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# Evaluating operator harvest technology within a high-fidelity combine simulator

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## Abstract

Farming today is more complex than it has ever been. Operators are increasingly reliant on technology to aid and improve harvest performance. New harvest technology is under development that will advise harvest operators on the proper adjustment of machine harvest settings, as well as automatically adjust these machine settings without operator intervention, improving the harvest performance of the machine, and reducing the cognitive load of the operator. In this work a high-fidelity, interactive harvest combine simulator is used to understand how harvest operators currently use existing harvest technology, and to evaluate the performance improvements provided by new prototype machine control algorithms and human control interface designs. The interactive harvest simulator is used to assess an intermediate advising step for machine controls adjustment compared with a path using fully autonomous machine adjustment. Testing novel harvest technologies using the virtual environment of the combine simulator introduces a specific set of constraints and challenges that are not found in most other vehicle simulation applications, including the need for accurate physical and visual crop flow representations and a requirement for realistic machine responses to a wide variety of operator input commands. Using a high-fidelity combine simulator for testing allows unique harvest scenarios to be repeated by experienced operators in a controlled virtual environment.

This study evaluates operator acceptance, performance, and feedback for two novel pieces of harvest technology, Advisor and Director. Advisor is an operator-in-the-loop system providing feedback on proper machine control adjustments during normal harvest operations. Director is designed to continuously monitor the overall harvest health and autonomously adjust the combine harvest settings. In this study, operators harvested the same virtual field twice, first using Advisor, and a second time using Director. Operators overwhelmingly perceived both the Advisor and Director systems as optimizing the harvest performance of the combine and recommended both Advisor and Director. The results presented in this work show that both systems improved the perceived harvest performance, although the Advisor was not as highly rated. Participants recommended the automated nature of Director, and both operator feedback and physiological measures indicates that this harvest technology reduced the cognitive load of the operator. This work demonstrates two main points. First, the interactive combine simulator can be used for evaluating novel harvest technology in the lab. Second, that operators can quickly acclimate to automation within the combine and were able to harvest in a more productive manner when using higher levels of automation.

## Keywords

Simulator, Combine simulator, Harvest simulator, Virtual environment, Automation

## Disciplines

Agriculture | Industrial Technology | Operational Research | Systems Engineering

## Comments

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Chase Meusel, Don Kieu, Stephen Gilbert, Greg R. Luecke, Brian Gilmore, Norene Kelly, and Tim Hunt

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## Introduction

Harvest operators today face an increasing number of distractions and demands on their mental resources. Combine operators not only manage the physical crop harvesting process, they also must plan logistics for grain transport, analyze weather reports, communicate with outside operators, and take phone calls from a variety of sources. A potential solution for reducing the workload of the

operator is to automate those aspects of tasks which demand high cognitive resources, such as the ongoing vigilance of driving and the complex input tasks required for machine adjustments. This approach has been shown to be effective in other comparable scenarios (Endsley and Kaber, 1999; Metzger and Parasuraman, 2001; Parasuraman et al., 2009). The tasks which demand the most of operators should be evaluated for potential automation benefits, such as the control and adjustments of the combine processing systems, including the fans, sieves, and implement arrangements. Automating the most important harvest controls can help reduce the overall cognitive load experienced by operators, as well as improve the performance from less experienced operators who might otherwise see low performance results. In this work, a new technology application is evaluated using two steps on the path to harvest automation, the first providing guidance for manual machine adjustments during harvesting and then the second fully automating the sensing and harvest adjustments required to improve the performance.

Two related technologies were evaluated in this study, *Advisor* and *Director*. Both technologies were developed by the research team and did not represent finished quality found in final production software interactions or robustness. Advisor technology offers expert level guidance to operators in real time via combine adjustment feedback and suggested actions. Performance gains have been demonstrated in other studies, where the assisted operator shows higher performance than fully manual or fully automated solutions in similar scenarios, (Endsley and Kaber, 1999; Endsley and Kiris, 1995). In this implementation, Advisor requires operators to input their observed harvest issues, accounts for the current system state of the combine overall, and delivers a recommended list of corrective changes in prioritized order. Because the Advisor must rely on the operator to identify and report issues, an implicit assumption is that the operators have enough basic knowledge of harvesting to initiate the system and report observed issues. After recommendations are made, the operator can either accept the current recommendation, view the next recommendation, or cancel the entire process. This affords the operator the opportunity to allow the adjustment to be made as suggested by Advisor, select an alternative action, or to cancel the process and make a manual change which may have been influenced by the earlier suggestions. The final step of the Advisor process then queries the operator to note whether the issue has been resolved or if a new issue is present. This answer can either end the engagement or begin anew with the new or modified issue.

Director is the next level of automation, where the system actively monitors the overall combine system state in real time and acts to improve harvest quality. After an initial setup to identify the harvesting preferences of the operator (e.g. Do you want a faster harvest with a lower quality sample or a slower harvest with a higher quality sample?) the system will make changes without interrupting the operator to improve the harvest process overall. Due to the ability of the Director to initiate change without involvement of the operator, operators with lower harvest knowledge stand to gain more benefit from this system as it has the capability to observe and autonomously make changes on issues that may have otherwise gone unnoticed. The system does notify the operator when a change is underway, but it does not have to wait for approval with every adjustment.

Both Advisor and Director represent incremental steps in available technology toward a fully automated harvesting system. These automation steps were designed to provide operator assistance without sacrificing quality. When comparing Advisor and Director to the established SAE Automated Driving Levels (SAE, 2014), Advisor falls within level 2 of *partial automation*, which requires multiple systems to be automated but ultimately requires the operator to still perform the remaining tasks to successfully operator the machine. Director then takes the next step and falls closer to level 3 of *conditional automation* where the operator hands over control of all aspects of the dynamic driving but needs to be

present for intervention. With these automated driving levels to consider, the value of a guidance-based system, Advisor, can be adequately compared with the more automated system, Director. To understand the full value each of these systems provides, the current state of combine adjustment must be understood.

When a problem occurs during normal harvesting operations, current practice calls for the operator to use acquired knowledge to adjust the combine settings. When the operator does not know the correct solution, the process ends in one of three situations. The operator may 1) seek additional help, 2) ignore the potential issue, or 3) miss the harvest cue altogether. Seeking help requires time and will likely slow progress within the field because of the efforts required to contact an outside expert (e.g., “I have to call Dad.”), consult outside knowledge such as the harvest slide rule (Deere, 2013), review the troubleshooting guide (IH, 2009), or refer to the owner’s manual. If the operator simply ignores issues or misses harvest cues outright, the harvest process will result in lost grain loss and the operator is indirectly indicating low harvest knowledge. Both Advisor and Director can improve these known issues by providing a faster resource for outside information in Advisor and performing changes that would otherwise go unintended with Director.

