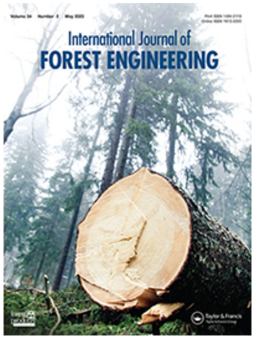

Taylor & Francis
Taylor & Francis Group

International Journal of Forest Engineering

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tife20

Effectiveness of simulator training compared to machine training for equipment operators in the logging industry

Erin Burk, Han-Sup Han, Mathew Smidt & Bruce Fox

To cite this article: Erin Burk, Han-Sup Han, Mathew Smidt & Bruce Fox (2023): Effectiveness of simulator training compared to machine training for equipment operators in the logging industry, International Journal of Forest Engineering, DOI: 10.1080/14942119.2023.2194751

To link to this article: https://doi.org/10.1080/14942119.2023.2194751

Published online: 11 Apr 2023.

INTERNATIONAL JOURNAL OF FOREST ENGINEERING
https://doi.org/10.1080/14942119.2023.2194751

Effectiveness of simulator training compared to machine training for equipment operators in the logging industry

Erin Burk[a], Han-Sup Han[b], Mathew Smidt[c], and Bruce Fox[a]

[a]School of Forestry, Northern Arizona University, Flagstaff, AZ, USA; [b]Forest Operations and Biomass Utilization, Ecological Restoration Institute, Northern Arizona University, Flagstaff, AZ USA; [c]USDA Forest Service, Southern Research Station, Auburn, AL, USA

ABSTRACT

Logging equipment operators traditionally learn the skills required for their job through hands-on training using a real machine in the forest. New developments in simulator technology enable operators to learn and practice operating logging equipment in a virtual setting. This study presents a summary of controlled experiments to evaluate the effectiveness of simulator training compared to machine training for logging equipment operators in terms of performance and cost effectiveness. Sixteen participants were trained on simulated or real logging machinery for 26 hours each. We compared the performance of simulator-trained participants to machine-trained participants by testing operators on real equipment in the forest. No significant differences were found in overall performance between simulator-trained and machine-trained operators; however, machine-trained students showed greater improvement than simulator-trained students on more complex equipment. A cost analysis of simulator vs. machine training found that contractors should expect to save 36–40% by sending their students to an external training facility using simulator-based training rather than conducting internal, machine-based training. Contractors considering the purchase of a simulator for in-house training would need to use their simulator for around 130 hours each year to break-even on the yearly average costs of owning and operating the simulator.

ARTICLE HISTORY
Received 13 December 2022
Accepted 20 March 2023

KEYWORDS
Simulator; workforce training; logging equipment operator; simulator-based training; forestry simulator

Introduction

Over the past two decades, the declining workforce in the logging industry in the United States has been attributed to a lack of newly hired workers (He et al. 2021). Recent surveys of logging business owners have indicated that finding qualified employees is one of the biggest barriers to contactors' successful operations (Allen et al. 2008;Baker and Greene 2008;Leon and Benjamin 2012;Conrad et al. 2018;Vaughan et al. 2021). This lack of skilled logging employees points to a need for recruitment and training to increase the logging workforce, among other needs for addressing issues such as deficits in pay and benefits and harsh working conditions (Xu et al. 2014). Without a strong logging workforce, keeping the forest products industry alive will prove difficult.

A new employee in the logging industry typically enters the field as an equipment operator. Traditionally, new equipment operators learn the skills required for their job mainly through hands-on training using a real machine in the forest (LaPointe and Robert 2000). Based on our recent visits with logging contractors and training instructors, we learned that whether a logging contractor uses a whole-tree, tree-length, or cut-to-length harvest system, the entry-level machine is generally the one that extracts material from the forest to the landing. In ground-based whole-tree and tree-length operations, this machine is a skidder. In cut-to-length operations, the machine typically used for extraction is a forwarder. A skidder can be wheeled or tracked and features a large grapple or a series of choker cables used to grasp one end of a bundle of trees. This machine "skids" or drags the trees from where they were cut to the landing, where they will be loaded onto log trucks for transportation to the mill (processing occurs either before or after skidding, depending on whether the contractor uses a whole-tree or tree-length harvest system). A forwarder can also be wheeled or tracked and features a boom-mounted grapple, with which an operator can pick up one or several logs and load them onto the "bunk" or the bed of the forwarder. This machine then drives the logs to the landing. Recent visits with logging contractors and training instructors also revealed that skidders and forwarders are considered entry-level machines for loggers because of their relative simplicity compared to other pieces of equipment that complete the harvest system (i.e. processors, loaders, and feller-bunchers in whole-tree and tree-length operations, and harvesters in cut-to-length operations).

Traditionally, logging equipment operator training occurs on the job. A logging contractor who hires a new operator will typically arrange the training to take place either in a training yard and/or at one of the contractor's active harvesting sites. An experienced equipment operator, or instructor, is present to mentor the new hire. Training can range from impromptu observation and practice sessions during breaks or after work, to more formal training during the workday with a general curriculum that includes safety briefings, machine orientations, curated training exercises, and on-the-job practice

CONTACT Erin Burk eeb297@nau.edu School of Forestry, Northern Arizona University, 200 E Pine Knoll Dr, Flagstaff, AZ 86011, USA

(Burk 2022). Student-to-trainer ratios are generally low – between one and three students per trainer – as the instructor needs to be present with the students due to the inherent danger of operating heavy equipment. This type of training can be effective for new operators, as the machine they learn their skills on is typically the same model, if not the exact machine, they will later operate as part of the harvest system. Getting a new operator up to speed, however, is both costly and time consuming. It typically takes anywhere from four to twelve months for a new operator to reach a productive operating level (i.e. when the operator is producing enough material that the product is worth more than the cost of operating the equipment) (Richardson and Makkonen 1994;Calabrese 2000; Pürfurst 2010;Wenhold et al. 2019;Pagnussat et al. 2021). When training operators during regular working hours, removing a machine from production for training purposes can create substantial opportunity costs for the contractor, as the machine is no longer being used for timber harvesting.

While access to logging equipment is essential to properly train equipment operators, new developments in simulator technology enable inexperienced operators to learn and practice operating logging equipment in a virtual environment. Logging equipment simulators incorporate hardware and software to provide physical and visual replicas of the operating environment. Simulators typically consist of a set of controls attached to a computer with one or more screens. The computer contains a simulation software that virtually places the user in the cab of a forestry machine. The user can manipulate the controls to "operate" the simulated machinery in a virtual environment portrayed on the screen(s).

The benefits of simulator-based training are numerous. Logging equipment simulators offer a cost-effective and safe method for students to learn about the basics of operating forestry machines (Ovaskainen 2005). The reduced safety concerns of operating in a virtual environment allows for higher student to trainer ratios, thereby reducing the cost of simulator-based training as compared to machine training. The modular learning curriculum pre-programmed into most simulators, whereby students are guided through a series of exercises, provides unbiased and standardized feedback to students after each module is completed (Burk 2022). These pre-programmed modules make it easier for an educational planner to plan, monitor, manage, and evaluate their training program (Ranta 2009). Simulators alleviate some of the problems associated with traditional machine training by reducing wear and tear on real equipment and eliminating opportunity costs associated with removing equipment from production for training purposes (LaPointe and Robert 2000).

