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[ORIGINAL RESEARCH ARTICLE]

Digital Literacy of Rural Farmers in Western Hills of Nepal: A Case of Rishing Rural Municipality

Abichar Bohara*
abhi2abhi@gmail.com
Yogendra B. Gurung*
gurungyb@gmail.com
***Central Department of Population Studies, Tribhuvan University, Kathmandu, Nepal
Corresponding author & Email:
Abichar Bohara; abhi2abhi@gmail.com

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Abstract
This study aimed to measure the digital literacy of rural farmers in the western hills of Nepal. Using a five-point Likert scale, 27 questions were initially designed based on six proposed factors: device and software operations, information and data literacy, communication and collaboration, digital content creation, safety, and problem-solving. Data collected from 383 participants revealed that 296 owned smartphones; thus, digital literacy was assessed for these individuals. Initial Exploratory Factor Analysis (EFA) suggested a more robust model with four factors and 15 indicators, subsequently validated through Confirmatory Factor Analysis (CFA). Descriptive statistics and mean scores were calculated, and digital literacy levels were analyzed across demographic variables such as gender, age, and education. Results indicated that approximately 53% of rural farmers demonstrated high digital literacy, with an overall mean score of 47.97 (SD = 15.49). The findings emphasized the need for targeted interventions to equip rural farmers with essential digital skills for modern agricultural practices and offer valuable insights for policymakers and institutions to enhance digital literacy in rural communities.
Keywords: digital literacy, smartphone, rural farmers, confirmatory factor analysis

INTRODUCTION

In an era where digital technologies have revolutionized agriculture worldwide, the ability of rural farmers to access and utilize these tools emerged as a critical determinant of agricultural productivity and food security. Despite the growing global focus on digital inclusion, little research explored rural farmers' digital competencies in Nepal, leaving a significant knowledge gap in this field. This study aimed to address this gap by investigating the digital literacy of rural farmers—a set of competencies required to operate and communicate using digital tools, particularly smartphones.

Existing literatures revealed various barriers to digital literacy among rural populations. Farmers often lacked information technology knowledge, faced language constraints, and encountered network problems (Pandey, 2022). Tools like mobile phones demonstrated the potential to improve smallholders' access to information, inputs, and markets, yet their use remained limited due to low ICT skills, inadequate facilities, and low literacy rates (Lama, 2018; Sandeep et al., 2022). Research indicated that demographic factors such as education level, gender, and access to extension services significantly influenced digital literacy globally ((Khan et al., 2019; Magesa et al., 2023)). However, the relevance of these findings to Nepal's rural farming communities remained unexplored.

Studies in similar contexts highlighted the challenges and opportunities of using digital tools for agricultural development. For instance, Bachhav (2012) found that rural farmers in Maharashtra, India, required daily information for agricultural work, with fellow farmers, newspapers, and government offices serving as their primary sources. In Kenya, traditional agriculture extension programs remained active; however, video-mediated learning was perceived as a viable and effective tool for disseminating agricultural knowledge (Ongachi et al., 2018). Similarly, Nepalese women farmers preferred printed picture-based lessons over advanced information and communication technologies (Devkota et al., 2020). These findings underscored the need to contextualize digital literacy initiatives to align with local preferences and constraints.

In Nepal, although the spread of mobile technologies improved smallholders' access to information, these benefits were not evenly distributed. Research indicated that agricultural information is often ineffective among farmers (ILO, 2019). Membership in cooperative organizations allowed farmers to access modern farming technologies and new interventions, but participation in such cooperatives remained low (Timilsina et al., 2022). Furthermore, Lama (2018) reported that although most farmers owned and used mobile phones, their use was primarily limited to essential functions like calling. Barriers such as limited ICT skills, insufficient awareness about the benefits of ICTs, and low literacy levels further constrained digital engagement.

Accurate and adequate information was essential for increasing agricultural production and productivity (Mishra & Bhatta, 2021). Alongside published information, farmers' knowledge base and literacy levels played a critical role in improved productivity (Chavva, 2008). Studies also suggested that factors such as education level, mobile use skills, and mobile possession duration positively influenced information-seeking behaviors, while age and limited contact with extension agents negatively affected these behaviors (Khan et al., 2019). Findings from Tanzanian farmers revealed significant associations between gender, ICT training, access to social media, and support from NGOs with digital literacy (Magesa et al., 2023). These insights informed the decision to consider demographic variables in this study of digital literacy among Nepalese farmers.

