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ARTICLE

Economic viability of robotic fruit harvesters to reduce large seasonal labor demands: Analysis of Gala and Honeycrisp apples

Diane Charlton[1] | **Stephen Devadoss**[2] | **R. Karina Gallardo**[3] | **Jeff Luckstead**[3] | **Stavros Vougioukas**[4]

[1]Montana State University, Bozeman, Montana, USA

[2]Texas Tech University, Lubbock, Texas, USA

[3]Washington State University, Pullman, Washington, USA

[4]University of California, Davis, California, USA

Correspondence
Diane Charlton, Montana State University, Bozeman, MT USA.
Email: diane.charlton@montana.edu

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Abstract

Fruit harvesting is labor intensive and relies heavily on a decreasing immigrant farm labor supply. This study develops a model to compare robotic and manual apple-harvesting profits. Given the anticipated performance of robotic prototypes, we find that a grower could spend $248.42 per acre per year on a robotic harvester and obtain the same profit as manual harvest. Marginal improvements in the percent of fruit harvested, harvester speed, and robot-induced damage would greatly enhance robot profitability and farmers could spend more on the harvester and still obtain the same profit as manual harvest.

KEYWORDS

agricultural mechanization, farm labor, technology adoption

JEL CLASSIFICATION

Q16, J43

1 | INTRODUCTION

For the last 20 years, and even longer, farmers have contended they could not survive without a continuous supply of new foreign workers (Martin et al., 2006). Today, more than two-thirds of the U.S. crop workforce is born in Mexico (U.S. Department of Labor, 2022). Nevertheless, rural Mexico is undergoing an agricultural transformation, causing the share of rural Mexicans who work in agriculture (whether in the United States or Mexico) to decline and real farm wages in the United States to rise (Charlton & Taylor, 2016, Zahniser et al., 2018). Even in the 1990s, when the number of Mexican immigrants living in the United States rose by nearly 5 million people, the share of recent arrivals employed in agriculture was declining (Card & Lewis, 2005). In the 2010s, following the 2008 Great Recession, net migration from Mexico to the United States fell to zero or negative, ending the largest wave of immigrants in history from any single country to the United States (Passel et al., 2012).

These changes in immigration trends put tremendous pressure on fruit and vegetable producers who must compete with producers in countries with access to a more abundant, lower-cost workforce. To remain competitive in a global marketplace as farm labor supply from Mexico becomes more tenuous, the U.S. fruit and vegetable sector will need to innovate methods to produce crops more efficiently with fewer labor inputs. In the long run, this will necessarily include using robotics to perform many of the routine tasks currently performed by hand. This study develops a model for the adoption of automated harvesting technology and empirically assesses the economic feasibility of adopting a robotic harvester to pick apples. Based on current robot protypes performance, we assume in this study that the robot will pick 60% of apples on the trees; therefore, our analysis calls for manually picking the remaining 40% of apples left in the tree. Toward this end, we compare variable costs, revenues, and profits from manual harvesting versus robotic harvesting of Gala apples. For the computation of profits, we utilize detailed apple production budgets from Washington State University. We also utilize parameters for robotic picking speed, robot-induced damage, and efficiency from the literature (Bac et al., 2014; Silwal et al., 2017). The upper ends of these parameter values are 'optimistic' (Hu et al., 2022) and explore how much performance should increase to make robots cost-effective.

One of the primary contributions of our paper is to demonstrate how the economic feasibility of adopting robotic fruit harvesters changes as robot performance and market prices vary. Specifically, we conduct four break-even analyses to determine (a) the maximum feasible up-front cost for the robotic harvester that will yield the same profits as manual harvesting, (b) how the economically feasible up-front cost changes for different picking speeds along with robot-induced damage rates (which we model as the difference between the packout rate from manual harvest and packout rate of the robot) and percentages harvested, (c) the tradeoff (e.g., elasticities) between the wage rate and changes in the three robotic parameters (picking speeds, robot-induced damage rates, and percentages harvested) given an initial up-front robot cost, and (d) the feasibility of robotic harvesters for Honeycrisp apples, which are of higher value and are more prone to robot-induced damage than most other varieties, including Gala. If farm labor costs continue to rise relatively quickly, as they have in recent years, our findings suggest that robotic harvesters may soon be economically viable for use on commercial apple farms. For instance, the results show that if the wage rate rises by 25%, growers could afford a robot that is 127% more expensive without being made worse off. This study highlights the urgency of improving technological innovations and testing robotic prototypes so that growers can make informed decisions regarding robot adoption and orchard investments. Further research is also needed to shed light on the potential economic impacts of new technologies, including economies of scale, changes in demand for labor and skills on farms, and impacts of technological advances in downstream markets.

While this paper focuses on apples, the insights and methods developed (i.e., the trade-off between robot-induced damage rates, percentage harvested, and picking speeds) generally apply to robotic use in fresh market tree fruits. Furthermore, the results contribute to the ongoing policy debate on agricultural labor shortages and the dwindling pool of agricultural field workers. As wages continue to rise, the ability of all high-value fruit and vegetable producers to survive and maintain a competitive edge will become tenuous. This study contributes to the agricultural economic literature by (a) quantifying the break-even up-front cost of robotic harvesting under an array of robot parameterizations and (b) utilizing a root-finding algorithm to compute the elasticities of robotic parameters to changes in wage rates since robots could become more affordable as labor costs rise. Our findings will benefit engineers designing robotic prototypes to assess tradeoffs between reducing robot-induced damage, accelerating the picking rate, and lowering the robot cost. Findings will also be useful to farm managers considering robotic harvesting technologies and to policy-makers considering changes to immigration, guest-worker policy, and government funding for research and development in agricultural mechanization.

The paper proceeds as follows. Section 2 presents background information on the U.S. apple industry, labor scarcity, and the need for mechanization in apple production. Section 3 develops an economic model for the adoption of a robotic fruit harvester. Section 4 discusses the data and methods for profit comparisons under these two operations. Section 5 presents four break-even analyses. The last section concludes the paper.

