Enhancing Engagement in STEM Education: Evaluating Learning Preferences and Improvements in a Digital Agriculture Camp

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Introduction

Digital agriculture is revolutionizing farming by integrating advanced technologies to improve efficiency, sustainability, and productivity. A key aspect of this transformation is precision agriculture, which optimizes resource use while reducing environmental impact (Ballabh, 2022; Feng, 2024). Drone technology and data science enhance these efforts by capturing and analyzing data for crop monitoring, providing key insights that inform decision-making for more profitable farming practices that boost yields (Das, 2024; Gopathoti, 2023; Raza et al., 2023). While these innovations are reshaping agriculture to meet growing global food demands, their widespread adoption depends on developing a skilled workforce. While nonformal learning opportunities, such as those provided by FFA and 4-H, can help bridge this gap by offering hands-on experiences with digital agriculture and fostering interest in the field (Ramsey & Edwards, 2011; Stripling et al., 2014) there remains a need for targeted efforts to connect specific digital tools with the broader discipline of digital agriculture.

To engage secondary students in digital agriculture, a three-week residential summer camp was established at Middle Tennessee State University, offering hands-on experiences with digital agriculture technologies. The camp ran for three consecutive summers (2022, 2023, 2024), welcoming new students each year. Campers entering grades 9-12 explored precision agriculture by collecting crop data with digital tools, worked with drones to gather additional data, and built foundational data science skills by learning to code in Python for data analysis. Throughout the camp, students applied newly acquired skills to develop solutions to hypothetical challenges.

The purpose of this study was to identify key insights for improving future camp program design. One research question guided this study's purpose: How did participants' perceptions of a digital agriculture summer camp evolve over three years? This study contributes to the broader field of experiential learning and STEM education by demonstrating how student-driven feedback can guide curriculum improvements in nonformal learning settings.

Theoretical Framework

Kolb's (1984; 2015) experiential learning theory (ELT) provided a framework for understanding how a digital agriculture camp can aid students in the development of essential skills needed to pursue careers or postsecondary education in digital agriculture. ELT posits that effective learning emerges from a cyclical of concrete experience, reflective observation, abstract conceptualization, and active experimentation. In this setting, students not only developed essential skills for pursuing careers or further education in digital agriculture but also provided ongoing, student-driven feedback that guided iterative curriculum improvements.

Methods

The population for this study included all participants (N = 39) in the digital agriculture summer camp conducted over three consecutive years. Participants were distributed across Year 1 (n = 11, 28.2%), Year 2 (n = 16, 41.0%), and Year 3 (n = 12, 30.8%). Utilizing census sampling, all camp participants (i.e. the population) were included in the data collection process. Each summer, a camp evaluation survey was administered on the final day of camp with a 100% participation rate. The survey included open-ended questions: (1) Which three learning activities did you enjoy the most (excluding meals and social time)? (2) Which three learning activities did you enjoy the least (excluding meals and social time)? and (3) What three recommendations would you suggest for improving the digital agriculture camp? Open-ended responses were analyzed and the frequency of similar statements based on the three questions were calculated.

Results

When asked to describe the learning activities they enjoyed the most, 11 (100%) of Year 1 participants stated they enjoyed building and flying the drones. The equine center tour was also a favorite activity of some Year 1 participants (n = 5, 45.45%). Year 2 participants echoed the previous year with 11 (68.75%) participants stating that drone building and flying were their favorite activities. New to this participant group, nine (65.25%) participants indicated that coding and soil testing were two activities they enjoyed. Year 2 participants also appreciated the opportunity to work with professors and fellow campers on projects (n = 7, 43.75%). Year 3 participants were more varied in their favorite activities with building and flying drones (n = 10, 83.33%), soil analysis (n = 9, 75%), and tours (n = 9, 75%) being the most popular. When participants were asked to describe their least favorite learning activities, all (n = 11, 100%) of Year 1 participants mentioned long lectures as their least favorite activity. While some Year 2 participants (n = 5, 31.25%) mentioned the length of lectures, half expressed frustration with the lack of hands-on application of what they learned (n = 8, 50%). No Year 3 participants mentioned lectures as their least favorite activity, however, many participants (n = 10, 83.33%) mentioned coding and the use of Python. When asked to identify areas of improvement for future camps, most (n = 8, 72.27%) Year 1 participants focused on environmental factors such as better dorms, busses, later curfews, and different meals. Most (n = 10, 62.50%) Year 2 participants also identified environmental factor improvements, while some (n = 7, 43.75%) indicated a desire for more tours and making the tours longer. In the final year of the camp, just more than half of participants (n = 7, 58.33%) desired more time to work on the final project and participate in the provided hands-on activities.

Conclusions, Implications, and Recommendations

The findings indicate that hands-on, interactive learning experiences were consistently the most engaging activities across three years of the Digital Agriculture Camp supporting the findings of Ramsey and Edwards (2011) and Stripling et al. (2014). Traditional lecture-based instruction was repeated as the least enjoyable aspect in Years 1 and 2, while Year 3 participants focused on challenges with coding and Python. Recommendations for practice include incorporating more hands-on learning (e.g. smaller group discussions or interactive demonstrations) while reducing extended lecture time to enhance engagement. Additionally, offering an introductory coding session before camp could help make the subject more accessible. The implications of this research extend beyond the digital agriculture camp, offering insights into effective STEM education strategies for high school students. The findings reinforce the need for adaptive teaching methods that balance technical instruction with interactive experiences and highlight the importance of experiential learning (Kolb 1984, 2015), emphasizing that engagement increases when students can apply concepts in real-world settings.

References

Ballabh, J. (2022). Advancements in precision agriculture technologies for enhancing crop yields. *Journal of Survey in Fisheries Sciences*, *8*(3) 403–408. https://doi.org/10.53555/sfs.v8i3.2399

Das, S. (2024). Transforming agriculture: Harnessing robotics and drones for sustainable farming solution. *Journal of Experimental Agriculture International*, *46*(7), 219–231. https://doi.org/10.9734/jeai/2024/v46i72577

Feng, H. (2024). The evolution and potential of precision agriculture in China anchored in "3s" technology. *Highlights in Science Engineering and Technology*, *81*, 592–597. https://doi.org/10.54097/43n29y21

Gopathoti, K. (2023). Precision agriculture and the role of machine learning. *International Journal of Scientific Methods in Intelligence Engineering Networks*, *1*(6), 1–8. https://doi.org/10.58599/ijsmien.2023.1601

Kolb, D. A. (1984). *Experiential learning: Experience as the source of learning and development*. Prentice-Hall.

Kolb, D. A. (2015). *Experiential learning: Experience as the source of learning and development* (2nd ed.). Pearson Education.

Ramsey, J., & Edwards, M. C. (2012). Entry–level technical skills that teachers expected students to learn through supervised agricultural experiences (SAEs): A modified Delphi study. *Journal of Agricultural Education*, *53*(3), 42–55. https://doi.org/10.5032/jae.2012.03042

Raza, A., Safdar, M., Shahid, M. A., Rasul, F., & Sabir, R. M. (2023). Applications of drones in high-tech agriculture. In *Handbook of research on AI-equipped IoT applications in high-tech agriculture* (pp. 88–108). IGI Global. https://doi.org/10.4018/978-1-6684-9231-4.ch005

Stripling, C. T., Roberts, T. G., & Stephens, C. A. (2014). Mathematical strengths and weaknesses of preservice agricultural education teachers. *Journal of Agricultural Education*, *55*(1), 24–37. https://doi.org/10.5032/jae.2014.01024