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# Forest owners' perceptions of machine learning: Insights from swedish forestry

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ABSTRACT

Machine learning is becoming increasingly important in environmental decision-making, particularly in forestry. While forest-owner typologies help in understanding private forest management strategies, they often overlook owners' relationships with technology. This is crucial for ensuring that data-driven advancements in forestry benefit society. Using Swedish forestry policy as a case, we applied Q-methodology to explore forest owners' perceptions of machine learning. We conducted 11 qualitative interviews to generate 33 **statements**, which were then ranked by 26 participants. Inverted factor analysis identified four ideal-type perceptions of machine learning, interpreted through self-determination theory. The first perception views machine learning as unhelpful and socially disruptive. The second sees it as a complement to forest governance. The third expresses no strong opinions reflecting a relative disengagement from forestry. The fourth considers it essential for decision-making, particularly for absentee forest owners. The extracted perceptions align with existing forest owner typologies when it comes to reliance on others and willingness to take advice. The discussion includes concrete policy recommendations, focusing on privacy concerns, educational initiatives, and strategies for communicating uncertainty.

## 1. Introduction

Technology is playing an increasingly vital role in environmental decision-making, with machine learning (ML) emerging as a key tool due to advances in computing power. In forestry, ML techniques are being applied to improve decision-making in areas such as road network planning, risk management, and water-ditch management (Mohtashami et al., 2023; Busarello et al., 2023). These technologies are intended to be integrated across various decision-making levels, including policy-making, policy implementation, and support for individual forest owners, potentially transforming forestry practices and policies (Skogsstyrelsen, 2023). This transformation is significant, especially in Europe, where a large portion of forests is privately owned, and the actions of these owners are crucial to achieving political and environmental goals. However, private forest owners are not a homogenous group, and little is known about their relationship with new technologies, particularly ML. Although there is optimism about ML's potential in environmental decision-making, there is a gap in understanding how individual forest owners perceive and adopt these technologies (Galaz et al., 2021; Wreford et al., 2021).

Research by Bergdahl et al. (2023) suggests that self-determination theory (SDT), with its focus on the psychological needs of competence, autonomy, and relatedness, may help explore individuals' perceptions toward new technologies. In this context, it is crucial to consider private forest owners in the development and implementation of ML in forestry (Li et al., 2021). Sweden, with its significant share of Europe's forests and diverse group of forest owners, serves as a valuable case study. The Swedish state has invested in ML as part of its environmental goals for forestry (Näringsdepartementet, 2022; Skogforsk, 2021), making it an ideal context to explore two key research questions:

(1) How do Swedish individual forest owners perceive ML in forestry?
(2) How can these perceptions be interpreted through the lens of self-determination theory?

Hence, through interviews and a Q-methodological survey, the aim of this study is to understand private forest owners' perceptions of ML in Swedish forestry, using SDT as a framework.

Sweden's forest policy is based on the principle of "freedom under

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responsibility," where landowners are expected to manage their forests in line with minimal legal standards while voluntarily exceeding them for conservation purposes (Appelstrand, 2012; Eriksson and Sandström, 2022). State steering primarily involves voluntary measures such as informational campaigns and advisory services. Critics argue that although the current governance model aims for balance, it prioritizes economic considerations over environmental ones. They also contend that cognitive burdens and uncertainties in decision-making hinder the adoption of more sustainable practices. (Beland et al., 2017; Benley et al., 2021). The Swedish government has acknowledged the need to provide forest owners with better information, including ML-generated digital knowledge bases that can guide environmentally friendly forestry practices (Näringsdepartementet, 2022; Lidberg, 2023).

In a law proposal (Prop.. 2021/22:58) the Swedish government saw it as their responsibility to provide “geographic information about natural values to identify objective conditions in nature” to forest owners (Prop.. 2021/22:58, p. 37). A government mission to the Swedish forestry agency (SFA) and the Swedish Environmental Protection Agency (SEPA) (Näringsdepartementet, 2022) then ensued. The agencies were tasked with developing “Digital knowledge-bases” showing “*probabilities of different forest values*” so as to facilitate forest owners’ environmental considerations. It was also stated that these knowledge bases are important in the governing bodies administrative work. One form of digital knowledge bases are maps. These maps show, for example, probabilities of wet areas, probabilities of forest damages, and ditches-and streams calculated with the help of ML-techniques (Lidberg, 2023, Skogsstyrelsen, n.d.). They are readily available for the public, including forest owners and are used by the authorities in their administrative work. There is thus a political expectation that their use will result in more environmentally friendly forestry planning (Näringsdepartementet, 2022; Näringsdepartementet, 2019; Skogforsk, 2021). ML has become part of policy implementation within the context. Policy implementation, meaning here, deliberate actions taken by a government authority with the intention of reaching a set policy goal. The goal needs to be realized through changing the actions of individual forest owners. It is then important to understand ML as part of a larger governance scheme, rather than as an isolated phenomenon.

Previous research has shown that forest owners respond differently to forestry policies, and various typologies have been developed to explain these differences (Ficko et al., 2019; Ekström et al., 2024). Hujala et al. (2007), (2009) identified three types of forest owners, “independent managers,” “active learners,” and “trusting realizers”, who have different approaches to receiving decision support. What differentiates these groups is how much they trust the advice of others, versus their own knowledge. As previously explained, there is hope that ML-tools will be used in decision making and these results give insight into how forest owners relate to decision-support. ML-tools introduce new dimensions that might affect how individual perceive the “advice” coming from ML, such as the relationship to technology, trust in the provider of the technology, the forest owner’s own experience and expertise.

However, the relationship between forest owner typologies and technology has been underexplored, with few studies addressing how these owners engage with technological tools like ML. Wreford et al. (2021) found that some forest owners have limited access to technology, influenced by socio-economic factors. Sousa-Silva et al. (2016)’s study deals with the relationship between technological knowledge and forest managers for tackling climate change. Their results points towards forest manager’s seeing technological knowledge as increasingly important for adapting to climate change. This technological dimension of forest ownership is becoming increasingly important both in the Swedish and European context as previously discussed, and worldwide as big data and AI are becoming increasingly important in environmental decision making (Kim, 2024; Li et al., 2021). Outside of the forest-owner typology literature, research on the forest owner’s relationship to ML is sparse. While not dealing with perceptions per se, an example comes from Rinaldi and Jonsson (2020) who explicitly include model mistrust in their theoretical framework for understanding decision making under uncertainty with the help of decision support systems.

### 1.1. Theoretical framework

The following section introduces self-determination theory (SDT) and exemplifies its applicability to understanding the context of Swedish forestry and ML-perceptions.

SDT addresses how three fundamental human needs – for autonomy, competence, and relatedness – are satisfied in each context, and how those contexts either support or obstruct those needs (Deci and Ryan, 2000; Ryan and Deci, 2017; Ryan and DeHaan, 2023). SDT has already been applied to understand public policy (Aknin & Williams 2021; Ryan and DeHaan, 2023, p. 246) and, in the current study, offers a lens for understanding the perceived effects of deploying ML in the context of forestry. Social and environmental changes, such as the adoption of new technologies, can impact individuals’ feelings of autonomy, competence, and relatedness (Ryan and DeHaan (2023). Cascio and Montealegre (2016) discuss SDT and its relationship to technology and human well-being and offer several examples of when technology thwarts these needs, leading to perceptions of oppression and loss of trust. SDT is thus helpful in understanding perceptions of ML. Past studies have used SDT to elucidate the motivations behind agricultural practices (Garini et al., 2017), assess the effectiveness of policy interventions in forestry (Léger-Bosch and Chervier, 2023) and attitudes towards artificial intelligence (Latikka et al., 2023). SDT has also served as a theoretical foundation for previous Q-method studies (Wang and Lewis, 2022).

