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An Agricultural Harvest Knowledge Survey to Distinguish Types of Expertise

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Gaining insight into the unique characteristics of participants during user research is a valuable tool for both recruitment and understanding differences within the target population. This work describes an agricultural harvest knowledge survey that was created for user research studies that observed experienced combine operators driving a combine simulator in virtual crop fields. Two variations of the survey were designed, utilized, and evaluated in two separate studies. Both studies found a difference between low and high knowledge operators' performance on the knowledge survey in addition to performance differences. Based on the success of this survey as a population segmentation tool, the authors recommend three criteria for the design of future knowledge surveys in other domains: 1) use real world scenarios, 2) ensure question are neither too difficult nor too easy, and 3) ask the minimum number of questions to identify operator knowledge successfully. Future research aims to create a tool that can discern between system experts (with deep understanding of the system) and practice experts (who primarily have the wisdom of experience).

INTRODUCTION

A difficult issue to assess within the world of operator performance lies in understanding whether expert performers have deep knowledge that is robust to novel situations or whether their knowledge is brittle, rooted in primarily normal operating experiences. This issue is of particular interest when rare operating conditions can be very costly and when systems have high degrees of automation. In both cases, the risk to the system designer is that experienced operators will fail dramatically in unusual or rare operating conditions.

Ideally, operator knowledge can be assessed prior to performing any skill-based task. Performing this assessment before a study has distinct advantages, such as the ability to screen out an operator who may fall below or exceed a particular threshold for expertise, or conversely to recruit a full spectrum of operators to gain a more comprehensive look at results and feedback across skill levels. The present research describes the practice of building a set of applied questions specific to the particular field of study which help identify those individuals who have a clear understanding of the system and its constraints (system experts) relative to those who do not, but who still operate the system well in routine conditions (practice experts). Introducing this type of brief knowledge survey has been successful in identifying those individuals who have a higher level of understanding beyond looking at years of experience or anecdotal impressions.

This knowledge survey has been employed in multiple studies within this research group's work on evaluating agricultural operator performance within a combine harvester simulator. For the purposes of this paper, two specific studies will be highlighted as examples of utilizing this knowledge survey technique. Both studies evaluated the perception and performance of novel automated combine technologies, the first covered a more comprehensive technology and the second a more specific aspect of operator interactions with the

novel technology. This differentiation between a more general application and a more specific application becomes important when designing the survey for the greatest level of impact.

In this research, we suggest that the knowledge survey approach can be generalized into other domains of operator-based research including flight control, robotic surgery, and construction equipment. Providing a tool to help differentiate sample populations by subject matter expertise benefits all work that is concerned with a knowledge based set of distribution skills.

PREVIOUS WORK

For this research, it is worth considering other efforts to distinguish between system experts and practice experts. Cognitive scientist Herb Simon and colleagues showed that experts and novices use notably different schema in their mental models of domains such as chess or physics (Chase & Simon, 1973), but their framework doesn't extend to address the schemas between an expert operator with deep system understanding and an expert operator with significant practitioner experience but superficial system knowledge. Wagner & Sternberg (1985) demonstrated that greater tacit knowledge improves individual performance and career advancement. Don Norman used the term "system image" to describe the mental model formed by the system designer and formed by the user after usage, and suggested that errors result when there is a mismatch (Norman, 1983). Hollnagel and Woods (1983) elaborated on the mental model concept using an engineering control systems lens, while Rasmussen (1983) introduced the Skills-Rules-Knowledge (SRK) model, and Johnson-Laird (1983) analyzed mental models from a cognitive perspective. Kraiger, Ford, & Salas (1993) delivered a model for training evaluation which went further than measuring recall and recognition by also gathering measures of understanding, automaticity, and affect. These researchers

gave us frameworks to use to create models of expert knowledge, but didn't distinguish brittle vs. robust expertise. More recently, in the field of engineering education, Haile (2000) has posited a hierarchy of engineering knowledge, and various researchers have created Concept Inventories (Hestenes, Wells, & Swackhamer, 1992), which are quizzes specifically designed to probe a student's deeper understanding of conceptual theory rather than her ability to solve problems. The goal of these quizzes addresses our goal for students, but we want to assess experts. Bransford, Brown, & Cocking (1999) address this purpose most closely, describing "adaptive expertise" vs. practitioners. However, their analysis did not focus on operators of human-machine systems.