Several factors make it particularly difficult to test this highly specialized technology. First, it requires several factors—the right season, uniform crops in the field, an expensive harvest combine machine, and a human operator. The North American harvest season occurs only once per year, and most operators will not encounter these specific requirements outside of that window, so the technology is only sporadically needed. Testing the algorithms requires multiple runs through the field with a variety of crop conditions. Even the most uniform field and crops have unknown variations, and once a field is harvested, there is not a duplicate with which to compare results. Even obtaining the operator may be problematic, as any time spent away from harvest may have a high cost in terms of lost harvest opportunities. That said, real conditions will vary from the simulator conditions, sometimes drastically. The simulator will be unable to train for all potential field conditions but will still benefit the operator in a variety of ways, importantly with experiencing new technology.

The limited time window of operation and infrequent use of this type of technology makes designing for this specific audience difficult and testing it prior to implementation nearly impossible. However, implementing the prototype harvest technology within the high-fidelity combine simulator gives the operator the opportunity to acclimate to the new automation system, provides a baseline for performance, and offers feedback for technology they have yet to encounter in the field, all without the pressure of monetary loss when using their own crops and equipment. Specific harvest scenarios can be built within the virtual environment; therefore, operators can make all normal adjustments that would occur in a real combine as both the operator and the technology are evaluated. Moreover, a simple reset of the simulation presents each operator with an identical field and set of crop conditions during the test.

Harvest scenarios include relevant exterior graphical cues (e.g. crop height and color), interior instrument cues (e.g. loss monitor, moisture monitor), and expected auditory cues. An emphasis is placed on observing operator feedback including verbal, performance, and physiological. All operators indicated preference to a system which helps them identify potential issues and the less experienced operators strongly prefer the system which helps them perform at a level closer to an expert. The software, hardware, and external components utilized to perform this study are outlined in the methods section.

## Background

Previous studies have shown that virtual environments and simulators are effective at training new technologies and developing new products, especially within domains which have highly specific or constrained use cases. Simulators and virtual environment training transfer work has found success in areas such as repairing the Hubble space telescope (Loftin and Kenney, 1995), fire-fighting aboard a naval ship (Tate et al., 1997), or even performing highly specialized medical procedures (Calatayud et al., 2010; Kruglikova et al., 2010; Triantafyllou et al., 2014).

### Automotive simulators

The largest area of simulator research centers around the automotive industry, and this research has been using driving simulators since the 1960s (Weir, 2010). Driving simulators allow researchers to simulate actual driving conditions and situations within a controlled and safe environment (Lee et al., 1998). Simulator use in research studies also allows for greater flexibility and cost savings when compared to performing studies with a physical vehicle (Mann et al., 2014). Simulators today continue to see reductions in cost, improvements in computational performance, and increased use as a research tool in human factors research, interface design, and operator research (Bella, 2008; Birrell and Young, 2011; Jamson et al., 2014; Weinberg and Harsham, 2009).

Automotive simulators have been used to investigate a broad selection of topics within automotive research. Topics range from more basic driver performance work (Mclane and Wierwille, 1975) to very specific examples of investigating the impact of brake pedal stiffness in racing applications (de Groot et al., 2011). This work is specifically interested in applications of operator performance, workload measures, and automation applications. Automotive simulator research indicates that people are poor at dividing attention (Lee et al., 2005) even when only engaging on phone conversations (Horrey and Wickens, 2006). More closely related to this work, though, are topics of vehicle assistance, helping drivers achieve better performance, in this case, fuel economy (Hibberd et al., 2015; Jamson et al., 2014).

### Non-automotive simulators

Automobiles and agricultural vehicles have certain commonalities but differ in terms of many purposes and functions. Thus, the development and use of simulators for agricultural vehicles has both similarities and differences from that of automobiles. For examples, tractors and automobiles are similar in requiring minor steering imperfections. However, the nature of the steering disturbances differ due to the differing forward speeds and driving surfaces of an automobile versus a tractor. Also, it is frequently the case that tractor operators are using a guidance system, which increases accuracy of straight-line driving. Karimi et al. (2008) developed and validated a simulation model of parallel swathing (driving in parallel paths to cover a field) in a tractor-driving simulator. The model accounted for tractor self-deviation and guidance system error. The study's field experiments were in close agreement with the simulator experiments regarding frequency composition of lateral deviations, thus showing the model's value in simulator fidelity.

While agricultural vehicle simulators differ from automotive simulators, there are also a variety of agricultural vehicles, which results in differing designs and research questions. For example, in the design of a tractor-air seeder driving simulator, the first step was to conduct a function-oriented task analysis to identify the required functions, tasks, and subtasks (Mann et al., 2014). A main finding was that operators allocated a substantial portion of their time to manually operating the air seeder.

Additionally, operators had to monitor the air seeder that was mounted behind the tractor. To simulate this characteristic of a tractor-air seeder, researchers put two computer monitors behind the cab (one to rear-left and one to the rear-right of the operator's seat). Thirty-two images created a single panoramic view, forming the field boundary for the tractor-air seeder. This simulator is being used for two research issues: to determine an appropriate automation design for agricultural vehicles and to understand the impact of display design on an operator's situation awareness in a semi-autonomous agricultural vehicle (Mann et al., 2014).

A primary use for agricultural simulators is in their use as a tool to evaluate operator performance and novel agricultural technologies (Bashiri and Mann, 2014; Duncan and Turner, 1991; Mann et al., 2014). Research in this area though is still relatively scarce which leaves opportunity to evaluate innovative technologies prior to their release within particular markets. Industry has at times introduced new automation features without sufficient testing, resulting in user problems and complaints. Such evaluation prior to implementation is increasingly crucial as the vehicles become more complex, more sensors are integrated into the system, and more functions are automated. While automation seems to be an obvious positive for the operator, that is not necessarily the case. Automation may, for example, result in information overload for the operator. Predicting the impact on the operator of proposed automation is an important part of the design and development process. A simulator is ideally suited to conduct user studies, from which researchers can predict the impact of automation (Mann et al., 2014).

Overall, automotive simulators are the most popular medium for simulator based research platforms, but other there are examples of non-automotive vehicles that have been modeled as simulators and used for research purposes. From construction vehicles (Son et al., 2001; Yoon and Manurung, 2010) to agricultural equipment (Karimi et al., 2008; Karimi and Mann, 2008; Mann et al., 2014) non-automotive simulators have a large opportunity to gain operator feedback in a meaningful way. This work utilizes a harvester combine simulator specifically and is an updated model from the initial platform built by Luecke (2012). Luecke's combine simulator is unique as it is constructed of many production parts enabling an active CAN bus, displays and intelligence features to provide fully functional and responsive John Deere combine setup which can integrate existing and future technologies for operator use and evaluation. Data collected in this way can be objectively measured to evaluate the value, issues, and expectations of operators long before they enter the field in a real combine.

The previous works measured an operator's ability to use the technology. More specifically in Duncan and Turner, (1991) a rank ordering of operator preference was also obtained. This paper goes beyond that to present a methodology to assess of an intermediate step in automation technology is needed for customer acceptance.

