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Technology Acceptance, Adoption and Workforce on Australian Cotton Farms

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Abstract: The future of work is influenced by the digital transformation of industries, including agriculture. The current study aimed to understand the social drivers of automated technology acceptance and adoption in Australian cotton farms. The study employed a mixed-methods approach to compare those who were (a) currently using automated technology, (b) not currently using automated technology but considering adoption, and (c) not currently using automated technology and no intention to adopt. The research found that social factors and workforce considerations influence growers' motivation to adopt automated technology on farms. Furthermore, differences on appraisals of perceived usefulness were observed when comparing growers with no intention to adopt automated technology with those considering adoption or who have adopted automated technology. Both perceived usefulness and ease of use barriers are challenges for those considering adoption of automated technology. Support that improves ease of use for those who have adopted automated technology is important for continued appraisals of perceived usefulness of automated technology. Further research to understand antecedents to appraisals of perceived usefulness and ease of use, and how these interact to influence acceptance and automated technology, is required to inform strategic workforce interventions that support the digital transformation of cotton farms.

Keywords: agricultural technology; cotton; technology acceptance model; technology adoption

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1. Introduction

Global trends such as rapid urbanization, climate change, resource scarcity, shift in global economic power, demographic and social change and technological breakthroughs are shaping the future of work across all contexts [1]. More recently, the global pandemic of COVID-19 has disrupted the world of work, with essential services such as agriculture experiencing the effects of disrupted supply chains and restricted access to the seasonal workforce due to border closures. Indeed, the world of agricultural work continues to face new and ongoing challenges that impact its workforce requirements for the future productivity of Australian agriculture, including the cotton industry. The volatility, uncertainty, complexity, and ambiguity of the future of work has led to increased interest in understanding how individuals can plan and be prepared with the skills and abilities required to successfully navigate the changing context. Furthermore, amidst the "fourth industrial revolution" [2] and rise of digital agriculture [3], the Australian cotton industry must develop a deeper understanding of how to strategically unlock the capability of people to drive this change. It is essential to identify the types of workers, skills, and workforce structures that will ensure cotton farm businesses are adaptable and benefit from the opportunities for improved productivity, efficiency, and sustainability that technology promises.

There is an extensive body of work in the form of industry and consultant reports that aim to identify potential futures and the factors that influence them, and strategic areas for development to drive change and capitalise on developments in the world of work for agriculture [4–7]. For example, Tomorrow's Digitally Enabled Workforce [4] proposes that the requirements for the future workforce depend upon workforce transitions. These transitions may include how individuals adapt to change at work (e.g., task performance) or change their jobs, and how workforce structures, including the number of people, the kinds of roles, and the permanency of labour requirements, shift. The report lays out four potential future scenarios based on the rate of change across two axes: the level of task automation that occurs in the workplace (high or low), and the institutional change that can occur with workforce structures (significant or limited) including employment models and organisational designs. Implications from the scenarios for individuals include the requirement for new mindsets and development of new capabilities, and a baseline of digital literacy skills as well as numeracy and literacy skills not previously required for all workers. The expected job market dynamic is predicted to require greater adaptability, resilience and entrepreneurial capabilities and career self-management skills to remain open to job and industry transitions. While this report is not specific to Australia's agriculture industry, it does highlight factors that are expected to be important in understanding and planning for farming businesses future workforce requirements, with the rise of digital agriculture continuing to occur in the cotton industry.

Within the peer-reviewed academic literature, the rise of digital agriculture, or agriculture 4.0, and the drive towards sustainable intensification of production has to date paid limited attention to the social implications of these developments. Understanding the "people" drivers and implications of the potential future changes stemming from technology adoption is needed to adequately plan for attraction, development and retention of the agricultural workforce in an increasingly digital workplace.

According to Vasconez et al. [8], there remains a long path to a fully autonomous agriculture industry due to the significant investments required and the complexity of processes and systems involved. Modelling each environment, crop and task can be extremely difficult; therefore, the continued interaction between people and robots needs to factor in continuous learning and adaptation of machines to new conditions. Some of the most successful autonomous solutions, such as GPS autosteer, have been implemented for repetitive tasks and aim to reduce workload, optimise process times and costs. For other more complex tasks, designing technology to include humans within the system (augmentation) means that decision making corrections and problem-solving, as opposed to physical labour, will be the skills required from the workforce. In the cotton industry, modelling has identified that the top three areas of productivity improvements will come from digital technologies associated with irrigation scheduling and application, crop nutrition, and optimising quality [9]. This is similar to commentary by Barnes et al. [10], which details commercial automation technologies currently available for cotton production, e.g., weed control, soil sampling and planting technologies. Production improvement is a clear outcome that automated technologies aim to achieve and is a factor for growers to consider when making adoption decisions. Other outcomes to be considered include what these technologies mean for the agricultural workforce in terms of replacing tasks and augmenting jobs.

