



A Tool to Measure Farmers' Training Needs in Drone-based Technologies

B. Arulmanikandan^{1*}, P. S. Shehrawat², J. S. Malik³, Bhavesh⁴ and Aditya⁵

¹Ph.D. Scholar, ²Principal Scientist, ³Professor, Department of Agricultural Extension Education, CCS HAU, Hisar, Haryana, India

⁴Research Scholar, Department of Agronomy, Western Sydney University, Australia

⁵Research Scholar, Department of Agronomy, CCS HAU, Hisar, Haryana, India

*Corresponding author mail id: manikandanarul02@gmail.com

HIGHLIGHTS

- The 34 out of 53 training need statements met statistical criteria, ensuring relevance for agricultural drone technology.
- Item-total correlation analysis retained items with strong associations ($r \geq 0.70$), improving scale reliability.
- Cronbach's Alpha for all constructs exceeded 0.80, confirming high internal consistency and construct reliability.
- The highest t-values indicated the importance of online courses, weather conditions, and irrigation management for drone adoption.

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ABSTRACT

A measurement tool has been developed to determine the training needs of farmers in the usage of drone-based technologies towards the sustainable agriculture. A list of 84 statements was collected and refined based on Edward's 14 principles and 53 statements were retained for administering to farmers from non-sampling areas for further analysis. The statements were categorised under four constructs viz. Training Need for Drone Technical Knowledge (DTK), Platform for Learning Drone Technology (PLT), Practical Applications in Agriculture (TNP), Regulations, Permits, and Safety Protocols (TRS). Finally, the t-value for each statement was calculated and found that 34 statements had a t-value greater than 1.75. The 34 statements were further computed by item-total correlation analysis. The four items were found less than the threshold level of 0.30 implies a very weak association, and were removed to improve scale reliability. The final 30 statements were retained for the final scale and administered for reliability and validity testing. The Cronbach's alpha coefficient validated that all four constructs demonstrated high reliability ($\alpha > 0.80$), signifying that the items within each construct were strongly correlated and confirmed the internal consistency of the developed scale. The content validity of the scale was established with the judgement of the experts.

INTRODUCTION

As India progresses towards Agriculture 5.0, defined by automation, data-centric farming, and intelligent technologies, drones are anticipated to be instrumental in the modernisation of the agricultural sector. Drones provide enhanced spatial and temporal resolutions compared to conventional techniques like manual scouting or satellite imaging, enabling farmers to monitor crop health, identify diseases, and evaluate soil conditions with remarkable precision (Sengupta, 2023; Martel et al., 2021). Drones equipped

with multispectral sensors can capture high-resolution images to identify variations in chlorophyll content, water stress, and nutrient deficiencies, allowing farmers to rectify issues before they worsen (Moses-Gonzales et al., 2021; Yue et al., 2018). This capability mitigates crop losses and diminishes dependence on chemical treatments. Drones outfitted with soil moisture sensors and thermal cameras offer critical insights into soil and plant hydration levels, facilitating accurate irrigation methods (Guebsi et al., 2024; Zhang et al., 2019). Despite their transformative potential, drones have numerous adoption challenges. The deficiency of technical

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proficiency among small-scale farmers presents a major challenge (Rejeb et al., 2022; Lahiri et al., 2024). Ethical and privacy issues must also be considered. Farmers must ensure that drone operations adhere to the privacy of properties nearby and conform to data protection regulations (Guebsi et al., 2024). The environmental consequences of frequent drone usage, including disturbances to wildlife, necessitate careful consideration (Mahroof et al., 2021). The availability of trained drone pilots might be another potential hindrance to the adoption of drone-based applications in the lo. This research article aims to address this gap by introducing a scale designed to assess the training requirements of farmers regarding the utilisation of drone-based technologies in agriculture. Consequently, the present study enhances the existing body of knowledge by offering a thorough and context-specific measurement instrument that can direct future research and inform evidence-based policies and programs. This research aims to enhance the understanding of farmers' training needs for the proper application of drone-based technologies in agriculture, thereby contributing to sustainable agricultural practices and development.

METHODOLOGY

The present study follows the summated rating method, as Likert suggested (1932), to develop a training needs assessment scale for farmers' usage of drone-based technologies in agriculture. The Likert scale measures individual differences among respondents regarding their possession or opinion on a specific attribute or aspect (Ramya et al., 2019). The methodologies employed by Kumar et al., (2016); Gupta et al., (2022) & Vijayan et al., (2022) were followed according to.

