European Journal of Forest Research
https://doi.org/10.1007/s10342-025-01808-y

RESEARCH

Effects of a mobile LiDAR-based thinning density assistant (TDA) system on harvester operator performance

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Received: 9 January 2025 / Revised: 23 April 2025 / Accepted: 16 July 2025

Abstract

Forestry machines can be equipped with mobile laser scanners that digitally perceive and map the surroundings of the machine. The data collected can be used to assist the machine operator in conducting forest thinning in real-time. The forest machine manufacturer Ponsse Plc has launched a technological concept called the Thinning Density Assistant (TDA), which provides operators with real-time guidance. This advanced driver-assistance system (ADAS) installed in cut-to-length harvesters helps operators manage thinning density, visualise trees that are too close to each other and display the distance to the previous strip road. This study investigated the effect of the TDA system on cutting productivity in forest thinning, the workload experienced by harvester operators and the profitability of the investment. The study involved five experienced operators who thinned four different forest stands in central Finland, totalling an area of 10.5 ha. In the study, we analysed data from 4967 trees and 490 m^3 solid overbark of harvested timber that was collected from the machine's production data during thinning operations. A comparative time study methodology was used, which initially involved dividing the work cycle into distinct work elements. Subsequently, each element was modelled individually, using either average values or regression techniques. The NASA-TLX questionnaire was used to assess workload. The TDA system led to a modest increase in productivity, with a 1.2% improvement in the first thinnings and a 1.0% improvement in the later thinnings. This new first-generation system did not aid in the selection of specific trees; it only highlighted areas of greater tree density. The study revealed a significant saving in boom-out time (the process of reaching the tree with the harvester head) but with significant differences between operators. The TDA did not influence the time spent during moving. Inexperience in using the assistant might initially reduce productivity, as the operator may instead focus on monitoring the functionality of the device. The observed productivity improvement of approximately 1% does not cover the current acquisition costs of the system for expert operators when viewed solely from a productivity perspective. The TDA is likely to be particularly beneficial for novice operators. Nevertheless, the device is assumed to have other benefits, such as improving the quality of harvesting operations and documenting the logging work at the tree level, as well as the collection of training data for large-scale airborne laser scanning-based surveys at the individual tree level. Further research and improved implementation of the TDA could unlock greater efficiencies and productivity benefits.

Keywords Comparative time study · Cut-to-length · Mobile laser scanning (MLS) · Productivity · Profitability · Thinning · Workload

Communicated by Eric R. Labelle.

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Introduction

The mechanisation of forestry has significantly altered the nature of the human work involved in the process (Silversides 1997; Kanninen 1999). Nowadays, commercial cuttings in Finland are essentially fully mechanised through the cut-to-length (CTL) forest harvesting system (Strandström 2024). As CTL forest machines have developed, the physical and cognitive ergonomics of the machines have also significantly improved. The work of the human loggers has progressively shifted away from heavy physical work and is now almost comparable to sedentary office work. Operators gather substantial amounts of information from their environment (Gellerstedt 2002; Kariniemi 2006; Kärhä et al. 2021) and largely work autonomously using their senses to perform logging tasks that require rapid, repetitive movements of machines (Gellerstedt 2002). During long and continuous work, this can become a burden for the operator, and physical and mental workloads can reduce well-being during work and reduce productivity (Kariniemi 2006; Kymäläinen et al. 2021).

Research on forest work has been conducted to measure and compare the performance of existing or proposed human–machine–environment systems (Björheden 1995). Although the foundation of forest work research is strongly related to the system's productivity and performance, work ergonomics and social aspects (e.g. safety) have become an essential part of the research. System productivity is defined as the ratio between outputs and inputs. In forestry, this is affected by many factors that include the skills of the operators, the characteristics of the machinery and forest stand conditions, which are generally known as *process variables* (Magagnotti and Spinelli 2012). The productivity of cutting work is primarily determined by the average stem size, as it influences felling and processing times (Nurminen et al. 2006), while removal density affects the time spent moving (Kärhä et al. 2018; Lageson 1997). Tree distribution may also affect productivity (Spinelli and Magagnotti 2013). In addition, the number of wood assortments that are bucked (Nurminen et al. 2006), tree species (Nurminen et al. 2006), branchiness (Glöde 1999), terrain and steepness (Spinelli et al. 2010), silvicultural methods (e.g. thinning type; Lageson 1997), understory vegetation (Kärhä and Bergström 2020) and human factors (Lageson 1997; Purfürst 2010) can significantly influence productivity. Both productivity and working conditions can be enhanced through the automation of forest machines and by a focus on human–machine interactions (HMI) (Burman and Löfgren 2007).

Assistance systems are widely used in various industries to simplify work and enhance safety. For example, advanced driver assistance systems (ADAS) play a key role in providing additional assistance and information for drivers in traffic, as well as improving safety and the driving experience (Bapin and Bensrhair 2021; Li et al. 2012). In forestry, ADAS also simplify and facilitate the decision-making of the harvester operators (Westerberg 2014; Hellström et al. 2009), thereby freeing up their mental and physical resources for the more important tasks in logging work. These systems are already widely used in forest harvesters and forwarders. Lighting systems and reverse cameras enhance safety, while on-board computer, map-based guidance and bucking systems provide highly valuable information to the operator about the machine, the stand, the terrain and optimal bucking (Kauppinen et al. 2016; Uusitalo et al. 2004; Kymäläinen et al. 2024). This information is mainly presented on the head-down display of the onboard computer. However, machine manufacturers and researchers have also tested and studied head-up display (HUD) technologies, which have received positive feedback but have offered limited benefits to operators (Englund et al. 2015). Boom tip control and automatic cab levelling ease the tasks of the operator and even boost productivity (Hartsch et al. 2023; Gellerstedt 1998; Manner et al. 2017). The work of the operator can also be improved by providing regular feedback (Manner 2024; Ylimäki et al. 2012). Advancements in ADAS technology in forest machines underscore their critical role in modern forestry. However, a shift towards precision forestry – from the stand level to the individual tree level – requires more intelligent and immersive ADAS solutions in forest machines.

Forest machine operators often work with incomplete information with regard to their work site (Ylimäki et al. 2012). Therefore, additional information and guidance can enhance the productivity and quality of forest thinning work (cf. Spinelli and Magagnotti 2013; Holzleitner et al. 2019; Kärhä et al. 2021; Pohjala et al. 2024). The preferences of operators for ADAS in future harvesters has mostly focused on thinning density and quality, as well as log quality (Kymäläinen et al. 2024). Through the technological development of mobile laser scanning (MLS) in the last decades (Kukko 2012), MLS sensors can be mounted on harvesters to collect extensive point cloud data of the surroundings (e.g. at distances of 10–50 m) close to the harvester (Melkas et al. 2014). The acquired point cloud data can be *in-situ* or post-processed for various purposes, thereby guiding the operator with targeted information from multiple sources, gathering training data for airborne laser scanning-based tree-level inventories and optimising bucking (Faitli 2024; Kärhä et al. 2017; Prendes et al. 2023). This process can include the parameters that are commonly used in forest inventories, such as tree location, diameter and height, or even the presence of crooks or other defects (Liang et al. 2016; Sagar et al. 2024). Tree species detection remains a challenging task for automated processes (Åkerblom et al. 2017; Boudra et al. 2021; Carpentier et al. 2018) and real-time data processing capabilities in the operational use of MLS and machine vision (MV) in forest machines pose a significant challenge compared to post-processing (da Silva et al. 2021). The absolute localisation error of the harvester can exceed 2 m even when robotic simultaneous localisation and mapping (SLAM) are used, especially if the harvester path does not provide loop closures (Faitli et al. 2024). Consequently, it is possible that the initial role of these systems will be more targeted at the production of averaged stand data rather than the provision of precise advice at the individual tree level for the harvester operator.

While initially ADAS will only assist the operator in movements, the performance of tasks and observation of surroundings, these systems in time will gradually transition from forest machines towards fully autonomous forestry machines. The ability to recognise a harvester's surroundings is an essential technology for automating machine movements as well as for the long-term vision of unmanned forestry vehicles (Gellersted 2002; La Hera 2024; Hyyti 2023; Lindroos 2019; Semberg 2024). Novel robotics, artificial intelligence, control systems and sensor fusion will enable the development and employment of entirely new types of ADAS to support harvester operators. Indeed, the CTL forest machine manufacturer Ponsse Plc has introduced a novel MLS-based tree mapping system called the Thinning Density Assistant (TDA), which assists operators in tree selection and also monitors thinning density and distance to adjacent strip roads. The Nordic Forestry Automation has also introduced an equivalent system to assist operators with regard to thinning intensity. However, it is unclear how this type of information system will affect the operator's productivity and mental workload, as well as the quality of the harvesting.

Therefore, the aim and originality of this study was to investigate the impact of the TDA system on the productivity of cutting work, as well as the perceived workload of the harvester operator. The main research questions (RQs) were: How does the use of the TDA affect productivity and the time spent on the different work elements compared to conventional cutting without the TDA system (RQ1)? Is the TDA system a profitable investment (RQ2)? Does the use of the TDA impact the workload experienced by the operator (RQ3)?

We hypothesised (H) that the TDA does not improve thinning productivity as the system does not make tree selections for the operator, which has been shown to decrease the time spent during boom-out or moving (Kärhä et al 2019; Pohjala et al. 2024) (H1). Currently, the TDA is not a profitable investment for the forest machine entrepreneur, because the productivity of harvesting work is not expected to increase sufficiently to cover the acquisition cost of the TDA system (H2). Moreover, the operator's workload will decrease because they can use additional information on the forest stand to support their harvesting work (Kärhä et al. 2021) (H3).

Forwarding was not within the scope of this study. The thinning quality of the study plots has been addressed in a separate study (Sagar et al. 2025).

Material and methods

Study sites

The study included three sites in Central Finland: Kyyjärvi (Stand 1), Karstula (Stand 2) and Kuopio (Stands 3 and 4) (Fig. 1, Table 1). The total harvested area of the three sites was 10.5 ha. Stands 1 and 3 were first thinnings and stands 2 and 4 were later thinnings. Forty-six study plots were established, of which 20 were first-thinning plots and 26 were later-thinning plots (Table 1). The average plot size was 0.23 ha. The main tree species in each site was Scots pine (*Pinus sylvestris* L.) or Silver birch (*Petula pendula*). Norway spruce (*Picea abies* (L.) Karst.) grew as a mixture, mostly as an understory tree species. Aspen (*Populus tremula*) and Grey alder (*Alnus incana*) grew occasionally as single trees on most sites. Stand 1 was harvested under winter conditions in March 2023, when snow covered the ground at the site. Stands 2, 3 and 4 were harvested under summer conditions in September 2023. All sites can be considered topographically flat, where the roughness of the terrain was deemed *relatively easy*. The average volume harvested was 0.102 m^3 solid overbark (henceforth m^3): 0.100 m^3 in the reference plots (n = 21) and 0.103 m^3 in the TDA plots (n = 25). Mean removed volumes ranged from 0.045 to 0.212 m^3 in the study plots. Mean diameter at breast height (1.3 m, DBH) of the whole dataset was 12.6 cm and ranged from 9.5 to 16.0 cm. Initial plot densities varied between 550 to 1961 trees ha^{-1}.