During the literature review, it became evident that scholars often used terms like digital literacy, digital skills, and digital competencies interchangeably. Using digital communication technologies such as smartphones required specific skills for accessing and sharing agricultural knowledge. This study examined digital literacy by focusing on smartphone usage, recognizing its significance in addressing rural farmers' challenges in

Nepal. Scholars also highlighted the lack of digital skills as a repeated issue. Hence, this research sought to identify the factors that determined the digital literacy of rural farmers.

In conclusion, this study pursued an understanding of the digital literacy of rural farmers, defined as a set of competencies required to operate and communicate using digital tools, particularly smartphones. By investigating the indicators of digital literacy—device and software operation, information and data literacy, communication and collaboration, digital content creation, safety, and problem-solving—as proposed by UNESCO, (2018), this research aimed to identify the factors that determined digital literacy levels. Additionally, it sought to provide insights into the demographic and contextual variables that influenced these competencies.

Research Objectives

The study investigated the state of digital literacy, focusing on the abilities of farmers in hilly regions to access, utilize, and share agricultural information via smartphone. The two main objectives were:

(i) to determine the factors for measuring farmer's smartphone literacy;
(ii) to determine the digital literacy level of farmers using the factors developed in (i).

Digital Literacy

Often attached to some competency, proficiency, or functionality, literacy is affixed with words to create compounding meanings (Ginger, 2015). Spante et al. (2018) suggested that the concepts of digital literacy and digital competence could potentially confuse readers, emphasizing the need for researchers to examine the origins of these definitions and evaluate how they align or diverge from one another. For this study, however, concepts such as skills, competence, and proficiency have also been considered literacy.

Zhao et al. (2022) informed that digital literacy was first defined by Paul Gilster in 1997, who described it as "the ability to understand and use information in multiple formats from a wide variety of sources when it is presented via computers". Scholars generally agreed that ICT-related literacies such as computer literacy, information literacy, and media literacy, converge under the broader concept of digital literacy (Magesa et al. 2023). The various definitions of digital literacy commonly focused on the ability to access, communicate, and create information and knowledge through digital technologies

The European Commission (EU), while developing and understanding digital competence, defined digital competence "as a combination of digital knowledge, skills and attitudes appropriate to the context" (Joint Research Center, 2013, p. 37). They further stated that key competencies were those that all individuals needed for personal fulfillment and development, active citizenship, social inclusion, and employment. UNESCO, defining it as individual ability, has indicated that "it includes competencies that are variously referred to as computer literacy, ICT literacy, information literacy, and media literacy" (UNESCO, 2018, p. 6). Hence, with the meaning and definitions of digital literacy revolving around individual skills, justified through multiple literatures, the working definition of digital literacy has been defined as the ability to communicate and create agriculture information securely by accessing smartphones (digital tools).

Digital Literacy in Agriculture

Demographic indicators such as age, gender, income, occupation, and farm size have been frequently seen to influence the adoption of digital innovations among smallholder farmers around the globe (Chandrasekaran, 2013; Khan et al., 2019; Palaiah et al., 2017; Prasad et al., 2018; Tumbo et al., 2018). Friends, neighbors, radio, TV, mobile phones, and the internet have been studied as sources of information and knowledge for farmers (Lama, 2018; Rajneesh, 2015; Zhang et al., 2016). In China, Zhang et al. (2016) found that the success of any model will depend on several people-related factors, such as farmers' ICT literacy, level of awareness and education, and motivation.

McCampbell et al. (2021) identified that farmers were limited to physical capability, psychological capability, and physical opportunity in their readiness measures. Apart from this, constraints and limitations (such as low access to physical infrastructure, financial services, and information asymmetries) have been one of the significant dimensions of articles on farmers' digital literacy. Low digital literacy has often been attributed to farmers' limited use of digital knowledge for their agricultural production. In the context of Nepal, the digital literacy of farmers remains an unexplored area of research. Based upon the review of the papers, this paper aimed to develop a digital literacy level of farmers of Nepal to realize the potential of digital technologies in agricultural production.