The statements related to different dimensions of training needs in drone-based technologies were collected from a comprehensive literature review and expert consultations with specialists in agricultural extension education, precision agriculture, and digital technologies. A tentative list of 84 statements was drafted to ensure applicability and these statements were then edited and refined based on 14 criteria suggested by Edwards (1957) to ensure clarity, relevance, and validity. After expert evaluation, irrelevant or redundant statements were removed, leading to a final selection of 53 statements for the training needs scale.

Finally, the statements were administered to 50 farmers from a non-sampling area and the responses were collected using a five-point Likert scale, where farmers could indicate their level of agreement or disagreement with each statement from strongly agree to strongly disagree. To ensure item validity, a t-test analysis was conducted for each statement. The computation of a t-value for each statement to assess its ability to differentiate between farmers with high and low training needs. The t-value serves as a measure of differentiation, identifying statements that effectively distinguish between farmers who require more training and those with existing knowledge. Statements with t-values significant at the 5% level ($p < 0.05$) were selected for the final training needs scale.

The current study involved Cronbach's Alpha to assess reliability using the Statistical Package for Social Sciences (SPSS 26.0). Different authors have varying opinions regarding the acceptable alpha value for internal consistency. Di-Iorio (2005) advocates for a value close to 1.0, while Streiner & Norman (2008)

propose that values between 0.70 and 0.90 are adequate. The construction and content validity of the scale aimed to establish the instrument's validity. Minor modifications to the wording and structure of the instrument were implemented based on the recommendations of the panel of experts selected in this study. Furthermore, validity is typically a matter of degree rather than an absolute characteristic, and validation is an ongoing process (Nunnally & Bernstein, 1994).

RESULTS

Selection of training needs statements for the final scale

Statements with t-values ≥ 1.75 and p-values ≤ 0.05 demonstrate strong differentiation and statistical significance. After computing the "t" value for all the items, 34 statements showing a significant difference between low and high groups with t-values ≥ 1.75 and at a 5% level of significance ($p < 0.05$) were selected. It has been concluded that 19 items failed to show strong statistical significance, with low t-values (< 1.75) and high p-values ($p > 0.05$), indicating that they do not significantly differentiate between groups for the measurement of training needs demanded to be measured. It has been decided these are to be removed from the scale. Statements with strong t-values and low p-values should be retained for scale development (Table 1). The range of t-values for the selected items ranged from a maximum of 8.66 to a minimum of 2.53. In this way, 34 out of 53 statements were retained for further analysis.

Item-total correlations were computed for 34 of the items. This practice is a commonly accepted procedure when developing a scale (Churchill, 1979). The Item-Total Correlation (r-value) is a measure that evaluates how well each item correlates with the total scale score, providing an important analysis of the consistency and reliability of individual items within a given scale. A higher item-total correlation (≥ 0.70) indicates a strong relationship between an item and the overall construct being measured, suggesting that the item is a meaningful contributor to the scale. Items with a varied range of correlation (0.30-0.69) also align with the construct and are still acceptable. However, a lower item-total correlation (< 0.30) implies a very weak association, which may indicate redundancy, irrelevance, or the need for removal to improve scale reliability. Following this, items such as 'understanding different drone types and their suitability' (0.239), 'the impact of wind speed and altitude on drone stability' (0.191), Collaborative research initiatives between universities and farmers (0.078) and Ethical considerations in drone-based farm monitoring (0.226) exhibited weak correlations (< 0.30), suggesting they do not contribute meaningfully to the scale. To purify the scale, these items were eliminated. This procedure resulted in 30 items, out of the original 34, being retained.

Validity and reliability analysis

Content validity was employed to assess the scale's validity. Content validity involves a systematic analysis of the test content to ensure it represents a comprehensive sample of the behavioural domain being evaluated. In this study, we established content validity by gathering statements from pertinent literature and obtaining the opinions of experts in the field of extension, who possess extensive experience in this area. The methodology of

