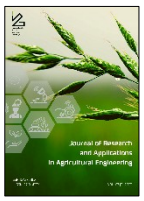
Article citation info:
Durczak K., Beba J. 2026. Differentiating agricultural tractor brands and models through user-reported quality profiles. *Journal of Research and Applications in Agricultural Engineering* 71 (2): 63–71. https://doi.org/10.53502/jraae-242607

Łukasiewicz Poznań Institute of Technology

Journal of Research and Applications in Agricultural Engineering

Journal website: https://www.jraae.com/



Differentiating agricultural tractor brands and models through user-reported quality profiles

Karol Durczak[a]*
Jan Beba[b]

[a] Faculty of Environmental and Mechanical Engineering, Department of Biosystems Engineering, Poznań University of Life Sciences, Poland
[b] top agrar Polska, AgroHorti Media Sp. z o.o., Poland

Article info
Received: 24 August 2026
Accepted: 06 November 2026
Published: 17 November 2026

Keywords
agricultural tractors
user-reported quality
brand differentiation
ergonomics
reliability
effect size
discriminant analysis
bootstrap

User experience with agricultural tractors is multidimensional and can be obscured by a single brand-level score. This study analysed 140 tractor-evaluation questionnaires covering 21 tractor brands and 44 detailed quality attributes rated on a seven-point scale. Descriptive analyses used the complete sample, whereas formal brand differentiation was restricted to six brands represented by at least five questionnaires (N = 108). Attribute-wise differences were evaluated by the Kruskal–Wallis test, epsilon-squared effect sizes, Benjamini–Hochberg false-discovery-rate correction, and stratified bootstrap confidence intervals. To test whether the 44-attribute profiles contained reproducible brand information beyond univariate contrasts, a shrinkage linear discriminant model was evaluated by stratified five-fold cross-validation and a label-permutation test. Spare-parts availability (6.26), engine reliability (6.16), and forward visibility (6.14) were the highest-rated attributes, whereas storage availability (4.64), passenger space (4.89), and vibration damping (4.94) were lowest. The strongest brand differentiation occurred for ease of radiator cleaning (ε^2 = 0.508), vibration damping (0.499), overall comfort (0.460), rear hydraulic-coupler access (0.448), and cab lighting (0.440). Cross-validated balanced brand-classification accuracy reached 0.371, compared with a six-class chance level of 0.167 (permutation p = 0.002). At model level, within-brand centring separated model-specific domain profiles from the corresponding brand baseline; 12 models represented by at least three questionnaire records were visualized. The results show that practical tractor quality is structured by specific ergonomic, maintainability, reliability, and ownership attributes and that these detailed profiles contain reproducible information at both brand and model levels.

DOI: https://doi.org/10.53502/jraae-242607
This is an open access article under the CC BY 4.0 license:
https://creativecommons.org/licenses/by/4.0/deed.en.

1. Introduction

Agricultural tractors are long-lived capital goods whose practical value is determined by much more than rated power, purchase price, or fuel consumption. Operators interact continuously with the cab, controls, transmission, hydraulic connections, service points, and after-sales infrastructure. Consequently, perceived tractor quality is a multidimensional construct combining technical performance with ergonomics, maintainability, reliability, and ownership conditions.

Previous tractor-selection studies have shown that farmers do not make purchase decisions on the basis of one technical parameter. Multi-attribute approaches have incorporated durability, fuel economy, purchase cost, maintainability, operator safety, and after-sales service into decision models (Cankurt

* Corresponding author: karol.durczak@up.poznan.pl

& Miran, 2010; García-Alcaraz et al., 2016). Survey evidence from agricultural machinery users likewise indicates that operating performance, failure frequency, durability, service, and replacement intentions are closely linked (Shin et al., 2014). These findings support treating the tractor as a human–machine–service system rather than as an isolated mechanical product.

Ergonomic attributes are especially important because tractor operators may spend many hours in the cab. Whole-body vibration, seating, postural load, visibility, noise, and control accessibility affect both comfort and occupational exposure. Tractor-driving conditions have long been associated with whole-body vibration and low-back disorders (Bovenzi & Betta, 1994), while field measurements show that vibration transmissibility depends on operating surface, speed, and machine configuration (Deboli et al., 2017). A broader review of mechanized agricultural operations also identifies vibration, shocks, awkward postures, and seat discomfort as recurring ergonomic risk factors (Benos et al., 2020).

However, broad satisfaction indices can conceal the detailed attributes that actually differentiate products. Two brands may obtain similar overall evaluations while differing substantially in radiator accessibility, vibration isolation, transmission operation, hydraulic coupling, cab lighting, spare-parts availability, or service experience. These contrasts are relevant both to farmers selecting machinery and to manufacturers identifying design priorities.