Simulated training does have its drawbacks as well. The reduced need for a trainer in simulator-based training restricts students' access to immediate and personalized feedback from an instructor. Furthermore, a pre-programmed, modular learning plan allows little room to tailor simulator training to individuals' needs. Perhaps the biggest drawback to simulator-based training is the fact that the simulated environment is entirely separate and inherently different from the working environment, so it is unlikely that skills will transfer as easily to the working environment as in traditional training (Burk 2022).

While these benefits and drawbacks are important to consider in deciding whether simulators should be used to train new logging equipment operators, perhaps the most important factor in this decision is whether they are an effective training tool. Few studies have examined how skills transfer from a simulator to real logging equipment (LaPointe and Robert 2000;Yates 2000;Hoss 2001;Freedman 2004). Only one study directly observed the effectiveness of simulator-based training as compared to traditional machine training (So et al. 2016), but this study was completed using construction equipment. No studies have evaluated the cost-effectiveness of simulator-based training as compared to traditional machine training for logging equipment operators. The overall goal of this study was to broaden our knowledge regarding how simulators can be effectively used to train new logging equipment operators by addressing the following questions:

(1) Compared to those who are machine-trained, how well do simulator-trained skidder and forwarder operators perform when operating logging equipment?
(2) Compared to those who are machine-trained, how do simulator-trained skidder and forwarder operators feel about operating real logging equipment?
(3) Compared to training new logging equipment operators using traditional machine training, how much does it cost to train them using simulator-based training?

Materials and methods

Evaluating operator performance

Participants

We trained a total of 16 participants on either a real or simulated skidder or forwarder (IRBNet ID 1,761,948–3). Participants were split into groups based on their availability and resource availability following a randomized block design. The number of participants was chosen based on being able to effectively train each participant for 20 hours given the resources available during the study period. To be included in the study, participants were required to be fluent English speakers, physically capable of operating heavy machinery, and have less than five hours experience operating heavy machinery. One participant in the simulated skidder training group had more than five hours experience operating farming equipment such as tractors and backhoes, but no experience operating logging equipment. Participants included four females and twelve males aged 18–60. All participants were recruited through partnering forestry agencies or companies. Most individuals had some background in forestry, although we did not distinguish these individuals within the study design due to a small sample size of participants.

Equipment used: skidder and forwarder

For the skidder portion of the study, participants were trained on John Deere branded equipment. The skidder we used was the John Deere 648-LII, the smallest of the John Deere grapple skidders. The simulator we used was a prototype of the John Deere Full Simulator with 848-LII skidder software. The controls on this simulator were slightly different from the real skidder – there was no parking brake, ignition switch, or blade switch, the driving pedals were different, and the steering direction was reversed from the real skidder. The simulator did not feature motion feedback (i.e. the seat was mounted on a still platform). Some simulators do feature a moving seat platform that simulates the forces typically felt when operating a machine in the forest.

For the forwarder portion of the study, participants trained on Ponsse branded equipment. The forwarder we used was the Ponsse ElephantKing, the largest of the Ponsse forwarders. The simulator we used was the Ponsse Full Simulator. This simulator was equipped with harvester controls rather than forwarder joysticks due to supply shortages during the COVID-19 pandemic. It did not feature motion feedback.

Study sites

The experiments took place at two different study sites during two different logging seasons. The skidder portion of this study was completed in Raymond, Mississippi during the summer of 2022. Simulator training occurred in a classroom at Hinds Community College. Machine training and testing took place at a 2-hectare training yard owned by the Mississippi Forestry Commission.

The forwarder portion of this study was completed during the summer of 2021 at the Oregon State University Research Forest just outside of Corvallis, Oregon in a coniferous forest dominated by Douglas fir (*Pseudotsuga menziesii*). The study site was part of a thinning and oak release project being executed by Miller Timber, our contracting partner for this portion of the study. Testing and training took place within about a half-mile radius zone where a harvester operator had created five operating trails on either side of the main road, varying from 100–400 meters in length. Testing occurred in the shortest of these operating trails.

Training program for participants

Before arriving at the study site, all participants were required to read the safety manual for their respective machine to ensure all safety protocols were met and participants arrived with a similar level of familiarity with the machine.

Four participants were trained on a simulated skidder or forwarder over the course of four days for a total of 26 training hours each. The following week, four different participants were trained on a real skidder or forwarder over the course of four days also for a total of 26 training hours each (Table 1). Each participant spent approximately six hours in the operator's seat during the training period. Training modules for the skidder were designed by the research team and based on the training modules used during the forwarder experiment. Training modules for the forwarder reflected those pre-programmed into the Ponsse Simulator and were replicated in the woods for the machine training group. Only one simulator or machine was available during each training session, so all four participants rotated between operating the simulator/machine and observing their classmates. Each participant spent approximately 10–30 minutes practicing before rotating, depending on the training module. Each participant was able to complete between one and three rotations in the two hours allotted for each training module.

The short training period (26 hours) limits our ability to evaluate the effectiveness of simulator training over the course of an operator's entire learning curve. As noted previously, getting a new equipment operator up to a productive performance level can take anywhere from four to twelve months; therefore, our 26-hour training period is not sufficient to make conclusions about the effectiveness of simulators as a long-term training tool. However, logging contractors and training facilities tend to primarily use simulators to train new operators at the beginning of their careers (Burk 2022). Therefore, this analysis of the initial learning curve for equipment operators reveals insight into the phase of training where simulators are most used.

Evaluating operator performance on the machine

For the skidder portion of the study, participants completed a test task on a real skidder before training began and at the end of each training day, for a total of four testing sessions (Table 1). The test task was designed to take about three minutes for an expert operator to complete. It involved starting the machine, retrieving a half-load of logs, skidding the logs 50 meters to a landing, properly placing them into a neat pile, then returning the machine to its starting position and turning it off (Figure 1A). In having participants begin and end in the same location, the test task was designed to mimic real-world operations by replicating one full machine cycle. Participants were unable to be accompanied by an experienced trainer in the cab of the machine, as there was only room for one person in the

Table 1. Sample schedule for participants in the study. Training modules differed for the forwarder and skidder.

Day/Time	Activity
Pre-Study Reading	Participants must read and understand the safety topics in the equipment manual before arriving on-site for the first day of the study.
	Sub-total: 1.5 hours
Day 1	Welcome & Introductions
8:00	Safety Training
8:30	Controls Training
9:30	1st Performance Test
10:30	Training Module
12:30	END
2:30	**Sub-total: 6.5 hours**
Days 2–4	Training Module
8:00	Training Module
10:00	Performance Test
12:00	END
2:00	**Sub-total: 6 hours/day**
	Total: 26 hours

Table 2. Variables used in the direct dollar per hour comparison between a Traditional Scenario and Training Facility Scenario.