## Methods

### Research Objectives

The primary research objectives of this work were to determine whether the two separate prototype harvest technologies could 1) increase operator performance 2) be accepted by the operator and 3) reduce operator workload. For operators today, this ultimately means they make more money. The two technologies evaluated in this work were Advisor and Director. Advisor is an operator in the loop system and by extension has more behavioral data to assess. Director takes the operator out of the primary loop and focuses on assessing the operator feedback and choice of interventions. Each

operator used both the Advisor and Director systems in sequence as Advisor will be available prior to Director.

Both Advisor and Director were evaluated via operator feedback to standard questions, operator behaviors in response to system actions, physiological measures, and qualitative comment analysis.

## Hypothesis

The first system, Advisor, was expected to increase operator performance and offload work from the operator to Advisor. Similarly, Director was expected to both increase performance and reduce workload by making beneficial adjustments without the operator's input. The systems were expected to perform comparably at the performance level because each system was delivering the same recommended change. If one system was to outperform the other, the expectation was that Director would do so as it would not wait for operator confirmation to make changes or give the operator a direct opportunity to veto any actions. Director was expected to have the greater effect at reducing workload though as it did not require any input for each suggested change where Advisor still required manual confirmation for each suggestion.

## Participants

28 operators were recruited to take place in this study with the requirement that they have at least two years' experience operating a combine in the past four years. Additionally, operators were recruited with a diverse set of primary crops including corn, beans, and wheat. Operators travelled to the Virtual Reality Applications Center at Iowa State University to participate in this study from Iowa, Montana, and Illinois.

Operators were recruited from a large pool of individuals who had indicated their willingness to participate in research for an agriculture equipment company. Operators were compensated \$150 for their effort and had travel expenses reimbursed. All operators were over 18 years old.

## Tasks

All operators completed the same harvest scenarios where the independent variable was the crop being harvested. The overall study consisted of two separate phases, one using Advisor and a second using Director. Prior to the simulator portion of the study, operators completed demographic questions, system knowledge questions, and prior experience questions.

## Independent Variables

Independent variables used in this work were visual feedback in the cab, such as yield, moisture, and harvested crop quality and between groups two separate crop types were harvested, corn and wheat. Each crop presented the same changes with respect to crop variables yield, moisture, and quality. The crop type visible was determined by the operator's personal harvest experience. Crop yield was displayed via changes in the visual graphics of the simulation and in the instrumentation on the combine hardware as seen in Figure 1. Crop moisture was displayed via changes in the visual graphics of the simulation and within the combine instrumentation. Crop quality was not explicitly identified by a single metric, but was presented with changing visual representations via a simulated grain tank window as seen in Figure 2.



Figure 1. Harvest information displayed on four primary displays. The top display showed GPS navigation information, the three small stacked displays (corner post) showed combine diagnostic information, the iPad mounted above the arm rest displayed the Advisor/Director interface being tested, and the bottom display (the command arm) showed the current yield rate.



Figure 2. Left, operator inspecting grain tank window, as represented by a large TV screen behind the operator. Right, grain tank window image.

## Dependent Variables

Dependent variable measures included system performance metrics, operator feedback, cognitive load and operator ground truth comments. Performance metrics included items such as whether the operator reported the correct issue, how they chose to implement the suggested resolution from the system, whether they used the system, if they decided to turn the system off at any point, how many times they visually attended to the grain tank window, time spent in the field, and whether they slowed down during the use of Advisor or Director. Operator feedback items included the single ease of use question (SEQ) (REF), the system usability scale (REF), and a net promoter style question (REF). Cognitive load was measured continuously via electrodermal activity, (EDA) (REF). Lastly, comments made and feedback given throughout the duration of the study were noted for specific mentions of emergent themes such as estimated operator fatigue, estimated operation times, and operator trust in the system. A summary tables of dependent variables can be seen in Table 1.

Table 1. Dependent variable summary table.

Dependent variable	Metric	Unit	Frequency of Collection	Data Type
Performance	# slows, stops, errors		Per field condition	Ordinal
Cognitive load	EDA	Microsiemens	Continuous (32hz)	Continuous
Perception	SEQ	Scale 1-5	Per field condition	Ordinal
Satisfaction	Recommender	Scale 1-10	Per technology	Ordinal

## Experimental Design

Dependent on the operator’s experience, either the corn or wheat variation of the simulation was set to run. The hardware setup did not change with respect to crop. Crops were identical in size and field variation including transitions, e.g., harvesting from a tall crop to a normal height crop happened in the same place in each field. Both corn and wheat fields were structured the same way with respect to crop variation and changes in the information displays as well. The virtual field was comprised of seven, 30-foot-wide, half mile passes totaling 12 acres (Figure 3).

Each operator experienced all five field conditions including a normal pass, low moisture, high moisture, low yield, and high yield sections. The operator’s performance, cog load, and perception of changes were tracked for each of the four primary field conditions. Satisfaction was measured at the end of each field via recommender and intent to purchase questions.

Operators used Advisor in the first field, followed by Director in the second field. No counterbalancing was performed between fields as the release order of this technology was intended to be Advisor followed by Director.

## Procedure

Operators initiated the research experience with an introductory survey on harvest knowledge and demographic information. After completion, they were brought into the combine simulator and prepared to begin harvesting the virtual field by explanation of the scenario and basic combine controls. No training was performed prior to the study. A researcher was present and sat next to the operator in the “buddy seat” for the duration of the study. The researcher was able to ask relevant questions during the study and answer any reasonable questions the operator may have had.

The first pass of each field was empty to give operators an opportunity to acclimate to the combine so they would be prepared for the first of four trials (or harvest events) in the remaining six passes. The first task was to complete the field using the Advisor system with only a description of what the system was intended to do. As gaining realistic operator feedback was an important goal, no specific instruction was given on how to use the novel harvest technology following best practices within UX testing guidelines (Krug, 2009). After task one was complete using Advisor, there was a short reset and then the second task of harvesting the field again using the Director system took place. Observations were noted during all harvest events to note if and how operators were engaging in technology use. In addition to observations as to the operator’s behavior and performance, operators also answered three questions after each interaction with the harvest technology when engaged during a harvest event (when field conditions changed). The three questions were 1) “Was the suggested solution appropriate?” 2) “Do you feel the combine is in an optimized state?” and 3) “How did you feel about the last adjustment overall? 1-5, 1 being poor, 5 being ideal.” Operators were also given an opportunity to

list any issues or suggestions they wanted to share after the interaction had concluded. The target total time spent for completing both task one and task two was between 90 minutes to 120 minutes, in addition to questions before and after the simulation.

During both harvest tasks a second research team member was operating the “Wizard of Oz” station which controlled the information displayed within the combine simulator and the image presented in the grain tank window monitor behind the operator. By tracking the operator’s position in real time and monitoring the operator’s actions, the second research team member could update the information displayed within the simulator to reflect the current field conditions in real time. Information displays changed in this way included the yield monitor, moisture meter, and grain tank window image.

Once the harvest tasks were complete, an exit interview was conducted to cover a variety of experiences and finally a survey was completed to allow the operator to provide feedback on the harvest systems, simulator, and overall experience. The entire session lasted, on average, three hours.