2 | BACKGROUND

This study examines the application of robotic apple harvesters in Washington state.[1] Rising wages and difficulty finding local farm workers have led producers to seek labor-saving alternatives. In this section, we describe the U.S. apple industry, including the large seasonal variation in labor demand, employment of H-2A guest workers, and current developments in robotic harvesters.

2.1 | U.S. apple industry

The United States is a major producer in the world's apple market, but rising input costs, especially the rising cost of labor, could jeopardize the long-term economic sustainability of producing apples in the United States (Gallardo & Sauer, 2018).[2] Labor constitutes approximately 54% of the variable costs in U.S. apple production, with wage rates steadily increasing (Gallardo, 2020). For U.S. apple producers, the availability of labor for harvest and other operations is a major and ongoing challenge (Gallardo et al., 2019). Similar challenges have been observed across numerous agricultural crops and regions (Calvin et al., 2022; Devadoss & Luckstead, 2011; Richards, 2018). This trend is underscored by the tightening labor supply at the national level and the declining share of farm workers who migrate to follow crop harvests and other labor-intensive crop production activities (Fan et al., 2015).

Washington has an estimated 40,000–50,000 seasonal harvest workers, many of whom work in apple orchards (Calvin et al., 2022). A labor shortfall during a critical operation, such as harvest, could cause growers to lose part or all their crops (Luckstead et al., 2012). Even though real farm wages are rising, growers indicate that it is difficult to attract new workers.[3] Few domestic-born workers are willing to perform the physically challenging work required for long hours in apple orchards (Devadoss & Luckstead, 2008; Luckstead et al., 2022; Sarig, 2005). To maintain access to a reliable labor supply, apple growers rely heavily on the H-2A agricultural guest worker program (Devadoss & Luckstead, 2019; Castillo and Charlton, 2022). In 2023, there were 378,000 certified H-2A workers in the United States, with 35,680 of these individuals employed in the state of Washington (U.S. Department of Labor, 2024).

The specialty crop industry, including the fresh apple sector, questions whether H-2A can resolve the farm labor scarcity problem in the long run (Rutledge & Merel, 2022). Hiring H-2A workers requires a substantial investment since the employer must provide housing to workers, transport workers from and return to their home countries, and file paperwork with multiple

[1]This study focuses on Washington state because this state produces approximately 70% of US apple production (U.S. Department of Agriculture-National Agricultural Statistics Service, 2023).

[2]In 2020, the United States produced 4.65 million tons of fresh apples, second only to China with 40.5 million tons (U.N. Food and Agriculture Organization, 2022). The United States was the third largest apple exporter, with 808 thousand tons, following China with 1.06 million tons and Italy with 935 thousand tons (U.N. Food and Agriculture Organization, 2022).

[3]In 2021, workers picking apples in Washington State under piece-rate wages earned at least 20 percent more than the minimum wage (Calvin et al., 2022).

government agencies and abide by strict protocols. The periods when the critical amount of labor is needed cannot be forecasted precisely since the timing of fruit ripening varies depending on growing conditions, which makes it costly to contract workers ahead. Furthermore, it is reported that agricultural operations in the United States face challenges getting workers across the border in time for harvest (Laudato, 2021).[4] Personal communications with principal operators of apple orchards in Washington indicate that, as of 2023/24, the fixed costs associated with hiring H-2A workers is about $4.50 per hour, which is in addition to the hourly Adverse Effect Wage Rate (AEWR), the minimum wage that employers are required to pay H-2A workers in their state.

Labor aids, like hydraulic platforms that move throughout the orchard and elevate workers to prune trees or pick apples without ladders, can make workers more productive on average and reduce labor costs (Brady et al., 2016). However, platforms must increase labor productivity by at least 13% to be economically feasible (Brady et al., 2016). In-person interviews with farm managers and field supervisors indicate that platforms are primarily utilized for horticultural activities, such as training, pruning, and thinning. During harvest, when picking crews are paid piece rate, they spurn platforms because the slowest worker constrains the pace of the platform as it moves through the orchard, thus limiting the income of the faster pickers.

With heightened global competition in apple production, rising U.S. labor costs, and the questionable long-run viability of the supply of H-2A guest workers, private and public enterprises have been working on robotics as a potential long-term solution to harvest apples and other labor-intensive fruits.

2.2 | Robots and labor

Engineers and growers agree that in the long run, multipurpose robotic machines that can complete several orchard operations such as pruning, thinning, chemical spraying, and harvesting will be most economical by reducing labor demand for year-round operations (Zhang et al., 2019). However, since harvest is typically the most labor-intensive operation, robotic harvesting is currently the primary engineering focus. Robotic-harvesting systems for fruits typically consist of a computer vision system (comprising of one or more cameras and appropriate software) to detect and locate target fruit and maneuver around obstacles; a manipulation system (comprising of one or more arms) to reach the target fruit; an end-effector to detach and collect the fruit from branches; and a conveyance system to bring fruit to a bin.[5]

Robotic fruit harvesting technology has remained at a pre-commercial stage for a long time (Vougioukas, 2019). Economic analysis of robotic strawberry harvesters in 2021 concluded that, although robotic strawberry harvesters held promise for reducing labor costs in the strawberry industry, the technology must improve and wages increase before the robots would be economically viable for large-scale use (Delbridge, 2021).

Most robotic apple harvester prototypes developed by academic research labs utilize a single picking arm (Au et al., 2023; Bu et al., 2022; Silwal et al., 2017; Zhang et al., 2019). Only recently, a multi-arm robot was developed to increase picking speeds (Li et al., 2023). Commercial agricultural tech firms such as FFRobotics Ltd., and Advanced Farms Technologies, Inc., have built multiple-arm prototypes. However, before robots are deployed commercially picking efficiency, packout rate, affordability, and performance reliability must improve (Vougioukas, 2019). When robots are sold for commercial use, many producers will wait to adopt them if they are difficult to operate and unreliable, anticipating significant improvements in future models.

[4]Conversations with apple growers in Washington State corroborated the story reported on CBS News (Laudato, 2021) that H-2A workers sometimes get held up at the border, possibly for several weeks, even though they have visas.
[5]See Zhou et al. (2022) for a detailed description of the technical aspects of robotic harvesting.

