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Beyond Access: A Learning-Centered Model of Digital Inclusion among Agricultural Women in Rural Pakistan

Rabia * , **Aqeela Saghir** and **Ijaz Ashraf**

Institute of Agricultural Extension, Education and Rural Development, University of Agriculture, Faisalabad, Faisalabad 38000, Pakistan; aqeelasaghir@uaf.edu.pk (A.S.); gilluaf707@uaf.edu.pk (I.A.)

* Correspondence: rabia.ejaaz@hotmail.com

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Abstract: Digital inclusion among rural agricultural women cannot be described based on availability of devices and connectivity alone. This study examines the learning-related factors with Information and Communication Technology (ICT) Accessibility (IA) and meaningful utilization (MU) among rural agricultural women in Faisalabad District. Quantitative data from 384 participants were statistically analyzed followed by three focus group discussions in Faisalabad District by an explanatory sequential mixed-methods design. Formal Education (FE), Learning-Related and Contextual Constraints (LRCC), and Daily ICT Time (DIT) were examined in relation to ICT Accessibility (IA) and Meaningful Utilization (MU). In Model I, FE was neither significantly associated with nor an independent predictor of IA, whereas LRCC was positively associated with and significantly predicted IA. In Model II, FE was positively associated with and significantly predicted MU ($\beta = 0.534$), whereas LRCC had a small, non-significant bivariate association with MU but a small negative conditional coefficient. DIT was positively associated with FE and MU but negatively associated with IA and LRCC. In Model III, FE positively predicted DIT, whereas LRCC negatively predicted DIT. Qualitative data identified four interconnected domains: Literacy, Language Competence, and Digital Skills; Awareness of Digital Opportunities; Informal Learning and Support; and Contextual Conditions shaping learning opportunities. Integration indicates that IA represents an opportunity rather than an endpoint. FE, learning capabilities, social support, and contextual conditions help explain how women convert digital opportunities into purposeful use, while DIT represents intensity rather than meaningful utilization. Therefore, the study develops a Learning-Centered Model of Digital Inclusion that distinguishes access, exposure, and meaningful use.

Keywords: Digital Inclusion; ICT Accessibility; Meaningful Utilization; Daily ICT Time; Agricultural Women; Formal Education; Informal Learning; Digital Skills; Pakistan; Explanatory Sequential Mixed-Methods

1. Introduction

Digital technologies increasingly influence how people obtain information, learn, communicate, access services, and participate in economic life. In the agricultural sector, information and communication technologies (ICTs) provide access to extension advice, market information, weather information, input knowledge, government services, and opportunities for learning. Yet, the availability of technology alone does not establish that individuals can use it in ways that are relevant to their needs [1–3]. Contemporary digital-inclusion scholarship therefore distinguishes physical or technical access from differences in skills, patterns of use, and the benefits people derive from being connected [4–8].

This distinction is particularly important for rural women engaged in agriculture. Women may have access to a

mobile phone, television, internet source, or social application while still encountering difficulties in reading digital content, understanding language, identifying useful agricultural resources, navigating applications, or applying information to everyday decisions. The ITU's current perspective on universal and meaningful connectivity similarly recognizes digital skills as one of several interdependent conditions for meaningful digital participation, alongside connectivity, affordability, devices, quality, and security [7,9]. OECD evidence likewise emphasizes that both access to and the ability to use digital technologies effectively are relevant to digital inclusion, while skills development and the conditions that support the effective use of skills are important for an inclusive digital transition [10–12].

The gender dimension is also important. Recent global evidence documents persistent gender gaps in mobile ownership and mobile-internet use in low- and middle-income countries, with South Asia remaining among the regions where substantial numbers of women are not connected to mobile internet [13]. For agricultural women, digital exclusion can therefore reflect overlapping inequalities involving gender, location, education, household responsibilities, and opportunities for learning. The FAO has likewise emphasized that gender inequalities in agrifood systems are embedded in unequal access to resources, services, information, and opportunities [14].

The Capability Approach distinguishes between resources and the capabilities needed to convert those resources into activities and outcomes that people value [15,16]. Applied to digital inclusion, a device or connection can be understood as an enabling resource, whereas the ability to understand, evaluate, navigate, and apply digital information represents a capability. Digital-capital scholarship complements this perspective by emphasizing the accumulation of digital competencies, experience, and social resources that shape individuals' capacity to participate effectively in digital environments [17].

Learning is central to this conversion process. Formal education may provide literacy, communication, and foundational learning capacities, while digital competence can also develop through non-formal and informal learning [2,7,10,18,19]. Informal learning and social interaction may provide opportunities to develop digital competence outside formal training settings [20–22]. Communities of practice emphasize learning through participation, interaction, and shared experience [22]. At the same time, contextual conditions, including household work and agricultural responsibilities, may influence women's opportunities to practice and extend what they know. Research on agricultural ICT use in Pakistan highlights the relevance of socioeconomic characteristics, digital literacy, infrastructure, and the suitability and credibility of digital content for technology use [23,24].

Research on farmers' decisions to use computers in agriculture highlights the relevance of prior knowledge to technology engagement [25]. Studies of smartphone use further demonstrate that frequency of use, digital skills, and the types of activities performed represent distinct dimensions of digital engagement, with users showing different patterns across these dimensions [26]. Research on mobile-only and hybrid internet use also indicates that the mode of access is relevant to digital skills, suggesting that access and accumulated experience should not be treated as equivalent to digital capability [27]. Evidence concerning meaningful connectivity among women and gender-responsive agricultural resources, technologies, and services further underscores the importance of considering the conditions under which women can translate technology access into practical opportunities [28,29].

The research gap addressed here is therefore narrower than the claim that rural women have been overlooked entirely. Existing research documents digital exclusion, digital skills, gender gaps, agricultural ICT adoption, and barriers to technology use [13,17,18,23,24]. However, how these dimensions intersect within the everyday learning experiences of agricultural women in rural Pakistan remains insufficiently understood. In particular, limited empirical work has simultaneously distinguished ICT Accessibility (IA), Meaningful Utilization (MU), and Daily ICT Time (DIT) while considering Formal Education (FE) alongside informal learning and contextual conditions. This study addresses this gap through an explanatory sequential mixed-methods design.

1.1. Purpose and Objectives

The study examines how Formal Education (FE), Learning-Related and Contextual Constraints (LRCC), ICT Accessibility (IA), Meaningful Utilization (MU), and Daily ICT Time (DIT) are related among agricultural women in rural Pakistan.

1. To examine the relationship between FE, LRCC, and IA.
2. To examine the relationship between FE, LRCC, and MU.
3. To examine the relationship between FE, LRCC, and DIT.

4. To explore the learning-related and contextual experiences that help explain the quantitative patterns, particularly literacy, language competence, digital skills, awareness, informal support, time, relevance, and interest.
5. To integrate the quantitative and qualitative findings into a learning-centered interpretation of digital inclusion.