Operational Framework of the Study

Scholars have defined digital literacy as a multidimensional and multidisciplinary concept aimed at understanding the development of digital skills in response to the evolution of communication technologies. The EU has measured digital competencies from five competence areas: Information, communication, content creation, safety, and problem-solving have been identified (Joint Research Centre, 2013). Similarly, UNESCO (2018) has proposed a framework with six factors, as discussed below. Employing different factors, scholars have conceptualized digital literacy differently. There is no universal, comprehensive list of factors to conceptualize digital literacy.

Likewise, the approaches to study were also different. In Thailand, Techataweewan & Prasertsin (2018) developed the measurement of digital literacy indicators for undergraduate students by using confirmatory factor analysis. Similarly, taking doctoral students as participants, Bell (2021) qualitatively explored how evidence-based practices and engagement can be employed to gain insights into the digital practices of doctoral students and guide the development of research services within academic libraries. In measuring Tanzanian smallholder farmers' digital literacy level, Magesa et al. (2023) have used confirmatory factor analysis with factors to access, manage, integrate, evaluate, create, and communicate. Reviews on digital literacy indicated that scholars focus on students or teachers while few farmers are taken as participants.

Given the conceptual flexibility and the absence of apparent factors and procedures for measuring digital literacy, this study focused on the rural farmers in the western hills of Nepal to quantitatively measure digital literacy—the research findings aimed to enhance rural farmers' digital literacy skills while improving their agricultural productivity. Additionally, the results are expected to inform government policies and help relevant authorities strengthen digital literacy training provisions and intervention designs. Ultimately, the research outcomes are expected to contribute to developing strategies for advancing digital literacy skills across various sectors in the future.

METHODS

In this research, a realist ontological position and a post-positivist epistemological stance have been adopted to investigate the digital literacy levels of farmers and the factors influencing their adoption. This research is grounded in the belief that digital literacy, as a construct, exists objectively and can be systematically assessed and measured. The research recognized that the digital literacy landscape among farmers is interconnected and influenced by various contextual factors, individual perspectives, and diverse experiences. To address this complexity, quantitative methods was employed to gather data and derive empirical insights. Given these philosophical foundations, the subsequent section outlined the research design employed to achieve these objectives, detailing the sampling methods, data collection techniques, and analytical strategies used in the study.

Research Design

The research design employed a cross-sectional approach, allowing for the collection of data at a specific point in time. A survey research design was utilized to gather information from a representative sample of farmers in Tanahu district. The survey questionnaire included items related to demographic characteristics, digital literacy assessment, socio-economic status, education, and access to resources for both ordinary and smart mobile phones. The data collected was analyzed using statistical techniques to examine relationships, correlations, and patterns between variables of interest.

Study Area

The study was conducted in Ward Number 8 of Rishing Rural Municipality, located in Tanahun District, Gandaki Province, Nepal. Rishing Rural Municipality comprises eight wards, all of which are designated as rural (National Statistics Office, 2023). Further, Tanahun has 85 wards, with 66 classified as rural by GoN. The area is predominantly agricultural, with most households engaged in farming activities. This rural setting provides a relevant context for exploring the information-seeking behaviors of farmers and understanding the factors influencing their access to agricultural information. By focusing on this region, the study aims to provide insights representative of rural farmers in Nepal, highlighting their practices, challenges, and needs.

Sampling and Sample Selection

The study aimed to reach all the households (399) of ward number 8 through a list provided by the office of Rishing Rural Municipality to ensure comprehensive data collection. Since all the wards were categorized as rural wards, ward number 8 was purposively selected. A total of 383 households were surveyed. All households were randomly selected and invited to participate, provided they owned either a smartphone or an ordinary phone. From the total response, 296 respondents used smartphones, while 87 used ordinary mobile phones. The households were validated as agricultural households according to criteria set by the Government of Nepal (GoN).