Picking efficiency is the share of apples the robotic harvester removes from the tree, limited by both sensing and actuation.[6] Fruit visibility is limited by occlusions from the tree, the orchard infrastructure, and nonuniform illumination, combined with imperfect vision hardware and software. Meanwhile, complex tree canopy structure and orchard infrastructure, combined with limitations in the mechanics and control of the arms and grippers, are the main actuation-related factors that lower picking efficiency (Vougioukas, 2019). The interaction of these factors also affects the picking rate (the time needed to harvest one fruit by removing it from the tree and transferring it to the bin). For instance, increasing the speed of harvesters often comes at the cost of increased bruising, which greatly diminishes the value of the harvest. Packout rate is the percentage of harvested fruit in the bin that meets the standards for sale in the fresh market. This rate depends on apple variety, the ability of the vision system to detect which fruit in the tree meets standards for picking, the damage-prevention capability of the mechanics and control of the gripper, and the fruit conveyance system. In this study, we denote picking efficiency times packout rate as the 'harvest efficiency'.

3 | MODEL

This section defines the cost–benefit model central to the grower's decision to adopt robotic harvest technology. We consider a risk-neutral grower who adopts the robotic technology if annual profits per acre from utilizing the robot (π_R), denoted with subscript R, are greater than annual profits per acre from manual hand-harvest (π_M), indicated with subscript M: $\pi_R > \pi_M$.

Profits from manual harvest can be expressed as

$$\pi_M = p \times Y \times \beta_M \times \gamma_M + p_C \times Y \times \beta_M \times (1 - \gamma_M) - (w_M \times HL_M + pck_M + w_M \times OL_M + ovc + \delta fc), \tag{1}$$

where p is the farmgate price for apples that meet fresh market standards in \$/bin, Y is the available amount of marketable fruits on the trees (produced yield) measured in bins/acre, γ_M is the packout rate (i.e., the percent of apples that meet fresh market standards), β_M is the percent of apples the picker removes from the tree, and p_C is the price of apples that do not meet the fresh market standards and could be used in processing. Thus, total revenues consist of revenue from the sales of apples that meet the fresh market standards, which is a significant share of the revenues, and on a smaller scale, revenues from the apples that do not meet the fresh market standard and are sold to the processing market. w_M is the hourly farm wage rate for manual labor, $HL_M = Y \times \beta_M \times s_M$ is the picking labor hours per acre for manual harvest with s_M defined as the picking rate in hours per bin (hrs/bin), $pck_M = (rc + pb \times fb_M) \times Y \times \beta_M$ is the packing cost, where rc is the receiving charge per bin by packers, pb is the variable cost or packaging fee per box, $fb_M = \left(\frac{T}{L}\right) \times \gamma_M$ is the number of boxes per bin, T is the weight of one bin of apples in pounds, and L is the number of pounds per box.[7] $OL_M = (K + H) \times Y \times \beta_M$ represents other labor hours for checkers (K) and hauling (H) in hours per acre, ovc are other variable costs for horticultural management, maintenance and repair

[6]This definition is different from the one used in Vougioukas (2019) because we need to separately consider the rate of fruit successfully removed from the tree and the packout rate to account for the share of picked fruit that is bruised by the robot. This distinction permits us to perform sensitivity analyses for picking efficiency and robot-induced damage. In this paper, we call the product of picking efficiency and packout rate the "harvest efficiency", which is what Vougioukas (2019) calls the picking efficiency.

[7]In Washington state, the unit to measure the amount of apples harvested by pickers is a bin. Following Gallardo and Galinato (2021), a bin has a capacity of 925 lbs. Harvested apples are transported in bins to the packing house. The packing house charges vary across different packing houses and consist of charges/receiving fees per bin and charges per box. Once apples are received by the packing house, growers are charged a receiving fee per bin. Apples are stored in bins until they can be sold to the next entity in the supply chain, that is many cases is the retailer. Then apples are washed, sorted by size, and apples that do not meet the strict Washington State fresh apple standards are separated to be sold as processed. Then fresh apples are waxed and put in boxes of 40 lb each. There are additional charges and fees per box (i.e., grower association assessments, royalties for nonpublic varieties, etc.) to the grower on top of the packinghouse charges.

costs for buildings and machinery, fuel and lubricant costs of equipment, and δfc is the annualized discounted fixed costs. These annualized fixed costs include depreciation on orchard infrastructure, machinery and equipment property taxes, insurance and management costs, and the opportunity cost of land, capital, and management labor in the form of foregone interest. See Gallardo and Galinato (2021) for a complete description of costs included in ovc and δfc.

In this study, we assume that the robot harvests only 60% of the apples, and workers hand pick the remaining apples. We assume that robotic harvest incurs the same ovc and fc costs as manual harvest and additionally the cost of the robot. Net revenue from robotic harvest (N_R), excluding the cost of the robot, is

$$\begin{aligned} N_R = {} & p \times Y \times \beta_R \times \gamma_R + p_C \times Y \times \beta_R \times (1 - \gamma_R) + p \times Y \times (1 - \beta_R) \times \gamma_M \\ & + p_C \times Y \times (1 - \beta_R) \times (1 - \gamma_M) - (w_R \times HL_R + w_M \times HL_C + pck_R + m_R + w_M \times OL_R \\ & + ovc + \delta fc). \end{aligned} \tag{2}$$