	Equipment Type	Machine Rate ($/hr)[a]	Trainer Wage + Benefits ($/hr)	Opportunity Cost ($/hr)[b]	Hours on Equipment	Training Cost ($/hr)
Traditional Scenario:	Skidder	144.79	40.01	11.58	100%	196.38
Machine-Based Training with Contractor	Forwarder	173.32	40.01	13.87	100%	227.20
Training Facility Scenario:	Simulator	56.43	40.01	-	66%	96.44
Simulator-Based Training at	Skidder	144.79	40.01	-	33%	184.80
Facility	Forwarder	173.32	40.01	-	33%	213.33

[a]Standard machine rate assuming productive machine hour (PMH) (Brinker et al. 2002). Values for the machine rate calculation were gathered from Chang et al. (2023) for all machines. Values for the simulator rate calculation were gathered through informal interviews with simulator manufacturers.
[b]Training Cost = Operating Cost + Trainer Wage and Benefits + Opportunity Cost

cab. Participants were informed that they would be timed, given time bonuses for loading, transporting, and unloading logs neatly, and given time penalties for collisions and dropped logs. Timing began when the operator started the machine and ended when the operator turned the machine off. Time penalties and bonuses were applied in the field to reinforce good operating habits, but our data analysis was completed using operators' raw time scores for consistency. The instructor, who was an expert operator, was timed once while completing the test task to ensure that the task did take them approximately three minutes to complete.

For the forwarder portion of the study, participants also completed a test task on a real forwarder before training began and at the end of each training day, for a total of four testing sessions (Table 1). The test task was also designed to replicate one full machine cycle and to take about three minutes for an expert operator to complete. Participants were asked to turn the machine on, drive 25 meters to gather three logs from an operating trail, transport the logs back to the starting position, stack them neatly next to the road, then turn the machine off (Figure 1B). Participants were accompanied by an experienced trainer in the cab of the forwarder for safety purposes. The trainer was instructed to refrain from giving participants information that would improve their time during the testing session. The same timing criteria described above were used for scoring, and the same method described above was used to ensure the test task took an expert operator approximately three minutes to complete.

All participants were allowed and encouraged to watch each other during all training and testing sessions. The order in which participants completed their training modules and testing sessions was randomized and changed each day. We purposefully designed the study's training schedule to allow interaction among participants, thereby opting for a more practical, real-world training scenario over a perfect statistical model. Furthermore, training and testing all participants independently would have been far too time consuming and costly. Because participants were allowed to interact during training and testing, we could see lower variances within each training group than we might see if each participant trained independently of one another. Training operators in a group setting could have caused us to see a larger difference between the two training groups than if the replicates (operators) were truly independent.

Subjective ratings on confidence levels, anxiety levels, and mental workload

Before completing each performance test, each participant was asked to fill out a Confidence and Anxiety Levels survey. After completing each performance test, each participant was asked to fill out a workload survey, the NASA Task Load Index (NASA-

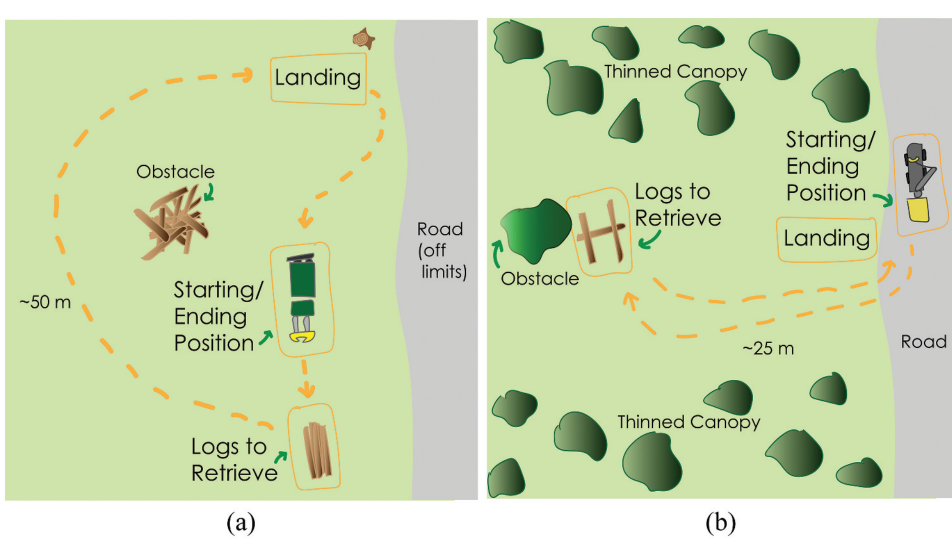

Figure 1. Testing sites for the skidder (A) and forwarder (B) experiments. Operators were asked to start the machine, grab/load the "Logs to Retrieve," unload the logs in the "Landing" zone, then return to the "Starting/Ending Position" and turn the machine off. Machines, logs to retrieve, and landing zones were oriented as illustrated above for each testing session.

Table 3. Direct dollar per hour comparison between machine-based and simulator-based training.

Equipment Type	Traditional Scenario: Machine-based Training with Contractor Total Training Cost ($/hr)[a]	Training Facility Scenario: Simulator-based Training at Facility Total Training Cost ($/hr)[b]	Cost Savings ($/hr)[c]	Cost Savings (%)[d]
Skidder	196	126	71	36%
Forwarder	227	135	92	40%

[a]Total Training Cost Scenario1 = Training Cost * Hours on Equipment (Table 3.2)
[b]Total Training Cost Scenario2 = (Training Cost simulator * Hours on Equipment simulator) + (Training Cost machine * Hours on Equipment machine) (Table 3.2)
[c]Cost Savings ($/hr) = Total Training Cost Scenario1 – Total Training Cost Scenario2)
[d]Cost Savings (%) = Cost Savings ($/hr) / Total Training Cost Scenario1

TLX), through an app on the researcher's phone. The NASA-TLX is the most widely accepted tool to assess subjective workload ratings after completing a task (Said et al. 2020). This rating system calculates an overall score based on a weighted average of ratings in six areas: Mental demand; Physical demand; Temporal demand; Performance; Effort; and Frustration. To calculate the overall NASA-TLX score, operators first complete a pairwise test in which each of these areas is compared to one another, and operators are asked to choose the one that was most important to completing the task. They are then asked to attribute a raw rating to each of these areas using a number scale. The total number of times they chose each area over another is multiplied by the raw rating they attributed to that area to obtain a total score for each area. The scores for each area are then added together for an overall NASA-TLX score. Higher scores signal that the task required more effort from the operator.

Cost comparison between simulator and machine training

The purpose of this cost analysis is to consider the cost of two scenarios that involve simulator training and compare them to the cost of traditional machine training carried out internally by a logging contractor (Traditional Scenario). Our intent was to compare two simulator-based training scenarios to the industry standard so that contractors can choose which scenario fits best with their business. First, we wanted to compare the cost of the industry standard Traditional Scenario to the cost of training a student externally at a facility that uses simulator-based training (Training Facility Scenario). To do so, we used a direct dollar per hour comparison (USD$) for these two scenarios. We also considered a third scenario in which a contractor might wish to purchase their own simulator for in-house training (Simulator Purchase Scenario). To compare this scenario back to the Traditional Scenario, we conducted a break-even analysis to find out how many hours per year a contractor would need to use their simulator for training purposes to break-even on the average yearly costs of owning and operating the simulator.