METHODS

This research team proposes three criteria to use when designing an effective knowledge survey:

- 1) The questions should be applied, real-world scenarios about what an operator would do in a situation, so that operators with any experience level will understand the question, even if they are unable to answer it.
- 2) The answers to the questions should neither be too difficult nor too easy in order to reveal a broad spectrum of knowledge across participants.
- 3) There should be as few items as possible for minimum time expenditure.

Both studies had operators drive a combine simulator through a virtual field with changing crop conditions. The combine simulator provides physical operator controls, such as steering and throttle, integrated with a virtual farm field environment that allows for realistic driving and harvest operations (Luecke, 2012).

Combine Technology, Study One

This study investigated operator perception and performance when using a novel combine technology; it included $n = 28$ participants. The researchers created a nine-question survey which investigated the harvest issues present within the research study and were relevant to the sample population of combine operators located in the Midwestern United States. The survey questions were designed to elicit answers covering all major parameter adjustments used by operators within a John Deere combine. By using similarly phrased questions and limiting questions to realistic scenarios encountered by target population, nine questions appropriately covered all content of interest for this study. Operators also answered a demographic survey and usability questions after using the combine technology.

First, the survey answers were based on simulator constraints. The simulator used was modeled on a 2009 John Deere 9770 STS combine; this allowed for a large variety of normal control operations to be performed from within the cab. The list of parameters can be found within Table 1.

Table 1. Harvest knowledge survey for corn harvesters, all parameters and scenarios.

Parameters	Scenarios
Fan speed	Threshing loss
Forward (ground) speed	Broken grain
Sieve opening	Chaff husks in grain tank
Separator vanes	Cobbs in grain tank
Cylinder speed	Unthreshed material in grain tank
Concave clearance	Poor straw quality
Chaffer opening	Separator loss
	Shoe loss
	Excess tailings

The second set of items to build for the survey were the harvest scenarios. This initial list of nine scenarios was determined by consulting subject matter experts at both Iowa State University and John Deere and then investigating agricultural extension documentation (Anderson, 2011; Fone, 2007; Mowitz, 2013; Wehrspann, 2004) to find issues operators commonly face. One of the scenarios was removed from the analysis since it was relevant to only corn operators, and wheat operators were included in the analysis.

With both the parameters and scenarios determined, questions were presented in this format, "Imagine you are harvesting, how would you adjust your combine if you experienced [insert scenario]?" Operators were given the full list of parameters and the option to indicate whether they would increase, decrease, or not change that particular parameter. The questions were presented to the operator in the form of a web survey via Qualtrics as seen in Figure 1.

Imagine you are harvesting, how would you adjust your combine if you experienced threshing loss?

	Increase (+)	Decrease (-)	No Change
Fan Speed	☐	☐	☐
Forward Speed	☐	☐	☐
Sieve Opening	☐	☐	☐
Separator Vanes	☐	☐	☐
Cylinder Speed	☐	☐	☐
Concave Clearance	☐	☐	☐
Chaffer Opening	☐	☐	☐

Figure 1. Example knowledge survey question, as seen by the operator.

To score the harvest knowledge survey, the top two answers were identified from all answers submitted in a "wisdom of the crowd" type evaluation (Aydin, Yilmaz, Li, & Li, 2014; Yi, Steyvers, Lee, & Dry, 2012). The top two answers were validated with expert engineers, combine performance software (Deere, 2012, 2013b), and the John Deere field adjustment guide (Deere, 2013a). After validation, the correct scores were then used to score the overall results.

Combine Reel Technology, Study Two

The next study investigated operator behaviors surrounding the use of the reel while harvesting soybeans. This particular study was split into two groups the first, $n = 15$, investigating reel use and the second smaller group, $n = 7$, utilizing a prototype reel technology. Operators were asked questions on reel use within a wide variety of scenarios

including anticipatory changes as opposed to just reactionary scenarios as used in the general harvest knowledge survey. The options available to operators included reel parameter increase, decrease, or no change at all. A representative list of scenarios and all parameters are listed in Table 2.

Table 2. Reel knowledge survey; parameters and scenarios.