1.2. Research Questions

1. What relationships exist among Formal Education (FE), Learning-Related and Contextual Constraints (LRCC), and ICT Accessibility (IA)?
2. What relationships exist among FE, LRCC, and Meaningful Utilization (MU)?
3. What relationships exist among FE, LRCC, and Daily ICT Time (DIT)?
4. What learning-related and contextual factors help or hinder meaningful ICT engagement?
5. How do women's experiences help explain the relationships identified in the quantitative phase?

2. Literature Review

2.1. Digital Inclusion beyond Access

The digital divide was initially discussed largely in terms of unequal access to computers, connectivity, and digital resources [1–3]. Subsequent scholarship demonstrated that inequalities also occur in digital skills, patterns of use, and the outcomes derived from digital participation [4–6]. Van Deursen and Helsper describe a third-level digital divide concerned with differences in the benefits people obtain from being online [6], while Helsper emphasizes that digital inequalities are connected to wider social inequalities [18]. These perspectives support a distinction between having a technological opportunity and being able to convert that opportunity into a valued activity.

Recent international frameworks reinforce this distinction. The International Telecommunication Union (ITU) Digital Skills Toolkit places digital skills within broader digital-transformation strategies and emphasizes the inclusion of under-represented groups [7]. The Global Connectivity Report 2025 identifies skills as a critical dimension of universal and meaningful connectivity and documents persistent connectivity inequalities associated with gender, income, age, and location [9]. OECD work similarly identifies digital skills, effective technology use, and inclusive access as interconnected dimensions of digital transformation [10–12]. Thus, the present study's distinction among ICT Accessibility (IA), Daily ICT Time (DIT), and Meaningful Utilization (MU) is consistent with contemporary digital-inclusion scholarship.

2.2. Agriculture, Rural Women, and the Gendered Digital Divide

Agricultural women use ICTs within rural social and economic environments shaped by gender roles and contextual conditions. GSMA's 2026 evidence also shows that women in low- and middle-income countries remain less likely than men to use mobile internet, despite continued expansion in mobile connectivity [13]. FAO documents persistent gender inequalities across agrifood systems, including unequal access to productive resources, services, information, and opportunities [14]. These patterns are relevant to rural Pakistan because technology availability does not automatically remove social, educational, linguistic, or practical barriers to effective use.

Agricultural ICT research has often examined technology adoption, availability, or the value of digital services [23–25]. These are important dimensions, but they do not necessarily reveal how women learn to recognize relevant information, understand digital content, obtain assistance, and apply information to agricultural decisions. The present study therefore focuses on the learning conditions surrounding ICT use rather than treating technology adoption as the endpoint.

2.3. Capability, Digital Capital, and Learning

The Capability Approach distinguishes between resources and the capabilities needed to convert those resources into valued functioning [15, 16]. In this study, ICT devices and connectivity are treated as resources or opportunities, whereas the ability to understand, navigate, evaluate, and use digital information is considered a capability-related outcome. Digital capital adds a social dimension by emphasizing how digital competencies, experience, and social resources accumulate and shape participation in digital environments [17].

Digital competence frameworks further emphasize information and data literacy, communication and collab-

oration, problem solving, and appropriate technology use [19,20]. Learning is not restricted to formal educational institutions but is a continuing process shaped by cognition, emotion, experience, and social interaction [30]. Communities of practice similarly emphasize learning through participation and interaction within social groups [22]. These perspectives are useful for understanding how family members, peers, and neighbors can become practical sources of digital learning for rural women.

2.4. Formal Education and Informal Learning

Formal education is relevant because literacy and schooling can support the interpretation of written messages, navigation of information environments, and acquisition of subsequent digital skills [2,6,10]. However, education should not be treated as a complete explanation of digital participation. Digital environments change rapidly, and many practical skills are acquired through repeated use, observation, assistance, and informal problem solving [2,20,22].

This distinction is important for the present study because formal education and informal learning are analytically different. Formal Education (FE) is measured as educational attainment, whereas Learning-Related and Contextual Constraints (LRCC) are represented through a seven-item constraint-oriented composite covering illiteracy, lack of awareness, language barriers, lack of digital skills, limited time, irrelevant content, and lack of interest. The earlier item concerning lack of access to tools/support was excluded from this composite because access is separately represented by the ICT Accessibility (IA) construct. Higher scores on the retained composite indicate greater LRCC. Accordingly, a negative coefficient indicates that higher levels of constraints are associated with lower values of the outcome, whereas a positive coefficient should be interpreted as a statistical association rather than as evidence that constraints are beneficial.

2.5. Daily ICT Time: Exposure Is Not Equivalent to Meaningful Use

Digital time deserves separate attention because duration and purpose are not identical. The amount of time spent using ICTs can reflect exposure, repeated practice, communication, entertainment, or other activities. It may create opportunities for learning, but it does not establish that the time is devoted to agricultural information or purposeful application. Research on digital use similarly distinguishes frequency or intensity of use from differences in the types of activities, skills, and outcomes associated with digital participation [4–6,26,27].

Accordingly, this study does not position Daily ICT Time (DIT) as a tested mediator between ICT Accessibility (IA) and Meaningful Utilization (MU). Instead, DIT is examined in Model III as a separate quantitative outcome associated with Formal Education (FE) and the Learning-Related and Contextual Constraints (LRCC) measure. This approach avoids implying a mediation pathway that was not formally tested in the cross-sectional analysis.

2.6. Research Gap and Study Rationale

Three gaps motivate the study. First, access and meaningful use are often discussed together even though they represent distinct dimensions of digital inclusion [1,4–6,8,9]. Second, digital capability is frequently reduced to technical skills [7,8,18], whereas rural women's experiences may also involve literacy, language, awareness, informal support, time, relevance, and interest [21,26–28]. Third, formal education, informal learning, and contextual conditions are rarely integrated within a single mixed-methods explanation of how rural agricultural women engage with digital information.

The study responds by examining three quantitative models of ICT Accessibility (IA), Meaningful Utilization (MU), and Daily ICT Time (DIT), followed by qualitative evidence used to explain and contextualize the observed relationships. The resulting Learning-Centered Model is an empirically informed conceptual synthesis rather than a tested mediation or causal model.

2.7. Conceptual Framework

Figure 1 organizes the study around five analytically distinct elements: Formal Education (FE), ICT Accessibility (IA), Learning-Related and Contextual Constraints (LRCC), Daily ICT Time (DIT), and Meaningful Utilization (MU). FE represents educational attainment; IA represents access to ICT tools, internet sources, and digital/social applications; LRCC captures learning-related and contextual barriers; DIT represents exposure/intensity; and MU

represents reported use of ICTs for agricultural information and purposeful application.