The additional annualized discounted cost of the robot is δfc_R, so profits from robotic harvest (π_R) accounting for the cost of the robot is

$$\pi_R = N_R - \delta fc_R. \tag{3}$$

In equations (2) and (3), β_R is the picking efficiency; γ_R is the packout rate for apples from robot harvesting, which differs from the packout rate of manual harvest. The total revenue consists of four components: revenue from fresh-market sales of apples from robot harvesting, revenue from sales to the processed market of bruised apples from robot harvesting, revenue from fresh-market sales of apples handpicked from manual labor after the robot harvest, and revenue from sales to the processed market of bruised apples from manual harvesting. w_R is the robot operator wage rate; $HL_R = Y \times \beta_R \times s_R$ is the robot operator hours per acre, where s_R is the picking speed of the robot in hours per bin; $HL_C = Y \times (1 - \beta_R) \times s_M$ is the picking labor hours per acre to manually pick the leftover apples after the robot harvest; $pck_R = (rc + pb \times fb_R) \times Y \times \beta_R + (rc + pb \times fb_M) \times Y \times (1 - \beta_R)$ is the packing cost for apples harvested by the robot and the remaining apples manually harvested by workers, $fb_R = \left(\frac{T}{L}\right) \times \gamma_R$; m_R is the annual per acre cost of robot maintenance, fuel, and lubrication; $OL_R = (K + H) \times Y \times \beta_R + (K + H) \times Y \times (1 - \beta_R) = (K + H) \times Y$ represents other labor hours for checkers (K) and hauling (H) in hours per acre; and δfc_R is the discounted annualized up-front cost of purchasing the robot. Thus, the total costs consist of the picking cost of the robots and manually harvesting the remaining apples, packinghouse charges, robot maintenance costs, checkers and hauling costs, other variable costs, and fixed costs.

In the analysis below, instead of taking the robot cost as given, we endogenously solve for the robot cost (δfc_R) such that profits from manual harvesting are equal to profits from robotic harvesting; we term this cost as the "break-even robot cost." That is, we solve for the robot costs such that

$$\delta fc_R = N_R - \pi_M. \tag{4}$$

In doing so, we determine the up-front robot cost that farmers could invest and earn profits equal to manual harvesting. Assuming robots incur a lower percentage of yield that meets the standards to be sold in the fresh market, harvest-labor savings from utilizing robots must sufficiently offset revenue losses associated with the increased cull rate and up-front investment in the robot.

4 | DATA ANALYSIS

Data and parameters for the baseline case of manual hand-harvest come from the "2019 Cost Estimates of Establishing, Producing and Packing Gala Apples in Washington" (Gallardo & Galinato, 2021). The 2019 Gala baseline enterprise budget is based on a representative 300-acre farm that grows apples on 225 acres, sweet cherries on 48 acres, and pears on 27 acres. We selected Gala apples for the analysis because it is the dominant variety based on the volume of apples produced in Washington State,[8] And in 2021, Washington accounted for 69% of all apples produced in the United States (Gallardo, 2023).

Costs for robotic operations are based on conversations with robot engineers and apple farmers. Table 1 summarizes key parameters embedded in the profit equations.

We utilize the information presented above in this section to conduct profit analyses between manual and robotic harvesting. The computations are presented in Table 2, and we provide a detailed explanation of the analysis and computations in Appendix A.

4.1 | Profit difference

Total revenues per acre from Gala apples that meet fresh-market standards are \$30,784 from manual harvest and \$29,630 from robotic harvest. Apples that do not meet the fresh-market standards are sold at a discounted price for processing generating revenues of \$1,036 for manual and \$1,191 for robot harvesting. Thus, the total revenue is \$31,820 for manual harvest and \$30,821 for robotic harvest, implying a revenue loss of \$999 per acre from the robotic harvester.

We assume that one worker can operate two robots and the hourly operator wage rate, including overhead costs, is 40% higher than the wage rate for manual labor. However, total operator costs would be lower if an operator could handle several robots as is the case of new robotic strawberry harvesters (Advanced Farms, 2023). We test the sensitivity of robot profitability by considering one operator for one robot and one operator for three robots. The picking cost per acre for manual harvest is \$2,255 and for robotic harvest is \$1,107, resulting in labor-cost savings of \$1,148 per acre from robot harvest. Note that for Gala apples, the labor-cost savings from robot harvest outweigh the loss in revenue. Packing costs per acre amount to \$18,360 for manual harvesting and \$17,972 for robotic harvesting because fewer apples are packed to the fresh market due to higher a bruising rate under robot harvest than manual harvest.

We assume other variable costs in hand harvest carry over to robot harvest, including the costs for checkers and haulers, but robots entail additional fuel and maintenance costs. Finally, we assume that all fixed costs, excluding the up-front robot cost, are the same across both harvesting methods.

The profit from hand harvesting is −\$10,721 per acre[9] and the net revenue for robotic harvesting, excluding the up-front cost of the robot, is −\$10,473 per acre. Thus, there is an annual net revenue difference (*ANRD*) of \$248 per acre under robotic harvesting compared to manual harvesting of Gala apples.

5 | BREAK-EVEN ANALYSES

Currently, robot apple harvesters are not commercially available, and thus the cost of the robot harvester is not known. In our analysis, we compute the plausible cost of the robot (δfc_R in equation 4) that will make profits from robot harvesting equal profits from manual harvesting, i.e., δfc_R is the difference between profits from robot harvesting and manual harvesting. Our primary

[8]In 2022, Gala apples represented 21% of the total volume of apples (Gallardo, 2023).

[9]Note that there are negative annual profits from growing Gala apples in the cost and return study used to calibrate this model. This is typical for perennial crops where the fixed costs are usually large.

TABLE 1 Parameters and values for manual and robotic harvests.

Parameters	Manual harvest	Robotic harvest
Price, fresh apples, \$/bin (p)	481.00	481.00
Produced yield, bins/acre (Y)	80.00	80.00
Picking rate, hrs/bin (s_M and s_R)	1.5	0.32
Packout rate, % (γ_M and γ_R)	80	75
Picking efficiency, % (β_M and β_R)	100	60
Price, culled apples, \$/bin (p_C)	64.75	64.75
Wage rate, harvest, hauling, checkers, \$/hr (w)	18.79	18.79
Wage rate, robot operator, \$/hr (w_R)	—	26.31
Weight of 1 bin of apples, lb (T)	925	925
Lbs per box	40	40
Time to pick 1 apple by the robot (seconds/arm)	—	5
Number of arms per robot	—	9
Robots per operator	—	2
Harvest labor, hrs/acre (HL)	120.00	15.57
Receiving charge, \$/bin (rc)	100	100
Packing fee, \$/box (pb)	7	7
Number of boxes per bin (fb)	18.50	17.34
Diesel use, gallons (g)	—	3.70
Diesel price, \$/gallon (p_D)		5.34
Annualized fixed costs for buildings, tractors, platforms, \$/acre (δfc)	9,771.64	9,771.64
Robot maintenance, annual per acre cost (m_R)	0.00	405.11
Horticultural management costs, \$/acre	7,267.94	7,267.94
Maintenance and repairs of tractors and machinery, \$/acre	340	340
Fuel and lube cost of tractors and machinery, \$/acre	300	300
Overhead cost adjustment (oc)	0.05	0.05
Interest costs (i)	0.05	0.05
Checkers hours (K)	0.426	0.426
Haulers hours (H)	0.373	0.373