Variables and Measures

Six factors were assumed following the UNESCO (2018) framework, while the indicators under each factor were designed with the farmer's specific preference for smartphone operations. Thus, indicators were developed, primarily using the functions described by UNESCO (for smartphones) and from different literatures as discussed above. However, indicators were modified after the pretest among a few volunteered farmers. Apart from the factors and indicators to determine digital literacy, demographic characteristics such as age, gender, mother tongue, family size, marital status, and variables specific to agricultural production have been collected.

Data Collection

A pilot study to pretest the data collecting instrument (survey form) was conducted. A slight modification was made in the instrument. For example, the combined questions of "calling and messaging" were separated, as few farmers were unable to read text but were able to call. Similarly, few farmers were able to read and reply, while others only read. The researchers provided instructions and asked participants to respond to all questions independently. Those who could read received support from the researchers, while the researcher administered the questions to participants who were unable to read. The instrument had four sections: respondents' information, household information, household agriculture information, and digital literacy assessment. In the questions measuring the indicators of digital literacy, participants were asked to score the level of their competencies from 1 to 5 using Likert scale questions. The responses were encoded after collection to maintain the confidentiality of participants.

Data Analysis

Data has been analyzed using STATA 16.0 and Lavaan (Latent Variable Analysis) package in RStudio 2024 software. The descriptive statistics on gender, age, education, and farm size in the demographic sections represented all 383 participants. A total of 296 records from respondents (with smartphones) were utilized for digital literacy. Descriptive statistics were calculated to analyze demographic characteristics (age, education, and gender) against levels of digital literacy. A CFA using the maximum likelihood estimator algorithm was conducted to examine the relationship between the factors and the underlying latent construct of digital literacy. However, exploratory factor analysis was conducted before CFA to identify the number of factors along with their indicators.

Exploratory factor analysis using the principal component factor suggested four factors and their corresponding indicators' factor loading. The four-factor model was analyzed for confirmation in RStudio software. As discussed in the findings, a series of iterations were conducted to fit the model, resulting in a four-factor model with 15 indicators. Along with the determinants of the model fit indices, the reliability and validity of the model were checked. A total factor score was calculated by adding up each score of indicators within that factor. Factor mean score and overall mean score for the responses were calculated and compared against the demographic characteristics using a t-test for two variables and ANOVA for three variables. The scores were categorized as *low* and *high* levels of digital literacy based on the mean, which was taken as a cut-off point. The higher scores above the mean were labeled as high, while those below the mean were labeled as low. Finally, low and high levels of digital literacy were compared with demographic variables.

RESULTS AND DISCUSSIONS

Demographics

Of the 383 respondents, 206 (53.79%) are female, and 177 (46.21%) are male. The education levels of the respondents are varied. A significant portion, 120 respondents (31.33%), have no formal education. Those who have completed lower basic education (grades 1 to 5) make up 87 respondents (22.72%), while 89 respondents (23.24%) have completed upper basic education (grades 6 to 8). Additionally, 48 respondents (12.53%) have reached lower secondary education (grades 9 to 10), and 36 respondents (9.4%) have completed higher secondary education (grades 11 to 12). Only a small number, three respondents (0.78%), have pursued education beyond the secondary level (grades 13 and above). Most respondents, 67.9%, fall into the age group 31-64, indicating a predominantly mature and experienced farming population. A significant proportion, 21.3%, belong to the 15-30 age group, suggesting a younger segment of farmers. Meanwhile, 10.8% of the farmers are aged 65 and above, representing a smaller proportion of the agricultural workforce.

Around 98.96 percent of the respondents indicated farm size below one hectare. The average farm size is 0.336, and more than 75 percent of the households have a farm size of less than 0.5 ha. However, all respondents reported having agricultural farm size criteria required to be labeled as an agriculture household. Almost 97 percent of households responded that crop production was the main agriculture focus, while the rest indicated livestock production. A significant percentage of households, 61.36 reported food sufficiency from agriculture for 4-6 months, while none responded for a year. Around 10 percent of the respondents reported having formal training on agriculture and 36.55 percent reported association with farmers' groups.

