A preliminary decision tree modeling of factors that determine readiness to use exoskeletons in construction

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The construction industry is labor intensive, with workers having to routinely perform tasks that involve exposures to well-recognized risk factors of work-related musculoskeletal disorders (WMSDs). Such risk factors include high muscle loads, repetitive exertions, and non-neutral postures associated with sustained bending or overhead work (Zhu et al., 2021). Exoskeletons (EXOs) are a promising intervention to address these ergonomic challenges. EXOs are assistive, wearable devices designed to reduce physical demands, especially on the back or shoulders. A number of laboratory studies have demonstrated the efficacy of EXOs in reducing physical demands (Huysamen et al., 2018; Kim et al., 2018; Madinei et al. 2020a, 2020b; Alemi, et al. 2020). However, data on practical adoption in the field is still limited.

In an effort to facilitate industrial adoption, Kim et al. (2019) gathered construction stakeholder perspectives to help understand opportunities and barriers for EXO adoption. We have conducted a subsequent study to follow up and elaborate on the issues that arose in our pilot work. The objective of the present study was to identify key factors that predict 'readiness to use' passive EXOs in the construction industry. Based on the Prevention through Design Adoption Readiness Model (PtD-ARM; Weidman et al. 2015), readiness can be defined as a "state-of-mind about the need for an innovation and the capacity to undertake technology transfer", and involves beliefs, attitudes, and intention where interventions can enhance readiness, and increase success of technology adoption.

A total of 361 participants responded to a 70-question online survey regarding prior EXO knowledge, work history, personal factors, task characteristics, perceived benefits, health and safety concerns, and facilitators for adoption and use. Machine learning methods such as decision trees can simultaneously process such large numbers of predictors and extract the importance of individual variables (Strobl et al. 2009). Hence, we conducted a decision tree analysis, which was done using the conditional interference tree (*ctree*) function of the *party* package in R (Hothorn et al., 2006), which corrects for multiple testing across a number of predictors. The *ctree* function uses *p*-values for both variable selection, and node splitting or stopping criteria. A conventional alpha level of 0.05 was used as the stopping criterion.

Responses (n=227) were obtained for the question, "If given the option, would you want to try an exoskeleton?" (*AgrTry*) Response options were "Yes", "No", and "Maybe". These were predicted using independent variables spanning: age, gender, work experience, company size, trades, perceptions of exoskeleton users, sharing, fit, storage, cleanliness, duration of use, job physical demands, safety concerns with other equipment or use locations, and reported shoulder and back pain levels.

The decision tree model for readiness to try an EXO (Figure 1) shows the hierarchy of the significant variables. To interpret a decision tree, one typically starts at the top or root node, which contains the first significant split in the data and traces a path down to a leaf node with the predicted responses. The root node variable *AgrProd* shown in Figure 1 was a statement "I think wearing an exoskeleton could make me more productive", where agreement was evaluated on a 5-point Likert scale ranging from Strongly Agree (1) to Strongly Disagree (5). Those who selected Strongly Disagree (5), representing 2.6% of the 227 responses, were split from all others (p<0.001) forming Node 7, with over 80% of such individuals indicating they were not willing to try an EXO.

Decision Node 2 split the data using the variable, *AgrFat*, which was a statement "I think wearing an exoskeleton would reduce my fatigue at the end of the day", using the same 5-point Likert scale as Node 1. Those who responded with Strongly Agree (1), representing 33% of responses, were split (p<0.001) from others at Node 3, with over 90% of them indicating they are ready to try an EXO. For the remainder of the *AgrFat* variable, agreement levels are then split using the *Roof* variable (p=0.006) that asked "Would you wear an exoskeleton on a roof?" Node 5 shows 29% of those would not wear an EXO while on the roof, while Node 6 combines the remaining Yes and Maybe opinions. While both Nodes 5 and 6 yielded mixed readiness responses, the unwillingness to wear an EXO on a roof brought down the overall responses indicating willingness to try an EXO.

This exploratory decision tree analysis of survey responses revealed three important factors contributing to EXO readiness-to-use in construction. Both productivity and fatigue factors can map to the PtD-ARM construct of Relative Advantage, with those more strongly agreeing to their benefits showing more readiness to use an EXO. Conversely the Roof EXO use factor mapped to the Compatibility construct reducing readiness.

This is ongoing research to study the complex interactions that decision trees can reveal. Some typical limitations of decision trees such as tree (in)stability, optimal choice of the alpha parameter to determine best split of each node, and correlations between predictor variables are being explored. It is expected that by relaxing the alpha parameter to grow larger trees, additional readiness factors and more complex interactions will be found. Such trees can then be interpreted from a variety of different lenses to guide decision making and adoption, such as for understanding to what extent specific issues such as hygiene or fit may affect EXO adoption readiness, whether different bottlenecks exist for EXO adoption among different subsets of users (based on demographic, anthropometric or task-based characteristics), or for determining specific training needs for different user groups.

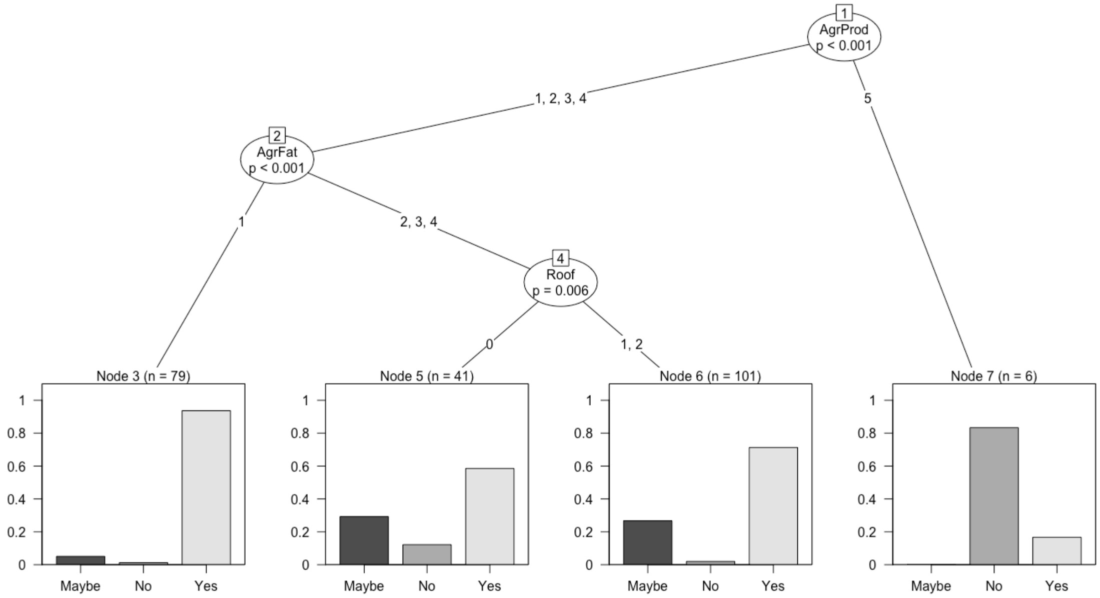

Figure 1: Decision Tree with alpha = 0.05. Nodes 1 and 2 split with 5-point Likert scale with Strongly Agree (1) and Strongly Disagree (5). Node 4 split with not use (0) and Maybe (2)/Yes(1)

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