The framework is an analytical architecture rather than a single causal chain. Daily ICT Time is a separately tested outcome in Model III, not a statistically tested mediator. **Figure 1** therefore distinguishes access, exposure, and meaningful use, while the figure in Section 4.8 provides the learning-centered interpretation of how these dimensions may be connected.

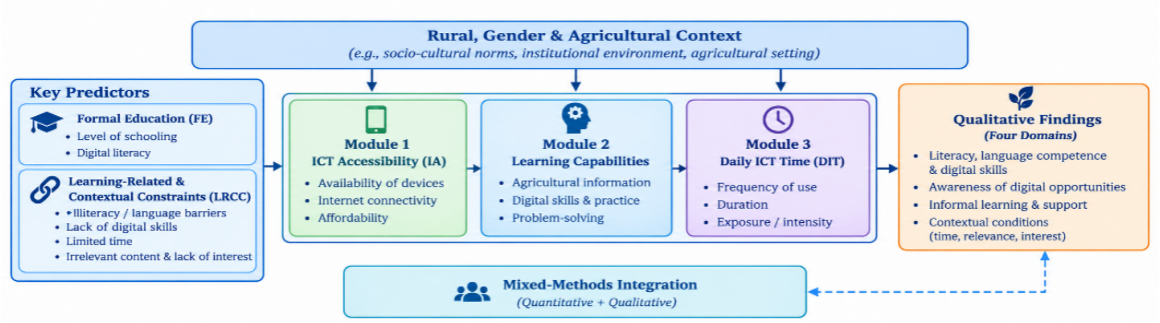


Figure 1. Theoretical Foundation and Pathway of Digital Inclusion among Agricultural Women in Rural Pakistan.

The framework in **Figure 1** positions Formal Education (FE) as a potential foundational condition, while Learning and Contextual Capabilities (LCC) and contextual conditions are considered relevant to the transition from ICT Accessibility (IA) to Meaningful Utilization (MU). Because FE was not significantly associated with IA in the final quantitative analysis, the framework does not present education as an empirically established determinant of accessibility. Instead, it integrates education, access, learning-related conditions, and meaningful use as analytically distinct dimensions informed by the Capability Approach [15,16] and digital-inclusion literature [4–6,17].

Contextual conditions, such as available time, household and farm responsibilities, relevance of information, and the surrounding social environment, may influence how learning capabilities develop and are exercised. Drawing on the Capability Approach, the framework therefore conceptualizes digital resources as requiring appropriate capabilities and enabling conditions to be converted into valued activities and outcomes [15,16].

The resulting conceptual pathway is Formal Education → ICT Accessibility → Learning and Contextual Capabilities (LCC) → Meaningful Agricultural ICT Utilization, with contextual conditions shaping the development and exercise of LCC.

3. Materials and Methods

3.1. Research Design

An explanatory sequential mixed-methods design was used [31]. The quantitative phase was conducted first to identify relationships among the principal constructs. The qualitative phase then used focus group discussions to explore women's experiences and provide explanations for the quantitative patterns. The two phases were analyzed separately before being integrated through joint interpretation.

The design was particularly useful because several relationships required explanation rather than simple description. For example, ICT Accessibility (IA) was not significantly associated with Formal Education (FE) in the final correlation and regression analyses, whereas Learning-Related and Contextual Constraints (LRCC) were significantly associated with accessibility. Meaningful Utilization (MU) showed a different pattern, with FE positively associated with utilization. Daily ICT Time (DIT) showed yet another pattern. The qualitative phase therefore focused on the learning and contextual conditions that could help interpret these differences.

3.2. Study and Sampling

The study was conducted in rural areas of Faisalabad District, Punjab, Pakistan. Participants were women aged 18 years or older who were engaged in agricultural activities. The quantitative sample comprised 384 women. A multistage sampling procedure was used across the district, with respondents selected from rural agricultural communities. The sample size was determined using Cochran's method [32]. Face-to-face data collection was conducted using a structured interview schedule that had been pretested with 30 participants.

The qualitative phase comprised three focus group discussions (FGDs), each involving 15 agricultural women, for a total of 45 participants purposively selected from the quantitative sample. Consistent with the explanatory sequential design, the qualitative phase served as a smaller follow-up component to explain and contextualize the quantitative findings [31]. The three discussions were conducted in rural communities located in 255RB (Faisalabad Tehsil), 168GB (Samundri Tehsil), and 232GB (Jaranwala Tehsil). The first author conducted the discussions with support from a local facilitator and field personnel. Participants were selected to provide explanatory perspectives on learning, ICT access, everyday use, and contextual conditions relevant to the quantitative findings. Each discussion lasted approximately 90 minutes. The qualitative sample size was not derived from the quantitative sample size; methodological research on focus groups indicates that adequacy depends on the study purpose, group structure, and the level of saturation sought [33]. No claim of statistical representativeness or formal saturation after three FGDs is made in this study.

3.3. Measures and Operationalization

The principal study constructs were operationalized separately to distinguish ICT opportunity, meaningful ICT use, Learning-Related and Contextual Constraints (LRCC), and daily ICT exposure. ICT Accessibility (IA) was measured using 22 indicators covering access to ICT tools, internet sources, and digital/social applications. Each indicator was coded on a four-category frequency scale ranging from 1 to 4, and the IA composite score was calculated as the mean of the 22 indicators. Higher scores represented greater reported IA.

Meaningful Utilization (MU) was assessed using 20 indicators covering the use of ICTs for agricultural information and purposeful activities. Items were measured using a five-point response scale, and the composite MU score was calculated as the mean of the 20 indicators. Higher scores indicated greater MU.

Learning-Related and Contextual Constraints (LRCC) were measured using seven retained indicators covering illiteracy, lack of awareness, language barriers, lack of digital skills, limited time, irrelevant content, and lack of interest. The item concerning lack of access to tools/support was excluded from this composite because ICT access was separately operationalized through the IA construct. The retained indicators were combined to form a constraint-oriented composite score, with higher scores indicating greater LRCC.

Daily ICT Time (DIT) was measured separately using an ordered five-category measure of reported daily time spent using ICTs. The categories represented increasing levels of daily ICT exposure. This measure was treated as an indicator of ICT exposure or intensity rather than as a measure of MU. Accordingly, DIT was analyzed as a separate outcome in Model III and was not treated as a mediator between IA and MU.

Internal consistency of the multi-item constructs was assessed using Cronbach's alpha, with the resulting reliability coefficients reported in Section 4.1.

3.4. Quantitative Phase

Descriptive statistics summarized participant characteristics and the principal constructs [31]. Pearson product-moment correlations were used to examine bivariate relationships. Three focused multiple regression models were then estimated with the same two theoretically central predictors: Formal Education (FE) and Learning-Related and Contextual Constraints (LRCC). Model I used ICT Accessibility (IA) as the dependent variable; Model II used Meaningful Utilization (MU); and Model III used Daily ICT Time (DIT).

