AARHUS BSS

DEPARTMENT OF MANAGEMENT
AARHUS UNIVERSITY

AACSB ACCREDITED · ASSOCIATION OF MBAS ACCREDITED · EQUIS ACCREDITED

The Smarterfarmer Project

Farms and the Digital Frontier: Mapping the Digital Landscape of Farming in Denmark

Appendix 1
How we measure farm digitalization

Authors
Martin Wurzer
Andrea Carugati
Claus Aage Grøn Sørensen
Katrine Duus Terkelsen
Lars Frederiksen
Pernille Kallehave
Pernille Smith
Rene Gislum

The Smarterfarmer project is funded by Aarhus University Research Foundation.

Appendix 1: How we measure farm digitalization

Digitalization and digital transformation are complex, multifaceted processes that can be examined from various perspectives. In this section, we outline how farm digitalization is measured within the SmarterFarmer project and explain the approach used to capture its different dimensions.

In Chapter 1, we applied a two-step approach to measure farm digitalization in the SmarterFarmer project. First, we distinguished between digital adopters and non-adopters based on whether farms reported using FMIS and/or precision agriculture (PA) technologies relevant to their stated primary operation (crop or livestock). Among the digital adopters, we further differentiate between active and passive adopters. Active adopters are those who also engage in data collection for decision-making and/or automation, while passive adopters use digital technologies without such data efforts. Based on this classification, we examined the associations between farm characteristics and the likelihood of being a digital (active or passive) versus non-digital farm. In the second step, we took a closer look at digital adopters only to explore how different farm characteristics relate to the degree of digital advancement.

To assess digital advancement, we utilized a modified version of the "Digital Maturity Index and Assessment Tool for the Agricultural Industry" developed by the Australian Commonwealth Scientific and Industrial Research Organisation (CSIRO; Zhang et al., 2019).

The original instrument was created through an extensive review and synthesis of existing digital maturity frameworks and consists of 54 questions, which cover 5 key dimensions, or "pillars," of digital maturity. These dimensions encompass:

- **Strategy & Culture**, which reflects a farm's orientation toward digitalization and the presence of a supportive environment.
- **Capability**, which captures the knowledge and skills required to work with digital technologies and data.
- **Data Rules**, which focuses on data management, integrity, and security.
- **Data & Analytics**, which assesses the scope of data collection, integration, and utilization, and
- **Technology**, which measures the extent to which digital technologies are currently in use.

The Strategy & Culture, Data & Analytics, and Technology dimensions can be further divided into three sub-dimensions. Strategy & Culture includes strategy, culture, and industry leadership;

Data & Analytics consists of data, analytics, and interoperability; and Technology is made up of infrastructure, in-business technology, and technology marketplace.

To reduce the burden on respondents and hopefully create a more precise measure, we developed a streamlined version of the original survey instrument by combining a statistical analysis with expert assessments. Thus, we undertook two complementary approaches to identify opportunities for scale reduction (Goetz et al., 2013). To determine which survey items work well together digital maturity both statistically and in strength, we conducted a pre-study using the full digital maturity instrument with participants recruited through the Prolific online platform. The resulting data allowed us to test different versions of the digital maturity instrument and retain the statistically most reliable and impactful items. In parallel, experts reviewed the survey items and selected the most relevant ones based on both face- and content validity. By integrating insights from both approaches, we derived a refined survey instrument that balances statistical robustness with practical relevance. Next, we describe both approaches in detail.

1. Data-driven scale assessment

To identify the most relevant digital maturity items through statistical testing, we conducted a pre-survey in November 2023 using the full 54-question digital maturity battery before launching our main study on agricultural digitalization.

As access to farmers and farm managers was limited at the time, we utilized participants from Prolific to perform the analysis. This allowed us to conduct an initial assessment of the instrument's reliability and factor structure before applying it in the Danish agricultural context. However, it is important to acknowledge that the original instrument was developed to be used by agribusinesses and filled out by "business managers who are involved in decision-making" (Zang et al., 2019, p. 8). The term "agribusinesses" is broadly defined to "include producers, consultants, processors, technology & service providers, logistics, marketers/merchants, [banks], and research & development corporations" (p. 4). To approximate key characteristics of on-farm decision-makers as closely as possible, we carefully screened participants based on relevant characteristics and applied strict selection criteria when constructing the testing sample.