Harvesters, operators and working methods

We used a CTL harvesting system and appropriate machinery in this study. The research was conducted using two Ponsse Scorpion King harvesters, each equipped with C50 11 m cranes and H6 harvester heads, with an engine power output of 210 kWh. These harvesters were also fitted with mobile laser scanners (Ouster LiDAR OS0) and separate screens for the TDA system (Fig. 2). The harvesters were operated by five different operators with varying years of skill and experience in forest machine work. Two of the operators (B and D) were in the early stages of their careers, with three years of experience using a forest harvester. The other three operators had over a decade's experience (Table 2). Therefore, it can be assumed that all the operators have reached their final performance level as this process takes an average of eight months to achieve the requisite competency (Purfürst 2010). In addition, the TDA system was new to operator A, while the other operators had used the TDA system as part of their work, but for less than one year.

Fig. 1 Locations of the three study sites in Central Finland: Kyyjärvi (Stand 1), Karstula (Stand 2) and Kuopio (Stands 3 and 4). The harvested plots are shown with unique plot IDs [1–46], operators [A–E], whether TDA was applied [1], and whether harvesting was carried out at night [1]. Red line indicates the route taken by the harvester. Map data: © OpenStreetMap contributors (data: ODbL, map: CC-BY-SA 2.0)

Table 1 Details and geographical coordinates of the study stands where the experiment was carried out

Stand number		1	2	3	4
Location		Kyyjärvi	Karstula	Kuopio	Kuopio
Northing	WGS 84	63° 02′ 05.9"	62° 49′ 56.4"	62° 53′ 02.2"	62° 53′ 13.6"
Easting	WGS 84	24° 42′ 56.3"	24° 30′ 19.2"	27° 11′ 51.0"	27° 11′ 31.4"
Soil type		Peatland	Mineral soil	Mineral soil	Mineral soil
Forest type		Sub-xeric peat heath	Sub-Xeric Heath	Herb-rich Heath	Herb-rich Heath
Treatment		First thinning	Later thinning	First thinning	Later thinning
Preclearing		No	No	Yes	No
Stand age	Years	37	55	27	42
Main species		*Pinus sylvestris*	*Pinus sylvestris*	*Betula pendula*	*Betula pendula*
Mean DBH	cm	15.6	18.0	13.8	16.1
Mean height	m	15.1	17.5	17.8	17.8
Dominant height	m	17.0	20.4	18.0	20.4
Number of trees	trees ha^{-1}	1137	896	1277	875
Initial stocking	m^3 ha^{-1}	198	262	138	193
Stand area	ha	2.6	4.3	1.6	1.9

DBH Diameter at breast height (1.3 m)

The operator can set the desired thinning density (stems ha^{-1}) in the application settings. In this study, densities were set at 600 stems ha^{-1} in stand 1400 stems ha^{-1} in stand 2800 stems ha^{-1} in stand 3 and 400 stems ha^{-1} in stand 4. The system guided the operator with real-time information with regard to the spatial location of the trees, visualised as a tree map where dense areas were shown in red and stumps were marked by a white dot. In addition, the number of remaining stems in the working location and the distance line to the previous strip road were available to the operator.

The work task for the operators was to thin the study stands described in Table 1. The planned method for thinning was thinning from below, where suppressed, co-dominant and lower-quality trees were removed. In all stands, both pulpwood and sawlogs were bunched. The lower diameter limit for pulpwood was 5–6 cm, 15 cm for pine sawlogs and 16 cm for spruce and birch. Operators used the strip

(a) (b)

Fig. 2 **a** The Ouster LiDAR OS0 (indicated by a red circle) on the cabin front of the Ponsse Scorpion King, and **b** the view from the harvester cabin

Table 2 Operators' experience (in years) and familiarity (Yes/No) with the Thinning Density Assistant (TDA) system prior to the start of the study

Operator	Experience in years	Familiarity with the TDA
A	19	No
B	3	Yes
C	15	Yes
D	4	Yes
E	30	Yes

road method (Kärhä et al. 2004), in which the recommended strip road width is 4–4.5 m (4–5 m for forests on peat soils). The recommended minimum distance between strip roads is over 20 m (Äijälä et al. 2019). The operators plan the strip roads and the selection of the trees to harvest. No strip roads or trees were marked beforehand on site. This approach is conventional in Nordic forestry and was not due to the study design. Only the starting point and end point of the time study plot were marked with ribbons.

The operators mostly used sector and felling on-side techniques (Grönlund et al. 2015; Ovaskainen 2009). First, they felled the trees from the strip road and then from the side of the machine. Operators bunched the logs on both sides of the strip road. In most cases, the felled trees were dragged over the strip road for bunching, leaving branches on the strip road to protect the roots and soil. In some cases, operators bunched the tree under a crane, close to the stump, to avoid the unnecessary movement of the stem. Sawlogs were colour-marked and the operators bunched timber assortments into separate piles or crossed them with an existing pile of different assortments making it easier for the forwarder operator to identify different timber assortments.

Data

We collected video material for the time study using a GoPro 8 camera installed inside the harvester cabin. In total, we gathered 37 h of video footage, which included short delays. The video material included 4,967 felled trees (504 m^3) from the four stands: 1,427 stems in stand 1, 1,557 stems in stand 2, 1,093 stems in stand 3 and 890 stems in stand 4. After each stand was harvested, we saved the harvester production (HPR) file to a memory stick to obtain stem data and harvester routes. We parsed the HPR files, formatted according to the StanForD 2010 standard (Arlinger et al. 2021), into a spreadsheet in Microsoft Excel that included a timestamp, operator code, stem number, global navigation satellite system (GNSS) position, tree species code, DBH, volume and assortment (Table 3). Finally, stem data from the HPR file was linked with the time study data from the video analysis. One researcher conducted all the video analysis using Laurén's Excel-based timing tool to record the time spent on each work element and to identify the main, complementary and unavoidable delays in direct work time (Björheden 1995).

In visual time analysis, we used a time element level measurement, where work cycles were divided into functional work elements. Hence, the cutting of one stem constituted one work cycle observation. The time elements associated with one work cycle may include moving, boom-out, felling, processing, moving logs, tops and branches, boom-in, clearing, miscellaneous time and delays. For the analysis, we combined clearing, moving tops and branches (slash), stacking logs and planning to *miscellaneous time* (Table 4). A similar division has also been used in previous time studies (Kärhä et al. 2004; Nurminen et al. 2006). In

Table 3 Description of the processed stems by stand and treatment

Stand		1		2		3		4	
Treatment		Ref	TDA	Ref	TDA	Ref	TDA	Ref	TDA
Plots	n	6	5	6	9	4	5	5	6
Harvested area	ha^{-1}	1.49	1.06	1.83	2.6	0.68	0.90	0.97	0.97
Volume	m^3	0.09	0.09	0.14	0.13	0.06	0.07	0.11	0.10
DBH	cm	12.8	12.8	14.0	13.8	10.2	10.8	12.8	12.3
Harvested volume	$m^3\ ha^{-1}$	56.1	44.5	45.2	52.7	46.7	40.8	52.2	43.2
Removal	stems ha^{-1}	600	502	318	396	787	620	464	454
Total removals	n	895	532	582	975	535	558	450	440
Night	n	308	70	0	103	108	0	221	120

TDA Thinning density assistant, *Ref* Reference, *DBH* Diameter at breast height, 1.3 m, Night = Stems cut at night

Table 4 Description of the various work elements in the harvester-time study

Work element	Description	Priority
Boom-out	Boom-out commenced when the harvester head was steered towards the next tree to fell and ended when the felling cut began	As it overlaps with the *moving* work element, boom-out was considered to have started only when the machine had stopped moving
Felling	Felling commenced at the felling cut and ended when feeding and delimbing began	As it overlaps with the *processing and moving* work element, *felling* was considered to end when the tree was fully felled onto the ground
Processing	Processing commenced with the feeding of the stem and ended when the last part of the stem was cut	
Boom-in	Boom-in included steering the harvester head to the front of the harvester before moving	
Moving	Moving commenced when the harvester began to move and ended when the harvester stopped to perform another task	As it overlaps with the *moving* work element, boom-in stopped when the machine started to move forward or reverse
Miscellaneous time	Included clearing, moving tops and branches (slash), stacking logs and planning of work	

some instances, the various work elements can overlap, in which case only one time can be recorded. This can happen, for example, when an operator approaches a tree while the harvester is still moving, or if the harvester needs to be moved before bunching a tree.

Moving data were acquired in the following way: The HPR file included the GNSS positions of the machine at the tree-level, which we linked with the time study data as described above. We imported the data, including the machine positions and moving times in one work cycle, into QGIS (Rosas-Chavoya et al. 2022). We summed the moving time every 20 m and assumed a 20 m working range on both sides (the maximum reach of the crane was 11 m) using the algorithm "Join attributes by location". After this, we were able to sum the moving time and the number of removed trees within the 0.04 ha sections along the strip roads using a simple expression in the attribute table.

The perceived workload experienced by the operator was assessed with the NASA Task Load Index (NASA-TLX). Data collection was performed via a questionnaire. The perceived workload was determined by measuring the workload in six dimensions: mental demand, physical demand, temporal demand, performance, effort and frustration level (Hart and Staveland 1988).

Statistical analysis

We conducted a comparative time study using a factorial design to investigate how the use of the TDA system affected the productivity and time spent on the different work elements (RQ1). The experimental design was not fully balanced due to unforeseen technical events during the experiment and the difficulty to ensure a balanced number of harvested stems between the reference and TDA plots.

We considered *treatment* and *operator* as fixed factors in the analysis: Treatment had two levels (reference and the TDA) and operator had five levels (operators A to E). The operator can be considered a blocking factor to account for the inherent variability between operators. Tree species with three levels (pine, spruce and birch), stem volume, removal density and night with two levels (Day and Night) were treated as random factors. Stem volume and removal density were adjusted by regression variables to ensure they were set at the same level for all operators in the analysis. Some of the cuttings were carried out during night, which was set as a dummy variable with two levels. We did not have identical conditions in the stands, as the forests differed with regard to the main tree species and also between timing of thinning. We checked for outliers and identified highly influential observations in the regression models. In most of these cases, the operator had to spend significantly more time ordering the work elements, although this was still part of the operator's normal work.

The time associated with boom-out, boom-in, moving logs, tops and branches, as well as miscellaneous time did not correlate with any continuous variable, such as stem volume, DBH or removal density. Therefore, these times were only summed and divided by the total number of observed cycles. Trees that were processed but rejected were also included in miscellaneous time. This occurred when the processed stem was either below the merchantable diameter limits or broke during processing. We employed two-way analyses of variance (ANOVA) to test the statistical significance of differences in mean values for boom-out and boom-in. In the combined model, we used the average times of the operators by summing the boom-out times achieved by the operators and dividing them by the number of operators.