Relatedness refers to how procedures and interaction inform an individual about their standing in a social group. This applies to both relationships between people and those between governing authorities and people. Vainio (2011) showed that institutional legitimacy and fair treatment was important for forest owner’s acceptance of decisions and Jakobsson stressed the importance of dialogue among forest owners and environmental- and state organizations to decrease conflicts (Jakobsson et al., 2021). Hence, understanding how deploying ML is perceived to affect how individuals relate to each other and their forests is central to understanding its potential effects in this context.

Competence refers to a person’s need to feel effective and capable in their interactions with the environment. Competing demands for environmental protection and production place high demands on forest owners’ competence as they make management choices (Löfmarck, Uggla, and Lidskog, 2017; Uggla, 2018). Competence could also be an issue for long-distance owners (sometimes called: *absentees*), an ownership category that has increased (Skogskunskap, 2024). ML is potentially helpful in allowing management decisions to be taken from afar (see Bergstén and Keskitalo, 2019). ML thus has the potential to increase feelings of being effectiveness for certain groups of forest owners.

Autonomy, the ability to make choices on one’s own behalf, is argued to be fundamental to well-being (Frey, Benz, and Stutzer, 2004; Deci and Ryan, 2012; Freundt, Herz, and Kopp, 2023; Léger-Bosch and Chervier, 2023) In the context of Swedish forestry, the legal framework theoretically gives forest owners a high degree of autonomy. However, the reality of such autonomy has been called into question (Löfmarck, Uggla, and Lidskog, 2017; Uggla, 2018; Follo et al., 2017). Danley also points out that cognitive burdens and uncertainties is hindering even environmentally minded owners from more environmentally focused management practices. ML is then a potential tool for increasing the autonomy of such forest owners (Danley, 2019).

We then suggest that an individual’s perception of ML is influenced by three evaluations: Do they perceive ML to change the range of actions available to them (autonomy); does it change their ways of interacting with and being appreciated by others (relatedness); and does it enable or hinder them from achieving autonomously set goals (competence)?

## 2. Material and methods

### 2.1. Overview of Q-methodology

Q-methodology is an approach to the study of subjectivity. It makes use of Q-sorts which are collections of statements about a particular topic that participants rank on a subjective dimension such as agree/disagree. The statements are prepared by the researcher utilizing various strategies (McKeown and Thomas, 2013). Through the Q-sort, each participant provides a model of their perception of the topic. The Q-sorts are then subjected to a by-person factor analysis, where the extracted factors signify a group of people who have similar perceptions on the topic (Watts and Stenner, 2012). The factors can thus be said to represent shared ways of thinking about the topic, and they are then interpreted qualitatively. Q-methodology has been employed to investigate subjective perspectives on public manager's perception of big data (Guenduez et al., 2020), forestry management (Barletti, Cronkleton, and Vigil, 2022) and perceptions of artificial intelligence in various public domains (Ezzeddine, Bayerl, and Gibson, 2023; Jeffares, 2020). The results of Q-method will allow us to group different forest owner's perceptions of ML and how it is perceived to influence their lived context.

The following sections will explain the approach taken, also summarized in Fig. 1.

### 2.2. Statement collection and content

In this study, the statements which respondents were asked to rank were gathered through semi-structured interviews guided by an interview protocol (appendix 1). We conducted 11 online-interviews with forest-owners across Sweden over the course of three months (April to June 2023). We started the interviews with open-ended questions regarding sentiments about forest policy in Sweden, the use of technology, and the owner's relationship to their forest. Next, the respondents were given a demonstration and explanation of an available ML tool, the SLU Soil Moisture Map (SLU, n.d). We then asked them about the usefulness of the tool and potential difficulties for them themselves to apply it to their own forestry practices. We then prompted the respondents to speculate regarding the consequences of increased use of ML would have in forestry. The interview ended with the question if the respondents had anything to add.

The interviews were then transcribed, and respondents then read through and approved the final transcripts. The analysis of interview data was deductive in the sense that the three notions of competence, relatedness, and autonomy were used to structure the analysis. Through an iterative process, answers were manually coded into the categories of relatedness, autonomy, or competence using the software "Taguette" (Rampin and Rampin, 2021). With the coding done, we had several examples of how ML and other factors was perceived to affect forest owner's autonomy, competence, and relatedness. These examples were then used to create the statements (short sentences containing an opinion) to be used in the Q-set. Sentiments expressed by interviewees that did not unambiguously fit into these categories but that we deemed to be relevant to understand an individual's perception were put into a separate "other" category. The "other" category also included Q-statements which captured sentiments about the general political context of forestry in Sweden which were also recurrent in the interviews. The statements were looked over and discussed by the researchers, certain

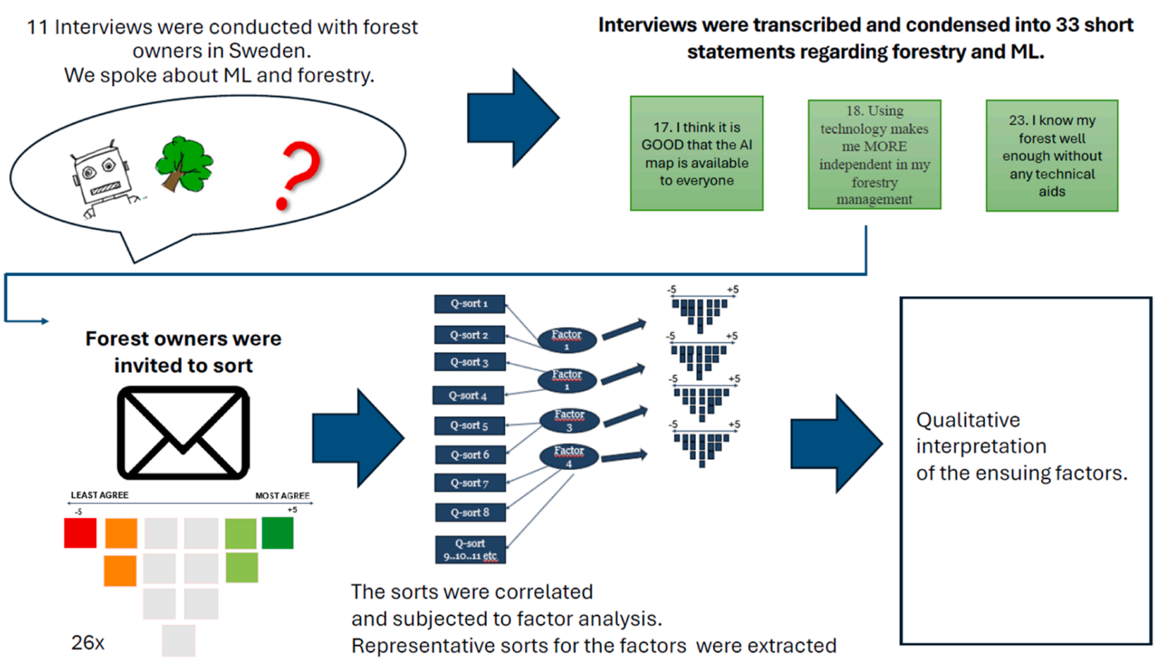


**Fig. 1.** Visual representation of the approach taken.

**Table 1**
Factor characteristics. Eigenvalues >1 and at least 2 loaded sorts were used as selection criteria.

| Factor characteristics. | Average Reliability coef | Loaded sorts | Eigenvalues | Explained variability | Composite reliability | Factor scores SE |
|---|---|---|---|---|---|---|
| Factor 1 | 0.8 | 8 | 5.60 | 21.54 | 0.97 | 0.17 |
| Factor 2 | 0.8 | 4 | 2.75 | 10.59 | 0.94 | 0.24 |
| Factor 3 | 0.8 | 5 | 3.63 | 13.95 | 0.95 | 0.21 |
| Factor 4 | 0.8 | 3 | 2.08 | 8.03 | 0.92 | 0.28 |

