Agriculture College – Wasit University

Dijlah Journal of Agricultural Sciences

ISSN 2790 – 5985

eISSN 2790 – 5993

Dijlah J. Agric. Sci.، 4(2):66-78, 2025

E-Agricultural Education - A Review Study

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Abstract:

The labor market determines the type of skills required of agricultural college students. They must be prepared to meet the comprehensive educational requirements with skills and a comprehensive understanding of agricultural work, including a broad understanding of design theory through the application of course material, not just the study of it. Therefore, appropriate flexibility must exist between agricultural education and the curriculum to ensure that the academic plan achieves the desired change. Public schools have worked to develop agricultural education in various classrooms. The primary goal of education was more precisely defined, focusing on various aspects of agricultural production and advanced agricultural mechanization. This change was intended to adapt to the rapid change in the contemporary world. Curricula became more adaptable, including the teaching of fields indirectly related to agriculture, curriculum integration and coordination across post-secondary institutions, advances in information technology, and the constant pursuit of high academic achievement. The emergence and spread of online education are a significant development since the invention of writing. Undoubtedly, online education has been criticized for the failure of educational policies and strategies in many countries to keep pace with the widespread use of information technology.

Keywords*: Agricultural education, e-learning,Corona pandemic, vocational education, labor market*

Received:15/3/2025 **Accepted:3/4/2025** **Published:28/7/2025**

التعليم الزراعي الإلكتروني – دراسة مراجعة

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الخلاصة

يُعدّ سوق العمل العامل الحاسم في تحديد نوع المهارات المطلوبة من طلبة كليات الزراعة، إذ ينبغي إعدادهم لتلبية المتطلبات التعليمية الشاملة، بما يمتلكونه من مهارات وفهم عميق لطبيعة العمل الزراعي، بما في ذلك إدراك واسع لنظرية التصميم من خلال تطبيق محتوى المقررات الدراسية وليس مجرد دراستها نظريًا. ومن ثم، لا بد من وجود قدر مناسب من المرونة بين التعليم الزراعي والمناهج الدراسية لضمان تحقيق الخطة الأكاديمية للتغيير المنشود.

وقد عملت المدارس العامة على تطوير التعليم الزراعي ضمن الصفوف الدراسية المختلفة، حيث أُعيد تعريف الهدف الأساسي للتعليم بشكل أدق، ليُركّز على جوانب متعددة من الإنتاج الزراعي والميكنة الزراعية المتقدمة. وقد جاء هذا التغيير استجابة للتطورات المتسارعة في العالم المعاصر. فأصبحت المناهج أكثر مرونة، وشملت تدريس مجالات غير مرتبطة مباشرة بالزراعة، بالإضافة إلى دمج وتنسيق المناهج بين مؤسسات التعليم ما بعد الثانوي، إلى جانب التقدّم في تقنيات المعلومات والسعي المستمر لتحقيق التميّز الأكاديمي. ويُعدّ ظهور وانتشار التعليم الإلكتروني تطورًا بالغ الأهمية منذ اختراع الكتابة، ولا شك أن هذا النوع من التعليم قد واجه انتقادات، لا سيما بسبب فشل السياسات والاستراتيجيات التعليمية في العديد من الدول في مواكبة الانتشار الواسع لتكنولوجيا المعلومات.

الكلمات المفتاحية: *التعليم الزراعي، التعليم الإلكتروني، جائحة كورونا، التعليم المهني، سوق العمل*

Introduction

Agricultural education is one of the sixteen occupational groups taught in vocational and technical education programs. These courses provide students with a learning environment similar to a formal workplace, The agricultural education officer is responsible for developing a model through which students understand, comprehend, and master the agricultural work environment. This has resulted in students' skill development not only developing the skills required for the labor market but also focusing on the need to enhance their knowledge of agricultural terminology and agricultural practices. Teachers are responsible for inspiring student interest and providing general knowledge of a specific agricultural course or job opportunity, while helping students develop mental, physical, and emotional skills through curriculum design. Curriculum design describes the purposeful, deliberate, and systematic organization of the curriculum within a course. The goal of curriculum design is to enhance student learning while also helping align learning objectives for each level. There are different types of curriculum, the three most common of which are: learner-centered, problem-centered, and subject-centered. Subject-centered curriculum design focuses on a specific subject or discipline and describes what will be taught and how it will be applied. The other two focus on students' ability to master skills in college and careers, such as speaking English fluently, learning mathematics, and problem-solving (1). In the Common Core Curriculum, objectives are predetermined, and teachers must develop lesson plans to achieve them, including the teaching strategies used across schools and countries. The main flaw in curriculum design is that it is not student-centered but rather subject-centered (2). This curriculum design does not take into account students' learning styles can cause different problems when students engage.