Time spent during felling (y_2), processing (y_3) and moving (y_5) correlated with stem volume or removal density. Time spent during felling and processing was regressed against stem volume (m^3) and moving time was regressed against removal density (stems ha^{-1}). We considered the relationship between felling, processing and moving times with different transformations to improve data normality and symmetry of residuals. We used a second-order polynomial transformation for stem volume to linearise the processing time model and used an inverse transformation for removal density. We applied analyses of covariance (ANCOVA) to evaluate the statistical significance of differences in mean values for felling (Eq. 1), processing (Eq. 2) and moving (Eq. 3), while controlling for stem volume and removal density as continuous covariates. We used Microsoft Excel to collect and combine the data into a data frame and R, a free open-source statistical programming language, for all statistical analyses (R Core Team 2024).

$$y_2 = \beta_0 + \beta_1 \times x_1 + \beta_2 \times Operator + \beta_3 \times TDA + \beta_4 \times Night + \varepsilon \tag{1}$$

$$y_3 = \beta_0 + \beta_1 \times x_1 + \beta_1 \times x_1^2 + \beta_3 \times Species + \beta_3 \times Operator + \beta_4 \times TDA + \beta_5 \times Night + \varepsilon \tag{2}$$

$$y_5 = \beta_0 + \beta_1 \times \frac{1}{x_2} + \beta_2 \times Operator + \beta_3 \times TDA + \beta_4 \times Night + \varepsilon \tag{3}$$

where: y_2, y_3, y_5 = dependent variables; x_1 = stem volume m^3; x_2 = removal density (stem ha^{-1}); β_0 = intercept; β_1, β_2, β_3, β_4 = coefficients; ε = error term. TDA and Night were employed as dummy variables: 1 if the TDA was used and 0 if the reference was used; 1 if it was nighttime and 0 if it was daytime. Note: In the operator-specific test, the Operator variable was excluded.

Independent variables were interpreted using p-values. The main criterion for including variables in the models was a low p-value ($p<0.05$). Operators logged differing numbers of stems, which caused an uneven sample size. We took variable sample sizes of the operators into account by using an average of the coefficients of the associated dummy variable and its interactions. The averages of these coefficients were added to the basic regression models for the common regression model estimates of felling (Eq. 4), processing (Eq. 5) and moving (Eq. 6).

$$y_2 = (\beta_0 + \frac{\sum_{i=1}^{n}\alpha_i}{n}) + \left(\beta_1 + \frac{\sum_{i=1}^{n}\gamma_i}{n}\right) \times x_1 + \left(\beta_2 + \frac{\sum_{i=1}^{n}\delta_i}{n}\right) + \varepsilon \tag{4}$$

$$y_3 = (\beta_0 + \frac{\sum_{i=1}^{n}\alpha_i}{n}) + \left(\beta_1 + \frac{\sum_{i=1}^{n}\gamma_i}{n}\right) \times x_1 + \left(\beta_2 + \frac{\sum_{i=1}^{n}\delta_i}{n}\right) \times {x_1}^2 + \left(\beta_3 + \frac{\sum_{i=1}^{n}\theta_i}{n}\right) + \varepsilon \tag{5}$$

$$y_5 = (\beta_0 + \frac{\sum_{i=1}^{n}\alpha_i}{n}) + \frac{(\beta_1 + \frac{\sum_{i=1}^{n}\gamma_i}{n})}{x_2} + \varepsilon \tag{6}$$

where y_2, y_3, y_5 = dependent variables; x_1 = stem volume m^3; x_2 = removal density (stem ha^{-1}); β_0 = intercept; β_1, β_2, β_3, β_4 = coefficients; k = coefficient of base level; α_i, γ_i, δ_i, θ_i = coefficients of the interaction terms; n = total number of interaction terms; i = index of summation; ε = error term.

We computed the total effective time spent by operators as an average by summing up the work element times (Eq. 7). Then, we converted the total effective time spent during cutting work into an effective hour productivity value (m^3 E_0^{-1}), also known as the productive machine hour (PMH), using Eq. 8.

$$T_{tot} = y_1 + y_2 + y_3 + y_4 + y_5 + y_6 \tag{7}$$

$$P_e = 3600 \times (x_1/T_{tot}) \tag{8}$$

where T_{tot} = total effective time spent during cutting work (s $stem^{-1}$); P_e = effective hour productivity (m^3 $E_0{}^{-1}$); x_1 = stem volume (m^3).

To investigate the profitability of investment in the TDA (RQ2), we converted effective hour productivity to gross-effective hour productivity, also known as scheduled machine hour (SMH), which included delays of < 15 min (m^3 $E_{15}{}^{-1}$). We did not use observations taken in this study. Instead, we used coefficients proposed by Kuitto et al. (1994) to correct the bias between the time study and the follow-up study (Eq. 9). We used the harvester cost calculator developed by Uusitalo and Kivinen (2024) to calculate the operating hour cost. Since only the variable costs can be reduced using the TDA, we only used a variable cost of €43.78 per hour in our profitability calculations (Table 5). All calculations were made with 0% VAT. The profitability calculation includes three scenarios, one of which highlights the advantage of prior tree marking. This scenario illustrates the maximum potential of TDA when further developed. Prior tree marking resulted in a 2.7% benefit in the first thinnings and 2.8% benefit in the later thinnings (Pohjala et al. 2024).

In general, the price of new technologies decreases over time as production quantities grow and R&D costs are gradually amortised. In our calculations, we assumed that the acquisition price of the device would evolve as follows: the cost of sensors would decrease by 25% within two years, while the prices of other system components and manufacturing costs would decrease by 50% over the same period. The depreciation period of the harvester was set at 6 years. Therefore, we decided on two investment periods: (1) 0 to 6 years, and (2) 6 to 12 years. The salvage value was set at 10% of the system's acquisition price. The revenues were the system's cost savings (€ year^{-1}), and the annual maintenance cost was €500 year^{-1}. We calculated the NPV of the investment discounting the cash flow (acquisition cost, cost savings, maintenance costs, residual value) using Eq. 10. The interest rate was set at 7% including the required return on both debt and equity.

$$P_{ge} = \frac{P_e}{1.197 \times 1.276} \tag{9}$$

where P_e = effective hour productivity (m^3 E$_0$$^{-1}$); P_{ge} = Gross-effective hour productivity (m^3 E$_{15}$$^{-1}$).

$$NPV = \sum_{t=0}^{T} \frac{cashflow_t}{(1+r)^t} \tag{10}$$

Table 5 Variable cost of harvesting at 2,699 operating hours per year

Cost factor	Harvester	
Variable costs	€ a^{-1}	€ h^{-1}
Fuel	64,765	24.00
Motor oil	1,889	0.70
Transmission oil	891	0.33
Hydraulic oil	1,619	0.60
Chain oil	2,953	1.09
Guide bar	2,860	1.06
Chain	2,226	0.83
Colour marking	863	0.32
Repair and service cost	18,455	6.84
Relocation	21,625	8.01
Total	118,146	43.78

where *NPV* = Net Present Value; *cash flow* = cash flow in year *t*; *t* = time period (year); *T* = total time during which the cash flow occurred; *r* = discount rate.

The perceived workload experienced by the operator was tested with ANOVA using Eq. (11).

$$Mentaldemand = \mu + \beta_1 \times Agegroup + \beta_2 \times TDA + \beta_3 \times (Agegroup \cdot TDA) + \epsilon \tag{11}$$

where μ = overall mean, $\beta_1 \times$ Age group: Effect of operators being under or over 30 years old, $\beta_2 \times$ TDA: Effect of the TDA system. $\beta_3 \times$ (Age group $\times$ TDA): Interaction effect between age group and the TDA system, ϵ = error term.

Results

Effects of the TDA on relative distribution and time spent on work elements, and productivity (RQ1)

Relative distribution of work elements

The difference between the relative distributions of effective time spent on the different work elements was small between the reference and TDA plots when the average values of the five operators were examined (Fig. 3). We observed only a minor difference in the relative proportion of boom-out, which decreased by 2 percentage points, while the differences in the other work elements were 1 percentage point or less. On an operator-by-operator basis, the proportion of the different work elements followed the average values, with an exception observed for operator A, who spent significantly more time on boom-out operations than the other operators. In addition, operator A had a 5-percentage point difference in the proportion of time spent processing between the reference and TDA plots. We only used average miscellaneous time for all operators. As a point of interest, disturbances and other delays represented a 9% share in the reference plots and an 11% share in the TDA plots for total gross-effective time. Effective time was converted to gross-effective time using a theoretical coefficient of 1.41, based on Kuitto et al. (1994), rather than on the empirical values observed in this study.

Boom-out

Operator and TDA had statistically significant effects on the time spent during boom-out. Correlations between boom-out time and stem volume ($r_s = -0.015$, $p = 0.303$), removal density ($r_s = 0.070$, $p < 0.001$) or DBH ($r_s = 0.001$, $p = 0.945$) were weak or non-existent. Therefore, boom-out times are described here as mean and relative times. We observed

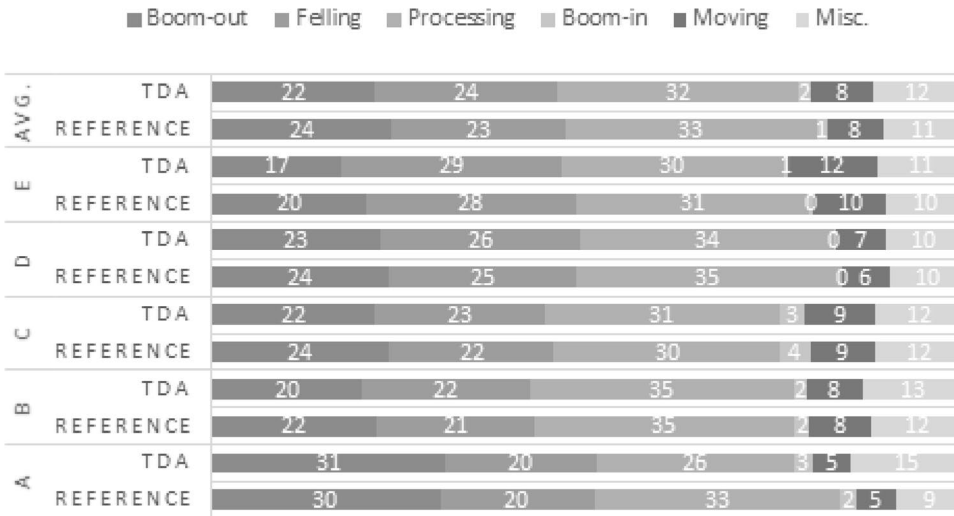

Fig. 3 Operator-specific (**A**–**E**) and average (Avg.) cutting work time as a percentage of total effective time in the reference and Thinning Density Assistant (TDA) plots

weak but significant differences between some operators' times ($F=134.8$, $p<0.001$). The TDA had a weak but significant effect ($F=6.3$, $p<0.05$) and no significant effect of cutting at night was observed ($F=1.7$, $p=0.19$). The operator-specific boom-out averages with distributional characteristics are presented in Fig. 4. The TDA reduced the average time spent during boom-out by 5% (from 6.6 s to 6.3 s (y_1)). Between the individual operators, the effect of the TDA on the time spent during boom-out ranged from a decrease of 15% to an increase of 10%.