**Table 2**
The factor array. This is a single ideal-typical Q-sort for each of the ensuing factors.

| The factor array is a single ideal-typical Q sort for each factor (Z-scores are reported in parenthesis). | Factor 1 | Factor 2* | Factor 3 | Factor 4 |
|---|---|---|---|---|
| 1. The state interferes too much in forestry | 3 *(1.43)* | 4 *(1.27)* | −4 *(−1.64)* | 2 *(0.57)* |
| 2. Freedom with responsibility mostly entails responsibility | 1 *(0.47)* | 2 *(0.81)* | −2 *(0.66)* | −1 *(−0.05)* |
| 3. I am dependent on someone else when making decisions about my forest | −4 *(−1.46)* | 1 *(0.58)* | −2 *(−0.82)* | 4 *(1.41)* |
| 4. There is a risk of becoming TOO technology-dependent in forestry management | −1 *(−0.55)* | 0 *(−0.01)* | 1 *(0.32)* | −2 *(−0.84)* |
| 5. I lack the prerequisites for using the AI map** | −3 *(−1.25)* | 0 *(0.32)* | 1 *(0.62)* | −4 *(−1.78)* |
| 6. The AI map does not help me achieve my forestry objectives | −2 *(−0.80)* | 1 *(0.66)* | 0 *(0.14)* | −3 *(−1.10)* |
| 7. When authorities use technology, I have less voice in the proceedings | 3 *(1.17)* | 2 *(0.73)* | −1 *(−0.39)* | 1 *(0.41)* |
| 8. It is important to be physically close to your forest | 2 *(0.89)* | 3 *(1.22)* | 4 *(1.84)* | 0 *(0.13)* |
| 9. The state does NOT respect me as a forest owner | 0 *(0.18)* | −1 *(−0.03)* | −5 *(−1.82)* | 1 *(0.35)* |
| 10. The existing support mostly benefits other forest owners who own a lot of forest. | −1 *(−0.56)* | 3 *(1.17)* | 3 *(1.09)* | −2 *(−0.41)* |
| 11. There is too little dialogue between forest owners and authorities | 1 *(0.42)* | −4 *(−1.68)* | 1 *(0.46)* | 0 *(0.22)* |
| 12. All government decisions on forests are taken over my head | 2 *(0.97)* | 5 *(1.42)* | −3 *(−0.89)* | 1 *(0.46)* |
| 13. If an authority makes a bad decision about my forest – the case will be resolved | −4 *(−1.54)* | 2 *(0.84)* | 1 *(0.16)* | −5 *(−1.96)* |
| 14. Supervision is necessary to achieve forest policy objectives | −2 *(−0.81)* | −2 *(−0.77)* | 2 *(0.81)* | −2 *(−0.93)* |
| 15. It is good that information from all forests is available to the public. | −3 *(−1.21)* | −3 *(−1.38)* | 2 *(0.78)* | 0 *(0.13)* |
| 16. The AI map is a control tool - for better or worse | 0 *(0.15)* | −1 *(−0.24)* | 0 *(−0.28)* | 3 *(1.02)* |
| 17. I think it is GOOD that the AI map** is available to everyone | 0 *(−0.21)* | −1 *(−0.34)* | 3 *(1.27)* | 2 *(0.72)* |
| 18. Using technology makes me MORE independent in my forestry management | 1 *(0.42)* | −3 *(−1.13)* | −2 *(−0.67)* | 4 *(1.42)* |
| 19. The use of the AI map by authorities means MORE RISK than benefit | 1 *(0.55)* | 2 *(0.86)* | −3 *(−1.05)* | −3 *(−1.20)* |
| 20. The less human intervention the BETTER | −3 *(−1.31)* | 1 *(0.58)* | −4 *(−1.80)* | −1 *(−0.20)* |
| 21. There is TOO MUCH to 'keep track of' when it comes to forestry | −2 *(−0.72)* | 4 *(1.26)* | −3 *(−1.24)* | 0 *(0.18)* |
| 22. I lack the knowledge to be able to manage the forest the way I really want | −5 *(−1.62)* | 3 *(0.92)* | −1 *(−0.57)* | 1 *(0.22)* |
| 23. I know my forest well enough without any technical aids | 0 *(−0.34)* | 1 *(0.39)* | 2 *(0.67)* | −4 *(−1.92)* |
| 24. Local knowledge is most important for good forest decision-making | 4 *(1.54)* | 0 *(0.18)* | 4 *(1.41)* | −1 *(−0.04)* |
| 25. Tools such as the AI map cannot replace local knowledge. | 3 *(1.01)* | −1 *(−0.09)* | 2 *(0.64)* | 0 *(−0.03)* |
| 26. Decisions based on the probabilities presented on the AI map are better than those based on intuition. | −1 *(−0.67)* | −2 *(−0.85)* | −1 *(−0.36)* | 3 *(1.31)* |
| 27. Technology helps me to manage my forest the way I want | 2 *(0.56)* | −2 *(−0.76)* | −2 *(−0.60)* | 5 *(1.73)* |
| 28. The forest owner's local knowledge of their forest is MORE VALUABLE than the information from the AI map | 4 *(1.56)* | 0 *(0.02)* | 3 *(0.86)* | −2 *(−0.63)* |
| 29. Sustainability and production are EQUALLY IMPORTANT in forest management | −2 *(−0.84)* | −5 *(−2.13)* | 0 *(0.05)* | −1 *(−0.26)* |
| 30. My forest is important for my economic situation | 2 *(0.83)* | −3 *(−1.28)* | −1 *(−0.46)* | 2 *(0.97)* |
| 31. My forest is important to me beyond economics | 5 *(1.78)* | −4 *(−2.00)* | 5 *(2.16)* | 3 *(1.14)* |
| 32. AI tools will be of great help in achieving the forest policy goals of high and sustainable production | −1 *(−0.39)* | −2 *(−0.83)* | 0 *(0.08)* | 2 *(0.55)* |
| 33. There is a risk that local knowledge about the forest will become less valuable when tools such as the AI map are used. | 0 *(0.37)* | 0 *(0.32)* | 0 *(−0.10)* | −3 *(−1.61)* |

*Factor 2 is inverted in the interpretation in the main text.
**The ML-tool shown in the introductory video is referred to as "the AI-map" for the respondents, which is why some statements refer to "AI-map" rather than ML.

Q-statements were edited for clarity or due to being too like other statements in the set. A total of 33 different statements were "extracted" from the interviews. See Table 2 for a full list of statements.

### 2.3. Participants and sorting procedure

After constructing representative statements from the interviews, we invited respondents to sort the statements using a Ken-Q analysis software (Banasick, 2019) that was hosted on a web server. The Swedish Land survey was asked to provide a sample of forest owners, with equal proportions in terms of gender, size of forest owned (small (<10 ha), medium (10–100 ha), large (>100 ha)), and geographical location.

The web link to the Q-sort was sent directly to 200 of these forest owners and posted to selected social media groups relating to forestry.

The 200 forest owners approached directly by letter were selected using strategic sampling (Watts and Stenner, 2012), to include a range of participants who relate to forestry differently rather than a representative sample. Selection criteria included gender, geographic location, and size of forest. These selection criteria were chosen due to gender, geographic location and size are common variables affecting management practices and relationship to one's forest (Follo et al., 2017, Mulu et al., 2022)

The Q-sorting procedure went as follows: the first page contained information about the research project, how data would be managed, and contact information for the responsible researcher. The respondent was also asked to watch a 3-minute video explaining an ML application in forestry, like the demonstration we held in the interviews. The second page showed the statements, and the respondent was asked to do a preliminary sorting of these, placing each statement into a disagree, neutral, or agree pile. This was done for all 33 statements. On the next page, the respondent was asked to drag and drop the statements into a quasi-normally distributed grid for a more fine-grained sort, ranging from do not agree to fully agree. The final page consisted of demographic questions about the respondent, such as gender, size of forest and whether they live on their land permanently.

