to provide multilingual, multimodal, personalized agricultural guidance through text, voice, and images.	Farmer.Chat improved the reach, timeliness, accessibility, and personalization of agricultural advice and reduced routine workload for Extension workers. However, its current model remains largely individualized and one-way, with limitations in farmer feedback, social learning, knowledge co-creation, equitable digital access, and accountability.	Demonstrates how generative AI can augment, not replace Extension agents by handling routine information requests while allowing agents to focus on complex problem-solving, relationship-building, trust, and farmer learning.
Jin et al. (2024)	Examine how GenAI affects creativity, ideation, revision, and decision-making in fashion design.	19 fashion design students, professionals, researchers, and practitioners.	Mixed-methods study using sketch experiments, interviews, focus groups, ratings, and thematic analysis.	Midjourney and DALL-E for text-to-sketch generation, concept ideation, sketch enhancement, and design revision.	GenAI provided rapid visual inspiration and enhanced ideation and decision-making but performed weaker in originality and customization; concerns included bias, IP/copyright, overreliance, and misalignment with designer intent.	Supports Extension/FCS fashion and textile education through AI-assisted creativity, design skill development, entrepreneurship, and workforce preparation while emphasizing AI literacy, ethics, and human-centered design.
Khairulanwar & Jamaludin (2025)	Examine lecturer perceptions, learning impacts, and barriers to AI integration in fashion design education.	3 fashion lecturers; Certificate of Fashion and Design program, Jeli Community College, Malaysia.	Qualitative descriptive phenomenological study using semi-structured interviews and thematic analysis.	AI for design ideation, information retrieval, design modification, virtual/3D visualization, prototyping, and fashion business applications.	AI improved access to design information, visualization, and understanding of fashion concepts; lecturers viewed AI positively. Barriers included technical limitations, student resistance, threats to foundational skills, and limited resources.	Supports Extension/FCS fashion education through AI-assisted design instruction, workforce preparation, digital literacy, and accessible community-based skills training; highlights infrastructure and training needs.
Kohli (2025)	Identify AI-related skills needed for future fashion jobs and assess whether the fashion design curriculum adequately prepares students.	Fashion industry professionals and the 4-year B.Des. Fashion Design curriculum at National Institute of Fashion Technology (NIFT), India.	Mixed-methods exploratory sequential design using literature review, industry benchmarking, and curriculum analysis.	AI/GenAI skills including prompting, text-to-image generation, analytics, patternmaking, pricing, production optimization, sustainability, and content development.	Current curriculum provides general, vocational, and basic digital skills but lacks sufficient AI-enabled competencies; curriculum revision is needed to prepare an AI-savvy workforce.	Highly relevant to Extension/FCS education, workforce development, textiles/apparel programming, AI literacy, and curriculum development for emerging technologies.
Li et al. (2025)	Examine factors influencing rural adolescents’	317 rural secondary students, grades 7–	Quantitative cross-sectional survey using	AI chatbots for accessible, personalized mental	Performance expectancy, ease of use, social influence, and	Highly relevant to Extension youth and rural programming;

Table 1. **Characteristics of the 20 Studies Included in the Scoping Review Continued.**