Felling

The TDA did not have a systematic effect on the felling times of the operators (Appendix 1). Felling time had a weak but statistically significant correlation with stem volume ($r=0.12$, $p<0.001$). Therefore, the time spent on felling was regressed against stem volume. In ANCOVA, we observed a statistically significant effect of the TDA system on felling times only for operators B ($F=5.55$, $p<0.05$) and D ($F=24.70$, $p<0.001$), where felling times increased by 0.3 and 1.0 s, respectively. Night-time logging did not affect the time spent on felling ($F=1.30$, $p=0.2548$). The estimated regression functions for operators are presented in Appendix 2. Among individual operators, the effect of the TDA on the time spent on felling ranged from a decrease of 2% to an increase of 14%. There was not sufficient evidence to include the TDA in the general felling time model (Eq. 12).

$$y_2 = 5.97 + 6.70 \times x_1 \qquad (12)$$

where: y_2 = felling time (s stem^{-1}); x_1 = stem volume (m^3).

Processing

The TDA did not have a systematic effect on the processing times of the operators (Appendix 1). Instead, stem volume, operator, tree species and night had statistically significant effects on the time spent on processing. In ANCOVA, the TDA had a significant effect only on operators A ($F=9.4008$, $p<0.1$) and C ($F=5.24$, $p<0.05$). The TDA decreased processing time for operator A from 7.0 s stem^{-1} to 6.3 s stem^{-1} and increased processing time for operator C from 5.3 s stem^{-1} to 5.4 s stem^{-1} (with a stem volume of 0.06 m^3). Tree species had a statistically significant effect on processing times ($F=127.05$, $p<0.001$): time spent with birch was 1.7 s stem^{-1} greater than with pine. Night conditions seemed to have a small effect ($F=10.60$, $p<0.01$) on processing times (an increase of 0.5 s stem^{-1}). In operator-specific models, operators A, B and C were focused on harvesting pine-dominated stands, and operators D and E focused on harvesting birch-dominated stands. Between the individual operators, the effect of the TDA on the time spent on processing ranged from a decrease of 13% to an increase of 2%. There was insufficient evidence to include the TDA in the general processing model presented in Eq. 13.

$$y_3 = 2.45 + 46.10 \times x_1 - 12.83 \times x_1^2 + 1.70 \times Birch \qquad (13)$$

where: y_3 = processing time (s stem^{-1}); x_1 = stem volume (m^3); tree species dummy = dummy variable; 0 if pine or spruce, 1 if birch.

Boom-in

The operator effect explained most of the variation in the time spent during boom-in ($F=51.532$, $p<0.001$). The TDA did not have a statistically significant effect ($F=2.08$, $p=0.149$) or symmetrical effect on boom-in time, nor did

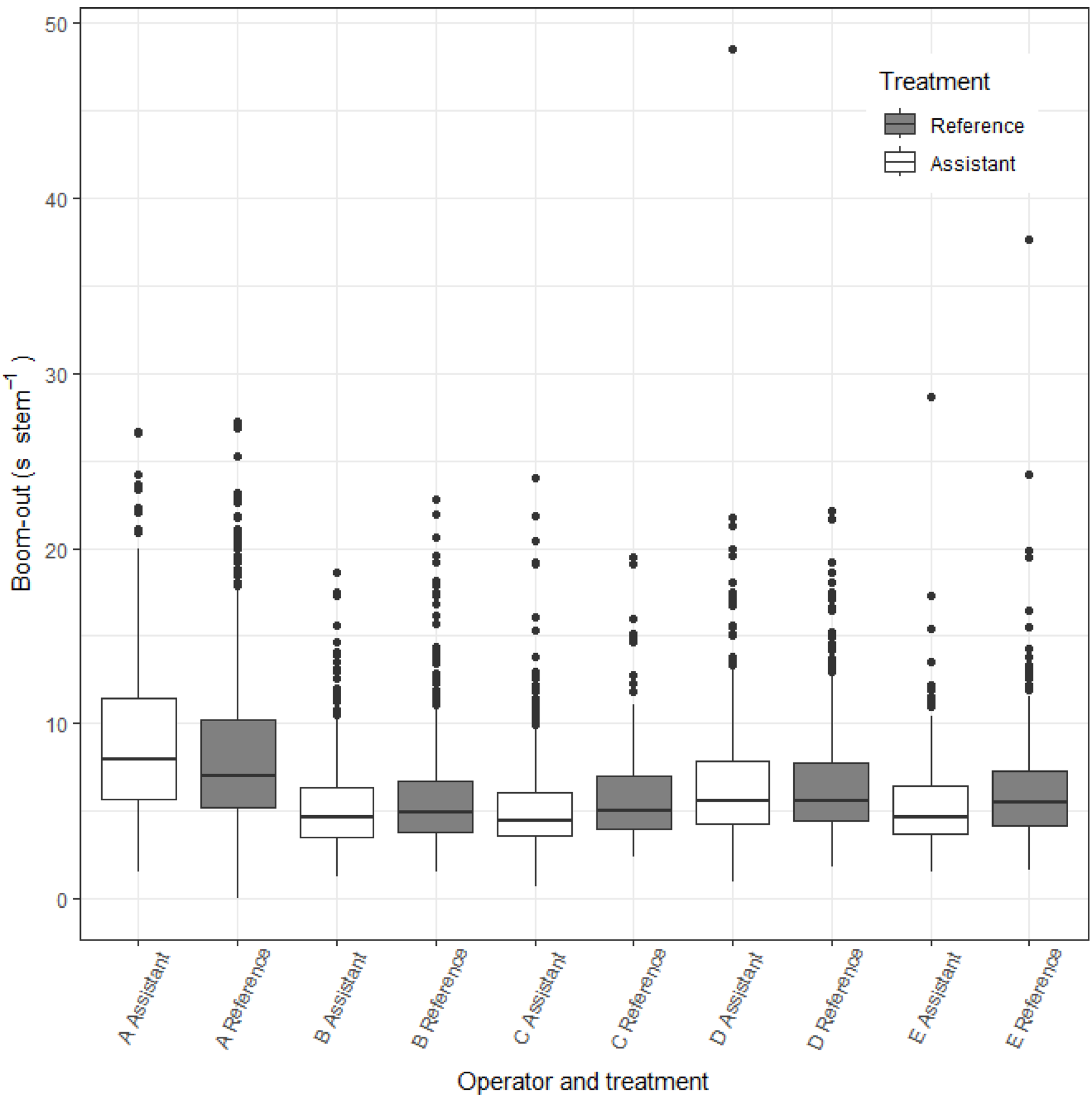

Fig. 4 Boxplot illustrating the time spent by each operator during boom-out in the reference and Thinning Density Assistant (TDA) plots. These values highlight the distributional characteristics, such as the minimum, maximum, first and third quartiles for each operator, and potential outliers

night (F = 2.551, p = 0.110). In the operator-specific analysis, the TDA slowed boom-in times from 0.06 to 0.16 s stem^{-1} for operators A (F = 3.38, p < 0.0664), D (F = 12.59, 0.001) and E (F = 12.59, p < 0.001). In contrast, the TDA accelerated boom-in times by 0.09 s stem^{-1} for operator B (F = 8.84, p < 0.01) and by 0.18 s stem^{-1} for operator C (F = 10.56, p < 0.01). Between the individual operators, the effect of the TDA on boom-in time ranged from a decrease of 18% to an increase of 47%. In the general model (y_4), we used an average time of 0.42 s stem^{-1} for both the reference and TDA plots.

Moving

The TDA did not have a statistically significant effect on moving time (F = 0.73, p = 0.39). Only removal density (F = 138.7, p < 0.001) and operator (F = 13.6, p < 0.001) had statistically significant effects on moving time per processed stem (Fig. 5). We observed differences between operators.

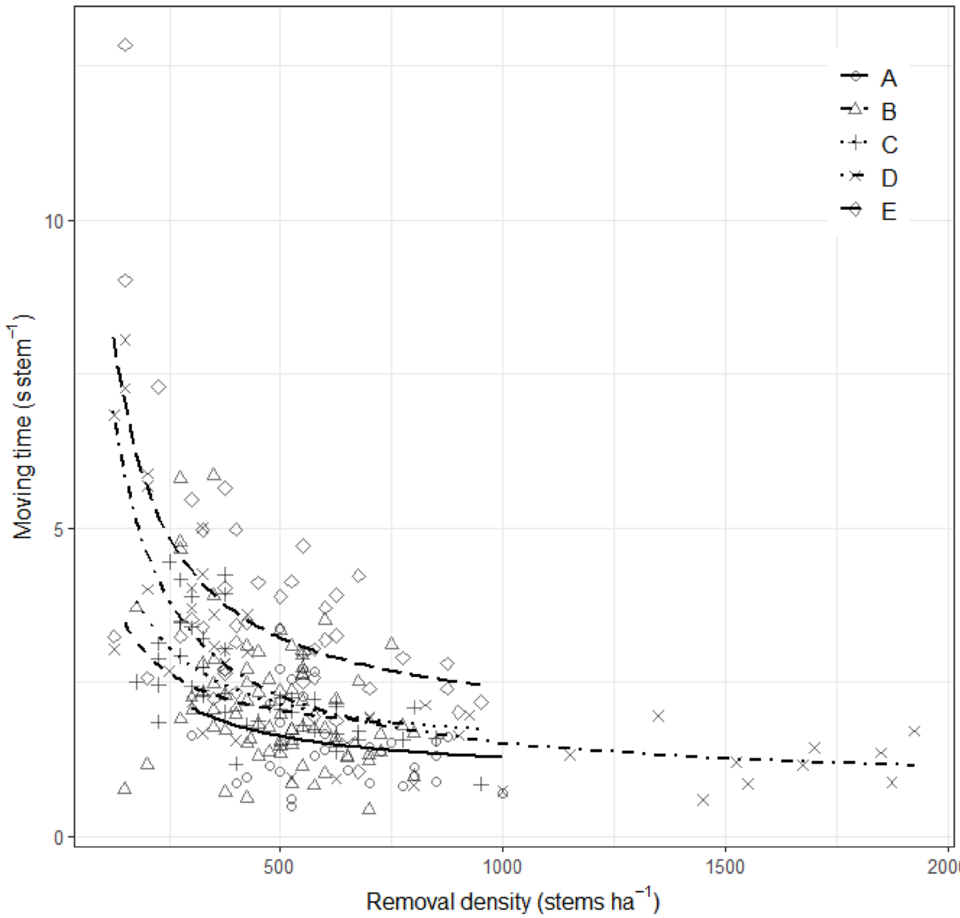

Fig. 5 Effect of removal density (stems ha^{-1}) on moving time (s stem^{-1}) across the different operators (**A**–**E**)

Compared to operator A, who spent the least amount of time, operator E spent twice as much time on moving. We did not observe a statistical difference between the night- and day-time cuttings (F = 2.27, p = 0.13). Therefore, both the TDA and night were excluded from the operator-specific (Appendix 1) and general moving model (Eq. 14). Operator-specific regression moving models are presented in Appendix 2. Based on this model, the estimated average moving time per tree during the first thinnings (where removal is typically ~ 800 stems ha^{-1}) was 1.7 s stem^{-1}, and was 3.2 s stem^{-1} in later thinnings (where removal is typically ~ 300 stems ha^{-1}).

$$y_5 = 1.13 + \frac{594{,}74}{x_2} \tag{14}$$

where: y_5 = moving time (s stem^{-1}); x_2 = removal density (stem ha^{-1}).