In conducting the direct dollar per hour comparison between the Traditional Scenario and Training Facility Scenario, we included machine rate, trainer wages and benefits, opportunity cost (if applicable), and hours spent training as factors in our cost analysis (Table 2). We used machine rate calculations from Brinker et al. (2002) to calculate average yearly and hourly costs for skidders, forwarders, and simulators. Data for the factors affecting hourly operating costs of skidders and forwarders were collected from Chang et al. (2023). The operating cost of a simulator was calculated based on the same factors as the machine rate calculation (fuel cost and fuel usage rates were substituted for electricity cost and electricity usage rates). We were unable to find published data for the cost of each factor used in a standard machine rate calculation for simulators, so data for the values of these factors were collected from multiple simulator manufacturers and averaged (LeConte C, John Deere, Iowa, USA; Jurvanen J, Ponsse Oyj, Vieremä, Finland; Najjar J, CMLabs, Québec, Canada; Freedman P, SimLog, Québec, Canada; Morris R, Empire Cat Southwest, Arizona, USA, personal communication). In both scenarios, we assume that a student is hired by the contractor and paid during training, so we included the operator's labor wages and benefits in the machine rate calculations. We used the 50th percentile wage for logging operators in the US as an estimate of operator wages (Bureau of Labor Statistics 2022) and assumed benefits cost an additional 32% of wages. We used the 90th percentile wage for logging operators in the US as an estimate of trainer wages (Bureau of Labor Statistics 2022) and assumed trainer benefits cost an additional 32% of wages. In the Traditional Scenario, we assume all training hours occur on a machine. For the Training Facility Scenario, we adapted the ratio of hours spent training on the machine (33%) and simulator (66%) from the Forest Equipment Operator Course Program produced by the Forest Operations Training Program in Flagstaff, Arizona (Edwards and Han 2021).

In conducting the break-even analysis to compare the Traditional Scenario and Simulator Purchase Scenario, we adapted a standard break-even analysis equation from Riggs et al. (1996), which states B=F/(P-V) where B is break-even point, F is fixed costs, P is selling price, and V is variable costs. We began by extracting the fixed and variable costs associated with simulator training found during our machine rate calculations. We then substituted P (selling price) for hourly cost savings associated with choosing simulator training over machine training for the skidder and forwarder. We solved the equation to find the break-even point in terms of hours of simulator use per year needed to break-even on the average yearly costs of simulator ownership and operation (Table 3).

In the Traditional Scenario, we assumed students are trained during standard working hours, and therefore included an opportunity cost associated with removing the machine for production for training purposes. We estimated the opportunity cost in the Traditional Scenario as equal to a 3% administrative overhead fee (Smith 2012) plus a 5% profit margin (Cools 2020). This may be a conservative estimate for a company with higher overhead and profit margins. We assume the productivity of the machine being used remains around zero for the entirety of the

Table 4. Simulator training hours needed each year to break-even on yearly simulator ownership and operating costs.

Equipment Type	Fixed Costs ($/yr)	Fixed Costs ($/hr)	Variable Costs ($/hr)[a]	Cost Savings ($/hr)[b]	Break-Even Point (hrs/yr)[c3]
Skidder	-	41	115	100	154
Forwarder	-	57	130	131	104
Simulator	9,887	21	36	-	-

[a]Variable costs = Opportunity Cost (Table 3.2) + Variable Costs from machine rate calculation
[b]Cost savings = (Fixed Costs Machine + Variable Costs Machine) – (Fixed Costs Simulator + Variable Costs Simulator)
[c]Break-Even Point = Fixed Costs Simulator / (Cost savings – Variable Costs Simulator) (adapted from Riggs et al. 1996; B=F/(P-V))

training period, as the productivity of a new equipment operator within the first week is minimal (Pürfurst 2010).

In the Training Facility Scenario, we assume a student is sent by the contractor to a training facility after they have been hired, and therefore the contractor pays the student for their time at the facility. We did not consider a scenario in which an individual signs up to attend the facility on their own accord and is later hired by a contractor; in this scenario, the contractor does not pay for the training of their new hire. We did not include the cost of transporting students to a training facility or the cost of housing students while attending the training facility. These costs will be highly variable depending on how far the students must travel and where the students are able to stay. Opportunity cost was excluded from our training cost calculation, as we assume the training institution does not use their machines for timber production. We also assume the training institution bought their equipment new and owns it outright. This is the most expensive scenario. Depending on available resources, training institutions may be able to purchase used equipment or use new machines from their local equipment dealer at little to no cost. Equipment dealers may be motivated to cut training institutions a deal on borrowing their equipment because if new students are trained on their brand of equipment, local contractors might be incentivized to purchase that brand in the future.

In comparing the Simulator Purchase Scenario back to the Traditional Scenario, we consider the break-even point for *average* yearly simulator costs rather than the break-even point for *upfront* costs associated with purchasing a simulator. These yearly costs are averaged over the lifetime of the simulator, which we assume to be 10 years. We chose to run the analysis in this way because the break-even point for upfront purchasing costs will be highly variable depending on financing options available to the contractor.

Data analysis

We used a mixed-effects repeated measures analysis of variance to analyze and compare the changes in operator performance over time for the simulator and machine groups (Table 5). Diagnostic tests revealed that the data were somewhat normally distributed, though this was difficult to distinguish given our small sample size. One of the assumptions of the repeated measures analysis is that the data is spherical (i.e. the variances of the differences between test trials are equal). Using Mauchly's test, we found that some of our test groups violated the assumption of sphericity while others met this assumption. Mauchly's test of sphericity is known to fail at detecting departures from sphericity when used for small sample sizes; therefore, we cannot be sure that we accurately identified when sphericity was met. We deliberately avoided making any adjustments to our analysis based on a test result that is likely inaccurate at small sample sizes.

Analyses of operator performance for each machine type were conducted separately due to the many confounding variables that differed between the skidder experiment and forwarder experiment (e.g. study site, instructor, training modules, etc.). Time was treated as a categorical variable, which allowed researchers to observe the improvement of operators between each training day. We used the power.t.test function in R to calculate the sample size required to see a significant difference in overall performance between simulator and machine training groups.

Confidence levels, anxiety levels, and workload scores were averaged for each operator across all their test sessions to account for the fact that multiple samples from the same individual are not independent of one another. We then averaged the operators' subjective ratings within each training group and machine type. A t-test was used to compare group means between the simulator and machine training groups for each subjective rating.

In all statistical analyses for operator performance and subjective ratings, each operator was treated as an independent replicate. We acknowledge that our small sample size limits the power of our statistical tests and our ability to extend our results to a larger population.

To calculate the dollar per hour costs associated with the Traditional Scenario and Training Facility Scenario, machine rate, trainer wage, and opportunity cost (if applicable) were summed for each equipment type under each training scenario to calculate the training cost for the simulator, skidder, and forwarder. The number of hours spent training was then multiplied by the training cost for each equipment type under each scenario (Table 2). Total cost savings between the Traditional Scenario and Training Facility Scenario in terms of dollars per hour and percentage was calculated (Table 4). A sensitivity analysis was conducted to check which variable has the largest effect on total cost. Each variable was increased by 10% and the change in total costs were observed.

To calculate the number of training hours needed each year for a contractor to break-even on owning and operating a simulator (Simulator Purchase Scenario), the fixed yearly cost of simulator ownership was divided by the difference in hourly variable costs between each machine and the simulator (Table

Table 5. Linear mixed model and ANOVA tables for random and fixed effects for the skidder and forwarder experiments.