### 2.4. Approach to statistical analysis and factor extraction

Of the 200 letters that were sent out, 26 respondents went through with the Q-sort. These Q-sorts were correlated, and the ensuing correlation matrix was subjected to a by-person factor analysis using Zabala (2014)'s Q-methodology package for the R programming language. Two criteria were used to decide on the number of factors to extract. Eigenvalues capture the amount of common variance contained by a factor and we decided to keep Eigenvalues larger than 1.0. Secondly, the factor should have at least 2 significantly loaded sorts, ($p-value < .05$) as this was important for interpreting the factor. Q-sorts that load significantly on the same factor share a similar sorting pattern and, thus, indicate a shared perception. Q-sorts with a factor loading higher than $p-value <$ 0.05 and Q-sorts whose square loading was higher than the sum of square loadings of the same Q-sort in all other factors were used as loading criteria (Zabala, 2014). With these selection criteria, the analysis was run starting with 7 factors and reduced by 1 until each ensuing factor met the above stated criteria. Using the two inclusion criteria discussed above (eigenvalues > 1, and at least two significantly loaded Q-sorts), 4 factors were extracted and kept.

Centroid factor extraction with varimax rotation was used, a standard approach in Q-methodological studies (Watts and Stenner, 2012). Varimax rotation means that each factor is rotated to maximize the variance of the loadings for each factor, leading to a lower number of factors extracted. This facilitates the interpretation because it makes factors more distinct from each other by making high loadings higher and low loadings lower (Akhtar-Danesh, 2023).

Factor arrays were then created from the extracted factors. Factor arrays are estimates of the resulting factor's perception and are important tools for interpreting them. An array can be understood as capturing: "how would the extracted factor have sorted the statements?", and it is calculated by taking a weighted average of all the individual Q-sorts that load on that factor and that factor alone (Zabala, 2014). The array thus exemplifies the extracted factor's perception, based on the weighted average of the Q-sorts that loaded on the factor (see Table 2 for the ensuing factor arrays).

The code and data for model selection and Figs. 2 and 3 are available as an appendix.

### 2.5. Approach to factor and statement interpretation

Interpretation of the factor arrays was conducted using a "crib sheet"-system (Watts and Stenner, 2012:150). This involves dividing the items for each factor into 4 categories. Two of these comprise the most important items, i.e. those ranked −5 and 5, regardless of how they are placed in the other factor arrays. The other two categories comprise the items that were ranked higher in that factor array than in any of the other factor arrays, and those that were lower than in any other factor array, respectively. This ensures that interpretation of the array is holistic. For each statement in each factor's crib sheet, the authors discussed and agreed what the statement meant for that factor in relation to the placement of other statements. Meanings were written down in short sentences which were later used to compile the full factor interpretation, aiming for coherence.

## 3. Results

The results section contains results from the interviews, statistical analysis and the interpretations of the extracted factors. The results from the qualitative interviews are presented below and describe how the Q-statements extracted from the interviews reflect SDT.

Following this, the results of the statistical analysis to extract the

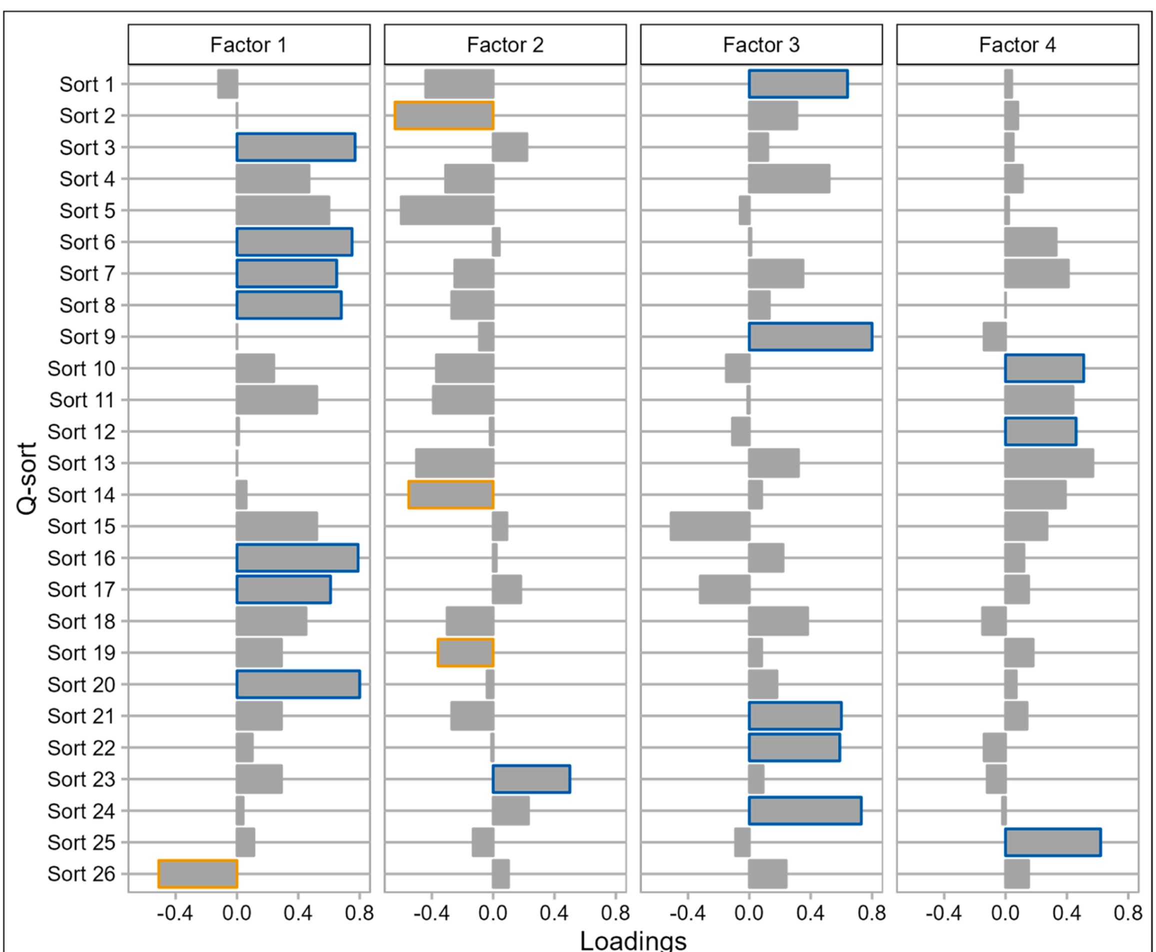


**Fig. 2.** Each Q-sort's respective loading on each factor. The colored outlines represent flagged Q-sorts for the factor. The Y-axis contains the 26 valid Q-sorts from our respondents. The x-axis for each factor shows the loading of each sort on that factor. Highlighted bars indicate loadings.