Miscellaneous time

The TDA did not have a systematic effect on miscellaneous time, which included clearing small undergrowth, moving tops and branches (slash) onto the strip road, stacking logs and planning work. The TDA seemed to have an effect only on the time usage of operator A, where it increased from 2.4 to 4.3 s stem^{-1} (F = 12.95, p < 0.001). This effect was not observed with the other operators; therefore, we used an average of 3.1 s stem^{-1} for all operators (y_6).

Productivity

The TDA improved effective hour productivity for four operators out of five (Table 6), though only marginally for operators A, B and D. Productivity improved by 1.3% in the first thinnings and by 1.0% in the later thinnings. The relative benefit of the TDA for the operators was not statistically significant (Table 7). In the first thinnings, effective hour productivity was, on average, 10.6 m^3 E$_0^{-1}$ in the reference plots and 11.0 m^3 E$_0^{-1}$ in the TDA plots (stem size was 0.06 m^3 and removal density was 800 stems ha^{-1}). Productivity per operator varied between 9.2 and 11.8 m^3 E$_0^{-1}$ in the reference plots and between 9.2 and 12.5 m^3 E$_0^{-1}$ in the TDA plots. Effective hour productivity in later thinnings was 19.9 m^3 E$_0^{-1}$ in the reference plots where it ranged from 18.1 to 23.9 m^3 E$_0^{-1}$. In the TDA plots, effective hour productivity was 20.3 m^3 E$_0^{-1}$, where it ranged from 17.4 to 25.1 m^3 E$_0^{-1}$ between the most and least productive operators. Effective

Table 6 Average time of the various work elements and total work cycle times with and without the Thinning Density Assistant (TDA) in first thinnings (average stem volume 0.06 m^3; removal density of 800 stems ha^{-1}) and later thinnings (average stem volume 0.13 m^3; removal density of 300 stems ha^{-1}) for each operator and overall

Operator	Boom-out		Felling		Delimbing & cutting		Boom-in		Moving		Misc		Total		Difference
	Ref	TDA	Ref	TDA	Ref	TDA	Ref	TDA	Ref	TDA	Ref	TDA	Ref	TDA	
	s stem^{-1}	s stem^{-1}	s stem^{-1}	s stem^{-1}	s stem^{-1}	s stem^{-1}	s stem^{-1}	s stem^{-1}	s stem^{-1}	s stem^{-1}	s stem^{-1}	s stem^{-1}	s stem^{-1}	s stem^{-1}	%
First thinnings															
A	**8.3**	**9.2**	5.2	5.6	**7.9**	**6.6**	0.6	0.6	1.4	1.4	3.1	3.1	26.5	26.4	−0.4
B	**5.7**	**5.2**	**4.7**	**5.1**	6.2	6.0	**0.5**	**0.4**	1.8	1.8	3.1	3.1	22.0	21.6	−1.8
C	**6.2**	**5.3**	5.4	5.3	3.9	3.8	**1.0**	**0.8**	1.8	1.8	3.1	3.1	21.5	20.2	−6.0
D	6.5	6.5	**6.4**	**7.4**	7.8	7.9	0.1	0.1	1.7	1.7	3.1	3.1	25.6	26.7	4.5
E	**6.2**	**5.4**	7.7	8.0	6.3	6.3	**0.1**	**0.2**	2.6	2.6	3.1	3.1	26.0	25.7	−1.3
Overall	6.6	6.3	6.2	6.2	5.3	5.3	0.4	0.4	1.7	1.7	3.1	3.1	23.3	23.0	−1.2
Later thinnings															
A	**8.3**	**9.2**	5.7	6.1	**11.4**	**10.1**	0.6	0.6	2.1	2.1	3.1	3.1	31.3	31.2	−0.3
B	**5.7**	**5.2**	**5.1**	**5.4**	8.1	7.9	**0.5**	**0.4**	2.4	2.4	3.1	3.1	24.9	24.5	−1.6
C	**6.2**	**5.3**	5.5	5.4	6.4	6.3	**1.0**	**0.8**	2.8	2.8	3.1	3.1	25.1	23.8	−5.1
D	6.5	6.5	**7.3**	**8.3**	11.4	11.6	0.1	0.1	3.3	3.3	3.1	3.1	31.8	32.9	3.7
E	**6.2**	**5.4**	8.1	8.4	8.7	8.8	**0.1**	**0.2**	4.3	4.3	3.1	3.1	30.5	30.2	−1.1
Overall	6.6	6.3	6.6	6.6	8.3	8.3	0.4	0.4	3.2	3.2	3.1	3.1	28.3	28.0	−1.0

For pine, delimbing and cutting times are adjusted by regression models. Statistically significant differences between the reference and TDA plots are shown in bold

hour productivity was converted to gross-effective productivity for pine trees (Fig. 6) using Eq. 6. Gross-effective productivity was used in the investment calculations.

TDA as an investment (RQ2)

The profitability of the TDA depends on the purchase price, the proportion of thinning during harvesting, annual expenses and the return requirement of the investments. The cost-saving benefit of the TDA is equal to its impact on gross-effective time (E_{15}). According to this study, the benefit would be 1.3% for the first thinnings and 1.0% for later thinnings. Typically, part of the work time is dedicated to the final felling. Cost savings achieved with the TDA before expenses were €868.50 (with a 70% share of thinnings) and €1,116.60 (with a 90% share of thinnings). If the harvester worked entirely on thinning and the technology develops to the level of prior tree marking benefits, the cost savings would be €3,249.50. In the calculation of machine costs, variable costs were €43.78 h^{-1}, with an annual work time of 2699 h calculated with 85% of direct work time on sites.

Due to the marginal increase in productivity, the acquisition of the system is a profitable investment only at low acquisition costs of €2883–4167 (acquisition price of the system for the NPV of €0), depending on the proportion of thinnings in the annual total harvest volume (Fig. 7). The acquisition price of the system can rise to €13,849, if the machine is only used for thinning and the productivity is at the level of prior tree marking, which was 2.7% in the first thinnings and 2.8% in the later thinnings.

Workload (RQ3)

We assessed the operators' workload using a survey based on the NASA-TLX questionnaire, which includes six dimensions. The NASA-TLX scores showed a statistically significant difference in mental workload ($F = 21.9$, $p < 0.05$) between operators under 30 years old and those over 30 years old, with average scores of 44.5 and 22.5, respectively. Mental demand (decision making, thinking and planning) and Temporal demand (time pressure and the sense of hurry) appeared greater among younger operators compared to the experienced operators (Fig. 8). However, the TDA did not affect this in either group. The difference in mental workload between the TDA system and the reference was not statistically significant ($F = 0.10$, $p = 0.76$), nor was the combined effect of experience and system ($F = 0.15$, $p = 0.71$). However, operators under 30 years old found the TDA to be slightly beneficial in facilitating decision-making and work planning and improving their satisfaction with the quality of the harvesting work, which was not observed in operators over the age of 30 years. In contrast, the TDA

Table 7 Relative impact of operators in the first and later thinnings

Effect	SS	df	%	MS	F	*P*-value	F crit
First thinnings							
TDA	2.50	1	4	2.50	0.35	0.57	5.32
Residual	56.87	8	96	7.11	–	–	–
Total	59.37	9	100	–	–	–	–
Later thinnings							
TDA	2.09	1	5	2.09	0.42	0.54	5.32
Residual	39.67	8	95	4.96	–	–	–
Total	41.75	9	100	–	–	–	–

The sum of squares (SS), degrees of freedom (df), % of total SS (%), mean square (MS), F-value, and *p*-value for each source of variation

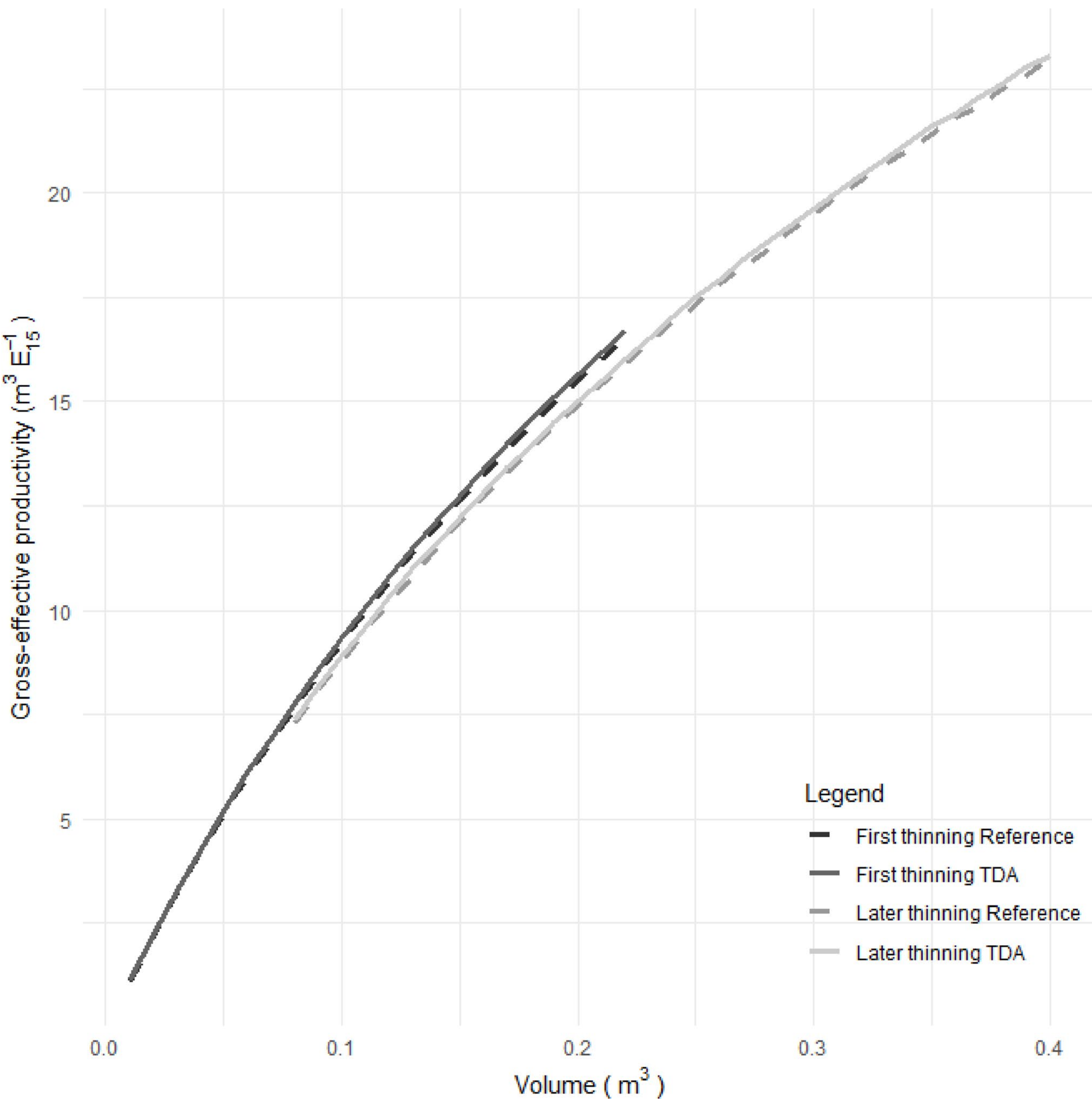

Fig. 6 Gross-effective cutting productivity for pine trees. Removal density during first thinnings was set at 800 stems per hectare (stem ha^{-1}), and at 300 stems ha^{-1} in later thinnings