Parameters	Scenarios
Reel up	Tall
Reel down	Weedy
Reel fore	Short or stunted
Reel aft	Droughty
Reel speed up	Lodged
Reel speed down	Slug feeding (poor feeding)
	Stacking on cutter bar
	Beans left on ground at head

To determine which parameters should be included in the reel knowledge survey, we investigated commonly available agricultural extension documents (Butzen, 2013; Huitink, 2000; Minnihan, Hanna, Isaac, & Couser, 2003) and also consulted engineers from both Iowa State University and John Deere who were experts on reel use. Eight unique scenarios and their variants resulted in a total of 20 scenarios to be considered by operators, each scenario with seven potential options to adjust the parameters. The survey as seen by operators in Qualtrics can be seen in Figure 2.

Imagine you are harvesting soybeans. How would you adjust your reel if you experienced:

	Up	Down	Fore	Aft	Speed up	Slow down	No change	Not sure
Tall	☐	☐	☐	☐	☐	☐	☐	☐
Weedy	☐	☐	☐	☐	☐	☐	☐	☐
Short or stunted	☐	☐	☐	☐	☐	☐	☐	☐
Droughty	☐	☐	☐	☐	☐	☐	☐	☐
Lodged	☐	☐	☐	☐	☐	☐	☐	☐
Slug feeding (poor feeding at cutter bar; not uniform)	☐	☐	☐	☐	☐	☐	☐	☐
Stacking (on cutter bar; looks like clumping)	☐	☐	☐	☐	☐	☐	☐	☐
Beans left on ground at head	☐	☐	☐	☐	☐	☐	☐	☐

Figure 2. Eight of the 20 questions on the reel knowledge survey as viewed by operators.

To score the reel knowledge survey, the top three popular answers were identified from all answers submitted and these answers were validated with expert engineers, combine performance software (Deere, 2012, 2013b), and agricultural documents (Butzen, 2013; Huitink, 2000).

By identifying the needs of each study, relevant questions could be identified as potential differentiators between those with lower and higher harvest knowledge. These questions were then used to assign operators to a spectrum of knowledge that can be divided into separate groups. This knowledge score is a useful moderating variable to divide participants into subgroups while exploring the primary goal of the study.

FINDINGS

Combine Technology, Study One

All 28 operators completed the general harvest knowledge survey. Upon inspection of the score distribution, all operators had a mean score of 11.21 (SD 3.24) out of a maximum of 16. Given this value, knowledge groups were split into low and

high subsets where low knowledge ≤ 11 ($n = 15$) and high knowledge was >11 ($n = 13$). Operators in the high knowledge group had a mean score of 13.92 (SD 1.5) which was higher than the low knowledge group's score of 8.87 (SD = 2.36), $t(24) = 6.8635$, $p < .0001$. A boxplot of these scores can be seen in Figure 3.

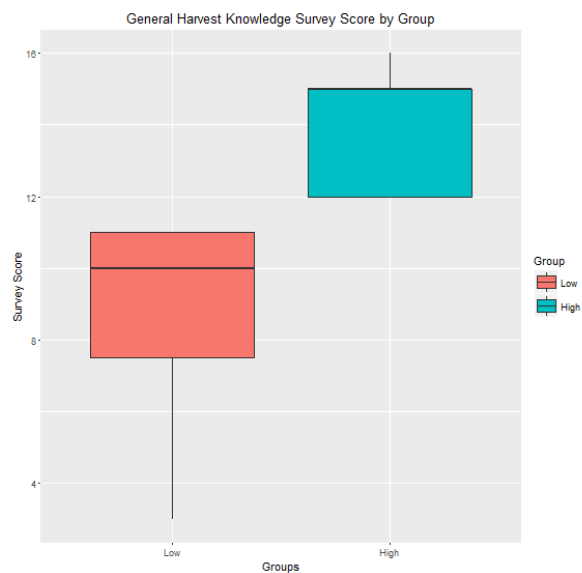


Figure 3. General harvest knowledge survey scores split into low and high groups.

Additionally, all operators were split into three knowledge groups where the medium group was defined as the mean score $\pm$ one standard deviation. The low, medium, high split can be seen in Figure 4. Using a one-way ANOVA, a difference between groups on knowledge scores can be seen $F(2, 25) = 53.71$, $p < .0001$. All three individual groups were different from one-another as confirmed by a Tukey posttest where all p values were $< .0001$.