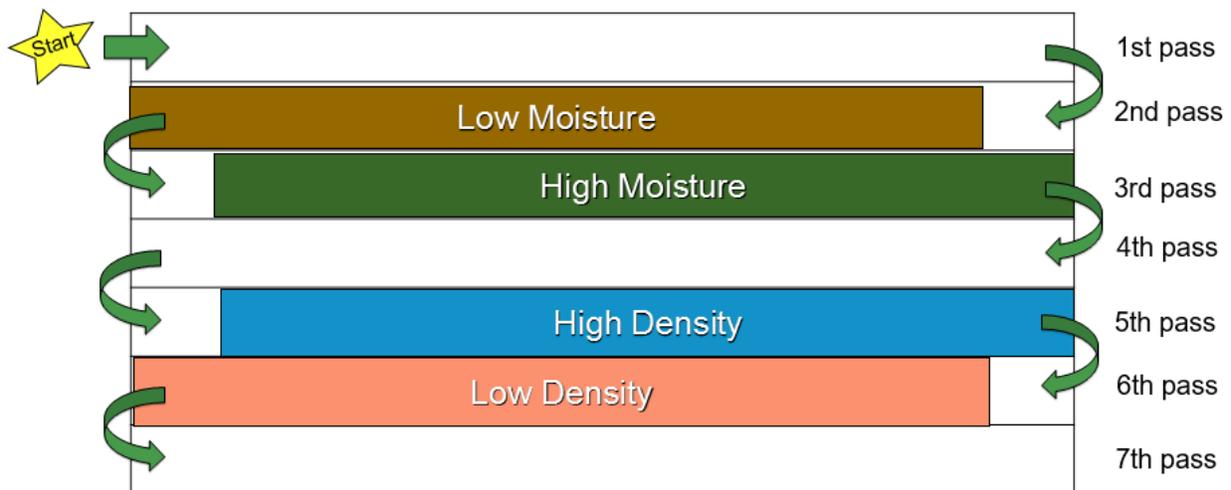


Figure 3. Top-down view of the 12-acre virtual field.

### Limitations and Assumptions

This study was not designed to measure literal crop harvest quality as the underlying simulation was not built to respond to all possible variable inputs. All changes displayed within the simulator were previously generated to appear as a realistic output for the corresponding section of field the combine was harvesting within. Additionally, this study was not designed to compare absolute ground speed as a measure of performance. This is due to the uniform nature of the field and the low number of constraints placed on the operator from a ground speed position. Future studies could potentially have a more sophisticated harvest model to account for all available inputs if harvest quality was an output of primary interest. While the actual harvest quality output is marginally useful, the freedom to run more than pre-scripted harvest events within the field would allow the study to commence without the second research team member adjusting in real time and allow a greater variety of field conditions to be evaluated.



Figure 4. Operator driving the combine simulator with a research team member riding in the buddy seat.

### Testing environments (hardware/software)

The combine simulator featured a modified John Deere 9770 STS interior, with projected displays setup in front of and to the left of the operator to simulator immersive virtual farming, see Figure 4. The cab included a John Deere 2630 in-cab monitor running GreenStar 2 and an Apple iPad 3. The iPad was used to display the working prototypes of the novel combine technology software. The combine simulator software, Greenspace (Luecke, 2012) was run on Ubuntu 12, 64 bit with a 3 GHz dual core Intel processor, 8 GB of DDR3 ram, and an NVIDIA Quadro K600 graphics card. Two external stereo speakers were used to produce audio in addition to an 8" subwoofer. A Butt kicker bass shaker attached to the cab seat was also utilized to simulate the vibrations felt when operating a full size combine. Primary displays to simulator the virtual field were two short throw, rear projected, projectors at 1280x800, displayed on two 8' x 6' screens positioned in front of and to the left of the operator giving approximately 95° field of view on the front display and a full left peripheral view from the left display. The simulation was rendered monocularly using the OpenGL graphics engine with displays handled by VRJuggler at an average frame rate of 31 frames per second. An additional 40" LCD television positioned immediately behind the operator and 4' off of the ground was used to simulator the grain tank window.

The second research team member operating the "Wizard of Oz" station utilized a Windows 7 computer to run the custom "wizard" application to monitor, record and manipulate combine simulator parameters in real time. Simultaneously the same team member was observing and recording the prototype interface evaluated on a second Apple iMac.

### Results

28 operators completed the combine simulator study. Operators were primarily between 41-50 years old, 36%, with 20-30 and 31-40 each having 23% of the total. The majority, 55%, of operators have over 12 years of experience with almost all others have between 4-7 years' experience. Most operators, 64%, were either the owner of their farm or worked on a farm their family owns. Operators spent an average of 102 minutes in the simulator. Dependent variables measured within this study are noted and expanded upon within Table 1.

## Performance

The two pieces of technology, Advisor and Director are both intended to improve operator performance, but Advisor was shown to require more input than Director. The amount of input was measured by number of interactions each piece of technology received from operators over the entire study. Two operator's data were removed due to video not being available for analysis. Advisor saw 13.7, 95% CI [8.832, 18.475] more interactions on average than Director over the course of the entire study,  $t(25) = 5.8327, p < .0001$ .

When investigating how operators used both Advisor and Director, no operators turned either system off. Performance within each system is reported as the % of operators who made *manual adjustments* instead of allowing the system to adjust, the % of operators who used the system as intended, (*used as intended*) and % of operators who did not make any errors, (*no errors*). *Used as intended* meant the operator successfully and intentionally used the system at least once by the final, of the four, trials available. *Without errors* represents % of operators who did not make a mistake through the entire field using that system. A mistake was noted when an operator would report the incorrect issue present, abandon the process prior to completion, or manually override the system suggestion. Fewer errors overall committed during the second half of the study, as Director had fewer errors than Advisor. All percentages are based on the total of 28 operators. The results can be seen in Table 2.

Table 2. Operator performance observed.

Technology	Manual adjustments	Used as intended	Without errors
Advisor	7%	89%	46%
Director	0%	89%	79%

Operators reduced their ground speed fewer times when using Director when compared with Advisor, 95% CI [0.39, 1.39],  $t(27) = 3.6728, p = .001045$ . The difference also displays a medium effect size  $r = .4456$ .

No difference in number of times operators brought the combine to a stop using Director when compared with Advisor as the 95% CI includes zero, 95% CI [-0.13, 1.20],  $t(27) = 1.6576, p = .109$ . While not significant, a small effect size does exist,  $r = .2148$ . Table 3 displays the number of operators who either slowed or stopped ground movement completely while harvesting.

Table 3. Operator ground speed changes observed.

Technology	# Operators who slowed	# Operators who stopped
Advisor	13	11
Director	1	6

Overall time spent in the field represents a measure of efficiency and potentially reduced operator fatigue. Operators spent less time in the field using Director when compared with Advisor,  $t(24) = 4.81, p < .0001$ . See Table 4 below for time spent by technology.

Table 4. Time spent (in seconds) in each section of the field in seconds, split by technology.