The conceptual foundation of AGRORANKING.pl is a product-centred interpretation of quality. ISO 9000:2026 defines quality through the extent to which inherent characteristics of an object fulfil requirements (International Organization for Standardization, 2026). For the assessment of agricultural machinery, Durczak proposed a deliberately narrower operational definition: "Quality is the degree to which a set of inherent, not directly measurable product attributes fulfils customer requirements." This formulation retains the requirement-based concept of quality, while explicitly identifying the product, its users and the attributes selected for questionnaire-based evaluation. It is a methodological specification for AGRORANKING, not a replacement for the general ISO definition. In particular, it does not imply that objectively measurable machine characteristics or legal and safety requirements are irrelevant to total product quality.

The restriction to attributes not directly measurable by conventional technical instruments has an engineering rationale. Rated engine power, dimensions, mass and fuel consumption can be specified in physical units and compared using standard test procedures. By contrast, perceived control accessibility, maintenance convenience, vibration comfort and serviceability arise from repeated human–machine interaction and cannot be adequately represented by a single catalogue parameter. They can nevertheless be operationalized as ordered user assessments. In AGRORANKING, these assessments are analysed as evidence of operator-perceived fulfilment of requirements, not as direct physical measurements. Purchase-price relations, parts availability and service support are retained as a separately identified ownership context rather than incorrectly described as inherent mechanical characteristics. This distinction links the conceptual definition of quality to a reproducible assessment methodology relevant to mechanical design, maintenance accessibility and machinery operation.

The objective of this study was therefore not to construct another single ranking, but to determine which detailed user-reported attributes (i) receive the strongest and weakest evaluations in the complete sample, (ii) discriminate most clearly between sufficiently represented tractor brands, (iii) jointly contain reproducible information capable of separating brands in out-of-sample prediction, and (iv) generate interpretable strength–weakness profiles at both brand and model levels. This positioning intentionally distinguishes detailed product differentiation from aggregate decision-support scoring.

2. Material and methods

2.1. Survey data and analytical structure

The AGRORANKING concept and original quality-assessment methodology were developed by the research team prior to the online survey. The online survey was conducted in cooperation with the agricultural publisher top agrar Polska, which provided the web-based questionnaire platform and helped reach tractor users. The analysed campaign covered September 2022 to February 2023 and participation was voluntary. The unit recorded in the dataset was a tractor evaluation rather than a verified unique person: a farmer could own and legitimately assess several tractors. Although 140 questionnaire records have distinct identifiers, neither the anti-duplicate safeguards of the original platform nor the number of unique individual respondents can be verified from the anonymized export. Accordingly, multiple assessments from one farm or respondent cannot be excluded, and questionnaire-level observations should not be interpreted as proven respondent-level independence. The 44 items capture operator-reported attributes and separately identified ownership conditions.

The empirical material comprised 140 tractor-evaluation questionnaires submitted by agricultural tractor users. The database covered 21 brands. Respondents evaluated 44 detailed attributes on a symmetric seven-point ordinal scale, where higher values represented more favourable user experience. The attributes were organized into five conceptual domains: cabin (15 attributes), handling and usability (12), operation and maintainability (8), reliability (5), and ownership environment (4). The ownership domain covered quality-to-purchase-price relation, spare-parts availability, authorized-service availability, and satisfaction with authorized service.

Questionnaire distribution across brands was strongly unbalanced. Descriptive results therefore used all 140 questionnaires, whereas formal between-brand inference was restricted a priori to brands represented by at least five tractor-evaluation questionnaires: CLAAS (n = 50), New Holland (n = 18), John Deere (n = 15), Zetor (n = 12), Massey Ferguson (n = 8), and Ursus (n = 5), yielding N = 108. The sample-size distribution is reported directly in the text rather than as a separate figure because it is a sampling descriptor, not a research result.

Model designations could be identified in 126 questionnaires, representing 78 distinct named models. Twenty-one models had at least two questionnaire records and 12 had at least three. Owing to this lower replication, model-level analysis was explicitly exploratory and no inferential claim of model superiority was made.

2.2. Attribute-level descriptive statistics

For respondent i, brand b, and detailed attribute k, the recorded score was denoted by $x_{ibk} \in \{1, 2, \ldots, 7\}$. The within-brand attribute mean was defined as

$$\bar{x}_{bk} = \frac{1}{n_b} \sum_{i=1}^{n_b} x_{ibk} \quad (1)$$

where
n_b is the number of questionnaires for brand b.

Means were retained on the original 1–7 scale for direct interpretation, while inferential tests remained rank-based.

2.3. Criterion-wise brand differentiation

Because the response scale was ordinal and group sizes were unequal, each attribute k was compared across the six best-sampled brands using the Kruskal–Wallis rank test (Kruskal & Wallis, 1952). For each test, the statistic H_k was converted to epsilon-squared effect size:

$$\varepsilon_k^2 = max[0, \frac{H_k - G + 1}{N - G}] \quad (2)$$

where
G = 6 and N = 108.