Digital Literacy Measurement

Digital literacy was measured for participants (296) who had smartphones, which represented the highest number. Before proceeding with confirmatory factor analysis, the indicators were explored through exploratory factor analysis which suggested four factor model in contrast to presumed six factors. Indicators with low factor loadings and those showing high multi-collinearity was omitted before the model was fit in confirmatory factor analysis.

Confirmatory Factor Analysis

The confirmatory factor analysis (CFA) procedure was conducted with the maximum likelihood estimator (MLE) algorithm, which is the most popular normal theory estimator because it has been found to produce asymptotically unbiased, consistent estimates of parameters (Finch et al., 1997). The four factors (obtained after EFA) were labeled as device operations, communication and collaboration, digital content creation, safety and problem-solving. The CFA model was executed, and the model fit indices were within the acceptable range, with the factor loadings for all 15 items exceeding 0.7. The model fit measures used to assess the model's overall goodness of fit were CMIN/df (Chi-square minimum divided by degrees of freedom), GFI (Goodness of Fit Index), CFI (Comparative Fit Index), TLI (Tucker Lewis Index), SRMR (Standardized Root Mean Square Residual) and RMSEA (Root Mean Square Error of Approximation). The four factors model yielded a good fit for the data as shown in table 1 below. The values obtained were CMIN/df = 2.66, GFI = 0.916, CFI = 0.973, TLI = 0.965, SRMR = 0.040 and RMSEA = 0.075, and all were within their respective acceptance level.

Table 1

Model Fit Values (recommended and obtained)

SN	Fit Indices	Recommended Value	Value Obtained	Status
1	*P*	Insignificant	0.000	Acceptable
2	CMIN/DF	2-5	2.66	Acceptable
3	GFI	>0.900	0.916	Acceptable
4	CFI	>0.900	0.973	Acceptable
5	TLI	>0.900	0.965	Acceptable

6	SRMR	<0.08	0.040	Acceptable
7	RMSEA	<0.08	0.075	Acceptable

Values for factor loading (LD) can be found in table 2 below. The table also represented Cronbach's Alpha (CA), Composite Reliability (CR) and Average Variance Extracted (AVE). The values have been calculated to inspect the reliability and validity of the model.

Table 2
Reliability and Validity

Factors	LD	CA	CR	AVE
DSO		0.825	0.949	0.862
dso1: I am competent in turning my phone on/off	0.817			
dso2: I am competent in charging my phone.	0.903			
dso3: I carry my phone while working.	0.775			
CNC		0.945	0.985	0.945
cnc1: I can search for and download apps.	0.923			
cnc2: I am able to message another farmer for information sharing.	0.909			
cnc3: I am able to inquire for agricultural goods and services through SMS.	0.89			
cnc4: I can create and set my online social network profiles (such as Facebook, Google, Instagram, etc.).	0.854			
DCC		0.946	0.97	0.89
dcc1: I can take pictures from my smartphone.	0.907			
dccc2: I am able to save a contact in my mobile phone.	0.954			
dcc3: I can record videos from my smart phone.	0.974			
dcc4: I show images/videos from my smartphone to fellow farmers with ordinary phone.	0.787			
SAF		0.932	0.987	0.952
saf1: I am able to call another farmer for information sharing.	0.898			
saf2: I do not disclose password or sensitive information about myself to his fellow farmer.	0.801			
saf3: I can call emergency numbers.	0.908			
saf4: I am able to call agriculture support number for agriculture information.	0.847			

After meeting the measurement model fit requirements, the construct reliability and validity of the model were evaluated. Construct reliability was assessed using Cronbach's Alpha (CA) and composite reliability, while convergent validity and discriminant validity were used to determine the model's validity. According to Hair et al. (2021) Cronbach's Alpha evaluated the degree to which indicators measuring the same construct are correlated. An item's Cronbach's Alpha should exceed the minimum threshold of 0.7 (Sideridis et al. 2018). The Cronbach's Alpha values obtained ranged from 0.825 to 0.946. Composite reliability (CR) measures the contribution of each item and is derived from the factor loading analysis of each item within the construct. Hair et al. (2021) suggested that a minimum CR value of 0.7 is required, and all the values obtained exceeded 0.9. Thus, as shown in Table 4, construct reliability was confirmed for each factor in the model.