Curriculum design primarily focuses on learners, their desires, needs, and aspirations to create choice and empower them. This curriculum design takes into account students' learning styles and aspirations. Differentiated instruction is an important and common method used in learner-centered curriculum design.

To effectively meet the needs of all students, educators must incorporate learner-centered approaches into their lesson planning. At the core of differentiated instruction lies the commitment to teaching fundamental communication and thinking skills to every student. (3) This approach is grounded in key principles such as ongoing formative assessment, an understanding of student diversity, collaboration, problem-solving, and offering learners choices. Recognizing that students have different interests, abilities, and learning preferences, differentiated learning encourages them to engage in tasks or activities that align best with how they learn. Ultimately, teachers who apply differentiated instruction understand the unique and shared characteristics of their students and intentionally use this insight to guide their instructional decisions.

The drawbacks of learner-centered curriculum design include the significant effort and relatively long learning time required by learners. Therefore, teachers must find a balance between the desired learning outcomes and learners' interests. Problem-centered learning is similar to teacher-centered learning. The difference is that student-centered learning poses a problem to learners and asks them to find a solution. This aligns with the job market by establishing a connection between the classroom lesson and real-world situations. This design, in turn, contributes to fostering creativity among learners and enhancing the relevance of the curriculum. Problem-focused design is a design that focuses on the subject itself, often without taking into account the student's learning styles. Curricula and their design provide opportunities for agricultural education students to engage in experiences that are considered one of the most important requirements of the agricultural sector. This enables management to identify real needs and for whom they must be met, and thus set clear learning objectives. Many agricultural careers require postsecondary education training. To ensure a smoother transition and qualified applicants, secondary and postsecondary education must also be synchronized to better prepare students. (4)

The study suggested that developing an effective and efficient program to create a trained and competent workforce extends beyond competency and skill development alone. Effective program development must include a broader view of program curricula, facilities, pedagogical methods, teacher education, agricultural organizations, student-teacher relationships, school-community links, curriculum globalization, and entry into agricultural professions to develop a trained and competent agricultural workforce (4).

Previous Studies

The five-step theory of diffusion and innovation is used in agricultural education, as well as in other non-agricultural fields. The theory of diffusion of innovations consists of five steps that discuss the factors affecting diffusion and how to deal with technologies from the perspective of individuals during communication within the social system (5). The number of elements that affect diffusion is four: time, communication channels, the social system, and innovation, while individuals go through five stages: knowledge, decision, persuasion, confirmation, and implementation. If the innovation is implemented, it spreads across the Internet and global networks through multiple channels. In fact, self-perceptions affect the spread of diffusion more broadly (5). This process occurs over a period of time until social systems achieve diffusion. A social system is characterized as a group of interconnected units engaged in joint problem-solving to achieve a common goal (6). Members of a social system may consist of individuals, informal groups, organizations, or subsystems.

Social systems are an important part of the adoption process; however, the social system can hinder innovation. Cognitive learning theory and behavioral learning theory are the two main approaches to how people learn in general. Jean Piaget's cognitive learning theory focuses on internal processes and how mental processes change and how external behavioral change occurs as a result of internal mental processes, including diagrams, the use of clear goals, directed practice, and practical classroom experiences. Behavioral learning focuses on external, visible changes in external behavior and how external stimuli influence positive change, student praise, and providing a safe and engaging classroom. (1). Social learning theory (7) claimed that cognitive and environmental factors play a powerful role in shaping behavior.

He says (7) Fortunately, much of what humans learn comes not from direct experience, but through observing others — a process known as modeling. If individuals had to depend only on the consequences of their own actions to guide their behavior, not only would learning be extremely difficult, but it would also involve significant risks.: by observing others, one forms an idea of how new behaviors are performed, and on subsequent occasions, this encoded information serves as a guide for action.

The creation of self-regulating learning abilities and techniques within the framework of social cognitive theory is a feature of the collaboration between "personal, behavioral, and environmental factors" (8). Social learning theory, which explains human behavior, describes the continuous interaction and exchange of behavioral, social, and environmental influences that span behavioral and cognitive framework (9). In classroom settings, the social behavior analysis approach is grounded in the idea that individuals tend to adopt integrated behaviors when these behaviors result in valuable outcomes (10. A key aspect of this theory is that people's decisions to accept or reject innovations are significantly influenced by the behaviors of others. Even when the benefits of an innovation are clear, not all individuals will adopt it immediately.