The regression models were intentionally theory-focused rather than fully adjusted causal models. Age, household size, farming experience, and income were described as sample characteristics but were not entered as control variables in the final three models. Consequently, the regression coefficients should be interpreted as conditional statistical associations within the specified two-predictor models, not as causal effects or estimates adjusted for all plausible confounders.

Model fit was assessed using R, R^2, adjusted R^2, and F statistics. Coefficients are reported as B, SE, standardized β, and p where available. The distinction between bivariate association and regression-based conditional association was maintained throughout.

3.5. Qualitative Phase

The focus group guide addressed literacy and language competence, digital skills, awareness of digital opportunities, informal learning and support, and contextual conditions such as time, relevance, and interest. The guide was used to explore the experiences underlying the quantitative patterns rather than simply to repeat the survey questions.

The three FGDs, each group involving 15 participants were transcribed and analyzed using thematic analysis following Braun and Clarke [34]. The analyses involved familiarity with the transcriptions, coding of the relevant segments, categorization of codes into candidate themes, reviewing all patterns across three discussions, refining boundaries of themes, and linking the final themes to the quantitative findings. Therefore, findings produced four interconnected domains: literacy, language competence and digital skills; awareness of digital opportunities; informal learning and support; and contextual conditions, including time, relevance, and interest.

3.6. Trustworthiness and Reflexivity

Credibility was supported through direct researcher involvement, comparison of emerging themes across the three discussions, attention to participants' own accounts, and discussion of interpretations with colleagues. Dependability was strengthened through field notes, transcripts, and documentation of analytical decisions. Confirmability was supported by grounding interpretations in participant accounts and maintaining reflexive notes. Transferability was addressed by describing the rural agricultural setting, participant eligibility, sampling approach, and analytic focus.

The first author led the qualitative phase and had prior experience in agricultural extension and ICT-related research. This background provided contextual familiarity but also created a possibility that prior expectations could influence interpretation. Reflexive notes were therefore maintained, and interpretations were discussed with others to challenge initial assumptions.

3.7. Mixed-Methods Integration

Integration occurred after the quantitative and qualitative phases. The quantitative findings identified relationships requiring explanation, and the qualitative phase was then used to explore the experiences underlying those patterns. The two strands were compared through a joint display and narrative integration. Particular attention was given to the distinction between access, exposure, and meaningful utilization, and to the contrast between prolonged everyday ICT exposure and limited dedicated time for digital learning. The integrated findings formed the basis for the Learning-Centered Model.

4. Findings

4.1. Participant Characteristics

Table 1 presents the educational attainment of the 384 agricultural women who participated in the study and **Table 2** shows the descriptive statistics of principal constructs.

Table 1. Formal Education (FE) of the respondents (n = 384).

Educational Level	Frequency	Percentage (%)
Illiterate	28	7.3
Primary	68	17.7
Middle	89	23.2
Matric	79	20.6
Intermediate	56	14.6
Graduation and above	64	16.7
Total	384	100.0

The largest share of respondents had middle-level education (23.2%), followed by matriculation (20.6%), primary education (17.7%), graduation and above (16.7%), and intermediate education (14.6%). Only a small share of respondents were illiterate (7.3%). Overall, respondents represented a range of FE levels, providing variation

for examining its relationship with digital inclusion.

Table 2. Descriptive statistics and internal consistency of the study variables (n = 384).

Variable	Mean	SD	Cronbach's α
IA	1.98	0.56	0.910
MU	3.65	0.77	0.960
LRCC	2.58	0.56	0.666
DIT	3.27	1.32	—

Descriptive statistics and internal consistency of the principal study variables indicates that IA had a mean score of 1.98 (SD = 0.56), while MU had a mean of 3.65 (SD = 0.77). LRCC had a mean of 2.58 (SD = 0.56), whereas DIT had a mean of 3.27 (SD = 1.32). IA (α = 0.910) and MU (α = 0.960) demonstrated high internal consistency, while LRCC showed lower internal consistency.

4.2. Correlations among the Principal Variables

Pearson's correlation analysis was used to examine the direction, strength, and statistical significance of the relationships among the principal study variables (**Table 3**).

Table 3. Pearson correlations among the principal variables.

Variable 1	Variable 2	Pearson Correlation Coefficient	*p*
IA	FE	0.047	0.363
	LRCC	0.516**	< 0.001
MU	FE	0.528**	< 0.001
	IA	−0.065	0.201
	LRCC	−0.075	0.141
DIT	FE	0.331**	< 0.001
	IA	−0.445**	< 0.001
	MU	0.364**	< 0.001
	LRCC	−0.307**	< 0.001

Note: ** $p < 0.001$.

Pearson correlations among the principal study variables show that IA was significantly positively correlated with LRCC ($r = 0.516$, $p < 0.001$), but not with FE ($r = 0.047$, $p = 0.363$). MU was significantly positively associated with FE ($r = 0.528$, $p < 0.001$), whereas its correlations with IA ($r = −0.065$, $p = 0.201$) and LRCC ($r = −0.075$, $p = 0.141$) were not significant. DIT was significantly positively associated with FE ($r = 0.331$, $p < 0.001$) and MU ($r = 0.364$, $p < 0.001$), while significant negative associations were observed with IA ($r = −0.445$, $p < 0.001$) and LRCC ($r = −0.307$, $p < 0.001$).

4.3. Multiple Regression Predicting IA

Multiple regression analysis was used to examine the statistical contributions of formal education (FE) and learning-related and contextual constraints (LRCC) in predicting ICT accessibility (IA) (**Table 4**).

Table 4. Multiple regression predicting IA for Model I ($R = 0.516$, $R^2 = 0.266$, adjusted $R^2 = 0.262$, $F(2,381) = 69.078$, $p < 0.001$).

Predictor	B	SE	β	*t*	*p*
FE	0.007	0.016	0.018	0.406	0.685
LRCC	0.507	0.043	0.515	11.706	< 0.001

Multiple regression model predicting IA shows that the model was statistically significant, $R = 0.516$, $R^2 = 0.266$, adjusted $R^2 = 0.262$, $F(2, 381) = 69.078$, $p < 0.001$.It indicates that FE and LRCC jointly accounted for 26.6% of the variance in IA. FE was not a significant independent predictor (β = 0.018, $p = 0.685$), whereas LRCC showed

a significant positive statistical association with IA (β = 0.515, $p < 0.001$). Because higher LRCC scores represent greater constraints, this positive coefficient should be interpreted as a conditional statistical association rather than as evidence that greater constraints improve IA.

4.4. Multiple Regression Predicting MU

Multiple regression analysis was used to examine the statistical contributions of formal education (FE) and learning-related and contextual constraints (LRCC) in predicting meaningful utilization (MU) of ICTs (**Table 5**).