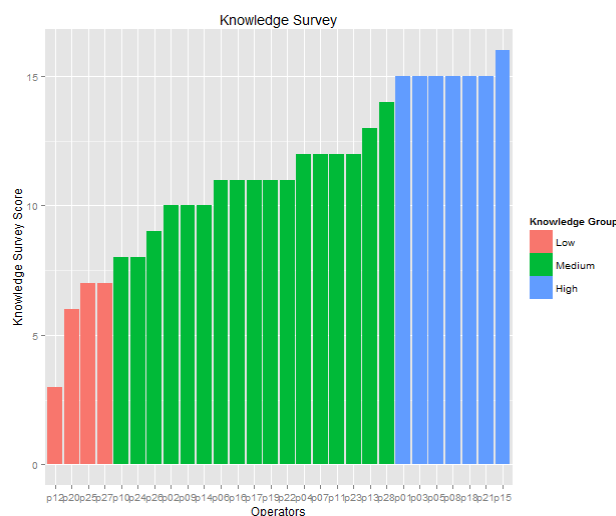


Figure 4. General harvest survey scores split into three groups, maximum score of 16.

Using the two factor split of low and high knowledge groups, additional testing was performed to investigate differences within the group. While no difference was found in operator satisfaction or System Usability Scale (SUS) ratings between the two groups, there was a performance difference between the number of times operators stopped the combine during the process of the study which was marginally significant. Operators within the high knowledge group brought the combine to a full stop more than operators in the low knowledge group, $t(17) = 1.8361$, $p = .084$ and an effect size of $d = .65$. No differences in knowledge group were found when comparing experience levels or other demographic data.

Combine Reel Technology, Study Two

Thirteen of the 15 operators completed the 20 question reel knowledge survey. The mean score was 22.69 (SD 7.48) with a maximum value of 43. Given this value, knowledge groups were split into low and high subsets where low knowledge ≤ 22 ($n = 5$) and high knowledge was >22 ($n = 8$). Operators in the high knowledge group had a mean score of 27.5 (SD 3.55) which was higher than the low knowledge group's score of 15 (SD = 5.05), $t(6) = 4.8395$, $p < .0023$.

Again, all operators were also split into three knowledge groups where the medium group was defined as the mean score $\pm$ one standard deviation. The low, medium, high split can be seen in Figure 5. Using a one-way ANOVA, a difference between groups on knowledge scores can be seen $F(2, 10) = 22.71$, $p = .0002$. While the low group was different from both medium, $p = .0007$, and high, $p = .0003$, medium and high groups were not different from each other.

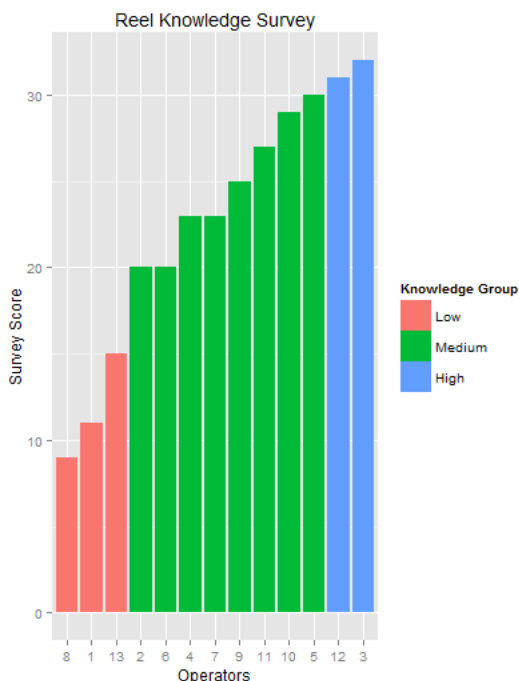


Figure 5. Reel knowledge survey scores split into low, medium, and high groups.

In the second part of the reel technology study, seven operators utilized the prototype combine technology. High knowledge operators ($n = 5$) scored 18 (SD 1) which was higher than the low knowledge group ($n = 2$) with 7.5 (SD 2.12) with marginal significance, despite the low group size, $t(1) = 6.7082$, $p = .06937$. Additionally, there was no difference between low and high groups when inspecting the reduction of total interactions between the first baseline trial and second trial with prototype combine technology. There was a large effect size, $d = 1.32$, yet the reduction in interactions in high knowledge participants, mean 133.8 (SD 68.7) was not statistically different from low knowledge participants, mean 49.5 (SD 40.3), as the confidence interval is wide and includes zero, mean = 84.3, 95% CI [-39.0, 207.6], $t(2.0) = 3.497$, $p = .125$. As the sample size is very small for these groups (high $n = 5$ and low $n = 2$) it is reasonable to collect additional data to see if this effect holds. These groups can be seen in Figure 6.