Effect size was treated as the primary measure of practical differentiation. Forty-four simultaneous tests were corrected by the Benjamini–Hochberg false-discovery-rate procedure (Benjamini & Hochberg, 1995).

2.4. Stratified bootstrap uncertainty and stability

Sampling uncertainty of each effect size was evaluated by 500 stratified bootstrap replicates. Respondents were resampled with replacement within each brand, preserving the original group sizes. Percentile 95% bootstrap confidence intervals were calculated for ε^2. In addition, a descriptive top-quartile stability proportion was used to identify attributes that repeatedly remained among the strongest one-quarter of the 44 effect sizes:

$$P_k = \frac{1}{B} \sum_{r=1}^{B} I[\varepsilon_{k,r}^2 \geq Q_{0.75,r}] \quad (3)$$

where
B = 500, $I[\cdot]$ denotes the indicator function, which equals 1 when the condition inside the brackets is satisfied and 0 otherwise,
and $Q_{0.75,r}$ is the 75th percentile of the 44 effect sizes in bootstrap replicate r.

This proportion was used as a stability descriptor, not as an additional significance test.

2.5. Multivariate out-of-sample brand separability

A second, independent question was whether the complete 44-attribute response vector contained reproducible brand information when all criteria were considered jointly. A shrinkage linear discriminant analysis (LDA) was used because the number of variables was high relative to the sample size and several user ratings were correlated. Regularization of discriminant models is particularly useful in small-sample, high-dimensional settings (Friedman, 1989), whereas shrinkage covariance estimation improves the conditioning and stability of the covariance estimate (Ledoit & Wolf, 2004). Missing item responses were handled inside the classification pipeline by median imputation based only on the training fold, followed by standardization. The regularized covariance estimator had the form

$$\Sigma_\lambda = (1 - \lambda)S + \lambda T \quad (4)$$

where
S is the empirical covariance matrix,
T is the shrinkage target,
and λ is the data-adaptive shrinkage intensity.

For brand g, the linear discriminant score was

$$\delta_g(z) = z^T \Sigma_\lambda^{-1} \mu_g - 1/2\, \mu_g^T \Sigma_\lambda^{-1} \mu_g + ln\, \pi_g \quad (5)$$

where
z is the standardized respondent profile,
μ_g is the class centroid,
and π_g is the prior class probability.

Predictive performance was quantified by balanced accuracy to avoid dominance by the largest brand:

$$BA = \frac{1}{G} \sum_{g=1}^{G} \frac{TP_g}{n_g} \quad (6)$$

Stratified five-fold cross-validation was used, with one observation from the smallest included brand appearing in each test fold. Statistical evidence for out-of-sample separability was obtained from 499 random permutations of the brand labels, repeating the complete cross-validation procedure for each permutation.

2.6. Within-brand model contrasts

To obtain a model-level result that was distinct from a simple ranking, model profiles were centred on their own brand baseline. For model m and user-experience domain q, the model contrast was defined as

$$\Delta_{mq} = \mu_{mq} - \mu_{b(m)q} \quad (7)$$

where
μ_{mq} is the mean score of model m in domain q,
and $\mu_{b(m)q}$ is the corresponding mean for brand $b(m)$.

Positive Δ_{mq} values indicate that the model was rated above its own brand average in that domain, whereas negative values indicate the opposite. The five domains were cabin, handling and usability, operation and maintainability, reliability, and ownership environment. To reduce instability, the model-contrast figure was restricted to models with $n_m \geq 3$; models with $n_m = 2$ remained in the database but were not used for graphical model comparison.

3. Results and Discussion

3.1. What tractor users value most and least

Across all 140 questionnaires, the strongest evaluations concerned functions that keep the tractor operational. Spare-parts availability achieved the highest overall mean (6.26), followed by engine reliability (6.16), forward visibility (6.14), front-wheel-drive engagement (6.10), drivetrain reliability (6.07), and transmission reliability (6.03). The pattern indicates that availability, reliability, and basic operating functionality remain central components of perceived tractor quality.

The lowest-rated attributes were concentrated mainly in cabin comfort and everyday ergonomics. Storage availability averaged 4.64, passenger space 4.89, vibration damping 4.94, air-conditioning/ventilation 5.10, and satisfaction with authorized service 5.11. Cab noise insulation was also relatively low (5.29). Thus, core mechanical functions were evaluated more positively than several comfort and service-experience attributes.

Low scores for vibration damping and noise insulation should not be interpreted as merely cosmetic preferences. Whole-body vibration and seating-related exposure are established aspects of tractor operator comfort and occupational health (Bovenzi & Betta, 1994; Deboli et al., 2017; Benos et al., 2020). The user-reported results therefore point in the same engineering direction as instrumented ergonomic research.