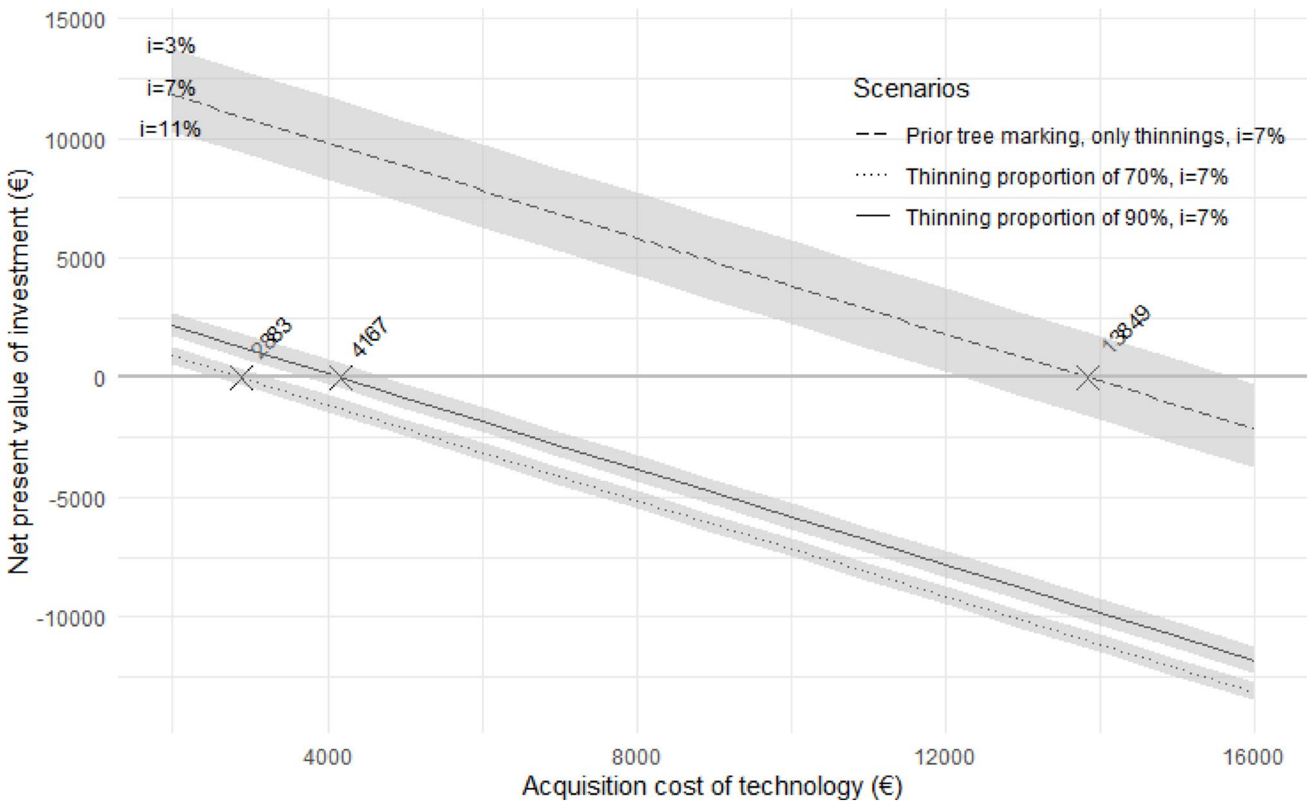

Fig. 7 Profitability of an investment in the Thinning Density Assistant (TDA) system under three scenarios. The proportion of thinnings in the different scenarios was set at 70%, 90% and 100% of the annual total harvest volume. In the last scenario, a productivity enhancement of 2.8% (Pohjala et al. 2024) was used as the system maximum. The intersection of these functions with the x-axis represents the purchase price at which the net present value (NPV) of the investment is zero. The discount rate (i) was set at 7%. The grey areas visualise the impact of the interest rate on NPV (range: 3% to 11%)

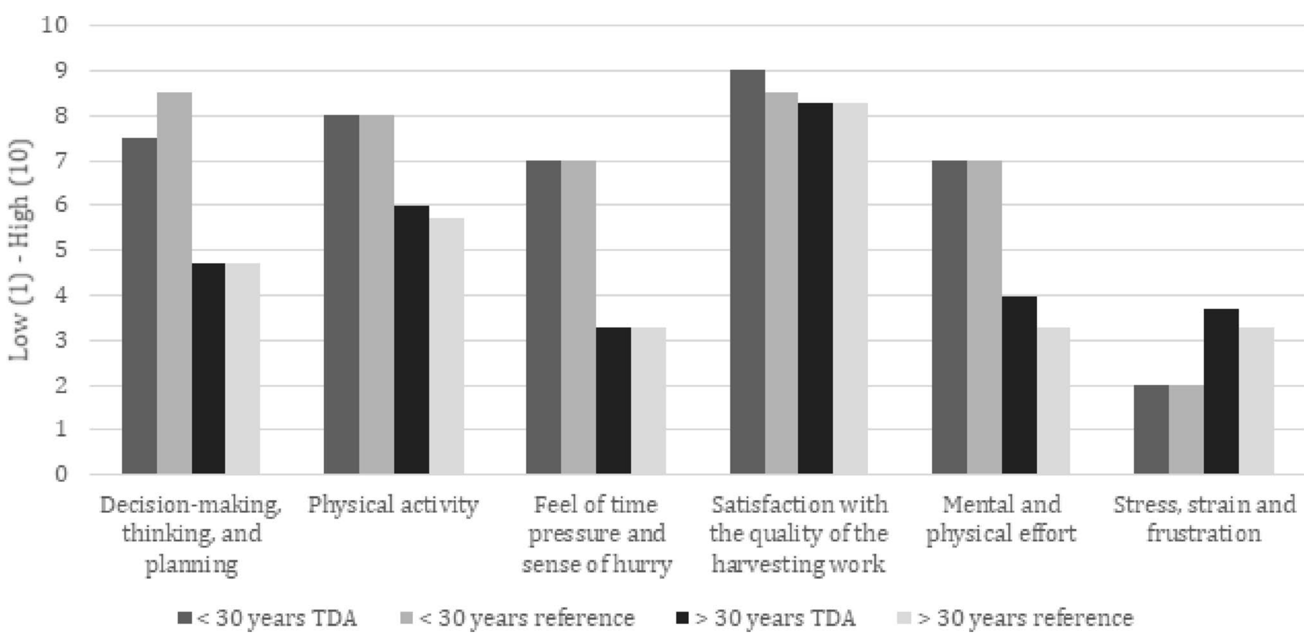

Fig. 8 Results of the NASA Task Load Index (NASA-TLX) questionnaire to assess the perceived mental workload of forest cutting work with and without the Thinning Density Assistant (TDA) system in two age groups (under 30 years, n=[2]; and over 30 years, n=[3]). The NASA-TLX measures six dimensions of workload: mental demand, physical demand, temporal demand, performance, effort and frustration

slightly increased the physical activity, mental and physical effort and perceived stress, strain and effort among the operators over 30 years old.

In addition, we investigated whether the TDA helps operators maintain the targeted number of remaining trees and assessed the overall usefulness of the TDA. Younger operators found the TDA significantly more useful, with average scores of 9.0 with regard to maintaining the targeted number of remaining trees and 8.5 for overall usefulness. In contrast, operators over 30 years old rated the TDA much lower, with average scores of 3.6 and 3.3, respectively.

Discussion

Study strengths and limitations

This study aimed to determine the benefits of the TDA on productivity in forest thinning and, consequently, the profitability of investing in such a system. In addition, we examined the effect of the TDA on the operator's perceived workload. We used a comparative time study method and applied regression techniques to account for the natural variations in forest stands, particularly with regard to tree size and removal density. The influence of the system on productivity was minimised by using the same machine type throughout the study. Productivity models were employed to compare the productivity and possible operator-specific differences in the use of the TDA system. Due to limited time study data and specifically selected stands, the productivity estimates reflect only the performance of five operators and one machine model in relatively easy terrain. Therefore, these models should not be considered valid estimates of thinning work productivity at a broader scale (cf. Lindroos et al. 2024).

Although the division of work elements followed previous studies, even small differences can affect the results. Therefore, the time differences between work elements should be interpreted with discretion when the results between the different studies are compared. In this study, the boom-in times may have been influenced by differences in the definition of the work element itself; boom-in time was calculated when the harvester head was moved in front before the harvester moved forward or reversed (cf. Nurminen et al. 2006). Moreover, the unique crane structure of the Ponsse Scorpion, with its base located behind the cabin, may have affected the operators' working routines.

The harvested area and the number of processed trees in this study corresponds to amounts in previous studies. Therefore, possible benefits from the TDA should already be evident in a time study of this size. We used both comparative and correlation methods to analyse the effects of the TDA. Both these methods have been widely used both separately and in combination in forest work studies (Lindroos 2010; Magagnotti and Spinelli 2012). Logarithmic transformation of the dependent variable would have resulted in even more symmetrical residuals. However, the models developed in this research are more user-friendly, as they do not require the consideration of back-transformation for predictions (as needed in logarithmic models). Operator time consumption and productivity in the reference and TDA plots were presented in absolute values and in relative values for comparison. In this study, the operator effect was examined by adding interaction terms to a model for felling, processing and moving. Generalisations of these models were derived by taking the average of operator-specific coefficients. With this procedure, we attempted to observe the operator effect (Lindroos 2010) and could create justified general productivity models. The operators were instructed to work at their normal pace, but there is still a risk that the operators worked at a faster pace throughout the study. We used the gross-effective and follow-up coefficients (Kuitto et al. 1994) in our investment calculations to avoid overestimating productivity based on a relatively short time study.

The observations of time spent moving were collected differently compared to previous time studies (e.g. Kärhä et al. 2018; Nurminen et al. 2006), where data was collected at the plot level. This resulted in a relatively small number of observations, making it difficult to build a model separately for all the operators or include the observed variation between operators. In this study, we utilised GNSS location data from the HPR file to estimate removal density over an area of 0.04 ha. This technique increased the number of observations from 46 to 230, thereby allowing us to model operator-specific moving times, which better accounted for the operator effect. However, there are also weaknesses in this approach due to the assumed working width of 20 m.

The distinction between first and later thinnings was unclear due to earlier forest management decisions. Stand 1 had a late silvicultural timing for the first thinning. In stand 2, the old strip road network was based on a 30 m strip road interval. In site 3, small-scale firewood harvesting had been carried out in part of the plots. Preclearing was only carried out on stand 3; on the other sites, a small number of undergrowth trees were present during harvesting. Clearing time was recorded as a separate time element, but it may hamper operators' performance in other time elements as well. Unnecessary clearing should generally be avoided, and the relatively sparse undergrowth should be tolerated (Kärhä and Bergström 2020). Therefore, we presented productivity solely by setting removal density at 800 stems ha^{-1} during the first thinning and at 300 stems per ha^{-1} in later thinning.