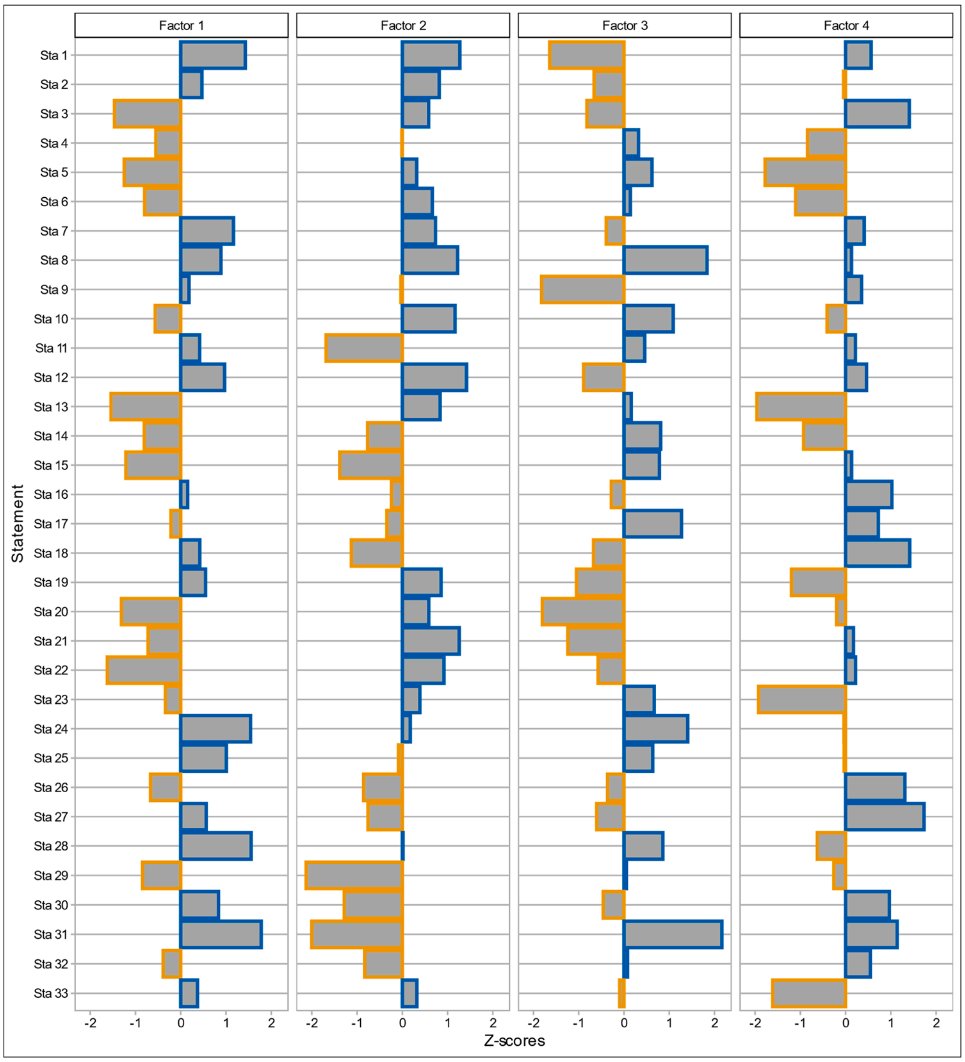


**Fig. 3.** Each of the statements and their Z-score. The z-scores (X-axis) indicate how much a factor "agrees / disagrees" with a statement (Y-axis).

factors from the Q-sorts are presented. After this, the four perception-interpretations from the view of SDT are presented.

### 3.1. Qualitative interviews

The following sections explain what statements were extracted and their relationship to SDT that resulted from the interviews.

#### 3.1.1. Autonomy

Recurring themes included state interference and how the current forest governance scheme forbids certain actions and thus thwarts autonomy. The principle of "freedom under responsibility" came up frequently as respondents were prompted to talk about the responsibility placed on them. One respondent saw forest management as a forced service conducted by forest owners for the collective benefit of society. Thus, the actions taken are not seen by some respondents as voluntary, despite government parlance. Another respondent disclosed that they felt that what they valued in their forests did not necessarily resonate with what the authorities saw as valuable, and that they lacked a voice in these matters. Lastly, one respondent disclosed that they were dependent on other people when taking management decisions.

It seems that respondents are apprehensive about the combination of technology and authority over decisions which relates to their ability to make autonomous decisions in the context of forestry. The statements relating to autonomy thus reflected dependence on others, autonomous action, and state interference.

#### 3.1.2. Competence

Recurring themes relating to competence included how useful ML could be for achieving one's set goals, and the competence needed to use these tools. Several respondents were positive about the potential for taking smaller, i.e. more precise, pieces of land into consideration when planning forestry operations. In this view, ML technology can support competence and create opportunities to diversify forests by lowering the costs involved in managing them accordingly.

Another theme was the knowledge that managing a forest demands, and that the sense that existing knowledge support focuses mainly on larger forest owners. A further recurring theme was that ML allowed remote forest owners to manage their forests more actively at lower cost, reducing the need to travel and be physically present on their land. Some respondents worried that local knowledge and experience (pertaining to both appropriate management and recreation, e.g. knowing which walking paths are popular with the local population) would be undervalued and disappear, leading to forests declining in quality. There was thus a conflict dimension between forest owner's "local knowledge" and the ML-maps "universal" knowledge. The statements about competence thus reflected the use of technology and ML for achieving goals, the prerequisites for using it, and the place and use of local knowledge.

#### 3.1.3. Relatedness

One theme relating to relatedness pertained to forest size and how this influenced how important the individual was seen to be. Two respondents expressed feeling that they were not considered important enough to reaching forest policy goals to receive support from public authorities.

Other themes relevant to relatedness included conflict between forest owners and “environmental activists”. One respondent expressed worries that ML tools would allow others to criticize the way that they managed their forests, despite having little to no contextual knowledge – amounting to a decontextualized critique. Another theme was that these ML maps and tools were available to the public, giving them access to potentially sensitive information (e.g. size of timber stand).

Lastly, several respondents spoke about being respected by state authorities. This related to the way in which official decisions have been made without consultation, making respondents feel that they had no voice in decision-making processes. One respondent expressed that there was a lack of gratitude for the service that forest owners provide by managing their forests to achieve political goals that are beneficial to all. The statements about relatedness thus reflected “voice” in administrative processes, the availability of information, and respect.

All the statements generated can be found in Table 2, translated from the original Swedish.

### 3.2. Factor extraction

The factors were extracted as described in Section 2.4. It resulted in 4 extracted factors that met the retainment criteria. All but 6 Q-sorts loads on one of the factors. Factor 1 has the most explanatory power and explains 21.5 % of the variability in the data and has 8 loaded Q-sorts. Table 1 summarizes the factor characteristics for each one of the extracted factors.

Fig. 2 shows the flags and loadings of each Q-sort on the respective factors. The X-axis shows how much a sort correlates with a factor, and whether it loaded significantly on the factor.

Fig. 3 shows the statements z-score for each factor. The item z-scores represent how a hypothetical person representing a factor would place the item. The factor array, Table 2, shows a weighing of the z-scores to receive a representative sorting for each of the extracted factors, together with the standardized Z-scored.

### 3.3. Four perceptions on forestry and ML from the lens of SDT

Table 2 shows the factor array for each representative Q-sort. In the following section, the parentheses in the factor interpretations (described in Section 2.5) can be understood as “anchors”. The anchors show what statement placement gave us “evidence” for a particular claim about that perception.

We extracted 4 different perceptions on ML in forestry through the factor extraction process (described in Section 2.4).

#### 3.3.1. Factor 1: the knowledgeable traditionalist

The knowledgeable traditionalists, who value their forest management knowledge highly, exhibit a strong sense of autonomy and confidence in their decision-making about forestry (s4: −4, s22: −5). Their feelings are characterized by distrust towards public institutions, particularly when official views conflict with their own forest management assessments. For the traditionalist, being a forest owner is not just about producing biomass for economic gain but is also as part of relatedness integral to their identity, including through recreation and hunting (s31: +5).

Their skepticism towards ML manifests in two ways. Firstly, they doubt its utility, expressing the belief that ’current ways of doing things’ are sufficient to meet both individual and collective societal/political goals, (s6: −2, s32: −1). Secondly, they are skeptical of agencies’ use of technology for the same reasons that they are skeptical of public institutions interfering in their forest management. They emphasize the significance of local knowledge, considering it highly important and irreplaceable (s25: +3). There is a pervasive fear among traditionalists that their expertise may not be heard and taken seriously. This perception is mingled with concerns about privacy, as evident in their strong disagreement with statement 15 (s15: −3).

It is important to note that their skepticism is not directed towards technology in broader terms, as indicated by statements 27 (s27: +2) and 18 (18: +1). Rather, they view ML as a different kind of technology and question the usefulness of the knowledge gained from it (s24: +4, s28: +2, s32: −1, s26: −1).

*3.3.1.1. ML as a threat.* The forest owners who load with factor 1 are independent and perceive themselves as competent without machine learning. ML offers little extra in affording an extra range of actions that will help in achieving their goals (competence), made clear by S28 (+4) and S22 (+5). Relatedness, ways of interacting and being appreciated by others is potentially threatened (S15: −3, S19: 1). The risk that is being perceived is that authorities will challenge their decisions and local knowledge more (S7: +3, S19: +1, S20: −3), as well as more critique from the public when information gets more easily available (S15: −3).