Table 5. Multiple regression predicting MU for Model II ($R = 0.539$, $R^2 = 0.290$, adjusted $R^2 = 0.287$, $F(2,381) = 77.906$, $p < 0.001$).

Predictor	B	SE	β	*t*	*p*
FE	0.270	0.022	0.534	12.360	< 0.001
LRCC	−0.143	0.059	−0.105	−2.431	0.016

Multiple regression model predicting MU indicates that the model was statistically significant, $R = 0.539$, $R^2 = 0.290$, adjusted $R^2 = 0.287$, $F(2, 381) = 77.906$, $p < 0.001$. It shows that FE and LRCC jointly accounted for 29.0% of the variance in MU. FE was a significant positive predictor (β = 0.534, $p < 0.001$), whereas LRCC showed a small but significant negative association with MU (β = −0.105, $p = 0.016$). Thus, higher FE was associated with greater MU, while greater reported constraints were associated with lower MU, after accounting for the other predictor in the model.

4.5. Multiple Regression Predicting DIT

Multiple regression analysis was used to examine the statistical contributions of formal education (FE) and learning-related and contextual constraints (LRCC) in predicting daily time spent using ICTs (DIT) (**Table 6**).

Table 6. Multiple regression predicting DIT for Model III ($R = 0.464$, $R^2 = 0.216$, adjusted $R^2 = 0.212$, $F(2,381) = 52.385$, $p < 0.001$).

Predictor	B	SE	β	*t*	*p*
FE	0.303	0.039	0.349	7.685	< 0.001
LRCC	−0.764	0.106	−0.326	−7.179	< 0.001

Multiple regression model predicting DIT indicates that the model was statistically significant, $R = 0.464$, $R^2 = 0.216$, adjusted $R^2 = 0.212$, $F(2, 381) = 52.385$, $p < 0.001$. FE and LRCC jointly accounted for 21.6% of the variance in DIT. FE was positively associated with DIT (β = 0.349, $p < 0.001$), whereas LRCC showed a significant negative association (β = −0.326, $p < 0.001$). Thus, higher FE was associated with greater daily ICT exposure, while greater reported constraints were associated with less time spent using ICTs, after accounting for the other predictor in the model.

4.6. Qualitative Findings: Four 'Learning-Related and Contextual Domains'

The qualitative phase depended on three FGDs (n = 15 in each group). The findings are presented thematically and are used to explain and contextualize the quantitative patterns across the study.

4.6.1. Literacy, Language Competence, and Digital Skills

Participants repeatedly described a distinction between basic operation of a device and the ability to use it for agricultural or livelihood purposes.

One participant explained,

"School helped me understand how to use the phone, but not how to use it for farming or earning."

Another stated,

"If a woman can read and write, she can at least understand some messages and use basic functions on the phone."

Participants also described difficulties with language and application use:

"Everything is in English or difficult Urdu so we cannot understand apps."

Another participant said:

"We know how to answer calls but using applications is difficult."

These accounts help explain why FE may provide a foundation for digital engagement without automatically producing advanced agricultural use.

4.6.2. Awareness of Digital Opportunities

Awareness emerged as a separate issue. Participants did not always know which digital services were relevant to agriculture.

One participant stated:

"Nobody told us that these applications could help us in farming."

Another explained:

"We do not know which websites or apps are useful for agriculture."

Thus, access to a device does not guarantee recognition of a relevant digital opportunity.

4.6.3. Informal Learning and Support

Participants described family and community members as practical sources of assistance.

One woman stated:

"Sometimes our children help us when we do not understand something on the phone."

Another explained:

"My son teaches me how to use functions whenever I need help."

A further participant said:

"We often ask relatives or neighbors when we have problems using mobile applications."

These accounts illustrate informal learning as a social process. At the same time, dependence on others can mean that learning opportunities vary according to household and community support. Informal assistance may therefore facilitate engagement without guaranteeing independent use.

4.6.4. Contextual Conditions: Time, Relevance, and Interest

Participants frequently referred to the competing demands of household and agricultural work.

One participant said:

"We are busy with household and farm work so we do not get time to learn these things properly."

Another stated:

"After completing all household tasks there is little time left for learning anything new."

A further participant explained:

"The whole day passes between home responsibilities and field work."

Perceived relevance and interest also shaped willingness to learn.

One participant stated:

"I never thought these things were meant for people like us."

Another remarked:

"Sometimes we lose interest because we do not understand how the technology can help us."

These accounts are particularly relevant to the quantitative time findings because they show that time is not simply a matter of duration; it is also an opportunity to learn, practice, and connect technology with valued activities. During the same discussions, women also described prolonged everyday exposure to mobile phones.

One woman explained:

"The mobile phone remains with me the whole day and in an active state."

Another added:

"Mobile phones are in my use whole day for communication."

These accounts help contextualize the higher DIT categories: a phone can remain available and be used intermittently for communication and other activities across the day without representing continuous agricultural learning. The qualitative evidence therefore distinguishes exposure from dedicated learning time.

4.7. Integrated Mixed-Methods Interpretation

The integrated findings are summarized in **Table 7** and inform the Learning-Centered Model presented in **Figure 2**. FE and IA are treated as resources or opportunities, while the conversion of these opportunities into purposeful use is shaped by LCC, including skills and literacy, awareness, informal support, and contextual conditions such as time, relevance, and interest. MU represents purposeful engagement with agricultural information rather than simple possession of technology or duration of exposure.

Table 7. Integration of quantitative and qualitative findings.

Quantitative Finding	Qualitative Explanation	Integrated Interpretation
FE was not significantly associated with IA (r = 0.047, p = 0.363; β = 0.018, p = 0.685).	Education supported basic literacy, message comprehension, and phone use.	FE supports foundational learning but was not an independent predictor of IA.
LRCC was positively associated with IA (r = 0.516, p < 0.001; β = 0.515, p < 0.001).	Literacy, language, digital skills, awareness, and practical barriers shaped engagement.	The positive coefficient reflects a statistical association, not evidence that constraints improve access.
FE was positively associated with MU (r = 0.528, p < 0.001; β = 0.534, p < 0.001).	Schooling supported basic understanding, while agricultural applications required further learning.	FE was more directly associated with purposeful use than with basic accessibility.
LRCC had a non-significant bivariate association with MU (r = −0.075, p = 0.141), but a small negative conditional coefficient (β = −0.105, p = 0.016).	Informal assistance and opportunities for learning and practice varied.	The conditional association suggests lower MU with greater constraints, without implying causation.
DIT correlated with FE (r = 0.331), MU (r = 0.364), IA (r = −0.445), and LRCC (r = −0.307), all p < 0.001; Model III R^2 = 0.216.	Phones supported daily communication, while household and farm duties limited dedicated learning time.	ICT exposure may coexist with limited opportunities for dedicated learning; DIT represents intensity, not meaningful agricultural use.
IA was not significantly associated with MU (r = −0.065, p = 0.201).	Phone and internet access did not always translate into the ability to use agricultural applications or identify useful information.	IA provides an opportunity, whereas MU also requires learning and supportive contextual conditions.