A) Pre-screening

To achieve this, we utilized Prolific's built-in filter options along with our own pre-screening surveys. As farmers are typically male and relatively older (European Commission, 2022), we used Prolific's pre-screening criteria to restrict the participant pool to male full- or part-time employees aged 30 and above. Furthermore, to ensure high response quality, we filtered for participants who are fluent in English and have a 98% or higher approval rating on prior studies. We experimented with additional filter options but found that this combination provided a sufficiently large pool of eligible participants while maintaining relevant demographic characteristics (N = 21.270).

Using this resulting pool of potential participants, we first distributed a short survey with 2.002 open slots to gather information on professional status and level of involvement with digital technologies at work. First, we screened out all participants who indicated that they were self-employed in single-person contexts (e.g., freelancers or consultants) or unemployed, as these roles typically lack the organizational context necessary for assessing digital maturity within a structured work environment. Next, we asked participants to select the areas in which they are involved at work from a list of eleven options, including a "none of the above" choice. This approach was chosen to obscure our intention of screening for respondents involved in digital topics at their workplace. Participants who did not select the option "I am actively involved in discussions and decisions concerning the investment and use of digital technologies" were filtered out. We further excluded participants who selected more than six available options, unless they stated that they work at a small company or startup, where broader responsibilities are more common. We also removed responses where participants selected multiple options alongside "none of the above". In the final stage of the pre-screening survey, participants assessed their level of involvement in digitalization by responding to six questions, each rated on a 4-point scale ranging from "not at all involved" to "substantially involved." Based on their responses, we further excluded participants who indicated having no insight into at least one aspect of digitalization. As a result of this rigorous screening process, 348 out of 2,002 participants qualified for inclusion in the digital maturity study.

B) Main Survey and Analysis

We distributed the main survey containing the full digital maturity scale to the 348 participants retained from pre-screening one day later. We adapted the digital maturity scale to fit a more general context beyond agriculture without changing the underlying meaning of the items, making it suitable for our testing sample. We also asked participants to confirm their professional status, again removing participants who indicated that they were self-employed in single-person contexts or unemployed. In total, we received 315 valid responses.

To check for response consistency, we repeated one question in the survey. Among the 315 participants, 120 provided slightly different answers, though 94 of them differed by only one point (e.g., having selected “agree” instead of “strongly agree” the second time). Given the length of the survey and the distribution of the duplicate question, these small variations are unsurprising. We conducted our primary analyses using the full dataset but also validated key findings with a subset of 195 participants whose answers were entirely consistent.

Exploratory Factor Analysis

First, we conducted exploratory factor analyses (EFA) using R and principal axis factoring (PAF) with varimax rotation to explore how the items clustered together without imposing a structure onto the data. This analysis offered initial insights into which items were most (or least) relevant for constructing a reduced scale, based on their factor- and cross-loadings.

We assessed the suitability of our dataset for factor analysis using the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity. The overall KMO value for the dataset was 0.94, suggesting that the dataset is well-suited for factor analysis. The MSA (Measure of Sampling Adequacy) values for individual items ranged from 0.54 to 0.96, with most items scoring above 0.90, further confirming the suitability of the data for factor extraction. Bartlett's test of sphericity was significant ($\chi^2 = 9612.17$, $df = 1431$, $p < 0.001$), indicating that the correlation matrix significantly differs from an identity matrix. This result supports the presence of underlying factors in the dataset.

We conducted a parallel analysis to determine the optimal number of factors to retain in the EFA. The results suggested a seven-factor solution, indicating that seven factors had eigenvalues greater than what would be expected by chance. However, upon closer examination of the eigenvalues, factor loadings, and theoretical coherence, we found that some factors were poorly defined or had significant overlap in content. Additionally, when extracting seven factors, we encountered Heywood cases and unstable factor loadings, suggesting that the model was overfitting to the sample.

To derive a more interpretable structure, we explored both a 5-factor solution based on the original scale division and a more streamlined 3-factor solution. By comparing these models, we identified items that remained consistently relevant or irrelevant. Our analysis showed that the model derived from the stricter 195-participant subset provided a clearer factor structure, explained slightly more variance, and exhibited stronger primary loadings compared to the full dataset. However, both models yielded similar factor structures, with no major deviations in loading patterns. For each model, we categorized items based on their factor loadings to guide scale reduction. Items with loadings above 0.6 were marked as strong candidates for retention in the reduced scale, while those with loadings between 0.4 and 0.6 were considered as secondary candidates. Items with substantial cross-loadings or loadings below 0.4 were identified as likely candidates for removal.