The contrast between the strongest and weakest overall user evaluations is summarized graphically in Fig. 1.

3.2. Which attributes really differentiate brands?

The 44 criteria differed markedly in their ability to separate brands. The largest effect was observed for ease of radiator cleaning ($\varepsilon^2 = 0.508$; FDR-adjusted $q < 0.001$), followed by vibration damping ($\varepsilon^2 = 0.499$), overall comfort (0.460), rear hydraulic-coupler access (0.448), cab lighting (0.440), storage availability (0.417), rear three-point-hitch access (0.414), and cab noise insulation (0.399). All leading contrasts remained highly significant after false-discovery-rate correction.

The bootstrap intervals confirmed that the largest effects were not narrow, sample-specific point estimates. For radiator cleaning, the 95% bootstrap interval for ε2 was approximately 0.396–0.673; for vibration damping, 0.378–0.678; and for overall comfort, 0.357–0.618. Radiator cleaning remained in the upper quartile of effect sizes in 93.2% of stratified resamples,

vibration damping in 87.6%, and overall comfort in 79.4%. The exact ordering of the leading criteria can therefore vary under resampling, but the same engineering themes recur.

The most discriminating variables are notable because several are not headline catalogue specifications. Radiator cleaning, hydraulic-coupler accessibility, hitch access, storage, lighting, and vibration isolation become important during repeated daily work. Detailed user evidence therefore complements conventional comparisons based on power, transmission type, or purchase price (Cankurt & Miran, 2010; García-Alcaraz et al., 2016).

To compare both the magnitude and uncertainty of the strongest between-brand effects, the 12 largest εk2 values together with their stratified-bootstrap confidence intervals are presented in Fig. 2.

3.3. Brand strength–weakness profiles and predictive separability

The heat map shows that the same attribute can represent a strength for one brand and a weakness for another. CLAAS, represented by 50 questionnaires, displayed a high and comparatively uniform profile. Among the strongest discriminators, mean ratings were 6.8 for radiator cleaning, 6.7 for overall comfort, 6.7 for rear hydraulic-coupler access, and 6.8 for three-point-hitch lever operation. The important feature is not one isolated maximum but the scarcity of pronounced local weaknesses.

Massey Ferguson (n = 8) showed a different internal structure. Rear hydraulic access and hitch-related functions were strong, whereas storage and vibration damping were clearly weaker. New Holland and John Deere occupied intermediate regions but differed locally: New Holland was stronger in several operational and reliability-related items, whereas John Deere showed comparatively favourable rear hydraulic access and work-light performance. Zetor exhibited a more practical than comfort-oriented profile, while Ursus retained selected practical strengths despite low comfort-related evaluations.

The multivariate classification analysis provided an out-of-sample check of these descriptive patterns. Shrinkage LDA achieved a stratified five-fold balanced accuracy of 0.371. With six brands, the nominal chance level is 0.167. None of the 499 permuted-label analyses reached the observed accuracy, apart from the finite-sample correction corresponding to p = 0.002. Therefore, the 44-dimensional user profile contains reproducible brand information that generalizes beyond the observations used to fit the classifier. The accuracy is not high enough for brand identification to be a practical classifier, nor was that the objective; its role is to provide independent evidence that the detailed profiles are structurally different rather than merely visually different.

To show how the strongest discriminating attributes combine into brand-specific strength–weakness patterns, Fig. 3 presents the mean profiles of the six best-sampled brands.

3.4. Model-level deviations from brand profiles

Model-level disaggregation substantially increased data sparsity. Of the 140 questionnaires, 126 could be linked to a named tractor model, but these represented 78 different designations. Twenty-one models had $n_m \geq 2$ and only 12 had $n_m \geq 3$. The analysis therefore focused on within-brand contrasts rather than a model ranking. This asks a more useful question: does a particular model depart systematically from the experience reported for its own brand?

For CLAAS, the most densely represented family, Arion 610 (n = 9) and Arion 440 (n = 6) were above the CLAAS brand mean in all five domains. Their largest positive deviations occurred in ownership environment (+0.33 and +0.36 score points, respectively), while both also remained above the brand baseline in cabin, handling, operation, and reliability. Arion 630 (n = 6) showed the opposite pattern for technical domains: its reliability contrast was −0.50, with additional negative deviations in cabin, handling, and operation, despite a positive ownership contrast (+0.19).

The centred profiles also exposed differences that would be hidden by a brand average. CLAAS Axion 810 (n = 5) remained slightly above the CLAAS baseline in the four technical domains but was below it for ownership environment (−0.56). Axion 850 (n = 3) showed a similar ownership deviation (−0.64) while remaining above the brand mean for cabin, handling, and operation. Among New Holland models, T7.210 (n = 3) was above the New Holland baseline in every domain, with the largest differences in handling and usability (+0.75), cabin (+0.71), and reliability (+0.60). T4.75 (n = 3) was most distinctive in ownership environment (+0.79). Zetor 7211 (n = 3) was above the Zetor baseline mainly in cabin (+0.58), operation (+0.51), and handling (+0.45), while its ownership contrast was close to zero (+0.04).