	adoption of AI chatbots for mental health education.	12, in Zhoukou, Henan Province, China.	Unified Theory of Acceptance and Use of Technology 2 (UTAUT2); Structural Equation Modeling (SEM) and hierarchical regression.	health education and support.	anthropomorphism increased adoption intentions; perceived risk reduced adoption. Privacy concerns were a key barrier.	demonstrates potential for AI to expand mental health education in underserved communities while emphasizing privacy, usability, trust, and adult/community support.
Mallya et al. (2023)	Develop ML models to predict watershed health and risk metrics in ungauged watersheds.	HUC-10 (Hydrologic Unit Code) watersheds across three U.S. river basins.	Quantitative predictive modeling using watershed, climate, soil, land-use, fertilizer, and geographic data.	Random Forest, AdaBoost, Gradient Boosting, Bayesian Ridge Regression, and ensemble ML for watershed health prediction.	ML successfully predicted sediment- and nutrient-related watershed health at ungauged locations; ensemble approaches improved predictive capability.	Supports Extension watershed education, conservation planning, nutrient management, and identificationof priority watersheds where monitoringdata are limited.
Mensah & Swortzel (2026)	Assess ChatGPT's accuracy in responding to Extension program planning and evaluation (EPPE) prompts.	U.S. Cooperative Extension; responses evaluated by two Extension programs planning and evaluation specialists.	Exploratory expert-judgment study using quantitative ratings and qualitative content analysis.	ChatGPT-4 applied to needs assessment, program design, resource allocation, program management, and participant engagement.	60% of responses were rated partially correct; none were irrelevant. Accuracy was limited by insufficient context and technical inaccuracies.	Demonstrates AI's potential to support Extension program planning and evaluation while emphasizing expert oversight, prompt engineering, ethical use, andAI capacity building.
Mohanty et al. (2016)	Evaluate deep learning for automated image-based identification of crop species and plant diseases.	54,306 images of healthy and diseased leaves representing 14 crop species and 26 diseases/healthy conditions from the Plant Village dataset.	Quantitative experimental machine-learning study comparing deep CNN architectures and training approaches.	Deep convolutional neural networks (AlexNet and GoogLeNet) for automated plant disease identification from leaf images.	Best model achieved 99.35% accuracy on held-out controlled images, but performance declined substantially on images collected under different conditions, highlighting real-world limitations.	Supports Extensioncrop diagnostics, plant- disease education, precision agriculture, and developmentof scalable smartphone- based tools that could help producers identify crop problems and access timely management information.
Sajja et al. (2025)	Develop and evaluate an AI-powered learning analytics tool for data-driven pedagogical decisions and personalized interventions.	University teaching faculty and higher-education learning environment, University of Iowa.	Original research involving system development, synthetic-data evaluation, and faculty survey feedback.	GPT-4 learning analytics to assess engagement, learning progression, emotions, study patterns, and cognitive development.	AI analytics showed potential to provide real-time instructional insights and support personalized interventions; faculty identified accuracy, privacy, and data-security concerns.	Transferable to Extension education for analyzing learner engagement, identifying educational needs, personalizing interventions, evaluating programming, and supporting educator decision-making.
Salhab & Aboushi (2025)	Examine how AI literacy and 21st-century skills influence students' acceptance of GenAI.	260 college students at Palestine Technical University-Kadoorie.	Quantitative cross-sectional survey using validated scales and multiple regression.	GenAI acceptance examined in relation to AI literacy, critical thinking, communication, collaboration, creativity, and problem-solving skills.	AI literacy and 21st-century skills significantly predicted GenAI acceptance; both were moderate among students, indicating need for targeted skill development.	Supports Extension digital literacy by demonstrating that successful AI adoption requires AI literacy, critical thinking, digital skills, and equitable access.
Tan et al. (2026)	Evaluate the feasibility and preliminary impact of an AI-assisted app for adolescent obesity-related behavior management.	172 primarily 6th-grade students from 5 public middle schools in Louisiana, largely serving socioeconomically disadvantaged populations.	8-week, one-arm pilot feasibility intervention with pre/post behavioral measures, engagement data, and NLP	GPT-4 supported ProudMe Tech provided personalized feedback for goal setting, self-monitoring, and reflection across diet, physical	Students achieved 63.8% of logged goals; screen time decreased 21.6%, while fruit/vegetable intake decreased 8.9%; physical activity and sleep did not significantly change. AI showed feasibility and	Highly relevant to Extension/FCS youth health and nutrition programming, demonstrating scalable AI-supported goal setting, personalized feedback, self-management, and

Table 1. Characteristics of the 20 Studies Included in the Scoping Review Continued.

			sentiment analysis.	activity, screen time, and sleep.	engagement but mixed behavioral effects.	behavior education in underserved school/community populations.
Zhu (2025)	Develop ML models to identify youth with low financial literacy and support targeted financial education.	989 youth ages 12 to 18 in Hong Kong.	Quantitative predictive modeling using cross-validation and ablation analysis.	Supervised ML: decision tree, random forest, light gradient boosting machine (GBM), and support vector machine (SVM).	Light GBM best predicted low objective financial knowledge (89.2% accuracy); random forest best predicted broader low financial literacy (93.3%). Financial, family, socialization, and parenting factors improved prediction.	Relevant to Extension financial education because ML could identify high-need audiences, support targeted interventions, reduce assessment burden/costs, and improve allocation of educational resources.