The NASA questionnaire included only the five operators who participated in the study. The views of these five operators cannot be generalised to a larger population of harvester operators, especially since the TDA is still in the development phase. The questionnaire was given to the operators immediately after the cutting work was completed, but it was agreed with them that they could fill it out at home at their own pace. It took several weeks for some operators to complete the questionnaire. As a result, some details might not have been entirely fresh in their memories.

Estimating the benefits on productivity of the TDA (RQ1)

The observed proportions of effective time were in most cases aligned with the averages reported in earlier studies (Ovaskainen 2009; Gellerstedt 2002; Kärhä et al. 2004; Nurminen et al. 2006; Pohjala et al. 2024), except for the low proportion of time used in moving (Fig. 1). Our results strongly support many earlier findings that productivity variations are mainly explained by the stem size, as well as by removal density and the human-effect. According to Dvorak et al. (2008), the importance of the operator is emphasised in the most technically challenging tasks: boom-out and processing. In our study, the largest benefits would be expected during boom-out and moving. However, it is not entirely out of the question that the operator selected the next tree or planned the work during other work elements, for example during processing of the stem or while moving (Sirén 1998).

The effect of the TDA on boom-out time was weak but statistically significant. The TDA reduced boom-out time from 6.6 to 6.3 s stem^{-1}. As expected, boom-out was not dependent on the volume of the trees or removal density (Kellogg and Bettinger 1994; Gellerstedt 2002; Nurminen et al. 2006; Ovaskainen 2009; Pohjala et al. 2024). Therefore, only average values for the reference and TDA were used. Nurminen et al. (2006) and Pohjala et al. (2024) observed average boom-out times of around 6 s, which aligns with our findings. In contrast, Kellog and Bettinger (1994), Gellerstedt (2002) and Ovaskainen (2009) reported boom-out times of approximately 10 s. The difference could be attributed to subjective definitions of work tasks rather than objective differences in the tasks themselves (Nuutinen et al. 2008), as well as advancements in harvester technology, such as boom-tip control.

Although we did not find any strong predictor variables for boom-out time, it is affected by many different factors because the operator must consider multiple items simultaneously. The operator might plan the work carefully to avoid damaging the trees or, conversely, quickly move to the next tree without much planning, having made the decision earlier (Ovaskainen 2009). A good working technique also minimises boom movement. Part of this unexplained variation comes from the distance travelled by the harvester head (Ovaskainen 2009). For future studies in boom-out predictions, we recommend using parameters derived from tree maps or GNSS, as TDA might suggest trees that are, on average, further away than the trees selected independently by the operator. In addition, unfamiliarity with the TDA system can cause unexplained variation, as observed with Operator A, who was using the TDA in thinning work for the first time.

The TDA did not affect the time spent on felling or processing elements, but night conditions did seem to have a small effect ($F = 10.60$ $p < 0.01$) on processing times, which were increased by 0.5 s stem^{-1}. As expected, stem volume had a significant effect on these time elements. Our model gives slightly lower estimates for felling but higher estimates for processing compared with the estimates proposed by Nurminen et al. (2006). However, there were clear differences between operators. Some of the variation may be explained by the moving of stems after felling to alternative places for processing, for instance, if slash is needed over strip roads to increase the bearing capacity or for root protection, particularly in the summer months. Moreover, operators may have paused for a short time to select the next tree or for other work planning during processing or perhaps were curious whether the TDA works correctly and changed the colour of the tree to white on the TDA map after felling. In addition, some of the slightly exceptional results associated with operator A may be explained by unfamiliarity with the TDA system. However, as there was no statistically significant nor systematic effects between the operators, we excluded TDA from the general felling and processing models.

The TDA did not affect the time associated with moving. Instead, consistent with previous studies, moving time was correlated with the inverse of removal density (Kärhä et al. 2018; Pohjala et al. 2024). Moving time estimates in this study were similar to those reported by Kärhä et al. (2018), who calculated a moving time of approximately 6 s stem^{-1} with a removal density of 500 stems ha^{-1}, but more than the 3–4 s stem^{-1} observed by Pohjala et al. (2024). These results indicate significant differences in moving time between operators. Magagnotti and Spinelli (2012) pointed out that tree distribution may affect moving time. Tree-maps, which include the position of the remaining trees and stumps, provide the possibility to examine this effect of tree distribution on moving times (in future studies), as well as on boom-out times. In this study, we relied exclusively on the data obtained from the HPR dataset due to the limited coverage of our tree-map data, which only included a subset of our test plots.

Operator effect explained most of the variation associated with boom-in time. The TDA was not statistically significant, even though the TDA had a statistically significant effect with some of the operators. Some of the operators may have planned their work during this work element, for example, by selecting the next trees to be felled, which can increase the time spent on boom-in. Observed boom-in time was, on average, 0.4 s stem^{-1}, which was slightly lower than times reported in earlier studies (Kärhä et al. 2018; Nurminen et al. 2006; Pohjala et al. 2024).

We modelled miscellaneous times as an average value for all operators, as these should not depend on the use of the TDA. Miscellaneous time averaged 3.1 s stem^{-1}. This was more than that observed in earlier studies where miscellaneous time ranged from 1.5 to 3 s stem^{-1} (Kärhä et al. 2018; Nurminen et al. 2006; Pohjala et al. 2024). To the best of our knowledge, the only reported time greater than our study was when cutting was performed after wind damage, when it reached 3.7 s stem^{-1} (Kärhä et al. 2018). The high consumption time in our study could have been caused by the undergrowth that hampered the thinning work (Kärhä 2006; Kärhä and Bergström 2020), while both stands 1 and 2 were uncleared. Another possible explanation may be the small difference in the start and end times of the individual work elements. In this study, processing ended at the last crosscut, and moving tops and branches onto strip roads for protection was included as miscellaneous time. There was even a statistically significant difference between the reference and TDA plots for operator A: The observed result may have been due to the unfamiliarity of operator A with the TDA. This would indicate that operators require practice to use the TDA effectively.

In this study, effective productivity was 17.8–18.7 m^3 E_0^{-1} with a stem volume of 0.13 m^3, which is slightly higher than in the most recent studies in Scandinavia that have reported 14.0 m^3 E_0^{-1} (Eriksson and Lindroos 2014) and 15.1 m^3 E_0^{-1} (Jylhä et al. 2019). In our study, the TDA improved productivity only for a subset of operators, with an average increase of 1.0–1.2% (range: −4.5 to 6% depending on the operator). The result indicates that guidance systems could enhance productivity as hypothesised by Kärhä et al. (2021). In addition, it aligns with observations by Ylimäki et al. (2012), Spinelli and Magagnotti (2013), Pohjala et al. (2024) and Kauppinen et al. (2016), and suggests that operators would benefit from additional information during cuttings. Cutting at night slowed down processing and reduced productivity by 1.5%. As noted above, all operators in this study were experts. The TDA may provide more benefits to novice operators, that is, those who have not yet reached their final performance level (Purfürst 2010).

TDA as an investment (RQ2)

In our investment calculation, we focused solely on the benefits that enhance the productivity of thinning. Therefore, different thinning proportion scenarios were considered (50%, 70%, 90% and 100%). Our results indicate that the acquisition cost must be relatively low to ensure that the investment yields a positive return. Logically, with higher variable costs of thinning (€43.78 h^{-1}, here), lower maintenance costs (€500 for the first 6 years of the investment period and €364 for the later 6 years), or a lower discount rate (7%, here), the profitability of acquiring the system would be more favourable.

The TDA is currently a technological concept by Ponsse Ltd. This development work is pioneering, but it is still in its early stages. Therefore, the results of our study are only valid for this implementation level. For instance, the operator must look at a separate screen and match it with the surrounding trees simultaneously with other cutting tasks, which is not an optimal method for presenting information to the operator. Moreover, profitability calculations used to illustrate the maximum benefit of the TDA equipment were based on prior tree marking (Pohjala et al. 2024), which might have been underestimated because the operators had no previous experience of cutting in prior tree marking stands and they also had to rely entirely on the markings made by the forester, as numerical data with regard to the trees that surround the harvester were not provided.

This calculation does not consider other possible benefits of the system. TDA's capability to observe and map the surroundings supports the development of autonomous forwarders, which is part of logging process where robotic operations are expected to increase in the near future (Visser and Obi 2017). Consequently, significant cost savings could be achieved here due to labour shortages and associated labour costs. Moreover, the system can document the location of remaining and retention trees, thinning intensity, buffer zones and the quality of trees removed, and, after further development, it can function as an intelligent coaching system (cf. Manner 2024; Sagar et al. 2024), giving hints for optimal working techniques to the operator. Furthermore, TDA equipment has been recognised to have the potential to generate large-scale environmental data and reference material (Faitli et al. 2024). From a forest machine entrepreneur's point of view, markets for environmental data remain uncertain and are a challenge to monetarise, but from an R&D perspective, the cost of the investment can be seen as an investment in all future financial benefits achieved with LiDAR technology in forest machines.

Operators' experienced workload (RQ3)

In our study, the operators under 30 years old experienced a statistically significant higher mental workload than operators over 30 years old. Young operators perceived that the TDA slightly facilitated their decision-making, thinking and planning, but this effect was not statistically significant. Furthermore, they experienced slightly higher satisfaction with thinning quality when the TDA was used.

Operators over 30 years old experienced an increase in physical activity and both mental and physical effort when using the TDA system, likely contributing to their increased stress, strain and frustration. The interaction between the operators' age group and the TDA system did not have a statistically significant effect on mental workload. However, the experiences of these two age groups differed little with regard to the perceived usefulness of the TDA system. Our results support previous findings and the hypothesis that young and novice operators may benefit the most from assistance systems.

Conclusion

Precision forestry and optimisation of tree-level selection for forest thinning necessitates automated sensing systems that are capable of processing information from various sources for different purposes and stakeholders. Advancements in MLS and ADAS, coupled with automatic algorithms for the calculation of forest data for *in-situ* and post-processing, provide opportunities to guide operators more precisely – for instance, in managing thinning density or the distance between strip roads.

The purpose of this study was to investigate the impact of a TDA on work productivity through comparative time studies (RQ1), explore the profitability of the TDA investment using NPV calculations (RQ2), and assess its effect on operator-perceived workload using a NASA questionnaire (RQ3).

This study indicated a modest and statistically non-significant 1% improvement in productivity, with significant variation between the individual operators. This result was expected and supported our first hypothesis (H1) that the TDA does not improve thinning productivity. However, the study found reduced boom-out times for some of the operators, which would suggest the potential benefits of the TDA in tree selection. While the TDA did not select the trees for removal for the operator, it did visualise them on a separate screen and highlighted trees that were too close to each other.

Based on the investment calculation, the increase in productivity enabled by the TDA system will not cover the acquisition and operational costs for experienced operators at this stage of development, as assumed in our second hypothesis (H2). However, the TDA system is still under development and as suggested in several other studies, some of the benefits of MLS-based equipment may be realised not only through productivity improvements but also through the optimisation of bucking, improvements in thinning quality and documentation, and the large-scale acquisition of reference data on forest resources.