These contrasts are exploratory rather than inferential because several models are represented by only three observations. Their value lies in demonstrating that a brand-level profile can contain materially different model-level patterns. In subsequent AGRORANKING editions, the same centred statistic can be recalculated as replication increases, allowing

apparently stable model deviations to be separated from single-sample fluctuations.

To extend the analysis from brands to models without reproducing a simple model ranking, Fig. 4 shows the within-brand domain contrasts Δ_{mq} for the 12 models represented by at least three tractor-evaluation records.

3.5. Practical meaning for tractor assessment

The results indicate that user-reported tractor quality is not dominated by one universal factor. Reliability and spare-parts availability are highly valued across the sample, yet the attributes that separate brands most strongly often concern maintainability and ergonomics: cleaning the radiator, damping vibration, accessing hydraulic couplers, operating the three-point hitch, and working in the cab. These are features whose importance emerges through repeated use.

For farmers, this means that brand or model comparison should be matched to intended use. A tractor used for long transport or field days may justify greater emphasis on vibration damping, seating, visibility, and cab environment, whereas a machine used in maintenance-intensive or seasonal operations may be judged more strongly by service access, parts availability, and routine-maintenance convenience. For manufacturers and dealers, detailed profiles can expose product-development priorities that global satisfaction scores conceal.

The results also reinforce the need to consider the ownership environment together with technical quality. A mechanically strong tractor may be evaluated less favourably because of service experience, while another may gain practical value from parts availability. Agricultural machinery satisfaction research has similarly linked technical quality, failure experience, after-sales conditions, and replacement intentions (Shin et al., 2014).

3.6. Limitations

The study is observational and self-selected rather than probability-based; repeated contributions by the same respondent cannot be excluded, so the results describe the participating user population and should not be generalized mechanically to all tractor owners. Brand sample sizes are highly unbalanced, which motivated the separation between complete-sample description and restricted inferential analysis. Tractor age, operating intensity, equipment specification, and type of work may influence ratings and were not controlled in the present analysis. Finally, most individual models remain represented by small samples.

The use of shrinkage LDA and balanced cross-validation reduces, but cannot eliminate, the effects of high dimensionality and class imbalance. The classifier was used only as a validation of profile separability, not as a tool for predicting brand from user responses. The strongest present evidence therefore concerns attributes with large rank-based effect sizes, bootstrap-supported uncertainty, and consistent engineering interpretation across the six best-sampled brands.

4. Conclusions

- The 140 questionnaires show that tractor quality is perceived through specific technical, ergonomic, maintenance, reliability, and ownership attributes rather than through one undifferentiated brand score.
- Spare-parts availability, engine reliability, forward visibility, front-wheel-drive engagement, drivetrain reliability, and transmission reliability were among the strongest overall attributes, whereas storage, passenger space, vibration damping, air-conditioning/ventilation, and authorized-service satisfaction were among the weakest.
- Brand differentiation was strongest for ease of radiator cleaning, vibration damping, overall comfort, rear hydraulic-coupler access, and cab lighting. Bootstrap intervals and stability analysis showed that these leading daily-use attributes remained prominent under resampling.
- The complete 44-attribute profiles contained reproducible multivariate brand information: shrinkage LDA reached a cross-validated balanced accuracy of 0.371 versus a chance level of 0.167, with a label-permutation $p = 0.002$.
- Within-brand model centring revealed patterns that are not visible in a simple model ranking. Among the 12 models with $n_m \geq 3$, several departed from their brand baseline in domain-specific ways, particularly in ownership environment, handling, and reliability. These model contrasts should be treated as hypotheses for subsequent AGRORANKING editions rather than as definitive superiority claims.
- The combined use of rank-based effect sizes, FDR correction, stratified bootstrap uncertainty, and cross-validated shrinkage discrimination provides a mathematically rigorous but interpretable framework for identifying which detailed tractor attributes genuinely differentiate user experience without reproducing an aggregate MCDM ranking.