According to the theory of innovation diffusion, there are five categories of adopters. Innovators, representing 2.5% of the population, are the first to embrace new technologies. They typically possess the technical skills needed to understand and implement complex innovations. Early adopters follow, accounting for 13.5%. This group includes opinion leaders and risk-takers who actively seek advancements in teaching strategies and learning tools made possible by emerging technologies. (5, 11).

The next group, the early majority (34%), adopts innovations after observing their effectiveness. They are followed by the late majority (also 34%), who are generally skeptical, economically constrained, and more dependent on peer influence. Finally, laggards and latecomers make up 16% of the population. This group is characterized by older age, lower educational attainment, and a strong resistance to change and innovation.. (5, 11).

Diffusion of Innovation Theory

A theoretical approach that examines how a new product, technology, technological concept, or new use of an old production concept is transferred. Some criticism has been directed at this theory's ability to easily generate hypotheses. However, it provides a valuable foundation. Understanding adoption and diffusion relies on a well-developed foundation in agricultural education. Extension and agricultural practitioners must clearly contribute to the growth and development of agricultural systems to increase the effectiveness of new technologies and educational technology and to be aware of their implications for classroom teaching and learning processes.

Humanistic psychologists were responsible for developing the concept of learner autonomy, which demonstrated that students can create a personalized learning plan at different stages by finding resources to study in their environments and assessing themselves (12Different educational settings determine the extent to which learner autonomy should be emphasized, whether in a more limited or expanded form. Beyond following a fixed curriculum, the structure of learning may also depend on how much self-direction the environment permits. When students are encouraged to engage in direct learning, they become more capable of reflecting on their own experiences and developing their own understanding. This approach highlights the importance of learner autonomy, acknowledging that students can construct personal meaning through guided independence. This concept gave rise to the theory of interactional distance, which demonstrates that distance is not simply a geographical division between learners and teachers, but rather a more important pedagogical concept. The way interactions are analyzed is the interactional distances between both teachers and learners with the possibility of misunderstandings due to communication and psychological distance.

Over the past generations, student learning has gradually evolved in response to ongoing technological developments. Today, the pace of technological change is faster than ever, creating both opportunities and challenges for its integration into educational settings (13). Despite these challenges, it is widely recognized that incorporating technology into classroom environments can enhance both learning experiences and academic performance (14).

Distance education, often referred to as online or e-learning, has become a central element in this transformation. According to (15), distance education involves instructional activities where the teacher and student are not physically co-located. Expanding on this, (16) described it as a structured form of teaching and learning that typically takes place in separate locations, requiring the use of technology and specific institutional frameworks to facilitate communication and organization. This form of education is commonly known as online learning, especially when the teaching and learning processes occur in a virtual environment (16). Online learning is broadly defined as learning that happens either partially or entirely online (17), with some sources specifying that at least 80% of the course content must be delivered online to qualify (18). In fully online courses, 100% of the content is delivered via the internet (19).

The rise of distance education became particularly prominent during the 1980s and 1990s, driven by the expansion of broadcast technology. Researchers during this period focused on comparative studies, often examining the differences between television- or audio-visual-based instruction and traditional in-person classrooms (20; 21). With the advent of the internet in the 1990s and 2000s, distance education increasingly relied on digital tools such as email, asynchronous forums, and educational websites to facilitate learning.

However, as (22) observed, there remains a shortage of comprehensive research comparing learning outcomes between distance education and traditional classroom settings. The complexity of these comparisons stems from the many variables involved. More recently, a notable shift has occurred as higher education institutions increasingly embrace online distance learning, not only as an alternative but as a core component of their educational offerings. This transition reflects the growing emphasis on leveraging the internet to expand access to courses and academic qualifications. (23).

Educational institutions have made notable strides in adopting technology and supporting teachers in using essential digital tools. However, as noted in the Office of Technology Assessment's 1995 report on teachers and technology, many educators still struggle with effectively integrating these tools into the curriculum. Online learning platforms, traditionally, have functioned primarily through learning management systems (LMS) like Canvas, Blackboard, WebCT, Moodle, and Schoology. These systems facilitate communication, course interaction, and access to digital content.

To enhance learning experiences, the use of both synchronous and asynchronous communication methods should be encouraged. These platforms often offer features that allow students to submit assignments, take tests, and track their academic progress, including grades. Engaging with these systems typically requires students to regularly log in, download course materials, view multimedia presentations, and participate in topic-specific discussions. (24) Virtual education is an advanced educational model that uses the internet and computer software to deliver education to students. Virtual education, also known as e-learning, digital learning, or online learning, is a potential means of improving access to education, improving student performance, and cost-effectiveness for schools through the use of information technologies such as online learning, teacher-led distance learning, and computer-based learning.