Effect	Skidder	Forwarder
Random	Model: Performance ~ Group + Trial + (1 | Operator) + Group:Trial npar logLik AIC LRT Df Pr(>Chisq) <none> 10 -54.988 129.98 (1 | Operator) 9 -54.988 127.98 0 1 1	Model: Performance ~ Group + Trial + (1 | Operator) + Group:Trial npar logLik AIC LRT Df Pr(>Chisq) <none> 10 -65.007 150.01 (1 | Operator) 9 -69.794 157.59 9.5732 1 0.001974 **
Fixed	Type III Analysis of Variance Table with Satterthwaite's method Sum Sq Mean Sq NumDF DenDF F value Pr(>F) Group 5.583 5.583 1 24 1.5487 0.2253 Trial 194.603 64.868 3 24 17.9925 2.463e-06 *** Group:Trial 7.452 2.484 3 24 0.6889 0.5677	Type III Analysis of Variance Table with Satterthwaite's method Sum Sq Mean Sq NumDF DenDF F value Pr(>F) Group 1.93 1.932 1 6 0.3718 0.56441 Trial 680.48 226.828 3 18 43.6379 1.833e-08 *** Group:Trial 56.90 18.966 3 18 3.6488 0.03245 *

3). This gave us the hours per year needed to reach the break-even point for each equipment type.

Results

Comparison of operator performance between simulator- and machine-trained groups

There was no significant difference in overall performance between simulator and machine training groups on either machine ($p = 0.23$ for the skidder; $p = 0.56$ for the forwarder) (Table 5). The number of days spent training was a significant predictor of performance for both training types on both machines ($p = <0.01$ for the skidder and forwarder) (Table 5). As operators spent more time training, their performance significantly improved. Using average observed differences and variances in operators' times between testing days, we found that the sample size required to see statistically significant overall differences in performance between simulator and machine groups was $n = 25$ for the skidder and $n = 7$ for the forwarder at power = 0.9 and alpha = 0.1 (n is the number in each group).

On the skidder, there was no significant difference in performance trends over time between simulator and machine training groups ($p = 0.57$) (Table 5) (Figure 2). Operators in each training group did not improve at a consistent rate. The machine and simulator training groups had similar average variances, but the machine-trained group had more outliers than the simulator-trained group (Figure 3A). Within-group variances generally decreased throughout the training period, but there were outliers during many of the testing sessions (Figure 3B). In considering individual operators as a random effect, we found no evidence that variance between individual operators in the skidder experiment had a significant effect on our results (Table 5).

On the forwarder, there was a significant difference in performance trends over time between the two training groups ($p = 0.03$) (Table 5) (Figure 2). Operators in each training group improved at a consistent rate. The average within-group variation for the machine-trained group was higher than the simulator-trained group, and each group had a single outlier (Figure 3C). Within-group variances generally decreased throughout the training period on this machine as well, though there were no outliers during any of the testing

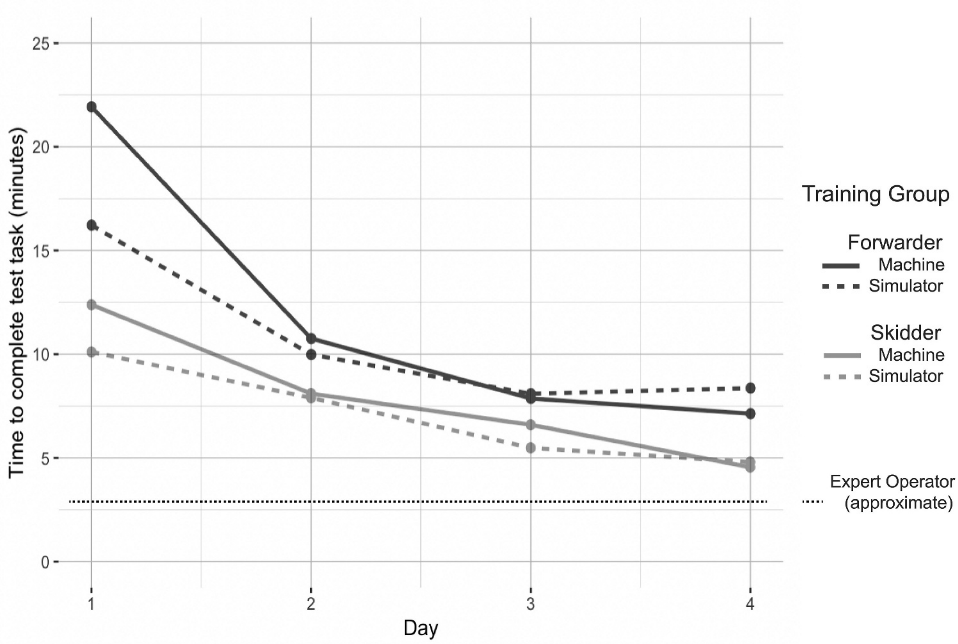

Figure 2. Trends in operator performance for simulator and machine training groups on the skidder and forwarder, averaged among operators. Each point references the average performance for all operators within the training group. Lines between points were added to help visualize general trends. Learning likely did not occur in a straight line between each point, as the graph may suggest.