4.8. Learning-Centered Model

The integrated findings provide the basis for the proposed Learning-Centered Model of Digital Inclusion among Agricultural Women in Rural Pakistan (**Figure 2**). **Figure 2** illustrates the learning-centered pathway through which FE, IA, LCC, and contextual conditions are considered in relation to MU.

The model is presented as a conceptual interpretation of the integrated findings rather than as a formally tested causal or mediation model. It emphasizes that digital inclusion among agricultural women cannot be understood solely in terms of whether technologies are available. Rather, meaningful digital participation depends on the LCC and contextual conditions that enable women to convert access into purposeful use.

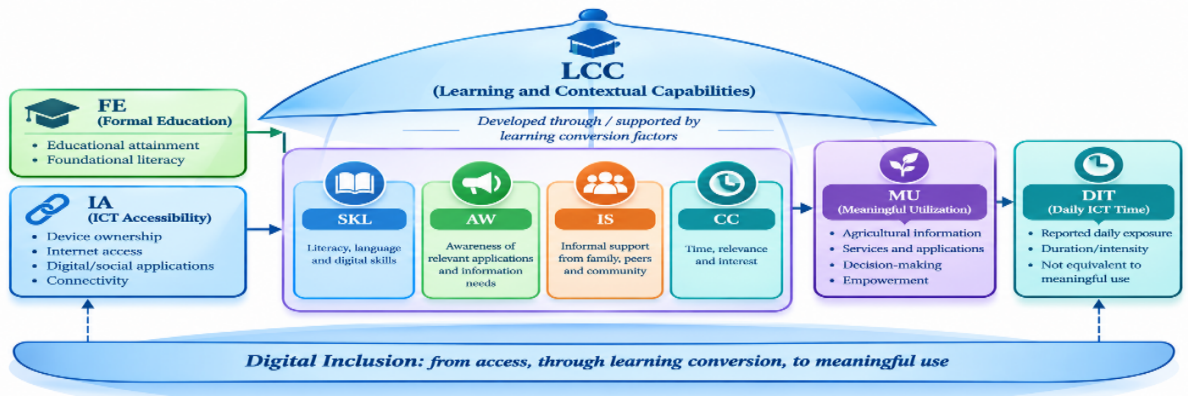


Figure 2. Learning-Centered Model of Digital Inclusion among Agricultural Women.

5. Discussion

5.1. Reframing Digital Inclusion as a Learning-Centered Process

FE was not significantly associated with IA in the final bivariate analysis and did not independently predict IA in Model I. This result indicates that educational attainment alone did not explain differences in reported IA in this sample. FE may still matter as a foundational resource because it develops literacy and general learning capacities, but the data do not support describing education as an independent statistical determinant of accessibility (**Tables 3** and **4**).

This pattern is consistent with digital-divide scholarship that distinguishes access from skills, use, and outcomes [1,4,5,26,27]. It also aligns with ITU's emphasis on skills as a core dimension of meaningful connectivity [7,9]. The study therefore contributes a rural agricultural perspective in which access is treated as an opportunity that must be converted into meaningful use through learning and contextual conditions.

5.2. Formal Education: Foundation, but Not a Complete Explanation

FE was positively related to MU and remained a significant predictor in Model II (**Table 3** and **5**). The qualitative accounts help explain why education and accessibility can show different patterns. Women described schooling as useful for understanding messages and basic phone functions, while agricultural applications required additional knowledge, awareness, and practical skill (**Table 7**). Thus, FE was more directly connected with purposeful use than with basic accessibility in the final analysis.

The utilization result requires greater caution. LRCC had a non-significant bivariate correlation with MU but a small negative conditional coefficient in Model II. Because higher scores indicate greater constraints, the coefficient is directionally consistent with lower utilization under greater constraints, but it remains a conditional association rather than evidence of causality. The coefficient is small, and the measure has modest reliability ($\alpha = 0.666$), so it should not be given the same interpretive weight as the highly reliable MU and IA composites.

5.3. Learning-Related and Contextual Constraints

The positive association between LRCC and IA requires cautious interpretation. LRCC showed a significant positive association with IA under the final raw-constraint coding and remained significant in the focused regression model ($\beta = 0.515$, $p < 0.001$), whereas FE was not a significant predictor of IA ($\beta = 0.018$, $p = 0.685$) (**Table 4**). Because higher LRCC scores represent greater learning-related and contextual constraints, the positive coefficient should not be interpreted as evidence that constraints improve ICT accessibility. Rather, it represents the statistical association observed under the study's coding and model specification.

One plausible contextual interpretation is that women with greater ICT exposure or access may also report more learning-related and contextual difficulties because greater engagement with ICTs provides more opportunities to encounter barriers related to literacy, language, digital skills, awareness, relevance, and time. In this sense, access and constraints may coexist rather than represent mutually exclusive conditions. Women who have access to ICTs may still experience difficulties in converting that access into confident, relevant, and sustained use. However, this interpretation remains contextual rather than causal. Given the cross-sectional design, the direction of the relationship cannot be determined, and the observed association should not be interpreted as evidence that

greater constraints lead to greater access.

The absence of a significant association between FE and LRCC ($r = 0.056$, $p = 0.276$) provides further context for interpreting these findings (**Table 3**). It suggests that LRCC is not simply a proxy for low formal education. FE and LRCC therefore represent related but distinguishable aspects of digital inclusion. Formal education may provide a broader foundation for engaging with digital opportunities, whereas LRCC captures specific learning-related and contextual barriers that can persist across different educational levels.

Taken together, these findings reinforce the distinction between ICT accessibility and meaningful digital inclusion. Access to devices, connectivity, or digital platforms does not necessarily imply the absence of learning-related or contextual difficulties. The coexistence of accessibility with reported constraints therefore supports the study's learning-centered perspective, in which digital inclusion involves not only whether ICT opportunities are available but also the conditions under which women can understand, navigate, and use those opportunities meaningfully.

5.4. Daily ICT Time: Exposure, Practice, and Meaningful Use

The inclusion of Model III strengthens the study by preventing time from being implicitly incorporated into the concept of digital utilization. DIT was positively related to MU ($r = 0.364$, $p < 0.001$), indicating that greater reported ICT exposure was associated with greater reported meaningful use (**Table 3**). However, the qualitative findings provide an important qualification: duration of ICT exposure should not be equated with purposeful learning or agricultural use.