Whilst benefits for people working on farms linked to increasing automation are often framed as bringing improved work conditions (including visibility, safety, simplicity) and related to better decision making (including access to greater information for feedback from the system and reducing cognitive load), there is also the potential for agricultural technology (agri-tech) to lead to changes that produce less desirable outcomes [8,11]. Adopting technology that reduces physical work and workers' presence could reduce farmers' engagement with and understanding of their land and environment. Devaluing of experiential knowledge and complexity of data issues including ownership and trust could lead to reduced job satisfaction and exacerbate stressors or mental health problems (Ref. [12] cited in [11]). Complete automation could also raise issues associated with changing reporting requirements or a concern for data privacy [13]. While agri-tech will create jobs, those jobs that are lost or changed through increasing automation may belong to workers who are not sufficiently skilled, prepared, or in possession of the abilities required to transition and adapt to these new roles in agriculture [14]. Failure of farms to keep up with the digital revolution and to transition to collect, manage, and present data in a way that attains transparency and traceability of the commodities they produce may mean they find themselves locked out of future markets [15]. Adding to this concern is that smaller to medium enterprises have been identified as being at greater risk of lagging due to the economies of scale that are sometimes needed to make the business case for adoption of new technology [8]. Cotton is a technology-intensive sector with a majority of farms being family owned, and small to medium enterprises [16,17]. It is therefore important to understand more about cotton farm enterprises digital agriculture opportunities, risks, and workforce adaptability to inform the strategic development of the workforce to purposefully build a desirable future for people in the industry.

2. The Technology Acceptance Model

One key aspect of the digitisation of agriculture is technology acceptance amongst farmers and workers. In general, much of the literature on technology acceptance is informed by the Technology Acceptance Model (TAM), which is a causal model initially proposed by Davis [18,19] to understand why individuals accept or reject information technologies. The model identifies two key aspects that predict technology acceptance: perceived usefulness and perceived ease of use. The former relates to the extent to which an individual believes that using the technology will improve their role. The latter refers to the perceived effort of technology introduction. Meta-analyses of earlier iterations of the TAM have found ease of use to be significantly related to perceived usefulness, and perceived usefulness to be significantly related to acceptance [20]. Another meta-analysis of 88 studies found similar results and further tested moderator effects of use types, finding that the model works similarly well for students and professionals [21]. Widespread continued use of the TAM as evidenced in a recent meta-analysis of 786 journal articles further validates the explanatory power of this model and points to the particular importance of positive attitudes towards technology use and social influence in the model [22].

Studies in agriculture have used the TAM to explore gender differences in technology adoption for farmers in developing nations [23,24], farmers information adoption in China [25], the intentions of agricultural consultants to extend precision agriculture technologies to farmers in Iran [26], and farmers' intentions to adopt precision agriculture technologies in the Ukraine [27]. These have consistently supported the core factors of perceived ease of use and perceived usefulness in impacting intentions to accept or adopt technology and information systems. Interestingly a study of 84 farmers in Germany found that perceived ease of use and not perceived usefulness led to an acceptance of AI systems [28]. This lack of significance for perceived usefulness was potentially due to the difficulty respondents may have when assessing the usefulness of AI machines given the limited market-ready systems that are available. In a study of Italian farmers, Caffaro et al. [29] found that perceived usefulness, but not perceived ease of use, significantly impacted intention to adopt two categories of digital technologies (sensors/drones for data acquisition or robots/autonomous machines). In a study of New Zealand dairy farmers, Flett et al. [30] also noted that perceived usefulness was given more weight amongst farmers, though perceived ease of use was still an important factor in adoption, particularly for those farmers already using technologies. While no literature was found applying the TAM to the Australian cotton industry, there have been several studies of interest considering the influence individual, economic and environmental factors have on technology adoption in Australian agriculture.

Within the Australian context, the use of technologies for variable rate fertiliser application and yield mapping in the grains industry identified barriers associated with access to, and cost of, technologies as significant impediments for adoption [31]. In that same study, farmers' higher education and a larger farm area were significantly associated with the use of technology for yield mapping, but not variable fertiliser application. Age was not associated with use of either technology [31]. Research specific to the Australian cotton industry is limited and little is known of the barriers and factors that influence technology adoption for this industry. One exception is the qualitative case study by Mackrell et al. [32], who explored the adoption of an agricultural decision support system (CottonLOGIC) by the Australian cotton industry. Using the innovations–decision model ([33] cited in [32]), product attributes including ease of use for record keeping and decision support contributed to adoption. Conversely, reasons to not implement CottonLOGIC included duplication of work and perception of data collation and analysis as unproductive compared to time spent outside. Though this work provided insight into the use of a specific agricultural decision support system by Australian cotton farmers, the implications of the research are narrow and provide little insight into industry adoption of other types of technologies, including automated technologies. Further research is needed to understand motivations of Australian cotton farmers' technology adoption, particularly as it relates to social impact factors including labour reduction, work flow management or improved workforce task effectiveness and efficiencies.

This present research is based on the 2018 Grower Practices Survey data [16], which is an annual survey of Australian cotton growers that collects information about the past season's crop production and other related issues. The questions are updated each year to ensure a wide range of data capture over time. In 2018, data relating to the on-farm workforce demographics/structures, attitudes of employers towards the workforce, and technology adoption relating to automation were captured.

The aim of the present research was to better understand technology acceptance, technology adoption, attitudes about workforce, and workforce structures in the Australian cotton industry. The research questions to be addressed include:

1. What are the automated technologies that are currently used by growers?
2. What technologies are being considered?
3. Why are people not currently using automated technology on farms?
4. Are there relationships between attitudes to technology adoption, human resource (HR) practices, and attitudes to workforce, farm size, number of employees, proportion of full-time employees, and proportion of entry level employees?
5. What variables predict the following group membership: (a) Yes, using automation; (b) no, but considering, and (c), no and not considering?