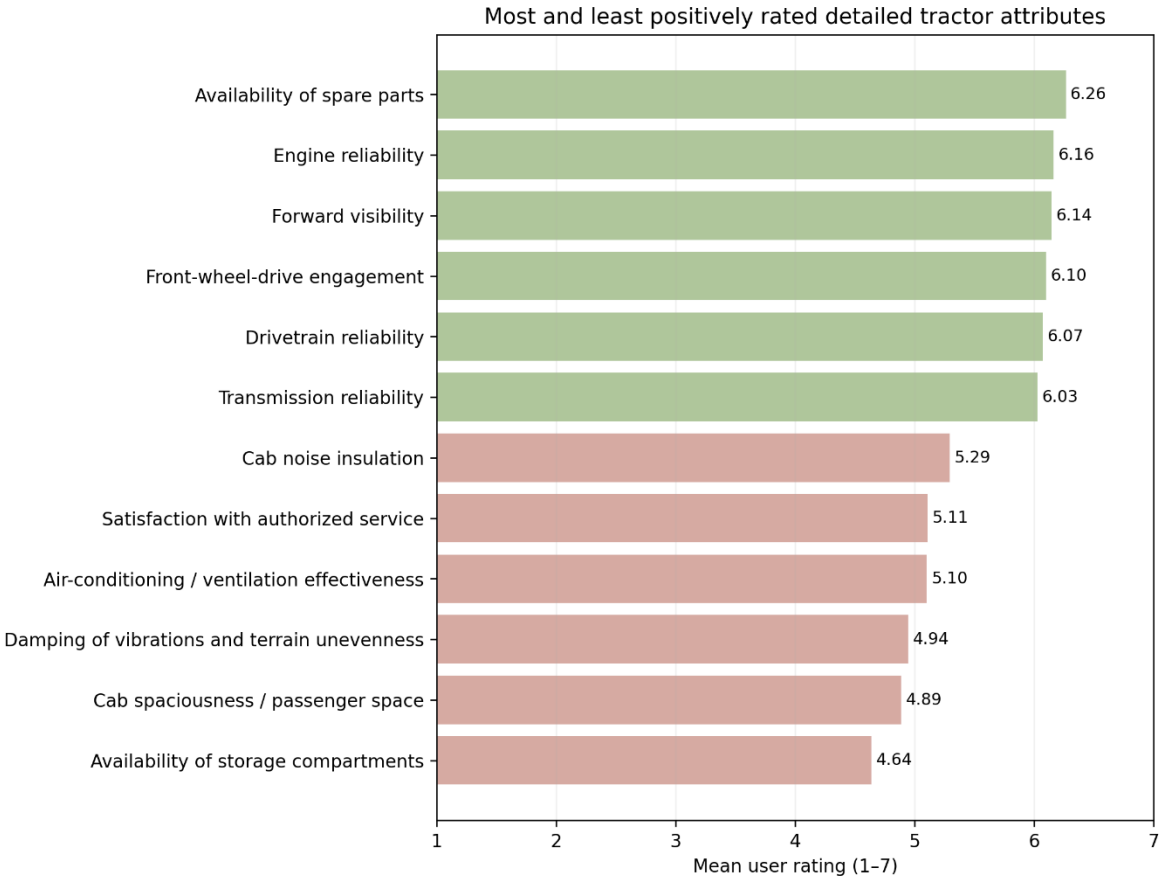


Figure 1. Six highest- and six lowest-rated detailed tractor attributes in the complete sample (n = 140). Source: authors' own study