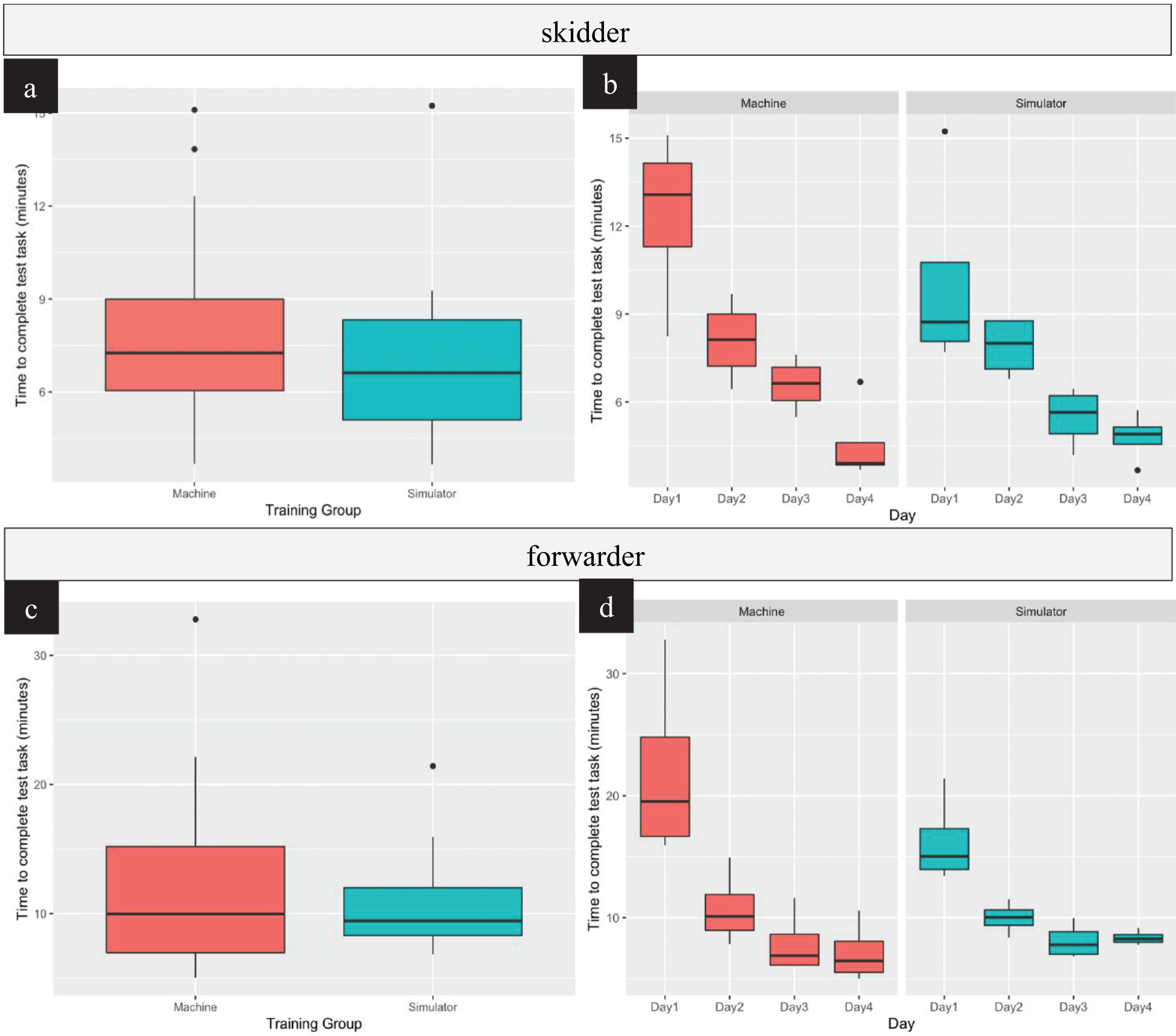

Figure 3. Within-group variation for machine- and simulator-trained groups on the skidder (A) and forwarder (C) averaged across all testing sessions. Parts (B) and (D) show within-group variation for each testing session for the skidder and forwarder, respectively.

sessions (Figure 3D). In considering individual operators as a random effect, the variance between individual operators in the forwarder experiment did significantly affect our results (Table 5).

Subjective ratings on confidence levels, anxiety levels, and mental workload

There was no significant difference in overall confidence levels between groups ($p = 0.93$ for the skidder, $p = 0.58$ for the forwarder), though forwarder trainees reported lower confidence levels, on average, than the skidder trainees. Confidence was a poor predictor of performance. In two of the four training groups, the person who completed the test fastest reported the highest confidence levels, and in another training group, the person who took the longest to complete the task reported the lowest confidence levels; however, as performance levels increased, no trend in confidence level was observed.

Individuals who were trained on a simulator reported slightly lower anxiety levels than those trained on a machine, though the difference was not significant ($p = 0.33$ for the skidder, $p = 0.32$ for the forwarder). Of all subjective ratings, anxiety was the best predictor of performance. In three of the four training groups, the operator that took longest to complete the test had the highest anxiety levels, and anxiety levels generally decreased as performance increased.

Individuals who were trained on a simulator reported similar workload (NASA-TLX) scores to those trained on a machine ($p = 0.78$ for the skidder, $p = 0.33$ for the forwarder), but forwarder trainees reported higher workload (NASA-TLX) scores than skidder trainees. Workload ratings were a decent predictor of performance. In three of the four training groups, the person who completed the test fastest also reported the highest NASA-TLX score. In two of those groups, the person

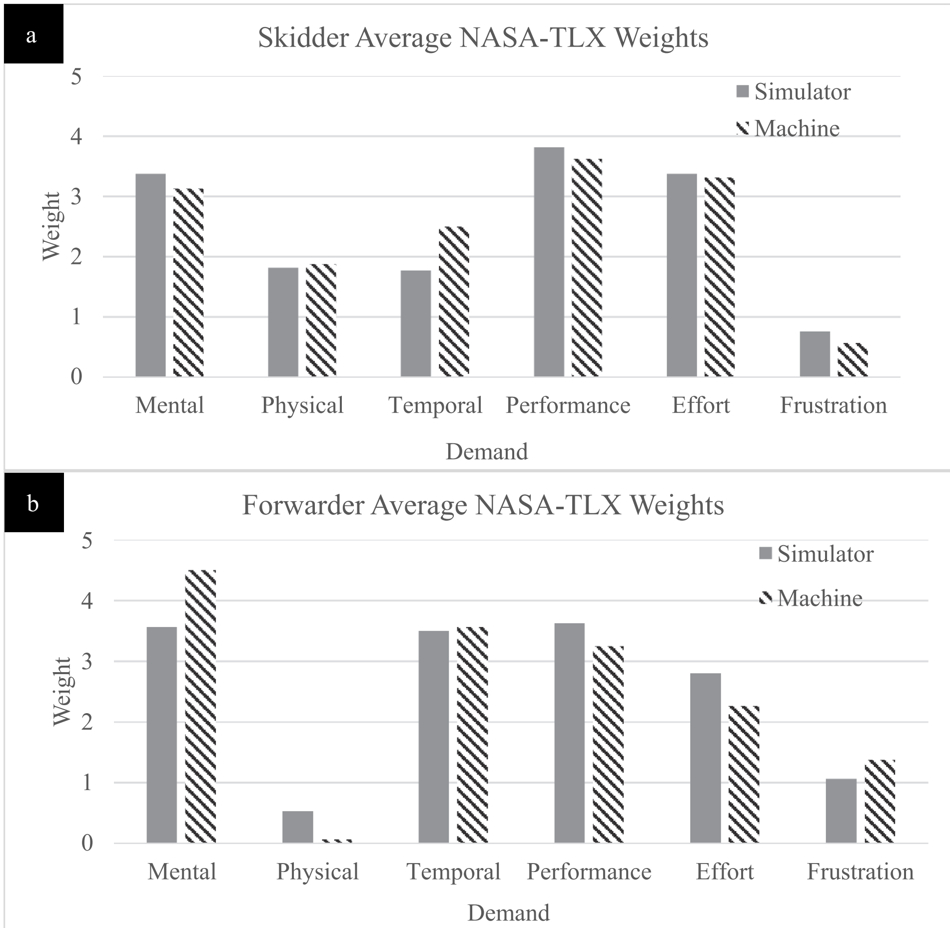

Figure 4. Average weights reported by simulator and machine training groups for the skidder (A) and forwarder (B) during the National Aeronautics and Space Administration Task Load Index (NASA-TLX) survey ($n = 4$). The survey presented the above demands in pairs and asked operators to choose the factor that was more important to the task. The number of times the operator chose each factor directly translated into the weight of that factor.

who took the longest to complete the test task also reported the lowest NASA-TLX score. Operators did not report any drastic differences in weights for different areas of the NASA-TLX between simulator and machine training groups on either machine (Figure 4). Operators trained on the forwarder reported slightly higher weights for mental demand, temporal demand, and frustration, and lower weights for effort and physical demand compared to those trained on the skidder.

Cost of simulator-based training

The cost analysis revealed that simulator-based training at a training institution costs 36% or 40% less than traditional machine training occurring internally with a contractor on a skidder or forwarder, respectively (Table 4). A simple sensitivity analysis revealed that the most important variable in this cost model is the ratio of simulator to machine training hours applied by the training facility. Any change in this ratio will impact the hourly cost of training at a facility, and therefore the cost savings potential between the Traditional Scenario and Training Facility Scenario.

In considering the Simulator Purchase Scenario, we found that on the skidder, the savings associated with simulator training catch up to the average yearly costs of owning that simulator after 154 hours of training each year. On the forwarder, the cost savings catch up after 104 hours of training (Table 3).