Technology	Total Time	Low Moisture	High Moisture	High Density	Low Density
Advisor	1305	374	347	314	271
Director	1081	273	281	285	242

Time spent in the field, (Figure 5) and time spent in each individual pass, (Figure 6) show larger standard deviations for Advisor when compared with Director. This can be interpreted as the process for Director was more in control as there was less variance in the time spent when using that technology.

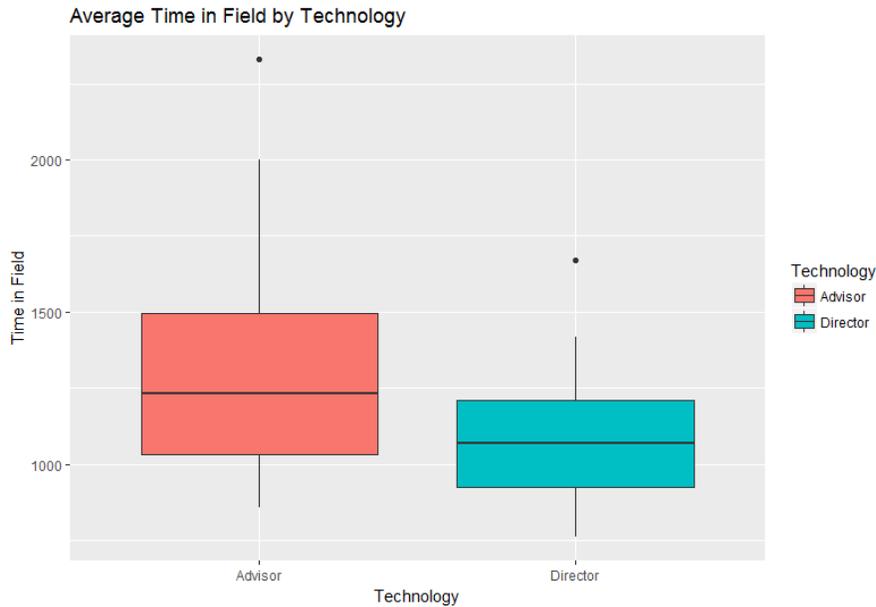


Figure 5. Boxplot of average time spent (in seconds) through entire field for Advisor and Director.

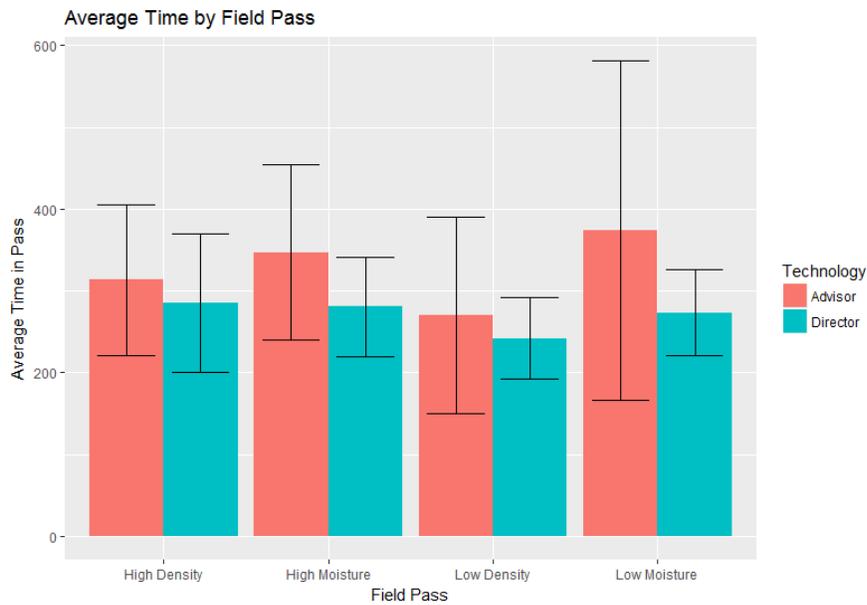


Figure 6. Average time (in seconds) all operators spent in each pass.

### Grain Tank Window

24 of the 28 operators looked 6 times or fewer at the grain tank window through the entire study. The other four operators looked 27, 30, 33, and 36 times respectively. This results in a total of 190 individual grain tank window looks that occurred, 126 or 66% of them were from four operators. Eight operators

only looked at the grain tank window one time. The histogram of grain tank window looks by operator frequency can be seen in Figure 7.

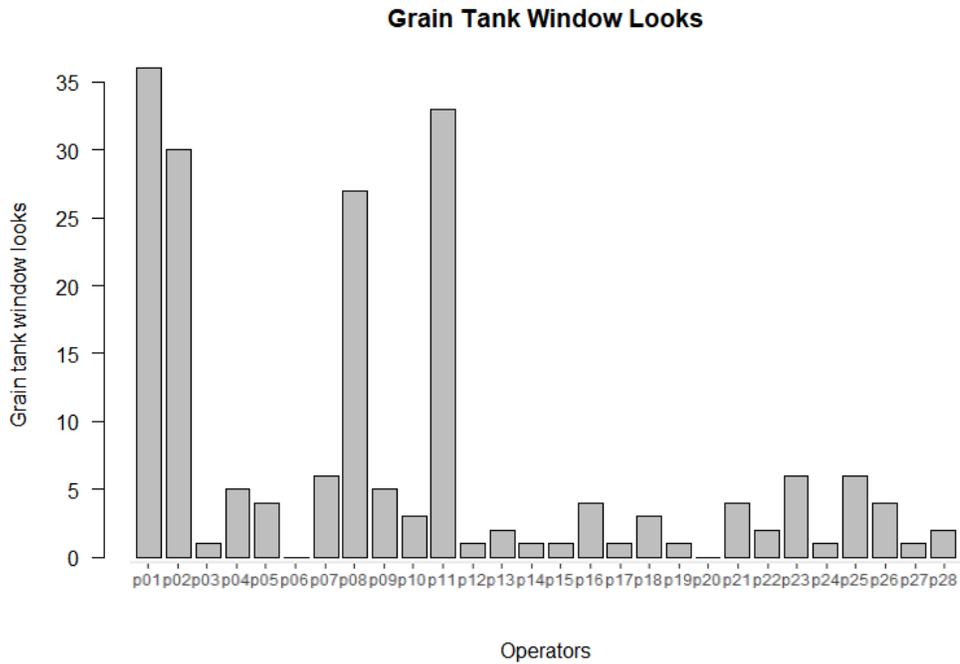


Figure 7. Number of grain tank window looks taken by operators, most operators do not look more than six times.

### Operator Harvest Knowledge Survey

Operators were surveyed on nine separate questions written to determine whether they would be able to correctly identify the correct adjustment needed to correct a harvest issue while harvesting.

Questions were created based on adjustments available within the combine simulator configuration, for conditions that commonly arise within farming large grain crops within the Midwestern United States. Original question answers were outlined based on research team knowledge, sponsor team knowledge, and agricultural extension office information (Anderson, 2011; Fone, 2007; Mowitz, 2013; Wehrspann, 2004). Subject expert engineers from a large agricultural machinery company and three experienced combine operators were also consulted in the creation of these questions and their correct answers.