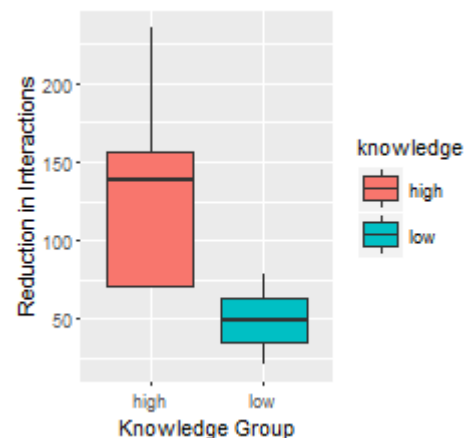


Figure 6. Interaction differences by knowledge group.

DISCUSSION

Following the three criteria outlined above of 1) realistic scenarios, 2) representative sampling, and 3) minimum questions, this work was able to successfully follow Criteria 1 and 2, but could improve upon 3. Scenarios were realistic enough as they represented issues that operators had some experience with and were able to answer questions about. For the eight-question general harvest knowledge survey, the questions were not overly difficult or too easy as indicated by the distribution of scores. The 20-question reel harvest knowledge survey, though, did not approach the maximum score of 43, indicating the questions were either too difficult or, more likely, too varied. The third criterion was better met with the general knowledge survey's eight-item list than the reel survey's 20-item list. Future variants of these surveys will likely change to better fit these goals overall.

The variation present in knowledge groups presents an opportunity to understand what type of understanding users have and what expectations engineers should have of their user when making updates and building new technologies for their users. This type of evaluation is one step closer to helping engineers successfully map their mental model to the

mental model of the user and bridge the gulf which exists between the two (Norman, 1988).

Using a knowledge survey can also be used to begin to identify what types of operators make up a more representative sample. For example, individuals who successfully reacted to cues within the virtual field by adjusting their ground speed identified they were able to recognize when something was not correct, but did not know how to optimally adjust the combine parameters to both maximize grain quality and efficiency; most of these individuals simply decreased ground speed to deal with issues. When ground speed is the primary adjustment made, operators indicate they are willing to take the decreased efficiency in ground speed, but this does not indicate whether they understand that they are also sacrificing the quality of the grain sample as well. In contrast, operators who scored high on the knowledge survey indicated they can both identify what the problem is and how to best address it. Both these groups were able to identify issues, but operators in the higher end of the knowledge spectrum were better equipped to both identify issues and also take the correct resolution action.

Somewhat counterintuitive is the finding that experience did not directly correlate with knowledge level. More experienced operators who were not required to improve their performance or understanding past the minimum level required to be financially successful will fall behind other operators of all experience levels who have a stronger grasp on which adjustments to make and further, why to make them.

This work suggests that low knowledge operators can be identified as a type of novice and the high knowledge operators can be identified as closer to experts, unfortunately this spectrum of expertise only identifies practitioner knowledge. This spectrum of practitioner knowledge identifies whether or not operators understand what action to take when they encounter an issue, but does not identify whether or not these operators understand the mechanical system knowledge underlying the parameters that were adjusted. An example here would be an operator with high practitioner knowledge, but low system knowledge understands that when they encounter corn cobs in the grain tank, the correct solution is to decrease the sieve opening. Although tightening up the sieve may alleviate the issue of cobs in the grain tank, this operator may not understand why the issue was solved. The operator who has both high practitioner knowledge and high system knowledge understands both how to fix an issue and why the selected resolution works.

Future work aims to understand what an operator's practitioner and system knowledge scores are as independent, but related, measures. With respect to scoring the surveys, as more data is collected more advanced crowdsourced scoring techniques could be applied (Aydin et al., 2014; Bachrach, Graepel, Minka, & Guiver, 2012). Additionally, the existing survey should be validated by in a more robust fashion such as performing a principal component analysis to confirm that all questions contribute strongly to the overall score (DeVellis, 2012). Cronbach's Alpha could also be utilized to evaluate the survey's reliability and consistency with additional responses. Lastly the survey could be validated against any known related metrics.

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