Blended learning, online learning and facilitated learning. Research indicates no significant differences in student satisfaction. (25; 26, 27) and learning (25; 28). (29) studies the "no significant differences phenomenon," referring (30), where research on online learnning is viewed as "collective amnesia (surrounding) changes that occurred in a more distant time frame." (30) went on pointed out that people ignore events of the distant past, preferring to believe what they see themselves. In modern e-learning disciplines, some researchers need to study process variables in greater detail and depth, drawing on previous research on the same topic to better understand e-learning. (31) recommended the use of technology to address a contemporary and engaging issue in curriculum development to help learners achieve a more realistic learning outcome. Research progress has begun to address the fragmentation of findings on the impact of interactivity and communication on student learning (32; 33; 34). Personal learner benefits include, but are not limited to, self-paced learning, where learners can control their schedules to some extent, anytime, anywhere, with convenience, self-responsibility, the opportunity for repetition, and the opportunity to apply critical thinking (35). Most online learning is asynchronous, meaning it is pre-recorded or available at any time of day and from any location (36). Online learning offers students the flexibility to progress through coursework at their own pace, while still adhering to established deadlines for assignments and assessments. Although high school students are often provided with computer access to complete their online courses, they are not necessarily confined to a traditional classroom setting. Depending on the policies of the school and the capabilities of the learning management system (LMS), students may complete their coursework during evenings or weekends, from outside the school environment. This flexible structure empowers students to take greater ownership of their learning process and manage their schedules more independently. Moreover, virtual reality-based platforms enhance this experience by providing interactive training programs. These programs allow students to repeatedly practice learning objectives in a simulated environment before being formally assessed, thereby increasing confidence and mastery of the material.. The learner personality is characterized by a set of characteristics, including: self-directed learning, which learners can adjust and control, determine their time and place, and handle smoothly, taking into account self-responsibility, convenience, the opportunity for critical thinking, and the opportunity for repetition. 35. Online education is not face-to-face, meaning it is pre-recorded and available anytime, anywhere. 36. Online education offers speed of work and more convenient completion of deadlines, tests, and assignments. Students are not restricted to a classroom environment, as high school students have access to computers to work on their online courses outside of school on weeknights and weekends. Virtual reality-based programs provide flexibility and freedom for students to be more responsible for their own learning, and the use of computer training programs provides students with numerous opportunities to practice learning objectives before subject assessment. (37).

This opportunity gives students the opportunity for repeated practice before a test to ensure a higher chance of understanding. Online learnning empowers students by promoting autonomy and encouraging individual responsibility in managing their learning. Unlike traditional settings where students may be put on the spot to answer questions, online courses provide the flexibility for learners to pause, reflect, thoughtfully craft their responses. This process fosters deeper engagement and the development of critical thinking skills. (38)Through structured discussions and interactive platforms, online education creates an environment where learners can actively participate without the pressure of immediate response, ultimately cultivating more thoughtful and independent learners.(39; 40). Students who fail to achieve their educational aspirations and do not practice self-accountability are at risk of being lost in online learning. (41).

These potential advantages make online learning more acceptable ; Nevertheless, successful implementation demands considerable preparation and dedication, and it is important to acknowledge that certain disadvantages may arise along the way. (42). The majority of students may not excel in an online learning environment if self-regulation skills are learned in an unconventional way, and poor training may have a negative impact on academic retention. (43; 44). To be effective in an online learning environment, students need to shift from passive learning, Through a constructivist approach that emphasizes active learning, the student builds on prior knowledge, while the teacher serves as the primary facilitator of the learning process. (45; 46; 47). (48) Information technology cannot produce learning and understanding if the current educational environment fails to provide opportunities for decision-making and communication to solve problems. She claimed that discussing the advantages and disadvantages of using technology in the teaching and learning process is misguided. “Technology is an effective means to achieve an end.”

Students’ perceptions of taking courses within an online learning environment were examined when (49) used a qualitative experimental research method with group discussion and then They used this data to develop a questionnaire to validate the quantitative data collected to address students' needs and expectations within virtual learning classrooms. The sample consisted of undergraduate students majoring in operations research.