Discussion

Operator performance

This study found that whether the first four days (26 hours total, six hours per day) of training for an inexperienced forestry operator occur on a simulated or real piece of equipment, the operators will perform similarly on a real machine throughout the training period. After 26 hours of training on a simulated or real skidder or forwarder (approximately six hours in the operator's seat), operators tend to show minimal improvements when performing a basic task. This is consistent with the findings of a similar study conducted by So et al. (2016) conducted using a simulated and real hydraulic excavator.

While learning did appear to level off for the test tasks assigned, we are not convinced that operators would be prepared to join a harvest system in the woods after this short training period. The tasks were designed to be simple, and the mastery of these tasks do not imply that operators have a full understanding of the challenges within a real operating environment. More training regarding the complex tasks associated with operating as part of a harvest system would likely be necessary for these operators to work at a productive level.

We hypothesize that the reason we were unable to detect a difference in performance trends over time on the skidder, but able to detect this effect on the forwarder, has to do with the complexity of the machines and the variability between operators in each experiment. A skidder has fewer controls, less functionality, and therefore is easier to operate than a forwarder. The data show that the inexperienced skidder operators consistently completed the test task in less time than the forwarder operators (Figure 2), even though both tasks took an expert operator around three minutes to complete. Because the skidder operators spent less time completing their test task, we observed that a small mistake had the power to make a large impact on their performance score (i.e. time to complete the test task). On the forwarder, we observed that a small mistake had less of an impact on an operator's test time since the operators spent more time completing the test task. This could explain why operators' learning patterns were more consistent on the forwarder (Figure 3D).

The power t-test revealed that our sample size was nearly sufficient to see overall differences in performance between the simulator and machine training groups on the forwarder ($n = 7$), but that we would need a much larger sample size to see significant overall differences on the skidder ($n = 25$). That said, there is no guarantee that even a sample size of $n = 25$ would deliver statistical significance. Every participant will inevitably have different skillsets, different learning styles, and different levels of experience. Even day-to-day performance can vary greatly for the same person depending on how much sleep they got, how focused they are, etc. Furthermore, the power t-test calculation assumes the use of a simple t-test to detect different group means, rather than a repeated measures analysis. It is difficult to say exactly how many individuals we would need to see the simulator effect over time on the skidder when accounting for the repeated measures component of this experiment.

Subjective ratings to inform performance outcomes

The higher anxiety levels detected in machine-trained groups could partially explain their greater performance improvements on the forwarder. This could be a result of the machine group having a better appreciation for the challenges they might encounter during the test. The Yerkes-Dodson law poses that different tasks require different levels of stress for optimal performance (Yerkes and Dodson 1908). Perhaps higher anxiety levels for the specific task required during the forwarder test created a more optimal performance environment for the operators. Given our findings that anxiety levels were the best predictor of performance within groups, we expect that taking measures to lower an operator's anxiety levels, no matter the type of training they receive, can result in better performance.

The fact that the forwarder operators reported higher NASA-TLX scores than the skidder operators, especially for mental demands and temporal demands (Figure 4), further reinforces our observation that the forwarder takes more effort to operate. Our finding that the operators who performed best typically reported the highest NASA-TLX scores, and vice versa shows that performance seems to be tied to the amount of effort an operator is willing to put into their work. This likely has more to do with the individual's inherent motivation levels than the type of training they receive. Because simulator and machine groups weighted most NASA-TLX demands similarly on each machine (Figure 4), operators likely had similar learning processes whether they trained on a simulated or real machine. This could explain why we didn't see any significant differences in overall performance between machine and simulator training groups (Table 5).

Cost of simulator-based training

Our Training Facility Scenario does not include the cost of transportation to the facility or housing for students while attending the facility. The distance of the training facility from the contractor's headquarters and the local housing market where the training facility is located will impact the total cost of this scenario. The 36–40% savings quoted in this scenario could drop substantially when factoring in these additional costs. In our Simulator Purchase Scenario, the 154 and 104 simulator training hours per year needed to break-even for the skidder and forwarder, respectively (Table 3), may be a small portion of the training hours conducted each year by a contractor. If so, any additional training hours in which a simulator is used instead of a machine would result in direct cost savings to the contractor.

These estimates assume that the simulator-based training scenarios produce the same performance results as internal, machine-based training. The results from our controlled experiments largely back this assumption. These estimates also assume that, in all training scenarios, the operator is not contributing to production during their training period. This cost model was developed to give a rough estimate of expected cost savings involved with different avenues of implementing simulator-based training. Contractors and training institutions are encouraged to edit the values for each variable in this model to reflect their unique situations.

Study limitations

The biggest limitation this study faced was machine availability. We had to reach a compromise between the number of operators we could train and the length of the training period given the number of hours we had access to the equipment. Simulator-trained individuals in both the skidder and forwarder experiment did spend between five and 30 minutes on the machine each day during their testing session. This could have contributed to better performance scores than if the operators were not exposed to operating a machine. If we had asked the simulator-trained operators to complete their test on the simulator, however, we would have missed the opportunity to observe how their skills transfer to the machine.

During the experiment, we observed marked differences between the simulated and real skidder and forwarder. On the skidder simulator, the steering controls were reversed as compared to the actual equipment, the pedal functions were not consistent between the skidder and simulator, and there was no startup sequence required for the simulated skidder. The forwarder simulator was outfitted with harvester controls instead of forwarder joysticks. While the buttons were in similar locations, switching between the two types of controls likely involved some transfer cost (Proctor et al. 2013). We acknowledge the differences between the simulator and machine for both the skidder and forwarder likely inhibited maximum skill transfer that could have been achieved when using these simulator models with controls that better matched the real machines.

Recommendations for future research

Future studies to evaluate the effectiveness of simulator training should consider using a larger sample size (20 participants) if resources are available. This would allow researchers to better detect the simulator training effect for logging equipment operators and reasonably extend results to a larger population. Similarly, a longer training and testing period would allow more insight into the effectiveness of simulator-based training as a tool throughout an extended training program for a new operator. One factor that this study did not consider is the fidelity of the simulators used. Given that the degree to which skills transfer to the real world is tied to fidelity (i.e. the degree to which the simulated environment emulates the real working environment) (Meyers et al. 2018), future studies could examine operator performance results for a range of simulator technology from basic (i.e. simple joysticks that plug into a desktop computer) to full (i.e. a realistic operator's chair complete with motion feedback, replica controls, and multiple display screens for maximum field of vision). Finally, conducting experiments similar to this one for different types of forest machines (e.g. loader, processor, feller-buncher, harvester) would allow for a better understanding of the effectiveness of simulator training across the forest operations industry.

Conclusions

The goal of this study was to evaluate the effectiveness of simulator-based training for logging equipment operators. Due to the minimal differences we detected between simulator-based training and machine training, we conclude that simulators are an effective training tool for new logging equipment operators learning simple tasks. The benefits and drawbacks of slight differences in operator performance trends over time and the cost savings associated with simulator-based training must be weighed by training programs and contractors when considering the effectiveness of simulator training for logging equipment operators.

This study has laid the groundwork for future studies in skill transfer from forestry simulators to equipment. It provides a model with which contractors and training facilities can conduct a cost analysis of machine training conducted by a contractor vs. simulator-based training occurring either in-house or externally at a training facility. The study also acted as an opportunity to prototype a simulator curriculum to train new forestry machine operators. The outcomes of this project have contributed to developing a stronger logging workforce in the US.