Convergent validity referred to the correlation between responses from different variables that assess the same construct and is evaluated by calculating the average variance extracted (AVE). According to Hair et al. (2021) the AVE values must exceed the threshold of 0.5. As shown in Table 3 below, the model demonstrated convergent validity. Discriminant validity, on the other hand, assesses the degree to which constructs are empirically distinct from one another (Magesa et al., 2023). Discriminant validity is established if the correlation between two constructs is lower than the square root of their respective AVE values (Fornell & Larcker, 1981). Table 4 below indicated the values of the square root of the AVE highlighted on the diagonal, while all other entries are the inter-factor correlations between the constructs. According to the Fornell and Larcker criterion, it showed the square root of the AVE exceeds the inter-constructs correlations, which means, in the model, the items of each latent variable differ significantly from the observed variable. Thus, the discriminant validity of the model is confirmed.

Table 3

Discriminant Validity in Confirmatory Factor Aalysis

Factors	AVE	MSV	MaxR(H)	DSO	CNC	DCC	SAF
DSO	0.862	0.419	0.695	**0.928**			
CNC	0.945	0.701	0.796	0.564	**0.972**		
DCC	0.890	0.701	0.814	0.611	0.837	**0.943**	
SAF	0.952	0.430	0.747	0.647	0.619	0.656	**0.976**

Finally, table 4 below indicated the values of Heterotrait-monotrait ratio of correlation (HTMT) which is considered as a superior compared to other method for assessing discriminant validity in variance-based SEM (Henseler et al., 2015). The discriminant validity between two reflective constructs will be confirmed if the HTMT value is less than 0.85, as suggested by (Kline, 2016) and 0.90, as recommended by (Teo et al., 2008). The table illustrated that all the HTMT values were lower than the required threshold value of HTMT, and hence, it can be concluded that discriminant validity was established among the constructs.

Table 4

Henseler et al. Criterion: *Heterotrait-Monotrait (HTMT)*

Factors	DSO	CNC	DCC	SAF
DSO	1			
CNC	0.546	1		
DCC	0.611	0.837	1	
SAF	.646	0.618	0.655	1

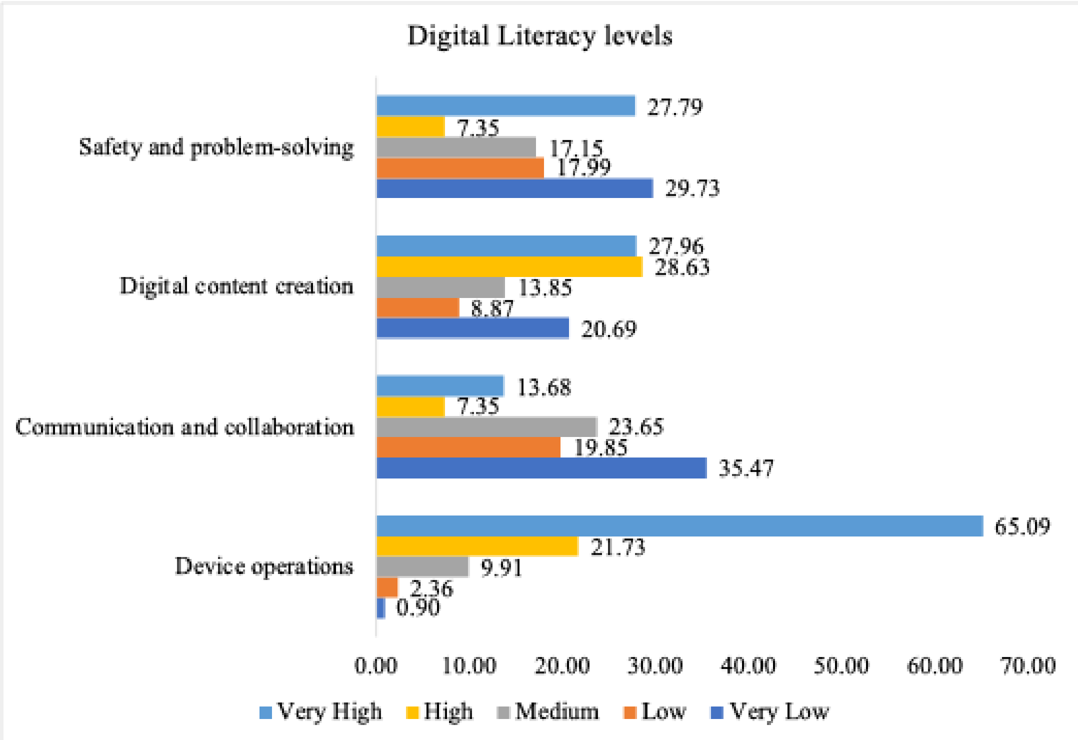
Therefore, with all reliability and validity criteria met, this confirmatory factor analysis model is suitable for evaluating the factors used to measure digital literacy levels of farmers. The digital literacy scale comprises four factors and 15 items, which are assessed using a 5-point Likert-type scale.