Women described mobile phones as remaining available to them throughout much of the day and being used for communication and other routine activities. At the same time, participants described limited opportunities for learning because of household and agricultural responsibilities. A woman may therefore experience prolonged device exposure and intermittent ICT interaction while still having limited dedicated opportunities to learn new applications, seek agricultural information, or apply digital information in depth. This distinction is consistent with research showing that the frequency or intensity of digital use does not necessarily capture the types of activities, skills, and outcomes associated with digital participation [6,26,27]. The integration of the quantitative results and qualitative explanations is summarized in **Table 7.**

FE positively predicted DIT ($\beta = 0.349$, $p < 0.001$), whereas LRCC was negatively associated with DIT in the regression model ($\beta = -0.326$, $p < 0.001$) (**Table 6**). The qualitative accounts help contextualize this pattern: household and agricultural responsibilities may reduce opportunities for sustained learning and practice. Thus, the relevant issue is not simply how long a device is present in a woman's day, but whether some of that exposure becomes an opportunity for purposeful learning and application.

The negative bivariate association between IA and DIT ($r = -0.445$, $p < 0.001$) further cautions against assuming that greater reported access automatically corresponds to greater daily exposure (**Table 3**). This result reinforces the importance of treating access, exposure, and meaningful use as analytically distinct dimensions.

5.5. Theoretical Contribution

The study brings together three complementary perspectives. Digital-divide scholarship explains why access alone does not exhaust digital inequality and why differences in skills, use, and outcomes require separate consideration [1,5,6]. The Capability Approach explains the distinction between resources and the capabilities and conditions required to convert those resources into valued activities and outcomes [15,16]. Learning perspectives further explain how capabilities can develop through formal education, informal support, practice, participation, and social interaction [22,30].

The resulting Learning-Centered Model therefore shifts attention from a single access question towards a conversion question (what learning and contextual conditions enable an available technology to become useful in a woman's agricultural life?). The model does not replace access-oriented digital-inclusion frameworks; rather, it adds a learning-centered interpretation of the relationship between technological opportunity, exposure, learning, and meaningful use.

5.6. Practical and Policy Implications

First, digital-inclusion programs for agricultural women should combine access initiatives with practical digital learning. Training can extend beyond basic device operation to include finding, interpreting, evaluating, and

applying agricultural information, consistent with digital-skills frameworks and broader digital-inclusion policy literature [7,9,17,18].

Second, language accessibility should be considered in the design of digital agricultural services. Where appropriate, agricultural platforms and advisory services should provide understandable local-language content and interfaces. Third, awareness should accompany technology provision so that women know which applications, websites, advisory services, market-information resources, weather services, and government platforms are relevant to their agricultural activities [13,23–25].

Fourth, informal learning should be recognized as a potential complementary resource rather than treating it merely as a substitute for formal training. Family members, peers, neighbors, extension personnel, and community-based learning arrangements can provide practical assistance and opportunities for problem-solving [22,30].

Fifth, time constraints should be considered in program design. Flexible, locally available learning opportunities and repeated practice may better accommodate women's household and agricultural responsibilities [22,30]. Training schedules that assume large blocks of uninterrupted time may be less suitable in these contexts [23,24].

Finally, program evaluation should avoid treating access, time, and meaningful use as interchangeable indicators. An intervention may increase device ownership or connectivity without producing corresponding changes in purposeful agricultural use. Monitoring should therefore consider skills, awareness, relevance, MU, and opportunities for continued learning alongside measures of access and connectivity [4,7,9,28].

6. Conclusion

This study examined digital inclusion among agricultural women in rural Pakistan by distinguishing IA, MU, and DIT. The final quantitative results show that FE was not significantly related to IA, whereas LRCC was positively associated with IA in the focused model. FE was positively associated with MU and remained a significant predictor in the focused regression model. DIT formed a third dimension. It was positively related to FE and MU and negatively related to LRCC and IA.

The qualitative findings explain these patterns through four interconnected domains: literacy, language competence and digital skills; awareness of digital opportunities; informal learning and support; and contextual conditions, especially time, relevance, and interest. They also clarify the apparently high DIT values by showing that mobile phones may remain available and in use for communication across much of the day, while dedicated time for digital learning remains constrained. Together, the findings suggest that access and exposure are important opportunities but are not sufficient descriptions of digital inclusion.

The Learning-Centered Model developed from these integrated findings therefore places LCC at the center of digital inclusion. It does not claim that the variables form a tested causal or mediation sequence. Instead, it offers a theoretically grounded and empirically informed way of understanding how FE, ICT opportunities, LCC, social support, and contextual conditions relate to meaningful digital engagement among agricultural women.

Limitations

The quantitative data are cross-sectional; therefore, regression coefficients indicate statistical associations and do not establish causality. The models included only FE and LRCC, without controlling for other potential confounders. The LRCC measure showed modest reliability ($\alpha = 0.666$), so related findings require cautious interpretation. The qualitative phase involved three FGDs with 15 women in each of three rural communities; findings are thematic rather than statistically representative. Finally, the Learning-Centered Model was derived from integrated findings but was not independently tested as a structural, causal, or mediation model.

Author Contributions

Conceptualization, methodology, investigation, data collection, formal analysis, qualitative analysis, interpretation of findings, writing—original draft preparation, R.; writing—review and editing, A.S. and I.A. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

This study was conducted in accordance with the ethical principles and guidelines of the Higher Education Commission of Pakistan and the University of Agriculture, Faisalabad. The research synopsis, including its ethical considerations, was approved by the Institutional Review Board on 26 January 2023 (Approval No. DGS 993-96).

Informed Consent Statement

Written and verbal informed consent was obtained from all participants prior to their participation in the study. Participants were informed about the purpose of the study, the voluntary nature of participation, and the confidentiality of their responses.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to applicable ethical requirements and the protection of participants' confidentiality.

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Conflicts of Interest

The authors declare no conflict of interest.

AI Use Statement

During the preparation of this manuscript, the authors used AI tools solely for language refinement. No AI tools were used for data analysis, interpretation, or generation of scientific content. All outputs were critically reviewed and edited by the authors. The authors take full responsibility for the integrity and accuracy of the work.