Using the TAM [18,19], the present research examines technology acceptance by the Australian cotton industry, using both perceived usefulness and perceived ease of use, as indicated by intentions to use and actual use, to predict the acceptance of digital technology.

3. Materials and Methods

3.1. Participants

There were 176 growers who responded to the survey's modules on automation and workforce. Their ages ranged from 20 years to over 65 years old, with an average age in the range of category 5 (45–49 years old) (mean = 5.24; median = 5.00) (Age was measured as an ordinal variable with categories listed as (1) under 20, (2) 20–34, (3) 35–39, (4) 40–44, (5) 45–49, (6) 50–54, (7) 55–59, (8) 60–64, (9) 65+). The area of these growers' farms that was dedicated to broad acre cropping ranged from 90 hectares to 62,400 hectares (mean = 3879.81 hectares, median = 1495.00 hectares). This was positively skewed, with 95% of growers reporting their farms had less than 11,000 hectares developed for broad acre crop production. Growers were located in the following production valleys: the Murrumbidgee (N = 32), lower Namoi (including Walgett; N = 24), the Darling Downs (N = 22), the Upper Namoi (N = 20), the Gwydir (N = 18), the Macquarie (N = 15), Border Rivers (N = 14), Central Queensland (N = 11), St George/Dirranbandi (N = 10), the Lachlan (N= 6), Bourke (N = 1), Murray (N = 1) and the Ord (N = 1).

Of the 246 growers who commenced the survey, a proportion of respondents (27%, N = 68) dropped out of the survey at the point at which questions on automation (module seven) commenced. Many of these respondents had withdrawn by the third module of questions (N = 65), so it is unlikely that an aversion to answering questions about automation or workforce was the cause of attrition. Using t-test comparison, there was no significant difference in age (t (210) = −0.99, p = 0.32), size of farm (t (232) = −0.36, p = 0.72), or total area of cotton planted (t (210) = 0.39, p = 0.69) between those participants who dropped out and those retained. Two participants data were removed due to a large amount of missing data. For one of these participants, this was potentially due to their status as an employee on a corporate farm, and hence they felt they could not answer questions about "their farm".

3.2. Procedure

The data analysed in the current study was provided to the research team by the Cotton Research and Development Corporation for secondary analysis. This data had been collected as part of the larger Grower Practices Survey in June–July 2018 [16]. The original Grower Practices Survey Report [16] noted that growers were initially contacted by phone and encouraged to complete the survey over the phone or online. Growers for whom email addresses were available were also contacted through these means and again, invited to complete the survey online. Information on cotton production for the season in which the survey was conducted described substantial production levels due to favourable conditions for irrigated summer crops; although a lack of rainfall throughout the season negatively impacted dryland production. Some farms were operating at optimum production levels with maximum levels of staffing, while others were not.

3.3. Measures

3.3.1. Demographic Questions

Demographic questions included age, area of farm developed for broad acre cropping, and location of farm. These were used to investigate any nuances between groups of cotton growers.

3.3.2. Adoption of Technology

Participants were asked "Are you currently using any automation (including automation for irrigation) on your farm? Examples of automation include unpiloted air and ground vehicles, intelligent decision systems, AI, etc.". They were able to select from three response categories:

(a) Yes, I currently use automation on my farm.
(b) No, but I'm considering options for the future.
(c) No, and I have no plans to implement the use of automation on my farm.

Participants were able to interpret automation; however, they wished and could report what technologies they were using and were considering for future use. Some growers in the "yes" category indicated that the automation they were thinking of was GPS autosteer tractors. This automated technology is already widely adopted across industry, and it is likely that many people in either of the "no" categories currently also use this type of automation. Therefore, the decision was made to change the research question to "Are you currently using any automation other than GPS tractor autosteer on your farm?". The data were reviewed and recategorized such that those who only referred to GPS autosteer tractors as their automated technology were assigned to category (b) or (c), depending on their responses to questions about what other technologies they were considering for the future.

3.3.3. Technology Use

Using the responses to the above question, qualitative data was collected with regard to the types of automation currently being used, the types of automation being considered for use, and reasons for not currently adopting automated technologies (other than GPS auto steer tractors) on farm. Questions asked included: "What are you using automation for on your farm?", "What automation solutions are you considering for your farming business, and please describe for what purpose?", and "Why do you currently not use any automation tools on your farm?".

3.3.4. Perceived Usefulness Scale and Perceived Ease of Use Scale

The Perceived Usefulness Scale and Perceived Ease of Use Scale were developed in conjunction with other researchers on CRDC-funded workforce projects and reviewed by a panel of experts from CRDC before inclusion in the Grower Practices Survey. To meet the current project objectives, these measures are specifically focused on workforce-related benefits that impact the organisation of labour on farms and the changing skill profiles required to successfully implement digital technologies on farms.

The Perceived Usefulness Scale was designed to measure growers' perceptions that automated technology provided them with benefits such as (a) reduced labour costs, (b) more efficient workforce performance, and (c) reduced the time and effort required managing staff or performing tasks, allowing them to find better work–life balance, or work on other parts of the business. The Perceived Usefulness Scale consisted of 5-items, for example "Automation will save me money on labour costs" or "Automation will help reduce the effort required to manage workers on my farm" that were rated on a Likert-Type Scale from (1) *strongly disagree* to (5) *strongly agree*. The final score was an average of the five items' scores. Good internal consistency reliability was demonstrated ($\alpha = 0.85$).