Table 2: **Thematic Distribution of Studies Included in the Scoping Review.**

#	Study	**Thematic Categories			
		Educational Delivery	Data-Driven Decision-Making	Outreach & Engagement	Challenges & Ethics
1	Cao & Phongsatha (2025)	X	X		
2	Costa et al. (2024)		X		
3	Dai (2025)	X			X
4	Delgadillo & Clouse (2025)	X			X
5	Dong et al. (2022)		X	X	
6	Ezenwa (2025)	X		X	X
7	Feng et al. (2025)	X	X	X	
8	Gangwani (2024)		X		X
9	High et al. (2025)	X		X	
10	Jin et al. (2024)	X	X		
11	Khairulanwar & Jamaludin (2025)	X			X
12	Kohli (2025)	X			X
13	Li et al. (2025)	X		X	X
14	Mallya et al. (2023)		X		
15	Mensah & Swortzel (2026)	X		X	X
16	Mohanty et al. (2016)		X		X
17	Sajja et al. (2025)	X	X		
18	Salhab & Aboushi (2025)	X			X
19	Tan et al. (2026)	X	X	X	
20	Zhu (2025)	X	X		
	Total	**15**	**11**	**7**	**10**

***Themes were not mutually exclusive; individual studies were coded within multiple thematic categories based on their reported AI applications, findings, and implications for Extension or community-based education.*

Thematic Categories	Summary of Thematic Distribution
AI in Educational Content Delivery	15 studies focused on how AI can personalize and enhance educational delivery across areas including financial education, fashion, health, agriculture, engineering, and digital literacy.
Data-Driven Decision-Making	11 studies examined the role of AI in supporting informed decision-making processes through AI/ML used to analyze data, predict outcomes, identify needs, support program planning, and inform educational interventions.
AI for Outreach and Engagement	7 studies explored AI's capacity to expand outreach and enhance community participation through digital platforms.
Challenges and Ethical Considerations	10 studies addressed digital literacy, access, and ethical concerns associated with AI integration.

Table 3: **Potential Applications of Artificial Intelligence in Cooperative Extension Programming**

Cooperative Extension Function	AI Application	Example Use
Needs Assessment	Data analytics and predictive modeling	Identifying emerging needs *(food safety, finance, health, agriculture, youth development, etc.) across counties*
Program Design	Adaptive learning systems	Personalized education modules in content areas
Outreach	Automated communication tools	Chatbots responding to community residents' questions
Program Delivery	AI-supported learning platforms	Interactive online courses or learning management system (LMS) modules
Program Evaluation	AI-driven analytics	Real-time program outcome analysis

Table 4: **Opportunities and Challenges of AI Integration in Cooperative Extension**

Category	Opportunities	Potential Challenges
Program Development	Personalized education programs	Limited staff AI training
Community Engagement	Expanded digital outreach	Digital literacy gaps
Data Analysis	Improved needs assessments	Data privacy concerns
Resource Efficiency	Automation of administrative tasks	Technology costs
Equity and Access	Broader program reach	Risk of widening digital divide

Table 5: Specific Examples of AI Tools Being Used to Enhance Cooperative Extension Programming.

AI Tools	Description
Chatbots and Virtual Assistants	Tools like IBM Watson and Google's Dialogflow are used to provide instant responses to common queries from community members, thus increasing efficiency in communication and outreach.
Predictive Analytics Software	Platforms such as RapidMiner are employed to analyze large datasets, enabling Extension professionals to predict community needs and tailor educational programs accordingly.
Adaptive Learning Systems	AI-powered platforms like DreamBox and Smart Sparrow customize learning experiences by adjusting the content based on individual learner's progress and comprehension levels.
AI Authoring Tools	Platforms such as Articulate 360, Jasper, Canva, ChatGPT, and Grammarly aid in content creation and course building for educational purposes.

Figure

Figure 1. PRISMA flow diagram for the Scoping Review ***(The PRISMA diagram highlights the final empirical studies selected). **All records were manually excluded; no automation tools were used.***