Table 1. Item analysis and item co-relational analysis of statements

S.No. Statements	t-value	p-value	r- value
Training Need for Drone Technical Knowledge			
1. Basic drone navigation and control techniques.	5.087	0.000	0.716
2. Drone software for flight planning and execution.	5.692	0.000	0.648
3. Drone maintenance and troubleshooting common technical issues.	5.692	0.000	0.704
4. Understanding battery management and maximising flight time.	5.159	0.000	0.673
5. Integration of sensors with drones for data collection.	5.382	0.000	0.658
6. Weather conditions and their impact on drone operation.	7.890	0.000	0.704
7. Understanding of GPS technology and its role in drone navigation.	5.367	0.000	0.573
8. Understanding different drone types and their suitability.	3.704	0.001	0.239
9. Impact of wind speed and altitude on drone stability.	2.307	0.025	0.191
Platform for Learning Drone Technology			
10. Agricultural extension services for learning drone technology.	4.717	0.000	0.753
11. Online courses or training modules on drone technology.	8.664	0.000	0.622
12. Hands-on workshops or field demonstrations for drone usage.	6.162	0.000	0.552
13. Learning platforms for sharing drone knowledge and experiences.	4.610	0.000	0.711
14. Government or private-sector-sponsored training initiatives.	6.284	0.000	0.659
15. Digital resources (videos, webinars) for self-paced learning.	4.128	0.000	0.653
16. Collaborative research initiatives between universities and farmers.	4.245	0.000	0.078
Training Need for Practical Applications in Agriculture			
17. Crop health assessment (disease detection through imaging).	6.308	0.000	0.681
18. Crop mapping and accurate field models using drone data.	4.454	0.000	0.629
19. Irrigation management and optimising water distribution.	6.614	0.000	0.635
20. Precise pesticide/fertiliser application.	6.079	0.000	0.736
21. Crop damage evaluation.	6.169	0.000	0.683
22. Soil health monitoring and nutrient deficiency detection.	4.301	0.000	0.781
23. Planting and seeding operations.	5.683	0.000	0.671
24. Integrate drone data for yield estimation and forecasting.	5.002	0.000	0.610
25. Livestock monitoring (tracking movement, health, and behaviour).	6.340	0.000	0.684
26. Monitoring and managing crop stress.	5.609	0.000	0.712
Training Needs for Regulations, Permits, and Safety Protocols			
27. Local drone flying regulations specific to agriculture.	4.532	0.000	0.663
28. Permits required for operating drones in agricultural zones.	5.159	0.000	0.677
29. Safety protocols, including pre-flight and post-flight safety checks.	6.465	0.000	0.616
30. Understanding airspace restrictions and drone no-fly zones.	4.390	0.000	0.834
31. Privacy and data protection laws.	4.462	0.000	0.808
32. Emergency procedures and drone recovery methods.	5.754	0.000	0.745
33. Obtaining and renewing licenses or certifications for drone operation.	6.340	0.000	0.719
34. Ethical considerations in drone-based farm monitoring.	2.527	0.015	0.226

content validity testing corresponds with the suggestions of Shitu et al., (2018) and has also been utilised by others (Gupta et al., 2022; Chandra et al., 2024; Tripathy et al., 2024) to evaluate the validity of their research instrument.

Reliability, as articulated by Ray & Mondal (2011), refers to the degree of consistency observed across multiple measurements of a specific variable. In this study, we employed the Cronbach alpha coefficient, a measure of internal consistency, to evaluate the reliability of the measurement instrument. The procedure entailed analysing the responses from the study participants utilising SPSS statistical software. Cronbach's alpha is a coefficient that measures the degree of correlation among items within a scale. A higher alpha value indicates increased reliability. A construct is reliable if the Cronbach Alpha (α) value is greater than 0.70 and, in some cases, a Cronbach coefficient of 0.6 and more is also considered good enough to prove the reliability of the measuring instrument.

Construct reliability was assessed using Cronbach's Alpha by using the SPSS tool. The results revealed that the Training Need for Drone Technical Knowledge (DTK) scale with eight items ($\alpha=0.856$) and the Platform for Learning Drone Technology (PLT) scale with six items ($\alpha=0.823$) were found reliable. Similarly, the Training Need for Practical Applications in Agriculture (TNP) scale with ten items ($\alpha=0.899$) and the Training Needs for Regulations, Permits, and Safety Protocols (TRS) scale with seven items ($\alpha=0.898$) were also found reliable. Reliability results are summarised in Table 2.

DISCUSSION

The scale development process involved a detailed selection and refinement of items that ensured the validity and reliability of the measurement tool. The selection of training need statements was based on statistical criteria, wherein items with t-values ≥ 1.75 and p-values ≤ 0.05 were deemed statistically significant and

Table 2. Reliability Statistics

Constructs	No. of Items	Cronbach Alpha (α)
Training Need for Drone Technical Knowledge (DTK) Basic drone navigation and control techniques. Drone software for flight planning and execution. Drone maintenance and troubleshooting common technical issues. Understanding battery management and maximizing flight time. Integration of sensors with drones for data collection. Weather conditions and their impact on drone operation. Understanding of GPS technology and its role in drone navigation.	07	0.856
Platform for Learning Drone Technology (PLT) Agricultural extension services for learning drone technology. Online courses or training modules on drone technology. Hands-on workshops or field demonstrations for drone usage. Learning platforms for sharing drone knowledge and experiences. Government or private-sector-sponsored training initiatives. Digital resources (videos, webinars) for self-paced learning.	06	0.823
Training Need for Practical Applications in Agriculture (TNP) Crop health assessment (disease detection through imaging). Crop mapping and accurate field models using drone data. Irrigation management and optimizing water distribution. Precise pesticide/fertilizer application. Crop damage evaluation. Soil health monitoring and nutrient deficiency detection. Planting and seeding operations. Integrate drone data for yield estimation and forecasting. Livestock monitoring (tracking movement, health, and behavior). Monitoring and managing crop stress.	10	0.899
Training Needs for Regulations, Permits, and Safety Protocols (TRS) Local drone flying regulations specific to agriculture. Permits required for operating drones in agricultural zones. Safety protocols, including pre-flight and post-flight safety checks. Understanding airspace restrictions and drone no-fly zones. Privacy and data protection laws. Emergency procedures and drone recovery methods. Obtaining and renewing licenses or certifications for drone operation.	07	0.898