The Perceived Ease of Use Scale was designed to measure growers' perceptions that (a) they could easily adopt digital technology in terms of the skills required to operate and maintain, (b) they could easily integrate digital technology into their existing farming systems, and (c) that they could attract a new workforce with sufficient skills, or their existing workforce were adaptive to develop the skills required to adopt new digital technologies. Perceived Ease of Use consisted of 4-items, for example "I have the skills, or I can learn the skills, to use new automated technology on my farm" and "Automated technology is easy to integrate into my current farm management system" that were rated on a Likert-Type Scale from (1) *strongly disagree* to (5) *strongly agree*. The final score was an average of the four items' scores. Acceptable internal consistency reliability was demonstrated ($\alpha = 0.72$).

3.3.5. Workforce Structure

Several open response questions were asked about workforce structure and the following are considered within the current study: (a) total number of workers employed on farm, (b) the fraction of permanent employees on farm, (c) the fraction of entry-level employees on farm, and (d) the fraction of entry-level employees on farm.

3.3.6. Attitudes and Practices Related to Workforce

Three measures were developed to capture attitudes that growers held towards their workforce and the level of agreement that they were performing tasks that had been identified as HR best management practices within myBMP, which is an industry developed accreditation system that identifies specific standards deemed best practice for farm management. The specific items selected reflect actions aimed at managing their workers' development and performance, as well as reflecting on feedback they gain from their workers that stay or leave the business. These scales were (a) The People Management scale (4-items; an example item is "I have encouraged workers to give me their suggestions and feedback about farming matters"), (b) The Satisfaction with Workforce Scale (4-items; an example item is "I am satisfied with the staff we have on farm"), and (c) The Value of Workers Scale (4-items; an example item is "Getting the right employees on farm is critical to my business success"). Each of these scales were rated on a 5-point scale from (1) *strongly disagree* to (5) *strongly agree*. The internal consistency reliability for each of these was adequate to good ($\alpha = 0.75, 0.80, 0.71$).

3.4. Analysis

3.4.1. Qualitative Analysis

Growers answered the questions regarding the type of automation currently being used, or considered for use, in two ways, either listing a technology to be used for a farm production task or describing their motivation in terms of the usefulness of adopting automation. For the first type of response, the short answers were broadly grouped into categories related to farm activity, e.g., seeding and irrigation. The selection of these categories were informed by the Australian Cotton Production Manual 2019 [34] and categories used to map the Australian agri-tech landscape [35]. The second type of responses were grouped into categories that represented similar motivations, whether this was related to labour/workload reasons, efficiency, accuracy and ease of management, or demonstration purposes.

For the question regarding barriers to technology adoption, a content analysis was conducted that considered the conceptual meaning of words and phrases in the coding of the data. Categories were developed that were used to group common responses (e.g., structural/environmental reasons; cost of equipment and implementation). The credibility and trustworthiness of all aspects of the qualitative analysis and the categories selected or generated were established through peer-debriefing amongst the authorship team and member checks with CRDC representatives [36].

3.4.2. Quantitative Analysis

Descriptive statistics for (a) demographic variables, (b) technology acceptance variables at the item level (individual questions) and the higher order constructs (perceived usefulness and ease of use), and (c) attitudes and practices related to workforce variables at the item level (individual questions) and the higher order constructs (people management, value of workforce, and satisfaction with workforce) were calculated.

The data were then screened for multivariate outliers, and four cases were removed. These outliers consisted of more than one variable with scores that were considered an extreme value. Spearman's Rho correlations were calculated using IBM SPSS Statistics for Windows [37] for the following factors: (a) perceived usefulness, (b) ease of use, (c) people management, (d) value of workers, (e) satisfaction with workforce, (f) total number of employees, (g) proportion of full-time employees, and (h) proportion of entry level employees.

Finally, a multinomial logistic regression was conducted using IBM SPSS Statistics for Windows [37] to identify factors that are significant predictors of technology adoption. The use of different reference groups was explored, though ultimately those who were not currently using automated technology and had no plans to adopt were selected as the reference group.

4. Results

4.1. Adoption of Technology

Growers were sorted into three groups based on their adoption and acceptance of automated solutions. These were:

(a) Yes, I am currently using automation (other than GPS auto steer) on my farm (N = 52).
(b) No, but I am considering automated solutions (N = 74).
(c) No, and I have no plans to implement automation (N = 50).

Growers currently using automation on their farm other than GPS auto steer machinery were using automation for tasks including: (a) seeding, (b) irrigation, (c) fertiliser application, (d) spray application, (e) crop monitoring and collection of field data by satellite, (f) soil moisture management, (g) module tracking, and (h) reducing reliance on the workforce (Table 1). The technology being considered was also analysed for those not currently using automated technology on farms (Table 1) These responses ranged from referring to specific technologies to being more general in terms of the purpose for which these automated technologies were to be used, or motivational factors for seeking these out.

Table 1. Comparison of growers currently using automated solutions and those who are considering automated solutions for type of technology and motivation to adopt.