#### 3.3.2. Factor 2: the curious environmentalist

*This factor is bi-polar, distinguished by three of the four Q-sorts being flagged negatively: it is thus interpreted negatively i.e. taking the factor array and multiplying the statement score by −1.*

The curious environmentalist is characterized by environmental concern aligned with the belief that forests are not all about money (s31: +4, s29: +5).

They express the belief that forest owners have a responsibility to manage their forests sustainably. This can be seen as a political belief in the sense of how to act in the collective best interest. Although accepting of environmental demands in the legal framework (s1: −4, s21: −4) their trust in state authority remains tempered. The curious environmentalist harbors a healthy skepticism, believing that the best way to manage their forests is sometimes different (s22, −3, s13, −2) to that promoted by state authorities (s11, +4). This skepticism extends toward large forestry actors and how they are currently managing their forests, leading to support for state intervention and supervision (s1: −4, s14: +2). The curious environmentalist firmly agrees that ML can be a complement to both state intervention and supervision (s14: +2, s15: +3, s17: +1) and aligned with forest policy goals (s32: +2). They are curious about the use of ML in planning their forestry operations (s6: −1, s23: −1, s26: +2) and see some cases for using the technology. The curious environmentalist is characterized by a mild techno-optimism, asserting that technology is a good complement to their existing knowledge of forestry management (s27: +2, s18: +3).

The curious environmentalist also feels that technology can complement how forests are managed on a collective level - improving supervision and the information available. The overarching view of ML from this perception is that it is a complement to current political steering, specifically in terms of supervision and information (s14: +2, s15: +3), and a potential complement to innovative forest management.

*3.3.2.1. ML as a complement.* For the people loading on factor 2, ML does not present itself to something revolutionary – but potentially autonomy and competence enhancing. The current viewpoint sees ML as a potential tool for the political steering of forests mostly how to govern forests collectively. The use of ML by public authorities is perceived to help in achieving the collective goals of sustainable forestry (s14: +2, s15: +3, s17: +1). With ML, forestry in Sweden is perceived to become more sustainable, creating new opportunities for alternative ways of managing forests, thus enhancing relatedness, autonomy as well as competence for these forest owners.

#### 3.3.3. Factor 3: the inadvertent forest owner

A modest average forest size of 12,6 ha set the inadvertent forest owners apart from other factors and informed the interpretation of this factor. Two of their most polarized statements related to non-decisions and the modest size of their land. S31 was placed at +5, showing that, for these forest owners, the essence of owning a forest transcended economic gain: rather, it is about prioritizing other ecosystem services. This perception is associated with passivity towards their ownership of forests. Proximity to the forest emerged as a recurring theme, not just geographical proximity but also closeness in terms of well-being and decision-making (s24: +4, s8: +4), placing high regard on local and human-experienced forest knowledge (s28: +3, s25+2). Curiously, the inadvertent forest owner expressed disinterest in incorporating technology into their forest management practices (s18: −2, s27: −2, s6: 0), although their reluctance to using technology or ML in forestry does not extend to other forest owners or state authorities using it (s17: +3, s19: −3). They place significant trust in public authorities governing the forest sector (s9: −5, s1: −4, s12: −3, s19: −3), and have faith in the way that forests are governed in Sweden.

*3.3.3.1. ML as nothing in particular.* Passivity and high institutional trust permeate this factor's view on ML. Despite seeing no direct use for it for their forest management (competence) they have no problems with its development and application for reaching broader political goals. Their passive acceptance of the ways in which forest-policy goals are pursued stems from their being largely unaffected by the decisions that are being taken. For the owners that load on factor 3, ML in forestry does not appear to be affecting competence, autonomy or relatedness at all.

#### 3.3.4. Factor 4: The tech-rationalist

The tech-rationalist is characterized by profound trust in technology and notable skepticism towards state interference. For tech-rationalists, owning forests is a strategic investment with both economic and recreational benefits (s30: +2, s31: +3, s29: −1). They acknowledge their limited knowledge about forest management and rely on others to take management decisions (s3: +4). However, this dependence could be alleviated by using technology (s18: +4, s23: −4), at which they see themselves as adept (s5: −4). In contrast to other factors, they place little faith in local and human-experienced forest knowledge (s24: −1, s28: −2, s26: +3) and see no risk of it being devalued through greater dependence on ML (s33: −3). None of the respondents loading on this factor live close to their forest, challenging the conventional notion that proximity equals effective forest management (s8:0).

A core tenet of the tech-rationalist perception was the conviction that state authorities are too focused on regulating management and should place greater trust in individual forest owners (s13: −5, s2: +2, s9: +1, s14: −2). State interference is perceived as a potential threat to the value of their forest investment, and they express a preference for autonomy in decision-making.

To the tech-rationalist, ML and technology are seen not as a complement to current forestry practices but as a prerequisite for being able to manage forests (s23: −4, s6: −3, s4: −2). In terms of the use of ML by state authorities the tech rationalist expects it to improve how decisions are made, reducing the risks of human error and "activism" (see: Olsson, 2009) having too strong an influence over agency decisions (s19: −3). They feel that anything is better than how official decisions are currently being made (s13: −5) and see ML as increasing the objectivity of authoritative decision making.

*3.3.4.1. ML as a prerequisite.* The forest owners who load on factor 4 see ML and its applications in forestry as a prerequisite to manage their forests. These people are dependent on others, and ML can increase their autonomy, reducing their reliance on others (s3: +4) to take decisions to reach to reach their own goals. ML is thus perceived as both autonomy and competence enhancing (s6: −3, S18: +4, s27: +5). Coupled with this technophilia is a distrust to forest authorities (s13: −5). Their perception contrasts with factor 1; where ML instead can improve their relationship with public authorities (s19: +3), ML is perceived as potentially relatedness enhancing rather than hampering.

## 4. Discussion

Here we discuss the ensuing viewpoints in relation to the SDT, previous forest owner typologies and forestry policy in Sweden.

### 4.1. Connections to previous forest owner typologies

This study has shown that it is possible to systematize stakeholders' fears, apprehensions, and hopes about ML with the help of SDT. This approach may help to inform how ML can be integrated into the pursuit of sustainability goals and better understand what role ML can play in forest owner decision-making in realizing policy objectives (Bennet & Dearden, 2014; Joshi et al., 2018).

Discussing the four extracted viewpoints in relation to SDT

Li et al. (2021) argued in this journal that citizens should be well equipped to make good use of the data to facilitate their personal decision making. This means that governing authorities are also in need of understanding citizen's perceptions of these technologies to be able to inform practices and informational campaigns to increase uptake and resolve potential apprehensions.

In our data we interpreted different ownership objectives, motivations and forest importance based on the placement of the statements. Our results show that forest owners' disposition towards ML in general is not unambiguously within forestry goals typologies nor with forest-ownership typologies (Ficko, 2019). This suggests that variance found in the disposition to ML is related to other factors of being a forest owner.

Our results resonate particularly Hujala's et al.'s (2007; 2009) decision making and advice-taking typologies. What Hujala et al. (2009) called "trusting realizers", forest owners who feel like they know little about managing forests and strongly reliant, still actively seek useful guiding information. The researchers' description of the "trusting realizer" resonates well with how we interpreted our "tech-rationalist" grouping – as does the demographical information we have (dominated by far distance owners). For both trusting realizers and our factor 4 – it is autonomy and competence that is lacking. This is translated into looking for information from ML as it is potentially autonomy and competence enhancing.

Hujala's (2009) grouping "independent managers" described as not being in need for guiding information and heavily relies on their own experience. This grouping also resonates well with how we interpreted our first factor "the knowledgeable traditionalist". For these groupings, neither competence nor autonomy is lacking. The introduction of new technology and potential new ways of looking at forest knowledge risks de-valuing their own knowledge and experience. It is clear then that forest owner groupings' relationship to technology is important in the increasingly datafied planet (Wickberg et al., 2024), and our results are one step closer to systematizing how forest owner's perceptions of technology can be systematized with the help of SDT.