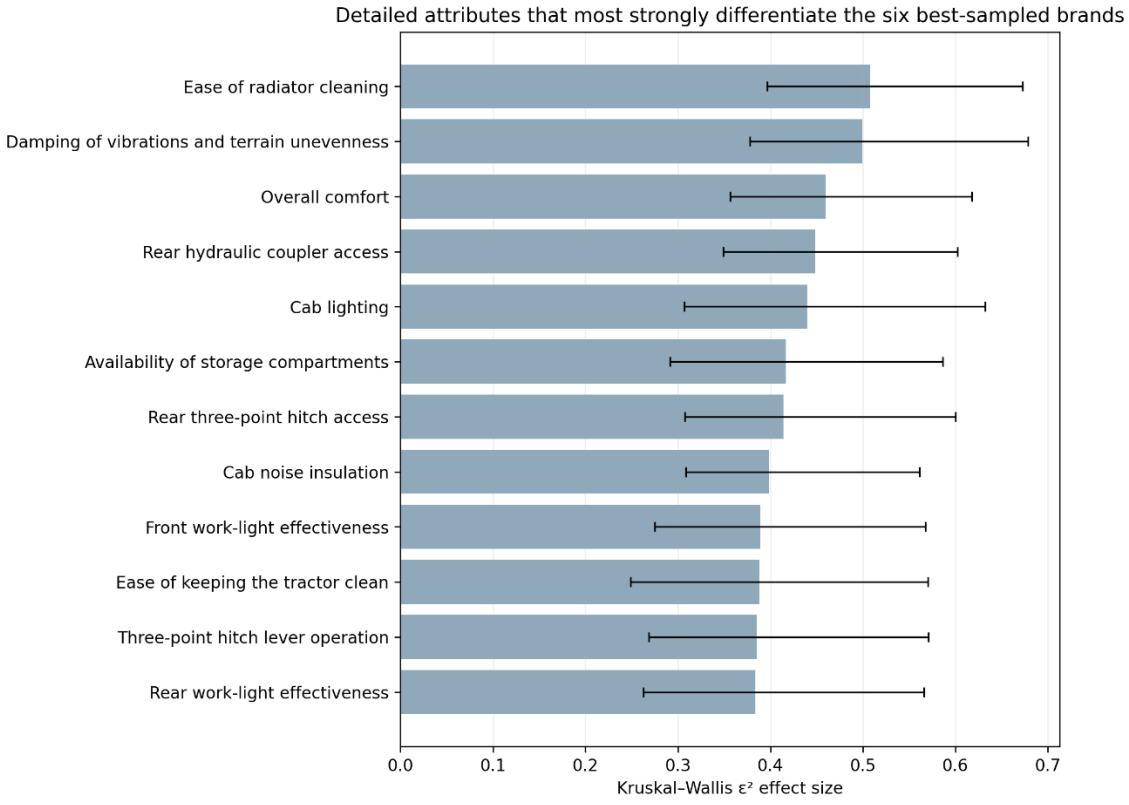


Figure 2. Twelve detailed attributes with the largest between-brand Kruskal–Wallis ε2 effect sizes. Error bars show stratified-bootstrap 95% percentile intervals. Source: authors' own study

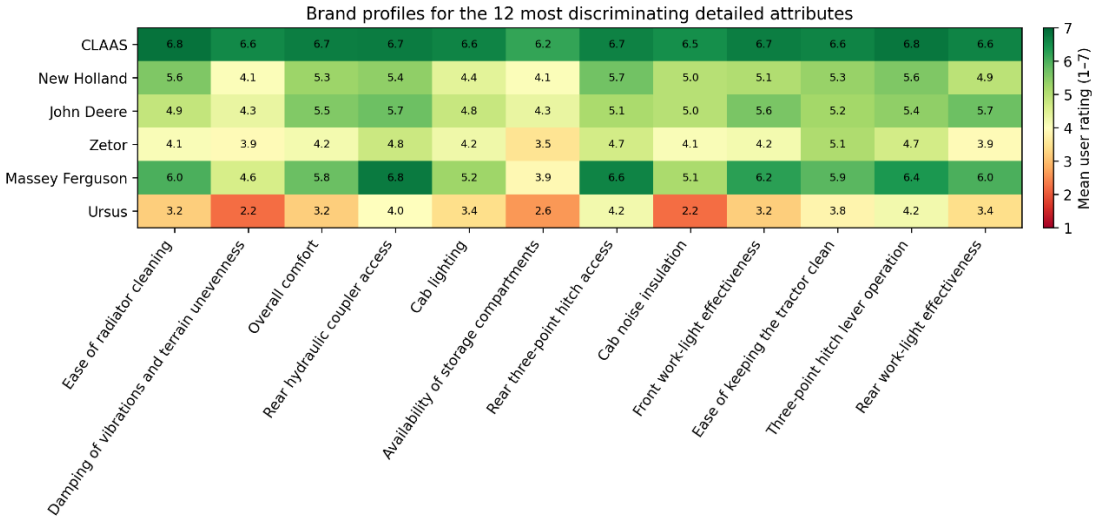


Figure 3. Mean ratings of the six best-sampled brands for the 12 attributes with the strongest between-brand differentiation. Source: authors' own study