<table>
<tr><th></th><th colspan="2">Automated Technology Adoption Group</th></tr>
<tr><th></th><th>Yes, I Am Currently Using Automation (Other than GPS Auto Steer Tractors) on My Farm (N = 52)</th><th>No, But I Am Considering Automated Solutions (N = 74)</th></tr>
<tr><td>Automated solutions being considered</td><td>• Irrigation (centre pivots, padman stops to open channel gates remotely, automated pumps, pump monitoring)
• Robotic sprayer
• Automation to shut down machinery
• Doing more with tractors/automated tractors and sprayers
• Mapping and inventory (data collection)
• Crop monitoring
• Energy (solar generation)
• Not considering more automated solutions beyond what is currently used (N = 17)</td><td>• Irrigation (automated bankless system, water gate automation/channels remote stop and start, water level monitoring, pump monitoring)
• Sprays and chemical application (unmanned spray vehicles, variable rate fertiliser, weather stations to inform spray decisions)
• Weed management (robots for killing weeds/automated vehicle with microwave for hard to kill weeds/weed seeking technology)
• Seeding and planting (precision)
• Crop monitoring and management (canopy temp sensors, drones, field mapping, normalized difference vegetation index (NDVI) scans)
• Driverless tractors
• Scouting (pests)
• Wi-Fi for all areas of the farm</td></tr>
<tr><td>Motivations for considering other automated solutions on farm</td><td>• Accuracy and ease of management (everyone knows what is happening)
• Labour saving/ run a smaller, better skilled workforce/reduce workload
• For demonstration purposes
• For efficiencies</td><td>• For efficiencies (save time, money)
• Labour saving, reduce workload</td></tr>
</table>

Growers who were not currently using automated technology beyond GPS autosteer were asked to provide reasons in a short response form. These results are presented in Table 2.

Table 2. Comparison on barriers to adoption between growers considering automated technology and those with no plans to adopt.

<table>
<tr><th colspan="4">Automated Technology Adoption Group</th></tr>
<tr><th colspan="2">No, But I Am Considering Automated Solutions (N = 74)</th><th colspan="2">No, and I Have No Plans to Implement Automation (N = 50)</th></tr>
<tr><th>Concept</th><th>Exemplar Data</th><th>Concept</th><th>Exemplar Data</th></tr>
<tr><td>Structural/ Environmental Reasons 14 responses (19%)</td><td>“Large distance and poor farm service”
“In the middle of a 6 year drought”
“I’m only leasing the land”</td><td>Structural/ Environmental Reasons 8 responses (16%)</td><td>“No irrigation facilities”
“We use contractors”
“No water”</td></tr>
<tr><td>Cost of Equipment and Implementation 26 responses (35%)</td><td>“Cost of implementation”
“Too expensive to change”
“Weighing up the pros and cons to cost involved”</td><td>Cost of Equipment and Implementation 15 responses (30%)</td><td>“Cost is a big factor”
“Cost is too high”
“Cost versus value to set up and maintain”</td></tr>
<tr><td>Investing in preparation for automation 5 responses (7%)</td><td>“Resources are being spent on development”
“Priority is first to change layout to a bankless system, second priority to automate”</td><td>Other investment priorities 1 response (2%)</td><td>“Other areas of improvement offer better returns”</td></tr>
</table>

Table 2. *Cont.*

Automated Technology Adoption Group			
No, But I Am Considering Automated Solutions (N = 74)		**No, and I Have No Plans to Implement Automation (N = 50)**	
Concept	**Exemplar Data**	**Concept**	**Exemplar Data**
Technology is not ready (yet) 14 responses (19%)	"The technology is not good enough to be used at the moment" "Nothing suitable off the shelf" "Waiting for the technology to be working (proven)"	Technology is not ready (yet) 9 responses (18%)	"Not good enough yet, technology is not there yet" "Don't quite believe it is fully developed"
Trust (Low) 1 response (1%)	"Low trust in them"	Trust (Low) 2 responses (4%)	"Just a bit hesitant lack of trust" "More trust in a human to look at field and make a decision"
New to cotton 3 responses (4%)	"New to the cotton growing industry" "Phase of changing irrigation systems—was producing rice and now cotton"	It won't save me money on labour 1 response (2%)	"Not going to be a labour-saving method for me"
Skills challenges 2 responses (3%)	"My staff keep changing so we haven't bothered to train them" "I am not sure how to implement the automation on my farm"	Happy with the status quo 4 responses (8%)	"I am a luddite, you can't automate syphons" "We are used to the way we have always done it"
Reliable support from providers is needed 4 responses (5%)	"Reliability and long-term support from automation providers are not guaranteed" "Physically getting someone to quote and implement in a timely manner is a challenge"	No Need 2 responses (4%)	"I can't see an economic need at this time" "nothing available that I need to use"
Time 4 responses (5%)	"Haven't got around to it" "We were waiting for the right time"	No response 10 (20%)	
No need (yet) 1 response (1%)	"We haven't seen a need as yet"		
	No response 14 (19%)		

Descriptive statistics for demographic variables are presented in Table 3. Additional descriptive statistics for (a) technology acceptance variables (Table S1), and (b) attitudes and practices related to workforce variables (Table S2) are presented in the supplementary information.

Table 3. Descriptive statistics for demographics by Automated Technology Adoption Group. M = mean; SD = standard deviation.