SDT was particularly helpful in uncovering the reasons behind perceptions, which may inform subsequent actions to inform about what citizens find unacceptable with these new technologies and how to maximize public utility while achieving policy goals (Li et al., 2021, p.245).

### 4.2. Implications for policymaking

Sweden's current forestry policy is being influenced by the development of machine learning (ML) tools and other forms of "digital knowledge." Danley previously examined the limitations of the "freedom-under-responsibility" principle, suggesting that within the existing voluntary framework, reducing the costs of sustainable practices for non-industrial private forest (NIPF) owners could enhance governance effectiveness (Danley et al., 2021). The developed ML-tools can be an asset to forest owners to promote sustainably management decisions, as it reduces the costs associated with mapping out natural values. Coupling ML-tools to already existing consultation-services to create value is one way in which these digital forest knowledges are expected to create outcomes. However, this relies on the assumption that NIPF owners are willing to engage with these consultations and recognize the advantages of digital knowledge. Therefore, it is essential to evaluate not only perceptions towards technology but also the broader social context in which these tools operate.

A report from the Swedish Forest Agency (Skogsstyrelsen, 2023/12, p.56) highlights the need for more knowledge on how to evaluate machine learning-generated maps from the perspective of forest owners. The current study provides one such approach. The results suggest that it is not only the actions that the ML-tools affords (competence), but also its perceived effects on autonomy and relatedness that shapes the forest owner's perception of the ML-tools. Some concrete suggestions also result from seeing the factors from the perspective of SDT.

Privacy was a recurring worry for autonomy and relatedness particularly for factor 1 and 4. A potential improvement is to only allow registered users to access the maps – or to allow individual owners to opt out their land.

Factor 2's perception of ML was contingent on competence enhancing and potential for collective steering of forests that the ML-tools affords. These results suggest that in consultation and educational measures, strengthening the connection between environmental goals and forest management and how these ML-tools can facilitate these is necessary.

As for factor 4, who sees technology as a prerequisite for their decision making in forestry, it may be advisable to communicate the limits of the technology, and the uncertainties involved in using it. ML tools can increase autonomy, which is particularly useful for urban forest owners, but being open about its limits would allow people who share this perception to calibrate their degree of trust in the technology appropriately. This information should be readily available on websites and even the UI of the maps, as people who load on this factor are unlikely to accept consultation from the SFA.

### 4.3. Methodological considerations

While Q-methodology offers an in-depth understanding of the perceptions of a particular pool of respondents, no conclusions can be drawn as to how representative or widespread these perceptions are across the general population of forest owners in Sweden. Q-method is not interested in taking "head counts" of existing perceptions, but rather understanding and explaining these perceptions. In deciding when to stop collecting Q-sorts, this study followed Watts & Stenner (2012)'s guideline of having "fewer participants than the number of statements" (p. 71).

While Q-methodology enables interpretations to be anchored in the factor array's ranking of statements, some placements were nonetheless ambiguous, for instance the placement of s20 by factor 3. We interpreted it as the view that humans should be part of governing forests towards environmental goals or indeed very active forest management methods such as continuous cover forestry, based on the placement of other factors that point to the precedence of environmental protection over timber production by the factor-perception. Another potential interpretation of the statement is that technological knowledge should take precedence over human knowledge in environmental planning. The latter interpretation did not resonate as well with the other statements. Such ambiguous cases were rare and, where they arose, they were interpreted so that the perception was as coherent as possible with the placement of other statements.

The coherence between the results of the interviews and of the statistical analysis in this study suggest that the approach taken was valid. It shows that the perceptions of interview respondents clearly resonate with one or more of the perceptions that emerged and that the themes emerging from the interviews resonated with the ensuing factors. It also shows that SDT is helpful in categorizing and understanding perception towards ML within this context. It has been claimed that SDT is applicable to any geographical or cultural context (Ryan and DeHaan, 2023:1152). Thus, while the result of this study is bound to Swedish forestry and our P-sample, the approach taken in this study could be fruitfully applied in other contexts to address concerns that individuals might have.

It should be noted that the perceptions interpreted are ideal types that emerged from the factor analysis, and thus that individuals may agree with them to varying degrees.

## 5. Conclusion

The application of ML in forestry management in Sweden and elsewhere presents both opportunities and challenges. We extracted 4 different perceptions of ML in forestry from our collected data. These highlight the complexity of integrating ML into forestry practices. While some forest owners see ML as a valuable tool that can enhance their autonomy and competence, others express skepticism, fearing potential effects for their privacy and the devaluation of local knowledge, a threat to relatedness. SDT allowed categorizing and analyzing the sorted statements as well as the shared perceptions of ML in the context of Swedish forestry.

It is important for policymakers to understand these diverse perceptions and address the concerns raised if the goal is for these tools to be used for social good in forest owner decision making. This could involve measures to protect forest owners' privacy or providing clear information about how ML can assist in sustainable forest management. The results of this study are particularly helpful when considered to previous research on forest owner typologies. The results show that forest owner typologies, particularly those relating to information seeking and advice taking resonates with the extracted perceptions of ML. It allows policymakers to better understand reactions and reasons for uptake among a diverse group of forest owners.

## CRediT authorship contribution statement

**Joakim Wising:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Camilla Sandström:** Writing – review & editing, Validation, Supervision, Resources, Investigation, Conceptualization. **William Lidberg:** Writing – review & editing, Validation, Supervision, Resources, Investigation, Funding acquisition, Conceptualization.

## Declaration of Competing Interest

None.

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## Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.envsci.2024.103945.

## Data Availability

I have attached data and code for replicating the statistical analysis. Interview data is confidential.

## References


Akhtar-Danesh, N., 2023. Impact of factor rotation on Q-methodology analysis. PLoS One 18 (9), e0290728. https://doi.org/10.1371/journal.pone.0290728. PMID: 37656676; PMCID: PMC10473483.

Appelstrand, M., 2012. Developments in Swedish forest policy and administration–from a "policy of restriction" toward a "policy of cooperation. Scand. J. For. Res. 27 (2), 186–199.

Banasick, Shawn (2019). "Ken-Q analysis (Version 1.0. 6)[software]". Can be retrieved from: ⟨https://shawnbanasick.github.io/ken-q-analysis⟩.

Barletti, J.P.S., Cronkleton, P., Vigil, N.M.H., 2022. Using Q-methodology to bridge different understandings on community forest management: lessons from the Peruvian Amazon. Ecol. Soc. 27 (4).

Bergdahl, J., Latikka, R., Celuch, M., Savolainen, I., Mantere, E.S., Savela, N., Oksanen, A., 2023. Self-determination and attitudes toward artificial intelligence: cross-national and longitudinal perspectives. Telemat. Inform. 82, 102013.

Bergstén, S., Keskitalo, E.C.H., 2019. Feeling at home from a distance? How geographical distance and non-residency shape sense of place among private forest owners. Soc. Nat. Resour. 32 (2), 184–203.

Busarello, M.,Ågren, A., Lidberg, W., 2023. May). Mapping streams and ditches using Aerial Laser Scanning. In: EGU General Assembly Conference Abstracts. p. EGU-12373.

Cascio, W.F., Montealegre, R., 2016. How technology is changing work and organizations. Annu. Rev. Organ. Psychol. Organ. Behav. 3 (1), 349–375.

Danley, B., 2019. Forest owner objectives typologies: instruments for each owner type or instruments for most owner types? For. Policy Econ. 105, 72–82.

Danley, B., Bjärstig, T., Sandström, C., 2021. At the limit of volunteerism? Swedish family forest owners and two policy strategies to increase forest biodiversity. Land Use Policy 105, 105403.

Deci, Edward L., Ryan, Richard M., 2000. The 'what' and 'why' of goal pursuits: Human needs and the self-determination of behavior. Psychol. Inq. 11 (4), 227–268.