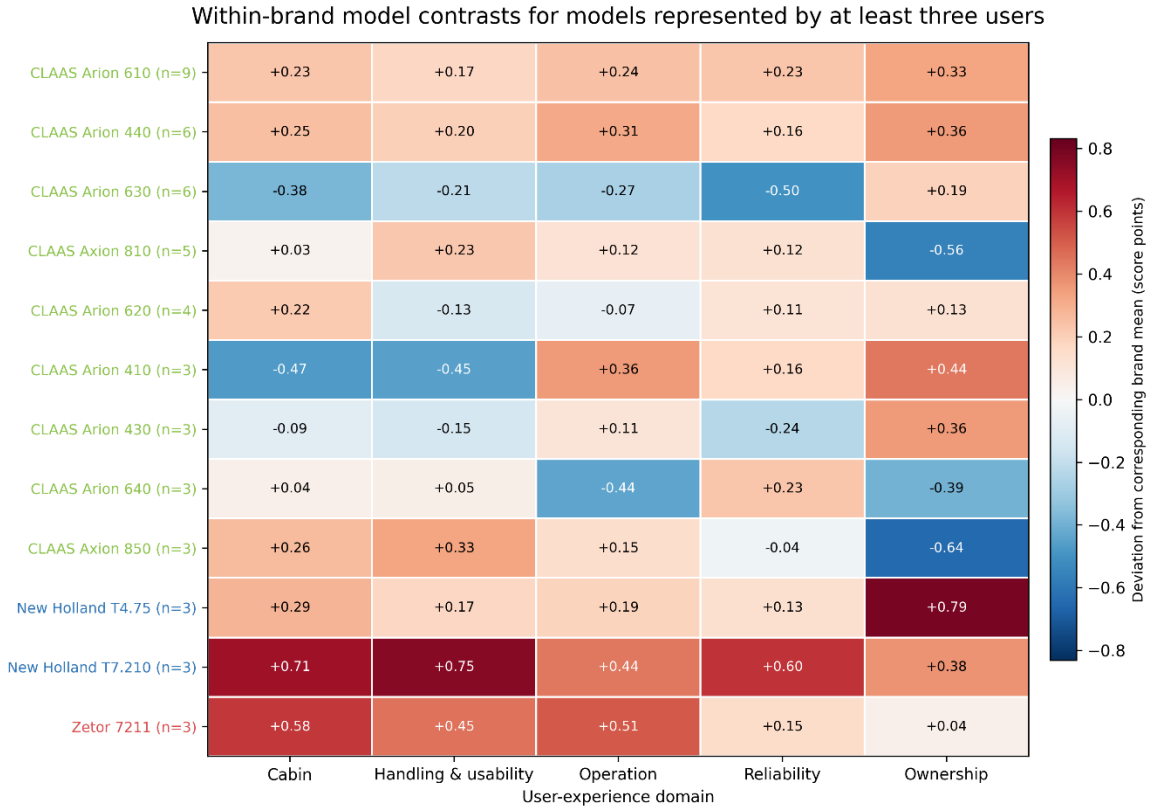


Figure 4. Within-brand model contrasts for the 12 tractor models represented by at least three tractor-evaluation records. Each cell shows Δ_{mq}, the deviation of the model-domain mean from the corresponding brand-domain mean; positive values indicate above-brand ratings and negative values below-brand ratings. Model labels retain the established brand colours. Source: authors' own study.

Acknowledgements

The authors thank the tractor users who contributed their experience to the AGRORANKING survey.

Funding

This research received no external funding.

Conflicts of interest

The authors declare no conflict of interest.

Data availability

The anonymized data supporting the findings of this study are available from the corresponding author upon reasonable request.

References

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society: Series B (Methodological), 57*(1), 289–300. https://doi.org/10.1111/j.2517-6161.1995.tb02031.x

Benos, L., Tsaopoulos, D., & Bochtis, D. (2020). A review on ergonomics in agriculture. Part II: Mechanized operations. *Applied Sciences, 10*(10), 3484. https://doi.org/10.3390/app10103484

Bovenzi, M., & Betta, A. (1994). Low-back disorders in agricultural tractor drivers exposed to whole-body vibration and postural stress. *Applied Ergonomics, 25*(4), 231–241. https://doi.org/10.1016/0003-6870(94)90004-3

Cankurt, M., & Miran, B. (2010). Tractor brand preferences of farmers: An analytic hierarchy process approach. *Tarım Makinaları Bilimi Dergisi, 6*(1), 13–17.

Deboli, R., Calvo, A., & Preti, C. (2017). Whole-body vibration: Measurement of horizontal and vertical transmissibility of an agricultural tractor seat. *International Journal of Industrial Ergonomics, 58*, 69–78. https://doi.org/10.1016/j.ergon.2017.02.002

Friedman, J. H. (1989). Regularized discriminant analysis. *Journal of the American Statistical Association, 84*(405), 165–175. https://doi.org/10.1080/01621459.1989.10478752

García-Alcaraz, J. L., Maldonado-Macías, A. A., Hernández-Arellano, J. L., Blanco-Fernández, J., Jiménez-Macías, E., & Sáenz-Díez Muro, J. C. (2016). Agricultural tractor selection: A hybrid and multi-attribute approach. *Sustainability, 8*(2), 157. https://doi.org/10.3390/su8020157

International Organization for Standardization (ISO). (2026). *Quality management — Fundamentals and vocabulary* (5th ed.) (ISO 9000:2026). https://www.iso.org/standard/9000

Kruskal, W. H., & Wallis, W. A. (1952). Use of ranks in one-criterion variance analysis. *Journal of the American Statistical Association, 47*(260), 583–621. https://doi.org/10.1080/01621459.1952.10483441

Ledoit, O., & Wolf, M. (2004). A well-conditioned estimator for large-dimensional covariance matrices. *Journal of Multivariate Analysis, 88*(2), 365–411. https://doi.org/10.1016/S0047-259X(03)00096-4

Shin, S.-Y., Kang, C. H., Yu, S. C., Kim, B., Kim, Y.-Y., & Kim, J. O. (2014). Satisfaction with the quality of agricultural machinery and the propensity for replacement purchases. *Journal of Biosystems Engineering, 39*(4), 261–266. https://doi.org/10.5307/JBE.2014.39.4.261