exhibited robust differentiation between low and high training need groups. Of the 53 initial statements, 34 satisfied the criteria and were retained for further analysis, whereas 19 items were removed due to low t-values (<1.75) and high p-values (>0.05). The results indicate that the retained items are highly relevant for evaluating training requirements in agricultural drone technology, while the excluded items failed to distinguish between training needs meaningfully, thus contributing minimal value to the scale. The t-values for the selected statements ranged from 2.53 to 8.66, with higher t-values signifying greater statistical differentiation between groups. The highest t-value (8.66) among the selected items was found for “online courses or training modules on drone technology,” highlighting the increasing inclination towards digital and remote learning platforms. Likewise, “weather conditions and their impact on drone operation” ($t=7.89$) and “irrigation management and optimising water distribution” ($t=6.61$) exhibited substantial significance, underscoring their importance for drone integration in agriculture. The 19 items exhibited inadequate differentiation, indicating that agricultural stakeholders may not regard these aspects as essential. The elimination of these items conforms to standard

scale refinement procedures to improve the accuracy and relevance of the measurement.

After item selection, an item-total correlation analysis was performed to evaluate the strength of each item's association with the overall scale score. Items exhibiting high item-total correlations ($r \geq 0.70$) were retained, as they indicated strong consistency and significant contribution to the overall construct being assessed. Items showing moderate correlations ($0.30 \leq r < 0.70$) were retained, as they corresponded with the construct despite some variability in their contributions. Items exhibiting low item-total correlations ($r < 0.30$) were considered weakly associated and subsequently removed to improve scale reliability. Four items revealed weak correlations and were consequently excluded from the scale. Ethical implications of drone-assisted agricultural surveillance ($r=0.226$). These items exhibited insufficient alignment with the core construct and were probably not regarded as essential training needs by respondents. Their elimination led to a final scale of 30 items, guaranteeing the retention of only relevant and statistically reliable statements for additional validation. Content validity and reliability testing were conducted to evaluate the scale's effectiveness. Content validity

was established via expert evaluations and item selection grounded in literature. The methodology employed aligned with prior scale development studies (Shitu et al., 2018; Chandra et al., 2024; Tripathy et al., 2024; Gupta et al., 2022), thereby supporting the strength of the scale's construct validity. Reliability analysis was performed utilising Cronbach's Alpha, a recognised measurement for internal consistency (Ray & Mondal, 2011). The findings validated that all four constructs demonstrated high reliability ($\alpha > 0.80$), signifying that the items within each construct were strongly correlated and assessed a unified training need dimension. The Training Need for Practical Applications in Agriculture (TNP) construct revealed the highest reliability ($\alpha = 0.899$), signifying strong coherence among items evaluating the agricultural applications of drones. Likewise, the TRS construct ($\alpha = 0.898$) showed substantial reliability, highlighting the significance of regulatory knowledge and compliance in the adoption of drones. Although DTK ($\alpha = 0.856$) and PLT ($\alpha = 0.823$) showed high reliability, their marginally lower coefficients indicate that these domains may include a wider spectrum of learning experiences and technical skills. All four constructs surpassed the widely recognised threshold of 0.70, validating their appropriateness for scale implementation.

CONCLUSION

The study effectively established a statistically validated and reliable scale for evaluating the training needs. The development of this training needs assessment scale provides a scientifically validated tool for measuring farmers' perceptions, attitudes, and requirements regarding drone-based technologies in agriculture. The final scale consists of 30 significant training need statements derived from thorough item selection, item-total correlation analysis, and reliability testing, categorised into four distinct constructs. The use of Likert's summated rating method and t-test validation ensures that the scale captures relevant and statistically significant training gaps. This structured approach will aid policymakers, extension professionals, and agricultural training institutions in designing targeted training programmes that enhance farmers' knowledge, skills, and adoption of drone-based technologies, ultimately leading to improved agricultural efficiency and sustainability.

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