Deci, Edward L., Ryan, Richard M., 2012. Self-determination theory. Handb. Theor. Soc. Psychol. 1 (20), 416–436.

Ekström, H., Danley, B., Clough, Y., Droste, N., 2024. Barking up the wrong tree?-A guide to forest owner typology methods. For. Policy Econ. 163, 103208.

Eriksson, L., Sandström, C., 2022. "Is voluntarism an effective and legitimate way of governing climate adaptation? A study of private forest owners in Sweden.". For. Policy Econ. 140, 102751.

Ezzeddine, Y., Bayerl, P.S., Gibson, H., 2023. Safety, privacy, or both: evaluating citizens' perspectives around artificial intelligence use by police forces. Polic. Soc. 33 (7), 861–876.

Ficko, A., Lidestav, G., Dhubháin, Á.N., Karppinen, H., Zivojinovic, I., Westin, K., 2019. European private forest owner typologies: A review of methods and use. For. Policy Econ. 99, 21–31.

Follo, G., Lidestav, G., Ludvig, A., Vilkriste, L., Hujala, T., Karppinen, H., Mizaraite, D., 2017. Gender in European forest ownership and management: reflections on women as "New forest owners". Scand. J. For. Res. 32 (2), 174–184.

Freundt, J., Herz, H., & Kopp, L. (2023). Intrinsic preferences for autonomy..

Frey, B.S., Benz, M., Stutzer, A., 2004. Introducing procedural utility: Not only what, but also how matters. J. Inst. Theor. Econ. (JITE)/Z. F. üR. die Gesamt Staatswiss. 377–401.

Galaz, V., Centeno, M.A., Callahan, P.W., Causevic, A., Patterson, T., Brass, I., Levy, K., 2021. Artificial intelligence, systemic risks, and sustainability. Technol. Soc. 67, 101741.

Garini, C.S., et al., 2017. Drivers of adoption of agroecological practices for winegrowers and influence from policies in the province of Trento, Italy. : *Land Use Policy* 68, 200–211.

Guenduez, A.A., Mettler, T., Schedler, K., 2020. Technological frames in public administration: What do public managers think of big data? Gov. Inf. Q. 37 (1), 101406.

Hujala, T., Tikkanen, J., Hänninen, H., Virkkula, O., 2009. Family forest owners' perception of decision support. Scand. J. For. Res. 24 (5), 448–460.

Jakobsson, R., Olofsson, E., Ambrose-Oji, B., 2021. Stakeholder perceptions, management and impacts of forestry conflicts in southern Sweden. Scand. J. For. Res. 36 (1), 68–82.

Jeffares, S., 2020. The virtual public servant: Artificial intelligence and frontline work. Springer. Nature.

Kim, E.S., 2024. Can data science achieve the ideal of evidence-based decision-making in environmental regulation? Technol. Soc., 102615

Léger-Bosch, C., Chervier, C., 2023. Effect of farmland arrangements for the protection of natural areas on the basic psychological needs of the farmers involved. Soc. Nat. Resour. 36 (11), 1418–1438.

Li, V.O., Lam, J.C., Cui, J., 2021. AI for social good: AI and big data approaches for environmental decision-making. Environ. Sci. Policy 125, 241–246.

Lidberg, W., Paul, S.S., Westphal, F., Richter, K.F., Lavesson, N., Melniks, R., Ågren, A.M., 2023. Mapping drainage ditches in forested landscapes using deep learning and aerial laser scanning. *J. Irrig. Drain. Eng.* 149 (3), 04022051.

Löfmarck, E., Uggla, Y., Lidskog, R., 2017. Freedom with what? Interpretations of "responsibility" in Swedish forestry practice. For. Policy Econ. 75, 34–40.

McKeown, Bruce, Thomas, Dan B., 2013. Q methodology, 66. Sage Publications.

Mohtashami, S., Hansson, L., Eliasson, L., 2023. Estimating Soil Strength Using GIS-Based Maps - A case study in Sweden. Eur. J. For. Eng. 9 (2), 70–79. https://doi.org/10.33904/ejfe.1321075.

Mulu, S., Asfaw, Z., Alemu, A., Teketay, D., 2022. Determinants of decision making by smallholder farmers on land allocation for small-scale forest management in Northwestern Ethiopian Highlands. Land 11 (6), 838.

Näringsdepartementet (2019). Uppdrag att uppdatera, utveckla och tillhandahålla digitala kunskapsunderlag med skogliga grunddata, N2019/01449/SK.

Näringsdepartementet (2022). Uppdrag att utveckla digitala kunskapsunderlag om skogens natur- och kulturmiljövärden, N2022/01391.

Olsson, J., 2009. The power of the inside activist: Understanding policy change by empowering the Advocacy Coalition Framework (ACF). Plan. Theory Pract. 10 (2), 167–187.

Prop 2021/22:58 Stärkt äganderätt, flexibla skyddsformer och ökade incitament för naturvården i skogen med frivillighet som grund. https://www.regeringen.se/rattsliga-dokument/proposition/2021/11/prop.-20212258/.

Rampin, R.émi, Rampin, Vicky, 2021. Taguette: open-source qualitative data analysis. J. Open Source Softw. 6 (68), 3522.

Rinaldi, F., Jonsson, R., 2020. Accounting for uncertainty in forest management models. For. Ecol. Manag. 468, 118186.

Ryan, R.M., Deci, E.L., 2017. Self-determination theory: Basic psychological needs in motivation. development, and wellness. Guilford publications.

Ryan, R.M., DeHaan, C.R., 2023. The social conditions for human flourishing: Economic and political influences on basic psychological needs. The Oxford handbook of self-determination theory. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780197600047.013.57.

Skogforsk (2021). "Handledning om markfuktighetskartor". URL: https://www.skogforsk.se/kunskap/kunskapsbanken/2021/handledning-om-markfuktighetskartor/ Received 2024-03-05.

Skogskunskap 2024, "Vem äger skogen?". URL: https://www.skogskunskap.se/aga-skog/fakta-om-skogen/vem-ager-skogen/Received 2024-10-17.

Skogsstyrelsen (2023). Rapport 2023/12, "Digitala värden i Skog: uppdrag att utveckla digitala kunskapsunderlag om skogens natur- och kulturmiljövärden".

Skogsstyrelsen (n.d). "Skador på skog" URL: https://www.skogsstyrelsen.se/skadorpaskog. Received: 2024-07-05.

SLU (n.d). "Soil Moisture Maps" URL: https://www.slu.se/en/departments/forest-ecology-management/forskning/soil-moisture-maps/about-soil-moisture-maps/ Received 2024-10-01.

Uggla, Y., 2018. Negotiating responsible forestry: forest owners' understanding of responsibility for multiple forest values. Environ. Sociol. 4 (3), 358–369.

Vainio, A., 2011. Why are forest owners satisfied with forest policy decisions? Legitimacy, procedural justice, and perceived uncertainty. Soc. Justice Res. 24, 239–254.

Wang, Y., Lewis, S.E., 2022. Towards a theoretically sound measure of chemistry students' motivation; investigating rank-sort survey methodology to reduce response style bias. Chem. Educ. Res. Pract. 23 (1), 240–256.

Watts, Simon, Stenner, Paul, et al., 2012. "Doing Q methodological research". : Theory, Method Interpret. 2012.

Wickberg, A., Lidström, S., Lagerkvist, A., Meyer, T., Wormbs, N., Gärdebo, J., Sörlin, S., Höhler, S., 2024. The mediated planet: Datafication and the environmental SDGs. Environ. Sci. Policy 153, 103673.

Wreford, A., Dunningham, A., Jones, A., de Oca Munguia, O.M., Villamor, G.B., Monge, J.J., 2021. Exploring the solution space for different forestry management structures in New Zealand under climate change. Environ. Sci. Policy 126, 1–10.

Zabala, A., 2014. Qmethod: a package to explore human perspectives using Q methodology. R. J. 6 (2), 163–173.