	All Growers (N = 176)		**Yes, I Currently Use (N = 52)**		**No, But Considering (N = 74)**		**No, No Plans (N = 50)**	
	M	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Age category [1]	5.24	2.15	5.13	2.10	4.91	2.02	5.84	2.32
	Median	**Range**	**Median**	**Range**	**Median**	**Range**	**Median**	**Range**
Broad acre cropping area (ha)	1495	90–62,400	2250	90–57,000	1500	100–62,400	965	141–8600
Total Employees	5	1–110	6	1–110	5	1–68	4	1–43
Proportion of Full Time Employees [2]	0.8	0–1.00	0.8	0–1.00	0.8	0–1.00	0.9	0.21–1.00
Proportion of Entry Level Employees [3]	0.17	0–0.93	0.20	0–0.93	0.17	0–0.76	0.00	0–0.71

[1] Age was measured as an ordinal variable with categories listed as (1) under 20, (2) 20–34, (3) 35–39, (4) 40–44, (5) 45–49, (6) 50–54, (7) 55–59, (8) 60–64, (9) 65+; [2] Proportion of Full Time Employees is the number of full-time employees divided by the total workforce; [3] Proportion of Entry Level Employees is the number of entry level employees divided by the total workforce.

4.2. Perceived Usefulness Scale and Perceived Ease of Use Scale

The potential relationships between technology adoption scales, attitudes to workforce scales and workforce structure, represented by Spearman's Rho correlations, are presented in Table 4.

Table 4. Correlations between technology adoption scales, attitudes to workforce scales and workforce structure. Bold denotes a statistically significant correlation where * = $p < 0.05$ and ** = $p < 0.01$. M = mean, SD = standard deviation.

	M	SD	PU	EoU	PM	VoW	SwW	Total E	P.FT
Perceived Usefulness (PU)	3.55	0.77							
Ease of Use (EoU)	3.48	0.72	0.44 **						
People Management (PM)	3.89	0.68	0.10	0.14					
Value of Workers (VoW)	4.24	0.63	0.10	0.13	0.48 **				
Satisfaction with Workforce (SwW)	3.38	0.87	−0.03	0.07	0.11	0.24 **			
Total Employees (Total E)	9.68	14.26	0.21 **	0.11	0.18 *	0.16 *	−0.16 *		
Proportion Full Time Employees (P.FT)	0.76	0.25	−0.07	0.05	0.01	0.06	0.25 **	−0.36 **	
Proportion Entry Level Employees (P.EL)	0.21	0.23	0.09	−0.09	0.08	−0.00	−0.29 **	0.45 **	−0.36 **

The results of the multinomial logistic regression using those who were not currently using automated technology and had no plans to adopt as the reference group (N = 50) are shown in Table 5. Perceived usefulness was a significant factor in distinguishing between the reference group and both those who were considering new automation solutions and those who were currently using automation on farm. Two age groups for growers (20–34 years old and 45–49 years old) were significant factors to distinguish between the reference group and those who were considering new automation solutions. However, the wide confidence intervals means that these age group findings should be interpreted with caution.

Table 5. Multinomial logistic regression results. Bold denotes statistically similar results where * = $p < 0.05$ and ** = $p < 0.01$.

		95% CI for Odds Ratio		
	B(SE)	Lower	Odds Ratio	Upper
Yes, I Currently Use vs. No, and I Have No Plans				
Intercept	−7.05 (1.69) **			
Area of broadacre cropping	0.00 (0.00)	1.00	1.00	1.00
Age 20–34 years old	1.34 (1.04)	0.49	3.83	29.63
Age 25–39 years old	0.67 (0.93)	0.31	1.96	12.23
Age 40–44 years old	0.66 (1.12)	0.22	1.93	17.36
Age 45–49 years old	1.48 (1.08)	0.53	4.38	36.23
Age 50–54 years old	0.72 (0.95)	0.32	2.07	13.25
Age 55–59 years old	0.10 (0.96)	0.17	1.10	7.19
Age 60–64 years old	0.61 (1.02)	0.25	1.84	13.62
Ease of Use	0.42 (0.39)	0.70	1.52	3.31
Perceived Usefulness	1.31 (0.40) **	1.71	3.72	8.10

Table 5. *Cont.*

		95% CI for Odds Ratio		
	B(SE)	**Lower**	**Odds Ratio**	**Upper**
No, but I Am Considering vs. No, and I Have No Plans				
Intercept	−7.60 (1.78) **			
Area of broadacre cropping	0.00 (0.00)	1.00	1.00	1.00
Age 20–34 years old	3.02 (1.31) *	1.57	20.49	267.30
Age 25–39 years old	2.14 (1.24)	0.76	8.53	96.18
Age 40–44 years old	2.35 (1.36)	0.73	10.45	149.88
Age 45–49 years old	3.13 (1.34) *	1.65	22.77	313.73
Age 50–54 years old	2.33 (1.24)	0.90	10.29	117.65
Age 55–59 years old	1.46 (1.26)	0.37	4.30	50.44
Age 60–64 years old	2.38 (1.27)	0.90	10.84	130.00
Ease of Use	0.27 (0.36)	0.64	1.30	2.66
Perceived Usefulness	1.31 (0.36) **	1.83	3.72	7.56

R^2 = 0.26 (Cox-Snell), 0.29 (Nagelkerke). Model χ^2 (20) = 52.92, $p < 0.001$. Age 65+ years old is the reference category for age group main effects.