Internal Consistency

Second, we assessed the internal consistency of the original five digital maturity dimensions and the more fine-grained 11 sub-dimensions using Cronbach's Alpha. The five broader scales demonstrated good to excellent reliability, with most values exceeding 0.8 and all surpassing the commonly accepted threshold of 0.7. One item was removed from the Strategy & Culture scale, as its exclusion slightly improved reliability. Additionally, 11 items were flagged for potential removal, as their absence did not lower the Cronbach's Alpha value.

When evaluating the more fine-grained 11-scale approach, we identified additional potential modifications. The Culture, In-Business Technology, and Interoperability scales exhibited weaker internal consistency as standalone measures, with Cronbach's Alpha values falling below 0.7 and no observable improvements after adjustments. Additionally, two items within the Strategy scale were flagged for removal to enhance the sub-scale's internal consistency. Five more items were also marked for potential removal, as their exclusion did not affect reliability. Our analysis yielded similar results for the full and the strict dataset.

Confirmatory Factor Analysis

Third, we conducted extensive Confirmatory Factor Analyses (CFA) using both datasets and Maximum Likelihood estimation with robust standard errors (MLR) to evaluate, refine, and compare the 5-dimension and 11-dimension models. We iteratively removed items with low loadings (< 0.5) or substantial cross-loadings, merged highly overlapping factors, and monitored model fit changes until no further improvements were observed. The resulting models from each analysis were largely similar and consistently pointed in the same direction regarding improvements and factor loadings. The fit indices suggest that while the models do not achieve perfect fit, they remain within an acceptable range and show improvements compared to the original models.

Following a similar approach to our EFA results, we categorized items based on their factor loadings across all final CFA models to guide scale reduction efforts. Items with high loadings (> 0.6) were marked as highly relevant for retention, while those with low loadings (< 0.5) or previously removed during the refinement process were flagged as potential removals. Items falling in between were designated as second-tier options for retention.

We compiled the well-performing items from each analysis into a table, integrating expert ratings to create a comprehensive evaluation for item retention. This combined approach guided our selection of the most robust and relevant items. In the next section, we will outline the expert assessment process, describe further modifications, and present the final reduced version of the scale used in the SmarterFarmer Project.

2. Expert-driven scale assessment

We also conducted an expert survey with eight specialists in business and agricultural digitalization. This survey aimed to evaluate item relevance and further guide the scale reduction process.

In the survey, the experts were presented with all items belonging to a particular sub-scale (11-dimension version), along with a definition of the construct the sub-scale was intended to capture. They were then asked to select the item(s) they found most relevant in representing the described sub-dimension. If a sub-scale contained four or fewer items, experts selected one item. For sub-scales with five to eight items, they selected two, while for the nine-item Capability sub-scale, they selected three. Each survey page also included a comment field, allowing experts to provide qualitative feedback. In addition to item selection, experts rated the importance of each sub-scale in assessing a farming business's digital maturity on a 4-point scale (1 = Not Important to 4 = Very Important). They were also given the opportunity to provide open-ended feedback on whether any key aspects of digital maturity were missing.

To systematically integrate expert assessments with statistical analyses, we first counted how often each item was selected by experts as the most relevant and color-coded them for visualization. Then we calculated the average rating for each sub-scale across all expert responses, distinguishing between higher-rated sub-scales (with an average score above 3) and lower-rated ones (with an average score of 3 or below). These expert evaluations were combined with statistical indicators from our factor analyses to ensure that both empirical performance and expert judgment informed the final selection process.

3. Synthesis and Refinement

To quantify item relevance, we weighed each item's factor loading—based on the model with the most observations and the most detailed sub-scaling[1]—by its expert selection count. We further combined this weighted factor score with the expert sub-scale ratings, allowing items that performed well across all evaluation criteria to stand out clearly. This comparative assessment served as the final and most critical guide in determining which items to retain in the reduced scale. During a meeting the SmarterFarmer research team discussed which items should be

[1] Since all models produced highly similar results, the model choice had minimal impact on this process.

retained, after which we conducted a final factor analysis using the reduced scale to validate our choice and checked that the reduction did not compromise the instrument's structural integrity We also streamlined the wording of the selected items to minimize participant effort and enhance clarity based on the expert feedback.

To gain better insight into the technological status of our surveyed farms, we decided to complement the original technology-related items "How would you rate the extent to which digital technologies are utilized in your business?" and "Our business uses decision support tools or systems for decision-making" by capturing what actual technologies are being used and what specific farm management functions are being supported by digital systems. To do so, we adopted approaches from prior research on precision agriculture technology and farm management information systems adoption and by a list of common precision farming technologies and farm management tasks. Respondents were asked to indicate which of these technologies are used on their farm and which management tasks are supported by digital management systems.