contribution is to conduct four break-even analyses. First, we examine the maximum robot cost that the grower could afford to invest (or the annual rental rate the grower could spend) such that profits are equal for both harvesting methods. Second, we analyze how the affordable cost of the robot changes for different picking speeds, robot-induced damage rates, and percentage harvested. Third, for a given up-front cost of a robot, we can compute the tradeoff between the wage rate and changes in these three robotic parameters. Fourth, because revenues, costs, robot-induced damage rates, etc.,

TABLE 2 Analysis for manual versus robotic harvesting for Gala apples.

Variable	Unit	Manual	Robot
Yield and revenue			
FOB price for fresh apples (p)	$/bin	481.00	481.00
Produced yield (Y)	Bins/acre	80.00	80.00
Picking efficiency (β_M and β_R)	%	1.00	0.60
Packout rate (γ_M and γ_R)	%	0.80	0.75
Harvested yield after culling ($Y \times \beta_M \times \gamma_M$ and $Y \times \beta_R \times \gamma_R$)	Bin/acre	64.00	36.00
Harvested yield for handpicking after the robot ($Y \times (1 - \beta_R) \times \gamma_M$)	Bin/acre		25.60
Fresh apple revenue ($p \times Y \times \beta_M \times \gamma_M$ and $p \times Y \times \beta_R \times \gamma_R$)	$/acre	30,784.00	29,629.60
Price for harvest-induced damaged apples (p_C)	$/bin	64.75	64.75
Harvest-induced damaged apple revenue ($p_C \times Y \times \beta_M \times (1 - \gamma_M)$ and $p_C \times Y \times \beta_R \times (1 - \gamma_R) + p_C \times Y \times (1 - \beta_R) \times (1 - \gamma_M)$)	$/acre	1,036.00	1,191.40
Total revenue		31,820.00	30,821.00
Revenue difference	$/acre		−999.00
Harvest-labor cost calculations			
Wage including overhead (w)	$/hr	18.79	18.79
Wage premium for operating robot			1.4
Wage robot operator (w_R)			26.31
Weight of 1 bin of apples (T)	lb	925.00	925.00
Weight of 1 apple	lb		0.44
Number of apples per bin (925 × 0.44)	Number		2,102.27
Time to pick 1 apple	Sec./arm		5
Number of arms per robot	Number		9
Picking rate (s_M and s_R)	Hours/bin	1.50	0.32
Picking Labor Hours ($s_M \times Y \times \beta_M$ and $s_R \times Y \times \beta_R$)	Hours/acre	120.00	15.57
Picking Hours for hand harvest after robot ($s_M \times Y \times (1 - \beta_R)$)	Hours/acre		48.00
Number of operators	Number		0.5
Picking cost ($s_M \times Y \times \beta_M \times w$ and $s_R \times Y \times \beta_R \times w_R + s_M \times Y \times (1 - \beta_R) \times w$)	$/acre	2,254.80	1,106.74
Checker labor (K)	Hours/bin	0.43	0.43
Hauling labor (H)	Hours/bin	0.37	0.37
Checkers labor cost	$/bin	8.00	8.00
Hauling labor cost	$/bin	7.00	7.00
Checker and hauling labor ($Y \times \beta_M \times (K + H)$ and $Y \times \beta_R \times (K + H) + Y \times (1 - \beta_R) \times (K + H)$)	Hours/acre	63.86	63.86
Checker and hauling cost ($Y \times \beta_M \times (K + H) \times w$ and $(Y \times \beta_R \times (K + H) + Y \times (1 - \beta_R) \times (K + H)) \times w$)	$/acre	1,200.00	1,200.00
Total harvest labor costs	$/acre	3,454.80	2,306.74

(Continues)

TABLE 2 (Continued)

Variable	Unit	Manual	Robot
Packing cost (*pck*)			
Number of finished boxes per bin ($T \div L \times \gamma_M$ and $T \div L \times \gamma_R$)	Number	18.50	17.34
lbs per box (L)	lbs	40.00	40.00
Packing cost ($(rc + (pb \times T \div L \times \gamma_M)) \times Y \times \beta_M$ and $(rc + (pb \times T \div L \times \gamma_R)) \times Y \times \beta_R + (rc + (pb \times T \div L \times \gamma_M)) \times Y \times (1 - \beta_R)$)	$/acre	18,360.00	17,971.50
Robot maintenance, repair, fuel, and lubrication cost calculations			
Maintenance and repair (*mc*)	$/arm	0.00	300.00
Number of acres to be covered by 1 robot (*na*)	acres	0.00	40.50
Maintenance and repair ($mc \times 9 \div na$)	$/acre	0.00	66.67
Diesel use (g)	Gallon/hour	0.00	3.70
Diesel price (p_D)	$/gallon	0.00	5.34
Fuel cost ($s_R \times Y \times \beta_R \times g \times p_D$)	$/acre	0.00	307.68
Lubrication cost (0.1 × Fuel cost)	$/acre	0.00	30.77
Maintenance, repair, fuel, and lubrication costs	$/acre	0.00	405.11
Other variable costs (*ovc*)			
Other variable cost-hort management	$/acre	7,267.94	7,267.94
Baseline variable cost-maintenance and repair	$/acre	340.00	340.00
Baseline variable cost-fuel and lube	$/acre	300.00	300.00
Total other variable costs	$/acre	7,907.94	7,907.94
Total variable cost			
Variable cost (vc_M) and (vc_R)	$/acre	29,722.74	28,591.30
Overhead cost adjustment (*oc*)	%	0.05	0.05
Interest cost (i)	%	0.05	0.05
Total variable cost ($vc_M \times (1 + oc) \times (1 + i)$) and ($vc_R \times (1 + oc) \times (1 + i)$)		32,769.32	31,521.9
Total variable cost savings	$/acre		1,247.42
Fixed cost (excluding robotic harvester)			
Fixed cost (excluding robotic harvester)	$/acre	9,771.64	9,771.64
Net revenue difference			
Net revenue per acre	$/acre	−10,276.96	−10,472.57
Net revenue difference (*ANRD*)	$/acre		248.42
Annualized cost for the robot			
Years of harvester life	years		10.00
Salvage values	$		0.00
Interest rate (i)	%		0.05