5. Discussion

This study discerned factors influencing acceptance and adoption of automated technology on cotton farms, and the interaction of these with workforce structures, management practices and attitudes about workforce. Differences about perceptions of usefulness and appraisals of ease of use were observed between groups categorized by their current technology adoption status. While no differences were observed on attitudes to workforce, there may be some impact of current workforce structures on acceptance and adoption of automated technology on farm. These findings are now further discussed.

The level of task automation and organisational change has been used in industry reports [4] to examine future workforce requirements and thus the research examined differences between different groups of adopters/non-adopters of automated technology to better understand what may influence or inhibit the industry to capitalise on the digital agriculture revolution, and the social/workforce factors that are driving them to do so.

Growers in the present study currently using automated technologies reported that purposes for these technologies included several on-farm production tasks, more precise application of inputs, and data collection for tracking and monitoring. Workforce considerations and reducing reliance on labour were also noted by some when asked about the purposes for automation. These participants have interpreted the question by identifying labour as a production constraint factor and not reporting the type of production task that was being automated. Workforce implications were also cited by those further considering adoption of other automated solution, including accuracy of task performance, ease of management in the co-ordination of people and reducing their own workloads, reducing labour costs and the number of people on farm. This indicates the motivation to adopt automation is not simply to improve application of inputs or to collect and use data in decision making, but that social factors are also drivers in grower appraisals of the usefulness of automated technology.

All groups were similar in the high level of value they placed on their workforce, their use of best practice people management approaches and their levels of satisfaction with their workforce. In terms of relationships between these factors, it would appear that the more growers valued their workforce, the more likely they were to agree they were practicing the targeted people management myBMP items, and the more satisfied they were with their workforce. The greater the proportion of workers on farms that were permanent, the more satisfied growers reported being with their workforce. Comparatively, the more entry-level employees there were, the less satisfied growers were with their workforce. There was also a small negative correlation such that the larger the number of employees on farm, the less satisfied growers were with their workforce. In general, larger teams had more entry level employees and more casual workers compared to smaller teams. Larger teams were positively correlated with perceptions of usefulness of automated technologies, suggesting that these farms recognised the value of automation to reduce labour costs, improve task performance, and save growers time to be spent on other priorities in the business or time with family. From this analysis, it can be argued that the comment from one grower who stated their motivation to adopt automated technology was to "run a smaller, better skilled workforce" would seem to be the strategic direction that others may intend to pursue, taking dissatisfactory seasonal, casual workers out of the system, leaving growers with a team they value and will invest in through good management practices.

Factors such as drought, finances, infrastructure, and legacy farming systems may prevent adoption of automation. These are common for those farmers "considering" and "not considering" automation, with the reported reasons for not currently implementing on-farm automation being similar between the two groups. The groups differ in that fewer people "considering" technology reported an absence of current need compared to those with no plans to implement automation. Growers who were considering automated solutions are more specific about ease-of-use barriers such as working out how to integrate technology, skills required, time needed to investigate, and needing to see reliable support. The reporting of these types of barriers to adoption shows greater acceptance of and critical engagement with automated technologies. Those "considering" are also more likely to report that they are investing elsewhere, indicating a growth and development approach to their farm business even if that does not include current adoption of automated technologies. In contrast, for those who are not considering any automated solutions, some (8%) disclosed an attachment to their current infrastructure and practices and hesitance to look beyond the status quo on their farm.

In terms of the core mechanisms of the TAM, the current research found a moderate correlation between ease of use and perceived usefulness (r = 0.44, $p < 0.01$). This is similar to meta-analyses by Ma and Liu [20], which also reported a significant relationship between ease of use and perceived usefulness, and that the latter was significantly related to acceptance. In the current study, a post hoc analysis showed the correlation between ease of use and perceived usefulness is stronger for those who are already using automated technology on farm (r = 0.53, $p < 0.01$) compared to those who are not using automated technology on farm (r = 0.32, $p < 0.01$ for those considering, and r = 0.39, $p < 0.01$ for those not considering). This indicates that ease of use appraisals are particularly important for assessing the usefulness of technology for those who have adopted some form of automated technology into their farming system (accounting for approximately 28% of the variance), but for those yet to adopt, their skill levels, ability to integrate technology, or the adaptability of their workforce accounts for less variance (15%) with regard to their assessment of the usefulness of automated technologies. This would indicate that ease of use becomes more salient to maintaining perceptions of usefulness for those who are using automated technology on farm. Ease of use, in addition to benefit cost, has also been reported by Robertson et al. [31] as the greatest contributors to automation technology adoption, particularly in the absence of technical support and training.

The research sought to quantitatively explore whether there was any relationship between attitudes to technology adoption (perceived usefulness and perceived ease of use) with people management practices and attitudes to workforce. No statistically significant results were found. A weak correlation was observed between growers' perceived ease of use and their people management practices. While this did not reach our set threshold for statistical significance, the p value was considered low (r = 0.07) such that a further post hoc analysis at the inter-item correlations was conducted. A closer look at the item level correlations revealed that the items "I have encouraged workers to give me their suggestions and feedback about farming matters" and "I have regularly provided feedback to my staff in relation to the performance of their jobs" are correlated with "My workers are capable of adapting in their work roles to use automated technology on my farm" (r = 0.25,

$p < 0.01$; r = 0.20, $p < 0.05$). This suggests that good people management practices that promote a two-way relationship and exchange of ideas may support workers to adapt in changing workplaces. Alternatively, growers who perceive their workers as adaptable may be more inclined to invest time and effort in effective people management activities. Further research investigating the impacts of management practices on workers' ability to adapt may help to address ease of use barriers to technology adoption.