All 28 operators completed the operator harvest knowledge survey. The survey was comprised of nine questions taken during the general pre-survey questions. Of the nine questions, only eight were used for analysis as one of the questions was specific to a corn condition and 12 of the 28 operators were primarily experienced with wheat harvest. The eight questions were worth a total of 16 points, or two points per question. Of the eight questions used, operators scored an average of 11.21 (SD 3.24).

Groups were created by separating scores into low, medium, and high groups. Grouping was done by taking the average +/- the standard deviation and including those scores as the “medium”, all scores above labeled as “high” and below labeled as “low.” See Figure 8 for all scores.

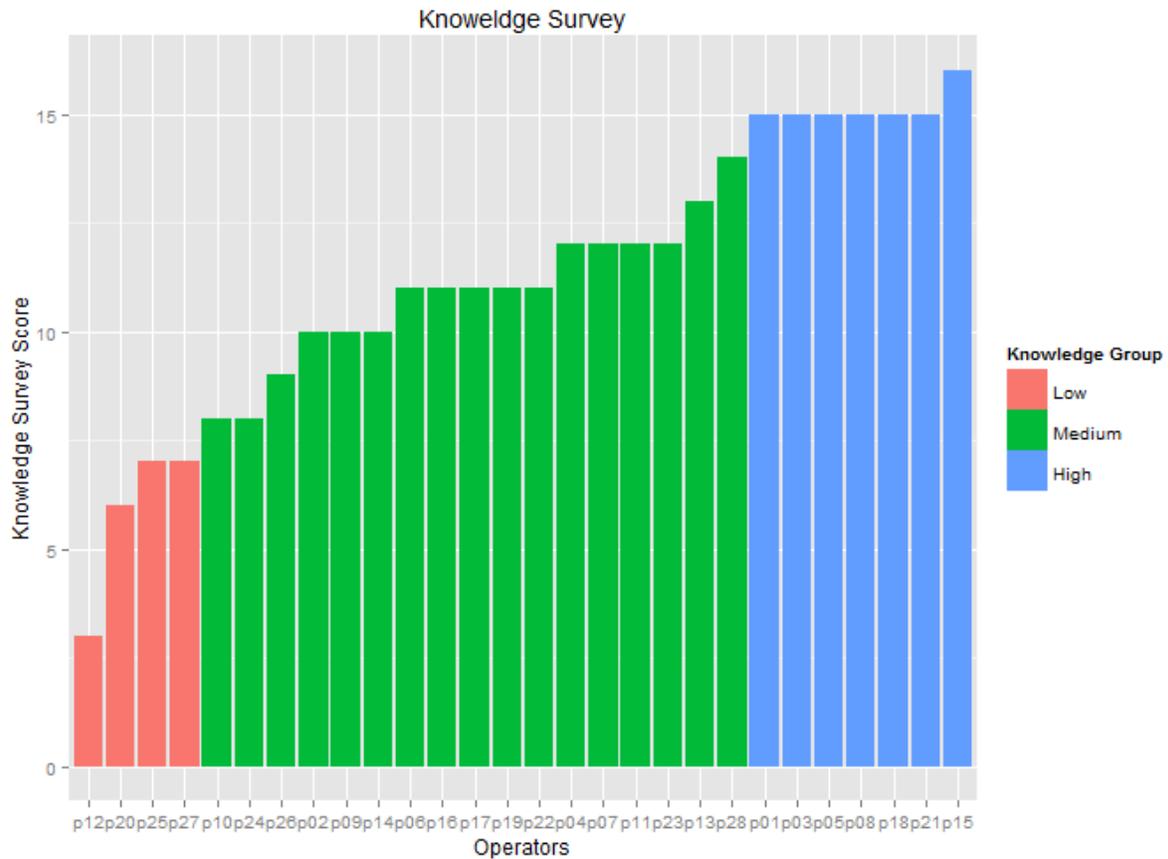


Figure 8. Operator knowledge scores, colored by group, max score of 16.

A one-way between subjects ANOVA was performed to determine whether knowledge scores between operator groups were different from each other. There was a difference on scores between knowledge groups for the three groups,  $F(2) = 53.71, p < .0001$ . Post hoc comparisons using the pairwise t-test with a Bonferroni adjustment indicated that the mean score for the Low group was different from the Medium group ( $p < .0001$ ) and High group ( $p < .0001$ ). Additionally, the Medium and High groups were also different from each other ( $p < .0001$ ). These differences can be visually seen in Figure 9.

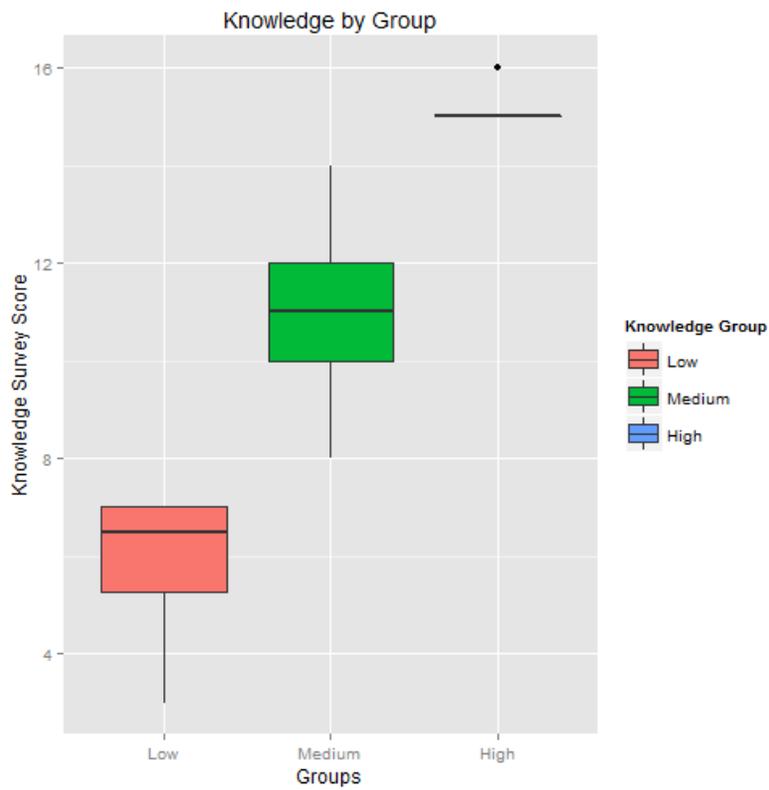


Figure 9. Knowledge scores split by group.

There was no difference found between operators of corn and wheat with respect to performance on the operator harvest knowledge survey, see Figure 10.