Digital Literacy Level

Digital literacy levels of rural farmers based on the four factors have been illustrated in the Figure 1 below. The figure showed the digital literacy skill levels of rural farmers on different factors or competencies. The findings indicated that farmers have high literacy on device operations while communication and collaboration are very low. Also, the farmers have high digital literacy levels on digital content creation such as take pictures, record videos, save contacts and share videos with fellow farmers.

Figure 1

Digital Literacy Levels of Rural Farmers



The descriptive statistics for the 15 items of the four factors measuring the digital literacy levels of smallholder farmers have been presented in Table 6 below. The results indicated that digital literacy levels vary according to factors, and items of the same factor have different values. Rural farmers demonstrated a high level of digital literacy when they scored "High" or "Very high" levels, while they demonstrated a low level of digital literacy when they scored the levels "Low" or "Very low". The results showed that rural farmers have high literacy levels related to two factors, i.e., their ability to operate the device for access to information (with an indicator score of more than 70 % for each item) followed by ability to create digital contents (the score for every item was above 50%). A significant number of farmers indicated low literacy levels in communication and collaboration. Similarly, the farmers displayed low literacy levels in safety and problem-solving skills, as shown in Table 5 below.

Table 5

The Levels of Digital Literacy Skills of Rural Farmers of Nepal

Factor Items	N (%)									
	Very Low (1)		Low (2)		Medium (3)		High (4)		Very High (5)	
Device operations										
dso1	1	0.34	1	0.34	8	2.70	64	21.62	222	75.00
dso2	0	0.00	3	1.01	23	7.77	61	20.61	209	70.61
dso3	7	2.36	17	5.74	57	19.26	68	22.97	147	49.66
Communication and Collaboration										
cnc1	110	37.16	44	14.86	64	21.62	35	11.82	43	14.53
cnc2	100	33.78	53	17.91	85	28.72	15	5.07	43	14.53
cnc3	94	31.76	69	23.31	76	25.68	16	5.41	41	13.85
cnc4	116	39.19	69	23.31	55	18.58	21	7.09	35	11.82
Digital content creation										
dcc1	49	16.55	21	7.09	35	11.82	101	34.12	90	30.41
dcc2	69	23.31	25	8.45	43	14.53	79	26.69	80	27.03
dcc3	63	21.28	26	8.78	36	12.16	85	28.72	86	29.05
dcc4	64	21.62	33	11.15	50	16.89	74	25.00	75	25.34
Safety and problem-solving										
saf1	15	5.07	69	23.31	99	33.45	31	10.47	82	27.70
saf2	61	20.61	49	16.55	50	16.89	40	13.51	96	32.43
saf3	122	41.22	58	19.59	30	10.14	9	3.04	77	26.01
saf4	154	52.03	37	12.50	24	8.11	7	2.36	74	25.00

Taking mean as a cut-ff point, the scores were finally categorized as *low* and *high* level of digital literacy. The higher score above mean were labelled as high while the scores below mean were labelled as low. Low and high levels of digital literacy were compared with demographic variables. Overall, the findings showed high digital literacy among 153 (51.5%) farmers and low among 143 (48.3%) who possessed smartphones. Table 6 below represents the categorization of digital literacy based on demographic characteristics such as gender, age group, and education level. A significant number of female respondents reported high digital literacy compared to male respondents. Young farmers showed high levels of digital literacy compared to farmers above 65 years old. Similarly, the findings also indicated a significant correlation between education level and digital literacy.