TABLE 2 (Continued)

Variable	Unit	Manual	Robot
Months loan is amortized (n)	Months		120.00
Discount factor ($Disc = ((1 + i/12)\^n\text{-}1)/(i/12(1 + i/12)\^n)$)			94.28
Break-even cost of robot ($I = ANRD/12 \times Disc$)	\$/acre		1,951.74
Break-even total cost of harvester for 40.5 acres	\$		79,045.64

differ across apple varieties, we compute the break-even cost of the robot for Honeycrisp apples, which fetch a higher farmgate price than Gala and bruise more easily.

5.1 | Break-Even cost for the robot

Following the mover-stayer model defined in Taylor and Charlton (2019), we calculate the amortized break-even robot cost (i.e., the cost of the robot that would result in profits from both operations being equal) of the robotic harvester using the formula:

$$I = \frac{ANRD}{12} \times Disc,$$

where $ANRD$ is the annualized net revenue difference between manual and robotic harvest excluding the up-front cost of the robot, $Disc = \frac{\left(1+\frac{i}{12}\right)^n - 1}{\frac{i}{12}\left(1+\frac{i}{12}\right)^n}$ is the discount factor,[10] i is the annual interest rate, and n is the number of months that the robotic harvester will be amortized. Since $ANRD$ is the annual net revenue difference and $Disc$ is based on the monthly interest rate, we convert $ANRD$ into monthly net revenue by dividing by 12.

Assuming the robot harvester lasts ten years, the loan is amortized over the life of the robot (120 months), and a monthly interest rate (based on an annual interest rate of 5%) of $\frac{i}{12} = \frac{0.05}{12} = 0.417\%$, the discount factor is $Disc = \frac{(1+0.417)^{120} - 1}{0.417 \quad (1+0.417)^{120}} = 94.28$ and the break-even cost of the robotic harvester is $I = \frac{\$248 \times 94.28}{12} = \$1,952$ per acre. Assuming the robot can harvest 40.5 acres per year,[11] the break-even cost is \$79,046 (=\$1, 952 × 40.5 acres), which can be amortized over the ten-year life of the robot.[12] This result does not represent the market price of the robot, rather it implies that a grower with 40.5 acres can afford to spend \$79,046 for a robot and obtain equal profits as would be obtained from manual harvest.

We consider a sensitivity analysis where the worker's hourly wage rate increases by 25% from \$18.79 to \$23.49.[13] With this higher wage, the break-even robot cost increases by 127.38% to \$179,734.49.

[10]This is the formula used in Taylor and Charlton (2019) and can be derived from the standard formula to calculate the future value of an annuity (Lee, 2005, p. 68). Importantly, the discount factor accounts for the opportunity cost of investing in the up-front cost of the robotic harvester since the grower could alternatively invest the up-front cost elsewhere.

[11]Assuming a harvest season of 90 days per year and robots in operation 10 hours per day, we calculate that the robot could feasibly harvest 40.5 acres per year given that the robot has 9 arms picking at a rate of 1 apple every 5 seconds.

[12]If we instead assume the robot lasts 15 years, the break-even purchase cost per acre is \$2,618 or \$106,020 for 40.5 acres. If instead we assume that one robot can harvest twice the number of acres, then the per acre break-even purchase cost per acre is \$2,240, but the total cost is \$181,479 for 81 acres.

[13]The current (2024) Adverse Effect Wage Rate (AEWR) that employers are required to pay H-2A workers in Washington is \$19.25. Adding 25% overhead for medical leave, payroll taxes, and administrative costs, this comes to \$24.06 per hour.

We conducted two sensitivity analyses to examine the break-even robot investment price with different number of robots per operator: one operator manages one robot, and one operator manages three robots. If a worker operates only one robot, the break-even robot price declines from $79,046 to $7,190 because, with a higher cost for the robot operator, the grower must spend less on the robot so that net revenue from robot harvest is equal to manual harvest. If one worker operates three robots, the break-even robot price is $103,002. Realistically, if one operator manages a small fleet of robots, then growers could rent robots as opposed to owning robots, which would be particularly suitable for smaller farms. The annualized break-even costs we calculate for investment in a robot can equivalently be considered the feasible annual rental rates per acre that a farmer could pay and obtain equal profits to manual harvest.

Further investigation is required to determine whether there might be additional costs related to grove preparation, orchard management, canopy structure, and characteristics of apple varieties to accommodate robotic harvest. Since canopy structure and tree spacing vary within and across orchards, the percentage harvested, bruising rates, and picking speeds are likely to vary, and our parameters might not be representative of all orchards or conditions within a single orchard.[14] We consider sensitivity analyses to various values of these three parameters and apple varieties in the following subsections.