Acknowledgements

This study was funded by the Economic Development Administration, US Department of Commerce (Investment No: 07 79 07629). While the grant covered the employment and travel costs of the research team, it did not cover the participants' time, land, or equipment required to carry out these experiments. This study would not have been possible without the generous support and donations we received from all our partnering companies, agencies, institutions, and individuals. Partnering companies, agencies, and institutions included: Miller Timber in Philomath, Oregon, Oregon State University Research Forest in Corvallis, Oregon, Ponsse Oyj in Coburg, Oregon, Intermountain Wood Energy in Redmond, Oregon, Hinds Community College in Raymond, Mississippi, Stribling Equipment in Richland, Mississippi, Mississippi Forestry Commission, Mississippi Loggers Association, USDA Forest Service, and the Travel Service team and Statistics department at Northern Arizona University in Flagstaff, Arizona. A huge thanks to the everyone who participated in this study.

Geolocation information

This study was completed primarily by researchers at Northern Arizona University in Flagstaff, Arizona. The skidder portion of the experiment was completed at Hinds Community College in Raymond, Mississippi. The forwarder portion of the experiment was completed at the Oregon State University Research Forest in Corvallis, Oregon.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

The work was supported by the Economic Development Administration [07 79 07629].

References

Allen T, Han H-S, Shook SR. 2008. A structural assessment of the contract logging sector in the Inland Northwest. Forest Prod J. 58:27–33.

Baker S, Greene D. 2008. Changes in Georgia's logging workforce, 1987-2007. South J Appl for. 32:60–68. doi:10.1093/sjaf/32.2.60.

Brinker RW, Kinard J, Rummer B, Lanford B. 2002. Machines rates for selected harvesting machines. Circular 296 (Revised). Alabama Agri Exp Station Auburn Alabama. 32.

Bureau of Labor Statistics. 2022. Occupational employment and Wages, May 2021: 45- 4022 logging equipment operators. https://www.bls.gov/oes/current/oes454022.htm (accessed 2022 Sept 8).

Burk E. 2022. Simulator-based training for logging equipment operators. Master's Thesis, Flagstaff, AZ, USA: Northern Arizona University.

Calabrese D 2000. Canadian switches to mechanized, cut-to-length. TimberLine Magazine. http://www.timberlinemag.com/articledatabase/view.asp?articleID=222 (accessed 2021 Sept 22).

Chang H, Han H-S, Anderson N, Kim YS, Han S-K. 2023. The cost of forest thinning operations in the western United States: a systematic literature review and new thinning cost model. J for. 121(2):193–206. In press. doi:10.1093/jofore/fvac037.

Conrad JL, Greene WD, Hiesl P. 2018. A review of changes in US logging businesses 1980s-present. J for. 116(3):291–303. doi:10.1093/jofore/fvx014.

Cools E. 2020. 2020 Contractor Survey. Simcoe, Ontario, Canada: Canadian Forest Industries.

Edwards R, Han H-S. 2021. Forest equipment operator course program and curriculum (draft). Flagstaff, Arizona: Ecological Restoration Institute. Unpublished.

Freedman P 2004. Operator training with simulator-based help in Quebec. Simulator- based training of forest machine operators – A presentation; 18 Nov; Quebec, Canada.

He M, Smidt M, Li W, Zhang Y. 2021. Logging industry in the United States: employment and profitability. Forests. 12(12):1720. doi:10.3390/f12121720.

Hoss C 2001. Harvester simulators as effective tools in education. Thinnings, a valuable forest management tool – An international conference; September. Quebec, Canada.

LaPointe JF, Robert JM. 2000. Using VR for efficient training of forestry machine operators. Educ Inform Technol. 5(4):237–250. doi:10.1023/A:1012045305968.

Leon BH, Benjamin JG. 2012. A survey of business attributes, harvest capacity and equipment infrastructure of logging businesses in the northern forest. Orono, ME, USA: University of Maine School of Forest Resources.

Meyers IP, Starr AW, Mullins K. 2018. Flight simulator fidelity, training transfer, and the role of instructors in optimizing learning. Int J Aviat, Aeronaut, Aerosp. 5. doi:10.15394/ijaaa.2018.1203.

Ovaskainen H. 2005. Comparison of harvester work in forest and simulator environments. Silv Fenn. 39(1):89–101. doi:10.14214/sf.398.

Pagnussat MB, Lopes EDS, Robert RCG. 2021. Machine availability and productivity during timber harvester machine operator training. Can J for. 51(3):433–438. doi:10.1139/cjfr-2020-0164.

Proctor RW, Dunston PS, So JCY, Lopez-Santamaria BN, Yamaguchi M, Wang X. 2013. Specificity of transfer in basic and applied perceptual-motor tasks. Amer J Psychol. 126(4):401–415. doi:10.5406/amerjpsyc.126.4.0401.

Pürfurst FT. 2010. Learning curves of harvester operators. Croat J Eng. 31:89–97.

Ranta P 2009. Added values of forestry machine simulator based training. Proceedings from the International Conference on Multimedia and ICT Education; 22–24 April; Libson, Portugal.

Riggs JL, Bedworth DD, Randhawa SU 1996. Chapter 12: break even analysis. In: Case K, Wolfe P, editors. Engineering Economics, 4th ed. USA: The McGraw Hill Companies, Inc; p. 473–511.

Richardson R, Makkonen I 1994. The performance of cut-to-length systems in eastern Canada. For Eng Res Inst Can. Technical Report TR-109.

Said S, Gozdzik M, Roche TR, Braun J, Rossler J, Kaserer A, Spahn DR, Nothiger CB, Tscholl DW. 2020. Validation of the raw National Aeronautics and Space Administration Task Load Index (NASA-TLX) questionnaire to assess perceived workload in patient monitoring tasks: pooled analysis study using mixed models. J Med Internet Res. 22:9.

Smith DW. 2012. Logging cost and productivity associated with labor and mechanization in the eastern United States. Theses and Dissertations 2969. Mississippi State University.

So JCY, Macrowski LM, Dunston PS, Proctor RW, Goodney JE 2016. Transfer of operator training from simulated to real hydraulic excavators. Proceedings from the 2016 Construction Research Congress; 31 May 2 June; San Juan, Puerto Rico. doi:10.1061/9780784479827.196.

Vaughan D, Edgeley CM, Han H-S. 2021. Forest contracting businesses in the southwest: current profile and workforce training needs. J for. 120:186–197. doi:10.1093/jofore/fvab060.

Wenhold R, Ackerman P, Ackerman S, Gagliardi K. 2019. Skills development of mechanized softwood sawtimber cut-to-length harvester operators on the Highveld of South Africa. Int J for Eng. 31:1–10. doi:10.1080/14942119.2019.1578561.

Yates B. 2000. High tech training of high-tech workforce in the forest industry. ; 11 - 13 September 2000; Kelowna, Canada.

Xu Y, Smidt M, Zhang Y. 2014. Logging worker wage, performance, and experience. For Prod J. 64(5–6):210–216.

Yerkes RM, Dodson JD. 1908. The relation of strength of stimulus to rapidity of habit-formation. J Comp Neurol Psychol. 18(5):459–482.