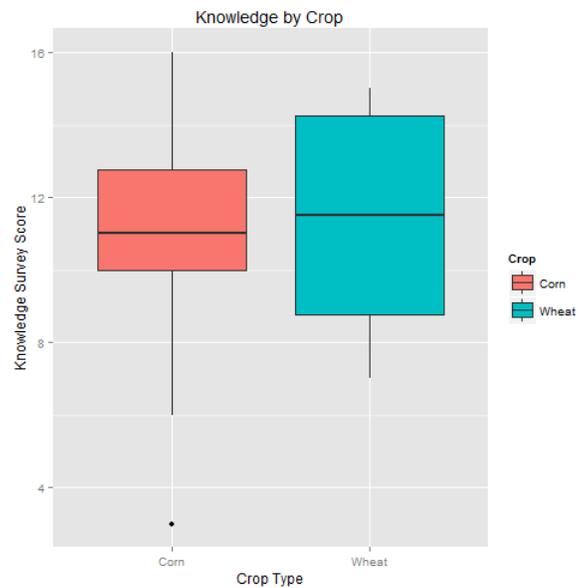


Figure 10. Knowledge scores split by crop.

## Operator Feedback

Table 5. Operator feedback on technology use in the simulator.

Technology	Interactions	Appropriate Solution?	Optimized combine?	Adjustment rating?
Advisor	75	89% Yes	89% Yes	4.2 (SD 1.0)
Director	96	NA	100% Yes	4.57 (SD 0.74)

Operators felt that Advisor offered an appropriate solution to the issue they reported in 89% of the issues. Advisor and Director saw operators report feeling that the combine was optimized in 89% and 100% of the scenarios, respectively. There was no statistical difference in mean adjustment ratings as seen in the last column of Table 5. A breakdown of which cues were acted upon by scenario can be seen in Table 6, the low-density scenario has the lowest observed interaction rate of 36% where the other three cues were >93% action rate. A low moisture scenario was not presented to corn operators, hence there is only a potential interaction for each of the wheat operators ( $n = 12$ ). Table 1

Table 6. Advisor Interaction observations by scenario.

	Low Moisture	High Moisture	High Density	Low Density	Total
Interactions observed	12	27	26	10	75
Potential Interactions	12	28	28	28	96
Action rate	100%	96%	93%	36%	78%

## Electrodermal Activity Results

Electrodermal activity (EDA) was measured continuously throughout the course of the study. Three specific results were tested in relation to change in operator mental effort. The first tested whether mean EDA values were different between Advisor and Director use, no statistical difference was found. The second tested if a correlation between SEQ scores and EDA data existed. Within Advisor, there was a moderate, negative correlation between SEQ and EDA  $r(20) = -.523$ ,  $p = .0012$ . There was no significant correlation within Director. Third, high knowledge operators reported lower EDA levels during Advisor than low knowledge operators  $t(13) = 1.8386$ ,  $p = .08971$ , 95% CI [-0.375, 4.565],  $r = .360$ . No difference found within Director.

## Ground Truth Findings

While not specifically sought out, operators also made many comments which shed insight into their thoughts and feelings as to the real-world performance and repercussions of using these new technologies. Eight operators (29%) mentioned that Advisor was similar to having someone give you a second opinion on what change to make. 13 operators (46%) mentioned they would be more vigilant, be able to work more hours, and likely have less fatigue while using Director; a number of these individuals cited their experience with GPS steering as a baseline for reducing fatigue in the combine. Lastly, 14 operators (50%) commented on their feelings of trust toward Director, of those all but one noted they could come to trust the system over time.

## System Usability Survey

System usability scale (SUS) scores are analyzed within this work as a scores arrived upon by using the suggested SUS scoring methodology as noted in the literature, (Brooke, 1986). The average SUS score for the entire study was 76.43 (SD 12.72) which places this technology above the industry average of 68 (Brooke, 2013). There was no difference found between operator's SUS scores when compared between crop and wheat operators. Additionally, there was no significant effect found when comparing SUS scores among knowledge groups,  $F(2) = 2.27, p = .124$ .

## Net Promoter

Only 27 of the 28 operators were used to calculate net promoters. One operator did not report net promoter scores. Net promoter is scored by determined by splitting operators into three buckets by their reported scores, detractors (0-6), passives (7-8), and promoters (9-10). The percent promoters, less the percent detractors gives the net promoter score. A perfect score, if all operators are promoters, would be 1. All scores can be seen in Table 7.

Table 7. Net promoter and purchase intent scores.

Technology	Recommender Score	Promoters	Detractors
Advisor Recommend	.33	15	6
Advisor Purchase	.11	10	7
Director Recommend	.78	21	0
Director Purchase	.59	18	2

Operators recommended Director over Advisor when comparing Net Promoter scores,  $t(26) = 3.98$  value,  $p = .0005$ . Similarly, operators indicated they were more likely to purchase Director than Advisor when comparing Net Promoter scores,  $t(26) = 4.01$  value,  $p = .0005$ .

## Discussion

The 28 operators represented a diverse group of individuals who were all fairly experienced and many were the owner of their operation.

## Performance

Advisor required more input than Director and that was evident in both observing operator behavior and when considering the needs of each system. Advisor required the user go through multiple steps with every issue encountered where Director required minimal user input. This large reduction in the number of interactions while harvesting allowed operators to engage more with other in cab requirements and should cause less general fatigue. Reduced load and therefore reduced fatigue will allow operators to be more vigilant for longer periods of time while operating the combine.

Only two operators (7%) elected to make a manual adjustment during the Advisor process which indicates operators were willing to tolerate the novel technologies within the context of this study. Additionally, operators did not turn off either system throughout the course of the study. It is possible operators would have intervened more in a real combine or specifically when harvesting their own crop though.

Fewer errors were committed in the second half of the study when using Director relative to the first when using Advisor. It could be concluded that operators learned how to use the technology over the duration of their experience. Another consideration lies in the fact that the system operators were evaluating was not a final product, but a prototype experience built to expose operators to the concepts of automated harvest products.

The major performance results show that operators could harvest in a more productive manner when using Director. Both scenarios had the same speed limitations set in place by observing the loss monitor, but Director saw fewer reductions in ground speed. This is likely because Director was operating in real time and gave operators less opportunity to observe issues with harvest quality or had fixed any observed issues prior to slowing ground speed. As operators slowed less when using Director, they ultimately spent less time in the same field when using Director, the breakdown of time spent can be seen in Table 4.

### Grain Tank Window

The measure of grain tank window looks by operator gives insight into the question “Do operators use the grain tank window during harvest? If so, how much?” While 18 of the 28 operators checked the grain tank window at least twice (once per field), eight operators only checked it at the time of explanation from the research team member and the remaining two of did not check it at all. The other interesting split though comes from the natural split in the data between 6 looks and 27 looks. 24 of the 28 operators looked 6 or fewer times, while the other four operators looked an average of 31.5 times. It appears the four operators who looked 31.5 times do use their grain tank window frequently, when all others use it less than once per pass.

### Operator Harvest Knowledge Survey

The harvest knowledge survey revealed a means to separate operators out based on their knowledge scores into ranked practice expertise scores, or scores which indicate their ability to make appropriate adjustments to the combine and gain a desired effect. A limitation of this work is the relatively small sample size, as more studies are completed, additional data will be gathered. A more complete discussion of the harvest knowledge survey can be seen in Meusel et al., (2016).