Operators' age group and experience had a significant effect on mental workload, while the effect of the TDA system was not statistically significant. The hypothesis was not supported (H3), even though the TDA system had a slight positive effect on the mental workload experienced by operators under 30 years old.

The TDA system may offer greater benefits to novice operators and those familiar with its use. Further research and improved implementation of advanced technologies, as the usability and immersive experience of the TDA system continue to improve, could unlock greater efficiencies and productivity benefits. We assume that the TDA sensor system will be a valuable tool for future improvements in harvesting operations and will lay the groundwork for further harvester automation, ultimately leading to increased productivity and reduced environmental impacts. However, further research and development are needed in this area.

Appendix 1

Statistical information on the felling, stem processing and moving regression models (seconds per stem). Independent variables are stem volume (m^3) and operator. Operator B was used as the reference level.

Parameter	Coefficient	Estimate of coefficient	Standard error of estimate	t-Value	Signif.
Felling					
β_0	Intercept	4.805444	0.158070	30.401	***
β_1	Stem volume (m^3)	4.675594	0.828195	5.646	***
β_2	Assistant	0.337888	0.177788	1.901	
α_1	Operator A	−0.011765	0.258638	−0.045	
α_2	Operator C	0.480925	0.309845	1.552	
α_3	Operator D	0.805576	0.231072	3.486	***
α_4	Operator E	2.589097	0.246481	10.504	***
γ_1	Stem volume (m^3) × Operator A	2.274293	1.796150	1.266	
γ_2	Stem volume (m^3) × Operator C	−2.809186	1.198207	−2.344	*
γ_3	Stem volume (m^3) × Operator D	8.116435	1.501082	5.407	***
γ_4	Stem volume (m^3) × Operator E	0.524721	1.387293	0.378	
δ_1	Operator A × Assistant	0.024180	0.320459	0.075	

Parameter	Coefficient	Estimate of coefficient	Standard error of estimate	t-Value	Signif.
δ_2	Operator C × Assistant	−0.442238	0.326662	−1.354	
δ_3	Operator D × Assistant	0.655023	0.268055	2.444	*
δ_4	Operator E × Assistant	0.004011	0.298787	0.013	
	R^2 = 0.12, RSE 3.355, F = 45.72*** on 14 and 4825 DF				
Processing					
β_0	Intercept	4.46100	0.25212	17.694	***
β_1	Stem volume (m^3)	30.57919	2.15361	14.199	***
β_2	Stem volume $(m^3)^2$	−18.25978	3.97448	−4.594	***
β_3	Assistant	−0.23745	0.21679	−1.095	
β_4	Spruce	0.04322	0.21786	0.198	
β_5	Birch	1.70165	0.17615	9.660	***
α_1	Operator A	−0.95459	0.39288	−2.430	*
α_2	Operator C	−2.92811	0.42573	−6.878	***
α_3	Operator D	−1.68688	0.33735	−5.000	***
α_4	Operator E	−1.97991	0.35289	−5.611	***
γ_1	Stem volume (m^3) × Operator A	21.40080	5.27467	4.057	***
γ_2	Stem volume (m^3) × Operator C	11.34286	3.37650	3.359	***
γ_3	Stem volume (m^3) × Operator D	24.90043	4.24641	5.864	***
γ_4	Stem volume (m^3) × Operator E	4.44908	3.73169	1.192	
δ_1	Stem volume $(m^3)^2$ × Operator A	10.18224	14.07929	0.723	
δ_2	Stem volume $(m^3)^2$ × Operator C	−13.63298	6.26171	−2.177	*
δ_3	Stem volume $(m^3)^2$ × Operator D	3.45213	9.52692	0.362	
δ_4	Stem volume $(m^3)^2$ × Operator E	21.70231	7.14822	3.036	**
θ_1	Operator A × Assistant	−1.05921	0.38857	−2.726	**
θ_2	Operator C × Assistant	0.33671	0.39530	0.852	
θ_3	Operator D × Assistant	0.40967	0.32597	1.257	
θ_4	Operator E × Assistant	0.31837	0.36205	0.879	
	R^2 = 0.44, RSE 4.051, F = 177.7*** on 21 and 4818 DF				
Moving					
β_0	Intercept	1.4248	0.3243	4.394	***
β_1	Density of removal (stem ha^{-1})	305.2977	131.1471	2.328	*
α_1	Operator A	−0.4989	0.7880	−0.633	
α_2	Operator C	−0.1707	0.5355	−0.319	
α_3	Operator D	−0.6741	0.4238	−1.591	
α_4	Operator E	0.1738	0.4600	0.378	
γ_1	Operator A × density of removal	43.7083	422.6482	0.103	
γ_2	Operator C × density of removal	145.6475	199.6146	0.730	
γ_3	Operator D × density of removal	462.6627	155.4912	2.975	**
γ_4	Operator E × density of removal	505.7514	170.6214	2.964	**
	R^2 = 0.52, RSE 1.083, F = 27.12*** on 9 and 229 DF				

$^*p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$.

Appendix 2

Felling regression models by operator.

Operator	Formula	Model
A	$y_2 = (\beta_0 + \alpha_1) + (\beta_1 + \gamma_1) \times x_1 + (\beta_2 + \delta_1) + \varepsilon$	$4.79 + 6.95 \times x_1 + 0.36 \times TDA$
B	$y_2 = \beta_0 + \beta_1 \times x_1 + \beta_2 + \varepsilon$	$4.46 + 4.67 \times x_1 + 0.34 \times TDA$
C	$y_2 = (\beta_0 + \alpha_2) + (\beta_1 + \gamma_2) \times x_1 + (\beta_2 + \delta_2) + \varepsilon$	$5.29 + 1.87 \times x_1 - 0.10 \times TDA$
D	$y_2 = (\beta_0 + \alpha_3) + (\beta_1 + \gamma_3) \times x_1 + (\beta_2 + \delta_3) + \varepsilon$	$5.61 + 12.79 \times x_1 + 0.99 \times TDA$
E	$y_2 = (\beta_0 + \alpha_4) + (\beta_1 + \gamma_4) \times x_1 + (\beta_2 + \delta_4) + \varepsilon$	$7.39 + 5.20 \times x_1 + 0.34 \times TDA$

where x_1 = stem volume m^3; β_0 and β_1 = constant coefficients; α_1, α_2, α_3, α_4, γ_1, γ_2, γ_3, γ_4, δ_1, δ_2, δ_3, δ_4 = coefficients of interaction terms, β_2 = TDA as a dummy variable: 1 if the TDA was used and 0 if the reference was used.

Processing regression models by operator without the effect of night. Operators A–C worked on pine-dominated stands and operators D–E on birch-dominated stands.

Operator	Formula	Model
A	$y_3 = (\beta_0 + \alpha_1) + (\beta_1 + \gamma_1) \times x_1 + (\beta_2 + \delta_2) \times {x_1}^2 + (\beta_3 + \theta_1) + \varepsilon$	$4.79 + 51.98 \times x_1 - 8.08 \times x_1^2 - 1.30 \times TDA$
B	$y_3 = \beta_0 + \beta_1 \times x_1 + \beta_2 \times {x_1}^2 + \beta_3 + \varepsilon$	$4.46 + 30.58 \times x_1 - 18.26 \times x_1^2 - 0.24 \times TDA$
C	$y_3 = (\beta_0 + \alpha_2) + (\beta_1 + \gamma_2) \times x_1 + (\beta_2 + \delta_2) \times {x_1}^2 + (\beta_3 + \theta_2) + \varepsilon$	$1.53 + 41.92 \times x_1 - 31.81 \times x_1^2 + 0.10 \times TDA$
D	$y_3 = (\beta_0 + \alpha_3) + (\beta_1 + \gamma_3) \times x_1 + (\beta_2 + \delta_3) \times {x_1}^2 + (\beta_3 + \theta_3) + \varepsilon$	$4.48 + 55.48 \times x_1 - 14.8 \times x_1^2 + 0.17 \times TDA$
E	$y_3 = (\beta_0 + \alpha_4) + (\beta_1 + \gamma_4) \times x_1 + (\beta_2 + \delta_4) \times {x_1}^2 + (\beta_3 + \theta_4) + \varepsilon$	$4.18 + 35.03 \times x_1 - 3.44 \times x_1^2 + 0.08 \times TDA$

where x_1=stem volume m^3; β_0,β_1 and β_2=constant coefficients; α_1, α_2, α_3, α_4, γ_1, γ_2, γ_3, γ_4, δ_1, δ_2, δ_3, δ_4=coefficients of interaction terms, β_3=TDA as the dummy variable: 1 if the TDA was used and 0 if the reference was used.

Moving regression models by operator. Operator B was used as the reference level.

Operator	Formula	Model
A	$y_5 = (\beta_0 + \alpha_1) + \frac{(\beta_1 + \gamma_1)}{x_2}$	$0.93 + \frac{349.00}{x_2}$
B	$y_5 = \beta_0 + \frac{\beta_1}{x_2}$	$1.43 + \frac{305.30}{x_2}$
C	$y_5 = (\beta_0 + \alpha_2) + \frac{(\beta_1 + \gamma_2)}{x_2}$	$1.25 + \frac{450.95}{x_2}$
D	$y_5 = (\beta_0 + \alpha_3) + \frac{(\beta_1 + \gamma_3)}{x_2}$	$0.75 + \frac{767.96}{x_2}$
E	$y_5 = (\beta_0 + \alpha_4) + \frac{(\beta_1 + \gamma_4)}{x_2}$	$1.60 + \frac{811.05}{x_2}$

where x_2=removal density (stem ha^{-1}); β_0 and β_1=constant coefficients; α_1, α_2, α_3, α_4, γ_1, γ_2, γ_3, γ_4=coefficients of interaction terms.

Acknowledgements We would like to thank Ponsse Plc for providing the TDA system for our research purposes, and especially the company's representatives, Tomi Piirainen and Jukka Laitinen, whose support with the forest machine systems has been invaluable. We also extend our gratitude to the forest machine contractors Metsä-Multia Oy and Karttulan Metsätyö Oy, their representatives, and harvester operators for providing the stands, machines and operators for this study.

Author contributions Conceptualization, J.P., V.K., J.H., K.K.; methodology, J.P.; formal analysis, J.P.; visualization, J.P.; writing—original draft preparation, J.P; editing, J.P., V.K., J.H., K.K. All authors have read and agreed to the published version of the manuscript.

Funding Open access funding provided by University of Eastern Finland (including Kuopio University Hospital). Open access funding provided by University of Eastern Finland (including Kuopio University Hospital). The study was funded by the Research Council of Finland flagship of science: UNITE Forest-Human–Machine Interplay (337127), and partly by Collecting Accurate Individual Tree Information for Harvester Operation Decision Making (359554). Moreover, the "IlmoStar" project (VN/27353/2022), funded by the Ministry of Agriculture and Forestry in Finland and the European Union's Next Generation EU program, provided funding for the project. The IlmoStar project was a part of the UNITE Flagship.

Data availability The research data is available on request from the authors of this article.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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