Table 6
Digital Literacy Level and Comparison Across Demographic Variables

		n (%)		Mean	SD
		High	Low		
Gender	Male	72 (50.3)	71 (49.7)	47.24	± 14.9
	Female	81 (52.9)	72 (47.1)	47.67	± 16.04
Age	15-30	59 (93.7)	4 (6.3)	60.63	± 10.12
	31-64	93 (43.6)	108 (53.7)	47.32	± 13.92
	65 and above	1 (3.1)	31 (96.9)	27.19	± 7.43
Education level	No education	8 (14)	49 (86)	32.75	± 10.68
	Lower Basic Education (1-5)	18 (25.7)	52 (74.3)	40.56	± 12.88
	Upper Basic Education (6-8)	55 (65.5)	29 (34.5)	53.32	± 12.51
	Lower secondary (9 to 10)	34 (73.9)	12 (26.1)	56.41	± 11.62
	Higher Secondary (11-12)	35 (97.2)	1 (2.8)	61.72	± 9.42
	More than secondary (13 and above	3 (100)	NA	66.67	± 10.41

DISCUSSION

This research represented a novel contribution to the study of digital literacy in the agriculture sector, particularly among rural farmers in Nepal. While most existing studies focused on populations such as students or teachers (Phyak et al., 2019; Techataweewan & Prasertsin, 2018), this study uniquely addressed the digital literacy levels of farmers—a largely underexplored demographic despite their critical role in rural economies. Phyak et al. (2019) identified that secondary teachers in Nepal predominantly exhibit '*beginner'* digital competencies, with significantly fewer demonstrating '*expert'* skills. However, like many others, their study did not extend to the farming community, highlighting a gap this research filled.

Most studies examining digital literacy adopt frameworks with six factors. For instance, UNESCO's framework for the agricultural sector outlined six competencies—device and software operation, information and data literacy, communication and collaboration, digital content creation, safety, and problem-solving—forming the basis for this study. Similarly, Magesa et al. (2023) utilized six factors to assess Tanzanian smallholder farmers' digital literacy. EU has defined five factors in its digital competence framework. However, after conducting EFA, this study found that four factors with 15 indicators were sufficient to measure digital literacy effectively among rural farmers, which was later confirmed through CFA.

CONCLUSION

The study of digital literacy, as measured through smartphone function capability among farmers of the hilly region of Nepal, is an empirical component of the analysis. Specific to smartphones, the study concluded that the four-factor model with fifteen indicators fit the CFA model. All the fit indices were found to be within the acceptable range. The independent t-test for gender and digital literacy indicated no significant difference between the digital literacy scores of males and females. The study concluded that the differences in digital literacy scores between the age groups are statistically significant. The older age group farmers have lower digital literacy. There were significant differences in digital literacy scores between levels of education, with higher education levels associated with higher digital literacy.

Among the information utilized by the farmers, information on livestock breeding stood as the most utilized information (more than 95 percent) followed by prices of output, uses of fertilizers, crop types to be produced, and prices of inputs. Hence, digital intervention programs focusing on livestock breeding are recommended. Many farmers with smartphones have up to 10th standard education, and most of the farmers' mother tongue is Magar, followed by Newari, Gurung, and Nepali.

Almost all the farmers indicated another fellow farmer as one of the sources of information, followed by farmers groups (or cooperatives), while around 6 percent of the farmers also utilized government extension services. Similarly, face-to-face discussion was the most common method of information exchange, followed by phone calls, television, internet, radio, press/newspaper, and agricultural apps. Although the use of the Internet (9.14 %) as a method of communication is low, the use of phone calls (37.6 %) concluded the possibility of intervention.

By narrowing the scope to four factors, this study provided a contextually tailored and empirically validated model that served as a benchmark for future research in similar rural settings. It underscored the importance of adapting global frameworks to local contexts and offered insights into how digital literacy can be meaningfully measured. Furthermore, the findings informed potential policy interventions aimed at improving digital literacy among farmers, ensuring equitable access to digital resources and fostering agricultural practices.

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