When considering the results of the multinomial logistic regression, it was the perceived usefulness of automated technology that determined the likelihood that someone is already using automation solutions or considering using automation solutions compared to those who have no plans to implement automation solutions. Understanding the value proposition of automated technology is important to start growers on their way to exploring and engaging in consideration and eventual adoption of digital agriculture. This was also reported in a survey of Australian grain producers [38], with the author's suggesting that promotion of agri-tech and subsequent integration into decision making process may help producers understand the value proposition and thus facilitate stepwise adoption.

While the analysis is underpowered in terms of sample size, it is interesting to note that the only age groups that differed from the oldest group of growers (aged 65+) in terms of whether they were considering technology compared to having no plans was those in the age group 20–34 years or 44–49 years. It may be that these two age groups represent growers who are at the start of their career and keen to explore new digital tools to use within their business, or growers who have children in teen years/early adulthood who are considering the future of their business for the next generation and what they will need to sustain the farm in the coming decades. The younger cohort observation is similar to Bramley and Ouzman [38], who found that 87% of surveyed grain producers who had been farming for less than 10 years (and therefore assumed to be the youngest of survey respondents) intend to use sensors as part of their work, compared to only 65% of those who have been farming for over 20 years. The treatment of age by groups in the current study, as opposed to a continuous variable, allowed for this non-linear relationship to be identified. The smaller sample size contributes to the very large confidence intervals for these findings, and as such these results should be cautiously considered. Nonetheless, it does indicate further research on life stage could be important in considering the growers' willingness to dedicate time and effort to engage in activities that leads to acceptance and adoption of digital technologies into their farming businesses.

The TAM model applied in this study is useful to predict the acceptance of digital technology in agriculture based on perceived usefulness and perceived ease of use alone. However, further iterations of the TAM now include precursors to these perceptions to provide further insight into adoption behaviour. For example, antecedents to perceived usefulness include social influence processes (including social norms, and image), cognitive appraisals (including job relevance, output quality, and result demonstrability), and perceived ease of use. Antecedents to perceived ease of use appraisals include computer self-efficacy, perceptions of external control, computer anxiety, computer playfulness, perceived enjoyment, and objective useability. Further research should seek to expand on the current findings and identify the relevant antecedents to perceived usefulness and perceived ease of use and the relationship between these for the adoption of digital technology in agriculture. Some of the qualitative findings on barriers to adoption may offer preliminary insight into these factors with grower responses on systemic/environmental barriers, trust in technology, a satisfaction with the status quo, and concerns about lack of support for implementation providing some description of issues relating to perceptions of job relevance, output quality, attitudes around subjective norms, and perceptions of external control. However, these links to the factors of interest are far from robust, and more in-depth qualitative research on the TAM antecedents is warranted. Furthermore, due to the practical limitations of data collection (i.e., using a secondary data set), we were unable to expand our study to include any quantitative exploration of the TAM antecedents. However, Yousafzai et al. [39] argue that an understanding of the relationship between these different antecedents is necessary to inform any intervention that seeks to improve technology acceptance. The findings of the current research would suggest future research needs to explore the factors that are influencing the progression of increasing perceived usefulness of automated technology to move those from not considering, to considering adoption, and then the factors that influence perceptions of ease of use to support those from considering to actual adoption of automated technology. Once adopted, interventions continuing to support ease of use are essential to ensure automated technology is not abandoned and the ongoing successful digital transformation of cotton farms.

6. Conclusions

The future of work in agriculture will involve the increasing digital transformation of the farming business. This depends on connecting with the next generation; the current workforce adaptability, acceptance and adoption of digital technology [40]. The current study explored Australian cotton growers' use of automation technology, including reasons for technology adoption and intentions for application. For the Australian cotton industry, it is clear that reducing a reliance on seasonal labour contributes to motivations to adopt technology, and that those with larger workforces are more likely to view reducing labour costs and their efforts spent managing workers, the opportunity for time-saving with regard to their job responsibilities, and more effective task performance, as providing an appealing value proposition to adopt automation. Growers considering technology use are able to identify the usefulness of automated solutions and are confronting ease-of-use barriers for implementation. These growers have a growth mindset and are less satisfied with the status quo compared to those not considering automation. Furthermore, those growers who engage in good people management practices are more likely to have a workforce that they believe can adapt to work with automation in their roles. The age/stage of life that growers are at in their career may influence their consideration of automation solutions. Finally, ease of use isrelated to perceived usefulness of technology and perceived usefulness is the factor that differentiates those not considering automation with those that are considering automation or have already adopted.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/agriculture12081180/s1, Table S1: Descriptive statistics for technology adoption items and scales. M = mean; SD = standard deviation.; Table S2: Descriptive statistics for attitudes toward workforce items and scales. ® indicates reverse scoring completed such that a higher score is a more positive appraisal. M = Mean, SD = standard deviation.

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