5.2 | Impact of changes in robot parameters on break-even cost of robots

Reported picking efficiencies in literature for single-arm robots harvesting apple or citrus trees range anywhere from 50% to 84%, and picking speeds (per fruit, not averaged) range from 3 to 14.3 s (Bac et al., 2014). Silwal et al. (2017) reported an overall picking efficiency of 84%, with an average time to pick an apple equal to 6.0 s per fruit. Hu et al. (2022) reported faster picking cycles of 3.5 s and 4.0 s per apple at a lower picking efficiency of 47%. Bu et al. (2022) reported a picking efficiency of 82.9% and a picking cycle of 12.5 s per apple. These results were based on a single-arm robotic apple harvester. Li et al. (2023) developed a four-arm robotic harvester and reported machine-picking efficiencies that ranged from 62.2% to 82.3% and picking cycles of 7.6 s to 8.8 s per fruit. The higher values are ‘reasonably optimistic’ and take into consideration non-peer-reviewed results from industry (e.g., picking efficiency 91% at 1 s per fruit as reported by Salisbury and Steere (2017) and ongoing research on using many arms (e.g., 6, 9, or 12) and optimizing their operation to increase picking speed proportionally with the number of arms (Pueyo Svoboda & Vougioukas, 2022). We consider a picking efficiency of 60% for the baseline and conduct sensitivity analyses of picking efficiency ranging from 50% to 80%. The low and mid-range values used in our analysis for picking speed and efficiency are based on reported literature. The optimistic parameters are used to explore how much performance should increase to make robots cost-effective.

We calculate break-even costs for various combinations of picking speeds, robot-induced damage rates, and picking efficiencies. In panel 1 of Table 3, we specify that the robot picks one apple per 3 s per arm and calculate the break-even costs between manual picking versus robotic harvest for a 40.5-acre farm for different combinations of robot-induced damage rates ($\gamma_M - \gamma_R$ = 0.01, 0.025, 0.05, and 0.075) and picking efficiencies (β_R = 0.50, 0.60, 0.70, and 0.80). Panels 2, 3, and 4 repeat these break-even analyses for picking speeds of one apple per 4, 5, and 6 s per arm, respectively. In doing so, we quantify the dollar value that farmers can afford to invest in robots such that net revenue from robot harvest equals that of manual harvesting. Note that the main result from the baseline analysis of current robot prototypes corresponds to the parameters evaluated in

[14]Furthermore, many apple varieties are harvested using a color pick (e.g., picking only apples of a specific color on the first pass and returning for a second pass when the remaining apples have further ripened). Given advanced optic technologies, we assume robots can color pick without losing speed. However, additional research is needed to test whether robots can perform color pick at predicted speeds and to determine whether robot efficiency changes in cloudy or obscured light.

TABLE 3 Break-even up-front robot cost in dollars (40.5-acres) for various picking speed and robot-induced damage rates ($\gamma_M - \gamma_R$).

		Robot-induced damage rates ($\gamma_M - \gamma_R$)			
		0.01	**0.025**	**0.05**	**0.075**
Panel 1: Time to pick one apple, 3 s per arm					
Picking efficiency	0.50	246,562	201,165	125,503	49,840
	0.60	300,552	246,076	155,281	64,486
	0.70	354,542	290,986	185,059	79,131
	0.80	408,532	335,897	214,837	93,777
Panel 2: Time to pick one apple, 4 seconds per arm					
Picking efficiency	0.50	214,798	169,400	93,738	18,076
	0.60	262,435	207,958	117,163	26,368
	0.70	310,072	246,516	140,588	34,661
	0.80	357,709	285,073	164,013	42,954
Panel 3: Time to pick one apple, 5 s per arm					
Picking efficiency	0.50	183,033	137,636	61,973	−13,689
	0.60	224,317	169,841	79,046[a]	−11,749
	0.70	265,602	202,045	96,118	−9,809
	0.80	306,886	234,250	113,190	−7,870
Panel 4: Time to pick one apple, 6 s per arm					
Picking efficiency	0.50	151,269	105,871	30,209	−45,454
	0.60	186,200	131,723	40,928	−49,867
	0.70	221,131	157,575	51,647	−54,280
	0.80	256,062	183,427	62,367	−58,693

[a]Indicates the result from the baseline break-even analysis with current prototype parameters.

Panel 3 with a picking rate of one apple every 5 s per arm, a robot-induced damage rate of 0.05, and a picking efficiency of 0.60, which yields a break-even cost of $79,046.

The results in Table 3 reveal that generally in the scenarios characterized by higher picking efficiency, lower robot-induced damage rates, and faster picking speeds, the robot is more profitable and growers can afford to invest more in it. For the fastest robot with a picking rate of one apple every 3 s per arm, the lowest robot-induced damage rate of 0.01, and the highest picking efficiency of 0.80, a grower could afford to spend the most ($408,532). Thus, generally moving from the southwest cell in each panel to the northeast, the robotic operation goes from being more profitable to less profitable than manual harvesting. However, in the last panel with the slowest picking speed of one apple per 6 s and for an additional bruising rate of 0.075, the robot is more economical (i.e., a break-even cost closer to zero) at lower picking efficiencies. This seemingly counterintuitive result occurs because, with a slow robot that has a high additional bruising rate, it is more economical to have a robot miss a larger share of fruit and have the workers pick these missed fruits. The negative outcomes in Panels 3 and 4 under an additional damage rate of 0.075 imply manual harvesting is more profitable than robotic harvest, and the grower needs to be compensated to utilize the robotic harvester to earn the same profits as under manual harvesting. These results are useful to engineers in determining threshold combinations of (a) robot-induced damage rates, (b) the accuracy of robots in detecting, detaching, and transferring the fruit to the conveyer, and (c) the speed of picking the fruits. In all panels, the robotic operation is more profitable, except in Panel 3 and 4 for an additional bruising rate of 0.075.