References

1. Van Dijk, J.A.G.M. *The Digital Divide*; Polity Press: Cambridge, UK; Medford, MA, USA, 2020. Available online: https://research.utwente.nl/en/publications/the-digital-divide-2/
2. Passey, D.; Netbuste, J.G.; Yazbak Abu Ahmad, M.; et al. Populations Digitally Excluded from Education: Issues, Factors, Contributions and Actions for Policy, Practice and Research in a Post-Pandemic Era. *Technol. Knowl. Learn.* **2024**, *29*, 1733–1750. [CrossRef]
3. Lybeck, R.; Koiranen, I.; Koivula, A. From Digital Divide to Digital Capital: The Role of Education and Digital Skills in Social Media Participation. *Univ. Access Inf. Soc.* **2024**, *23*, 1657–1669. [CrossRef]
4. Zhao, L.; Cao, C.; Li, Y.; et al. Determinants of the Digital Outcome Divide in E-Learning between Rural and Urban Students: Empirical Evidence from the COVID-19 Pandemic Based on Capital Theory. *Comput. Human Behav.* **2022**, *130*, 107177. [CrossRef]
5. Kuhn, C.; Khoo, S.-M.; Czerniewicz, L.; et al. Understanding Digital Inequality: A Theoretical Kaleidoscope. *Postdigit. Sci. Educ.* **2023**, *5*, 894–932. [CrossRef]
6. Van Deursen, A.J.A.M.; Helsper, E.J. The Third-Level Digital Divide: Who Benefits Most from Being Online? In

Communication and Information Technologies Annual; Emerald Publishing: Bingley, UK, 2015; 10, pp. 29–52. [CrossRef]
7. International Telecommunication Union. Digital Skills Toolkit. Available online: https://www.itu.int/hub/publication/d-phcb-cap_bld-02-2024/ (accessed on 27 July 2026).
8. Van Deursen, A.J.A.M.; van Dijk, J.A.G.M. IQ and Digital Inequality: An Empirical Investigation. *New Media Soc.* **2023**, *25*, 1248–1270. [CrossRef]
9. International Telecommunication Union. *Global Connectivity Report 2025*; ITU: Geneva, Switzerland, 2025. Available online: https://www.itu.int/itu-d/reports/statistics/global-connectivity-report-2025
10. OECD. *OECD Skills Outlook 2023: Skills for a Resilient Green and Digital Transition*; OECD Publishing: Paris, France, 2023. [CrossRef]
11. OECD. *OECD Digital Economy Outlook 2024, Volume 1: Embracing the Technology Frontier*; OECD Publishing: Paris, France, 2024. [CrossRef]
12. OECD. *OECD Digital Economy Outlook 2024, Volume 2: Strengthening Connectivity, Innovation and Trust*; OECD Publishing: Paris, France, 2024. [CrossRef]
13. GSMA. *The Mobile Gender Gap Report 2026*; GSMA: London, UK, 2026. Available online: https://www.gsma.com/gender-gap/
14. Food and Agriculture Organization of the United Nations. *The Status of Women in Agrifood Systems*; FAO: Rome, Italy, 2023. [CrossRef]
15. Sen, A. *Development as Freedom*; Oxford University Press: Oxford, UK, 1999. Available online: https://sen.scholars.harvard.edu/publications/development-freedom
16. Nussbaum, M.C. *Creating Capabilities: The Human Development Approach*; Harvard University Press: Cambridge, MA, USA, 2011. [CrossRef]
17. Ragnedda, M.; Ruiu, M.L. *Digital Capital: A Bourdieusian Perspective on the Digital Divide*; Emerald Publishing: Bingley, UK, 2020. [CrossRef]
18. Helsper, E.J. *The Digital Disconnect: The Social Causes and Consequences of Digital Inequalities*; SAGE: London, UK, 2021. [CrossRef]
19. Redecker, C. *European Framework for the Digital Competence of Educators: DigCompEdu*; Publications Office of the European Union: Luxembourg, Luxembourg, 2017. [CrossRef]
20. Vuorikari, R.; Kluzer, S.; Punie, Y. *DigComp 2.2: The Digital Competence Framework for Citizens: With New Examples of Knowledge, Skills and Attitudes*; Publications Office of the European Union: Luxembourg, Luxembourg, 2022. [CrossRef]
21. Qualter, D. From Digital Exclusion to Digital Inclusion: Shaping the Role of Parental Involvement in Home-Based Digital Learning—A Narrative Literature Review. *Comput. Sch.* **2024**, *41*, 120–144. [CrossRef]
22. Wenger, E. *Communities of Practice: Learning, Meaning, and Identity*; Cambridge University Press: Cambridge, UK, 1998. [CrossRef]
23. Khan, N.A.; Shah, A.A.; Tariq, M.A.U.R.; et al. Impact of Farmers' Climate Risk Perception and Socio-Economic Attributes on Their Choice of ICT-Based Agricultural Information Services: Empirical Evidence from Pakistan. *Sustainability* **2022**, *14*, 10196. [CrossRef]
24. Aslam, S. Digital Exclusion in Agricultural Communication: Exploring Socioeconomic and Infrastructural Barriers to ICT Use in Rural Pakistan. *Soc. Sci. Humanit. Open* **2025**, *12*, 102264. [CrossRef]
25. Shahzad, A.R.; Ahmad, S.; Anjum, F. An Investigation on the Effect of Prior Knowledge on Farmers' Decisions to Use Computers in Agriculture: Empirical Evidence from Rural Punjab, Pakistan. *J. Asian Dev. Stud.* **2024**, *13*, 1443–1454. [CrossRef]
26. Wenz, A.; Keusch, F. The Second-Level Smartphone Divide: A Typology of Smartphone Use Based on Frequency of Use, Skills, and Types of Activities. *Mob. Media Commun.* **2023**, *11*, 459–483. [CrossRef]
27. Correa, T.; Valenzuela, S.; Pavez, I. For Better and for Worse: A Panel Survey of How Mobile-Only and Hybrid Internet Use Affects Digital Skills over Time. *New Media Soc.* **2024**, *26*, 995–1017. [CrossRef]
28. Banerjee, R.; Trappel, J.; Van Audenhove, L. Evaluating 'Meaningful Connectivity': Digital Literacy and Women in West Bengal, India. In *Digital Inclusion*; Yates, S., Carmi, E., Eds.; Palgrave Macmillan: Cham, Switzerland, 2024; pp. 225–248. [CrossRef]
29. Hidrobo, M.; Kosec, K.; Gartaua, H.N.; et al. Making Complementary Agricultural Resources, Technologies, and Services More Gender-Responsive. *Glob. Food Secur.* **2024**, *42*, 100778. [CrossRef]
30. Illeris, K., Ed. *Contemporary Theories of Learning: Learning Theorists... in Their Own Words*, 2nd ed.; Routledge: London, UK, 2018. [CrossRef]
31. Creswell, J.W.; Plano Clark, V.L. *Designing and Conducting Mixed Methods Research*, 3rd ed.; SAGE: Thousand

Oaks, CA, USA, 2017. Available online: https://www.sagepub.com/shop/buy-a-book/designing-and-conducting-mixed-methods-research-3-241842
32. Cochran, W.G. *Sampling Techniques*, 3rd ed.; John Wiley & Sons: New York, NY, USA, 1977. Available online: https://www.wiley-vch.de/en/areas-interest/mathematics-statistics/sampling-techniques-978-0-471-16240-7
33. Hennink, M.M.; Kaiser, B.N.; Weber, M.B. What Influences Saturation? Estimating Sample Sizes in Focus Group Research. *Qual. Health Res.* **2019**, *29*, 1483–1496. [CrossRef]
34. Braun, V.; Clarke, V. Using Thematic Analysis in Psychology. *Qual. Res. Psychol.* **2006**, *3*, 77–101. [CrossRef]



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