To identify students’ expectations within the online learning environment, researchers conducted a general discussion followed by an analysis of eight distinct categories. These categories were subsequently organized into two main groups : independent work included installation, software environment, content, user guidance, and online functions, while self-assessment focused on learning assessment, examples, help functions and feedback (50). Both the quantitative and qualitative aspects of the research support students' desire to work independently. Students expressed a desire to customize learning materials by incorporating common features, including comments, highlighting tools, and bookmarks. Both men and women felt it was essential to customize their learning materials so that students who take control of their learning know how and where to acquire the skills necessary to excel in the modern online learnning environment (51). “Technology can play a vital role in helping students meet higher standards and perform at increased levels by promoting alternative and innovative approaches to teaching and learning” (52). The self-regulated learning model suggests that Before individuals can enhance and develop effective learning skills, certain psychological, developmental, or environmental factors must be addressed. (53)By actively engaging with these influences, learners can strengthen their abilities and adopt more effective strategies for self-regulated learning. (54). “E-learning requires more maturity and self-discipline from students than traditional classroom instruction, which may explain the higher dropout rates in e-learning programs compared to traditional programs” (55). Traits demonstrated by learners include

Critical thinking, active participation in the learning process, and accountability for their learning. (56) examines the advantages and disadvantages and compares the effectiveness of e-learning versus traditional classroom instruction. Each group was allocated an equal lecture timeframe and consistent experimental procedures were used. Learning effectiveness was then collected using unbiased measures, from pre- and post-lecture test scores and subjective measures of post-experiment satisfaction observed using a 7-point Likert scale. The findings consistently demonstrated that students achieved significantly higher evaluation scores in e-learning environments compared to traditional classroom settings. However, the difference in perceived satisfaction between the two modes of instruction was not statistically significant. Despite this, a majority of students in the e-learning group expressed satisfaction with the self-directed learning model, which offered high interactivity and substantial flexibility within the virtual learning environment (57).

Data also indicate that online learning is gaining global popularity and is being increasingly incorporated into agricultural education programs(58). However, a study examining the objective self-awareness of teaching competencies found that faculty members in the Faculty of Agriculture and Life Sciences exhibited limited familiarity with the fundamentals of online learning(59). saw how online of learning in agricultural sciences could improve agricultural production. The results showed that virtual reality technology could increase agricultural productivity and that the proposed virtual of reality could stimulating agricultural research, education and training. (60) conducted a study on agricultural e-learning to identify the potential for increasing returns on agricultural production. To broaden students' horizons, they are required to participate in online courses. According to McDonald (2002), online learning programs facilitate open learning opportunities for individuals who share common interests. A objective of (60)'s was a search determine whether e-learning was more beneficial than traditional learning in agricultural education in terms of engaging a larger number of students. They followed a qualitative approach, to study the benefits, basic principles, and applications of e-learning in agricultural training and education.

The result's indicated that e-learning achieves a wide-ranging use of educational training in developing agricultural education by facilitating new technology to increase productivity and agricultural productivity methods in a limited time through online learning. (60) However; when examining the advantages, benefits and disadvantages, limitations of implementing e -learning for students in agricultural higher education, (61) found opposing results. The results indicated that online of learning has many potentials in a aforementioned fields, but the obstacles related to infrastructure and teaching have led to the abandonment of the integration of online learning environments into agricultural teaching and training. Online learning removes the constraints of traditional curricula in terms of time, space, resources, and direct access to other forms of education, enhancing the international dimension of educational services and assessing the rate of improvement in courses. Unfortunately, online learning has suffered from a lack of instructors, access to unsupportive information, and limited assessment and student input.

(62) explore the perceptions of participating teachers as well as high school students. in an integrated online learning experience in technology, science, engineering, mathematics (STEM) within poultry science. The online learning modules combined (STEM) with the challenges of successful management of laying hens.

Conclusion

Learning within an online environment is likely to improve knowledge transfer and retention (63; 64). (65) proposed integrating technology into STEM education in terms of teaching and delivery. Program (65) highlighted technologies used in good facility management, including compost management, climate control, and egg collection and processing, is essential for students' learning through an online software platform, requiring high school students to interact authentically with simulations. Participating teachers and high school students commented that the program helped them better understand both science, technology, engineering, and mathematics (STEM) and agriculture as disciplines, and served as a useful integrated learning experience for students. helped connect learning to real-world problems (65). Online of education has grown rapidly over the past two decades. However, online research in agricultural education on teachers' perceptions of online courses remains limited. (66) challenged teachers to shift to more active learning environments rather than passive learning environments (67) modern technological developments, online courses, social media, widespread communications, and improvements in thinking and problem-solving skills have had a significant impact on the spread, growth, and planning. (68).

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