### Operator Feedback

Operators had 96 opportunities to act on each of the four scenarios over the course of all interactions with Advisor. Corn operators were only given three scenarios, hence the reduced potential interactions for the low moisture scenario as seen in Table 6. For the duration of the Advisor field, 67 of the 75 scenario interactions observed indicated operators had been given an “appropriate solution.” The same number of interactions were also reported to have ultimately placed the combine in an “optimized state.” Finally, Advisor received an average of 4.2 (SD 1.0) out of 5 when operators were asked “How do you feel about the last adjustment overall? 1-5, 1 being poor, 5 being ideal.” In comparison, Director received 100% positive feedback when operators were asked if they felt the combine was in an “optimized state” and received an average rating of 4.57 (SD 0.74) when asked the last adjustment question. Operators seemed to favor Director when discussing afterward and recognized the potential value of a system which would act without approval when operating correctly.

## Electrodermal Activity Results

While Advisor and Director did not show overall differences in EDA as expected, EDA did change as expected when compared with SEQ values and between low and high knowledge operator groups. Higher SEQ values indicate the operator rated the specific encounter more favorably, indicating a lower level of imposed mental effort. As EDA should increase with higher mental effort, the inverse correlation found supports this. Similarly, because high knowledge operators have a deeper understanding of the combine as a system they should then exhibit lower EDA levels when exposed to novel harvest interactions as done within the study. This supports that experts with a greater number of mental schemas outperform novices who do not have advanced knowledge within their domain (Larkin et al., 1980; Simon and Newell, 1971). Both the inverse correlation between SEQ & EDA data, and the difference between high and low knowledge operators only occur within Advisor and not Director. This also makes sense considering the amount of knowledge required to successfully use each. Advisor requires the operator to have an existing knowledge of the combine use successfully, thus the gap between high and low knowledge operators is wider. As Director operators independently of the operator, the gap is much smaller as expected, hence no differences within EDA to report.

## Ground Truth Findings

While operators seemed to prefer Director, positive comments were made about both systems, especially when compared to not having either instead of comparing with each other. Advisor was compared to having an expert or knowledgeable friend give you a second opinion or advice while out combining without having to stop to ask.

A strong case was made for Director when operators would make comparison between Director and using a GPS guided steering and tracking system. Operators who were familiar with GPS controlled steering inputs (which was the majority of operators) made the general comment that enabling GPS steering was able to free up cognitive resources from the operator so they could concentrate more fully on other measures and alerts that would have likely gone under-observed or neglected all together. The parallel was that Director could potentially free up additional cognitive resources for additional monitoring or even accomplish other tasks while completing the target harvest task.

Lastly, the operators trust within this system was also discussed with roughly half of all operators. Again, past successful interactions with in cab technology such as GPS steering applications have given operators confidence that future technologies will also work and have helped improve their likelihood to adopt and rate of adoption.

## System Usability Scale

The average SUS score for the entire study was 76.43 (SD 12.72) which places this technology between “good” and “excellent” on the adjective ratings scale (Bangor et al., 2009). SUS has been used in a wide variety of technology domains such as Web, Cell Phones, GUIs, Hardware, and others. Applying the SUS measure to technology within the combine makes sense and is a measure that will be taken in future combine simulator studies going forward.

In addition to calculating the SUS, an ANOVA model was tested and found no differences between the three knowledge groups with respect to SUS scores. SUS scores broken into knowledge groups can be seen in Figure 11.



Figure 11. SUS scores by knowledge group, no significant differences.

## Net Promoter

Of the 27 operators who did report Net Promoter scores, they more highly recommended Director over Advisor and additionally reported they were more likely to purchase Director over Advisor. This is not surprising given the experimental setup as Advisor did require more input and attention than Director. Also, Advisor had the potential to perform poorly if given incorrect operator instruction either by missing a cue within a scenario or identifying the incorrect cue altogether. Director by default would perform optimally if never adjusted and therefore saw improved performance over Advisor at any time the scenario went unnoticed as it reduced the potential operator error to 0%. Overall, operator preference for Director is supported. While Director than Advisor when comparing promotor and purchase scores, Advisor may be more appropriate in scenarios when the operator wants to learn from the system or be more involved in the harvest process. Expert operators specifically made comments that Advisor has less value to them as they do not need help adjusting, but they do see value in full automation with Director.

## Conclusion

Overall, both combine technologies, Advisor and Director, were well received by operators and given positive recommender scores with Director receiving slightly more favorable scores than Advisor. Exit interview comments and positive scores indicate that operators are open to the idea of semi-autonomous and fully autonomous combine technology aids operating in real time while they harvest. A common thread of comparison with GPS based steering technology leads operators from all brand experience to be positive and welcoming of additional technological implementation. Assisting

technologies such as Advisor and Director are welcome for both their reduction of operator workload and general fatigue reduction.

Ultimately though, operators in this study preferred and showed improved performance measures when using Director relative to Advisor. Operators performed fewer mistakes, opted to interrupt the system less, and spent less time in the field when using Director. These improvements to performance and efficiency cannot be understated in a domain where efficiency and quality of harvest are directly tied to the financial outcome of the operator in the combine. While there is no baseline data to identify the statistical improvement for Advisor, operators did review Advisor favorably as well and in particular novice operators appreciated the feedback offered to them without having to call someone else for help while harvesting.

Advisor and Director were not viewed as direct competitors by the operators, but as complimentary services on a spectrum of automation. Similar to the current discussion surrounding automated driving in commercial road vehicles (SAE, 2014), Advisor and Director can be seen as subsequent levels of automation following the initial step of GPS guided steering and other single system automation tools within the combine. It is important to note that although operators approved of these systems, many operators expressed their preference to take control for emergency and unusual scenarios.

Overall, the largest implication here is that when technology works as intended, humans seem to prefer the system which takes full responsibility and returns comparable or better results when compared with their own performance. If there are other tasks available for humans to spend their mental resources on, offloading other tasks becomes increasingly attractive. To offer a counterpoint though, some operators did mention that operating the combine manually was akin to “going fishing” and the brief time they are able to operate the combine during the year is somewhat therapeutic. In this scenario, the operator is not seeking automation, simply better tools and controls to successfully complete their task.

## Future work

With any automation technology, it is critical to evaluate whether it leads to higher efficiency overall for the operator, across both nominal and off-nominal conditions. As demonstrated in this research, significant evaluation is possible with a simulator. In future work, studies will focus on validating the fidelity of the simulator experience as representative of the field, so that researchers using the simulator can be assured that the simulator itself is not a distraction from the operator experience. A series of simulation benchmarks could be created, based on known behaviors of operators in the field. If operators in the simulator perform similarly on these benchmark situations in the simulator, those actions serve as evidence that the simulator is providing an accurate experience that will predict behavior in the field. This approach will also allow researchers to measure individuals' specific learning curves regarding the simulator, i.e., the amount of simulator usage required (e.g., training on the Advisor technology) before the operator performs equally well in the simulator as in the field.

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