5.3 | Tradeoff between wage and robot parameters

In addition to the parameters of the robot harvester, growers' net revenues are also heavily influenced by rising wage rates for field workers. Since more workers are employed for manual harvest than for robot harvest, rising wages cause net profits from manual harvest to decline by a larger magnitude than net profits from robotic harvest. Therefore, higher farm wages lead to more cases (higher up-front robot costs, lower percentage harvested, higher cull rates, and slower speeds) under which robotic harvesters are feasible. To demonstrate these tradeoffs, we solve equation (4), which is a function of the wage rate and also depends on all robotic parameters, by utilizing a root-finding algorithm to calculate the robot-induced damage rate, percentage harvested, or picking speed that corresponds to a wage rate such that the net revenues from both operations are equal for an assumed annual cost of a robotic harvester of $150,000 for a 40.5-acre farm. By repeating this break-even analysis for various wage rates, we compute the corresponding robot-induced damage rate and then calculate the elasticity of the robot-induced damage rate to the wage rate. This elasticity is computed as the percent change in the robot-induced damage rate (rp = γ_M − γ_R) divided by the percent change in the wage rate:

$$\varepsilon_{rp,wage} = \frac{\%\Delta rp}{\%\Delta \mathrm{Wage}}.$$

Specifically, the elasticity measures the percentage change in the robot-induced damage rate that would result in the same net profit between the robotic harvester and the traditional manual harvesting following a 1 percent wage increase, holding all other parameters constant. This analysis yields break-even robot-induced damage rates of 0.01, 0.042, and 0.075 for hourly wage rates of $15.32, $20.79, and $26.34, respectively. For these robot-induced damage and wage rates, the elasticity ranges from 9.04 to 2.08, with an average of 3.52 over the wage range. Therefore, for every 1% increase in the hourly wage rates, robots could have a 3.52% increase over the current robot-induced damage rate, holding constant all other parameters.

A similar analysis shows a break-even picking efficiency of 40%, 60%, and 80% for hourly wage rates of $26.14, $22.12, and $20.08, respectively. The elasticity for these picking efficiencies and wage rate ranges from −2.17 to −3.31, with an average of −2.74 over the wage range. Therefore, for every 1% increase in the wage rates, robots could have a 2.74% decrease in the percentage harvested tolerance, holding constant all other parameters.

The results for picking speeds demonstrate that the picking rate of one apple per 2, 5, and 8 s per arm yields a break-even hourly wage rates of $16.96, $22.06, and $28.47, respectively. The elasticity for these picking rates and wage rates ranges from 5.47 to 1.50, with an average of 2.66 over the wage range. Therefore, for every 1% increase in the wage rates, robots could be 2.66% slower than the current picking speed, holding constant all other parameters.

5.4 | Analysis for Honeycrisp apples

The above baseline analysis uses cost and return data for Gala apple varieties. We extend this analysis for Gala apple to the Honeycrisp variety because it is one of the most popular varieties shipped out of Washington (Gallardo, 2023). Honeycrisp receives a higher farmgate price than Gala apples. However, Honeycrisps also bruise (one of the most common forms of robot-induced damage) more easily than most other varieties (Gallardo, 2023, Gallardo & Galinato, 2020). Thus, we expect the profitability difference between manual and robotic harvesting and the adoption rate to differ across Gala and Honeycrisp varieties to changes in robot-induced damage and wage rates.

Detailed analysis of net profits from robotic versus manual harvest of Honeycrisp apples are presented in Appendix B and follows the same methods used to compute net profits for Gala apples. The results show that net revenues are positive for Honeycrisp under both manual ($4,768.74 per acre) and robotic ($4,415.66 per acre) harvesting. The difference in net revenue between robotic and manual harvesting is −$353.08, implying that the grower would find adopting robots less profitable than manual harvesting. For this net-revenue difference, the break-even cost of robots for a 40.5-acre farm is −$112,348.57 (obtained using the formula in Subsection 5.1), implying farmers would have to be compensated to secure equal profit from using the robot compared to manual harvest. However, a gentler robot with an additional robot-induced damage rate of only 0.017 would have net revenues equal to manual harvest if its up-front cost were $150,000. For Honeycrisp, the average elasticity of robot-induced damage rate, picking efficiency, and picking time to the wage rate is 2.00, −3.80, and 4.56, respectively.

6 | CONCLUSION

Labor scarcity during time-sensitive operations in specialty crop cultivation is an endemic problem for the industry, largely addressed by hiring foreign guest workers through the H-2A program. However, the H-2A program may not suffice to meet U.S. farm labor demand in the long run since rural Mexicans are transitioning from farm to nonfarm work (Charlton et al., 2019; Zahniser et al., 2018). Many farm operations are keenly interested in innovative methods to mechanize labor-intensive stages of fruit production to reduce their dependence on large seasonal crews of workers. This study presents a detailed analysis of adopting robotic apple harvesters versus manual harvesting using unique data and insights from agricultural engineers. While the model and analysis are applied to robotic harvesting in apple production, the methods are applicable more generally to assess the feasibility and tradeoffs between robotic harvesting and manual harvesting for a wide range of high-value fresh market fruits and vegetables.

Given the performance of current robotic prototypes, a baseline wage rate of $18.79 and an up-front robot cost of $79,045.64 for 40.5 acres amortized over 10 years would result in equal profits from robotic and manual harvest. However, as the wage rate increases, growers can afford to pay a higher up-front cost for the robot. Since the primary cost-savings from the robot is in reducing the labor required to harvest apples, robots may become more economically feasible if farm wages continue to rise. However, the profits from robotic harvest decline sharply as apple cull rates increase. For robot harvesters to become economically feasible, engineers need to design robots that can harvest apples quickly and without missing apples on the tree and/or causing additional damage to the harvested fruit. The break-even analysis of wage rate versus robot-induced damage rates from robot harvest indicates that with a 1% increase in the wage rate, the additional robot-induced damage rate could increase by 3.52% over the existing damage rate, holding constant all other parameters. As engineering designs advance and parameters for robotic harvesters can be measured more precisely, the calculated breakeven costs and elasticities will likely vary from our calculations for current prototypes.

Although robotic harvesters are not yet commercially available, this study shows that innovations in robotic harvesting technologies might be economically feasible for apples in the near future. Ongoing research must also include investigations into the potential consequences of robotic adoption on employment, wages, and required skills up and down the agricultural supply chain.

Findings from this and related research will have important policy implications for farm labor employment, immigration, international trade, and agricultural research and development.

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CONFLICT OF INTEREST STATEMENT
The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT
Data are disclosed in the article text and tables. Any additional data or information regarding data sources can be made available on request from the authors. The data that supports the findings of this study are available in the corresponding tables and supplementary material of this article.

ORCID
Jeff Luckstead http://orcid.org/0000-0002-8318-7020

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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