Introduction

In recent years, agriculture has emerged as a key industry in applying artificial intelligence (AI), which holds the potential to drive a transformative process in the industry (Kisliuk et al., 2023). California's reputation as the hub for technological innovation (Glasner, 2024), as well as being the leading agricultural producer in the United States (Bauer, 2022), suggests that the state will become important to the advancement of AI in agriculture. While there has been steady expansion of AI across the state, which has largely been driven by increasing demand for labor and a large tech industry based out of Silicon Valley (Kenney et al., 2021), the continuing development and adoption of AI in California agriculture remains at the forefront for farmers, business leaders, policy makers, and researchers.

Research has consistently shown that public attitudes about emerging technology can often shape behavior toward, and public policy about, the use of said technology (Bingaman et al., 2021; Brewer et al., 2022; Brossard & Nisbet, 2007; Dudo et al., 2011; Nisbet et al., 2002; Scheufele & Lewenstein, 2005). For agriculture, research has shown that the general public can often influence regulations and policy efforts (Malyska et al., 2016). Moreover, a better understanding of public perceptions of these technologies can help agricultural professionals in their communication efforts with the public (Hill, 2020; Zimbelman et al., 1995).

When it comes to existing research, public opinion polls and surveys of the U.S. population highlight that people tend to see both the benefits and risks of adopting AI (Brewer et al., 2020; Northeastern University & Gallup, 2018; West, 2018; Zhang & Dafoe, 2019), with recent polls indicating more negative perceptions regarding generative AI such as ChatGPT (Schreckinger, 2023). Specific to California, recent polls indicate that almost 70% of residents believe California should be the leader in AI technology (Artificial Intelligence Policy Institute, 2023). In addition to public opinion polls, research has consistently found links between media viewing and attitudes about different types of emerging technology like AI (Bingaman et al., 2021; Brewer et al., 2022; Dawson et al., 2022; Olawuyi & Enuwah, 2025).

This study sought to expand on these existing lines of inquiry by exploring how media communication factors influence Californians' attitudes toward the development and adoption of AI in agriculture. Specifically, this study distinguishes itself by examining attitudes on the use of AI within specific areas of the agricultural sector, including livestock management, crop production, water management, and the supply chain. Grounded in an extension of cultivation theory (see Gerbner 1969, 1970, 1973, 1998) known as programmatic or genre-specific cultivation (Bingaman et al., 2024; Brewer et al., 2023; Cohen & Weimann, 2000; Lee & Niederdeppe, 2010; Potter & Chang, 1990; Stise et al., 2024), this study examined media viewing behavior of Californians, including news media and science fiction. Additionally, this study also analyzed how underlying value predispositions like deference to scientific authority, political ideology, and religiosity potentially influence attitudes. Given California's standing as one of the largest agricultural producers (Bauer, 2022) and leader in AI development (West, 2023), this research offers key insights into public attitudes that can potentially guide communication strategies, development, and investment decisions for the continued utilization of AI in agriculture.

Theoretical Framework

Cultivation Theory

A staple of mass communication scholarship, the theory of cultivation was born out of research by George Gerbner in the late 1960s and early 1970s (see Gerbner 1969, 1970, 1973, 1998). As described by Shanahan and Morgan (1999), this theory explains how individuals who are engaged with prolonged media viewing will typically hold "conceptions that are congruent with the most consistent and pervasive images and values" of that media (p. 3). That is, those engaged with media content are more likely to hold attitudes, beliefs, and opinions that reflect that media content. Although initially focused on overall television viewing, cultivation theory has applicability across several media and genres, with Gerbner et al. (1994) explaining that the theory focuses "on the implications of accumulated exposure to the most general system of messages, images, and values" (p. 21).

When it comes to cultivation theory, existing research has found support for overall television viewing influencing attitudes towards a range of topics, including crime (Gerbner & Gross, 1976; Morgan & Shanahan, 2010; Romer et al., 2006), science (Brewer & Ley, 2021; Gerbner et al., 1981; Dudo et al., 2011; Nisbet et al., 2002), or general understandings of the social world (Busselle & Ven den Bulck, 2019). Although not considered a direct media effect, cultivation effects are often assessed using survey methodology that examines how media viewing habits relate to attitudes held by individuals. Despite critiques against cultivation theory for its lack of applicability outside of broad television viewing (see Potter, 1993), the theory remains important to our understanding of how audiences are influenced by media messages (Morgan et al., 2015). As cultivation has developed over the years, scholars have shifted their focus away from overall television viewing (a pervasive medium during the 1970s and 1980s but has lost some of its cultural significance) and instead focused on exploring how media genres and programs themselves can influence individuals (Shannahan & Morgan, 1999; Morgan et al., 2015).

Programmatic & Genre-Specific Cultivation

In challenging cultivation theory, Hawkins and Pingree (1981) argued that scholars should look to explore the influence that distinct programs or media genres have on individuals. This perspective was echoed by Calzo and Ward (2009), who argued that specific genres themselves are important to consider when using cultivation theory, as not all media covers issues in the same way. This approach to cultivation research has been supported by existing scholarship (see Cohen & Weimann, 2000; Lee & Niederdeppe, 2010; Potter & Chang, 1990), including in the context of science and emerging technologies (see Bingaman et al., 2024; Brewer et al., 2023; Stise et al., 2024).

Research by Brewer et al. (2023) found that specific genres of drama television cultivated attitudes toward applications of facial recognition technology. Likewise, Stise et al. (2024) found that specific media programs influence paranormal attitudes. When it comes to genres, although some research has found support for science fiction viewing influencing individuals' science and emerging technology (see Bingaman et al., 2024; Brewer et al., 2024; Green, 2019; Hamilton, 2003; Nisbet & Goidel, 2007), other research found that genre-specific cultivation effects did not occur. For example, Dawson et al. (2022) found that science fiction viewing did not influence

individuals' attitudes toward gene editing practices. Despite these conflicting findings, the basic premise of this extension of cultivation theory is that since media messages potentially differ across programs and genres, it stands to reason that various types of programs and genres should be considered when exploring individuals' attitudes about these topics. This approach has yet to be applied in the context of agricultural attitudes, and thus, the following research question was posed:

RQ1: How do media communication factors shape Californians' attitudes toward AI in agriculture?

Value Predispositions

In addition to media viewing behaviors, research has routinely highlighted the strong role that value predispositions play in shaping attitudes toward science (Brewer & Ley, 2021; Pechar et al., 2018), emerging technologies (Brewer et al., 2022, 2023; Brossard et al., 2009; Dawson et al., 2022), and agriculture or food (Boeuf, 2019; Calabrese et al., 2021; Olper, 2007). As described by Ho et al. (2008), value predispositions can act as heuristic cues to help in the formation or fortification of attitudes. Specific to this study, three value predispositions were selected based on their salience in extant research related to media behaviors and attitudes toward emerging technologies (see Brewer et al., 2022, 2023; Brossard et al., 2009; Dawson et al., 2022): deference to scientific authority, political ideology, and religiosity.

Deference to Scientific Authority (DSA)

Deference to scientific authority (DSA) refers to "the extent to which people believe that decision-making concerning science and technology should be the purview of the scientific community and not part of larger democratic discourse" (Howell et al., 2020, p. 801). In the U.S., this belief is rooted in persisting socialization that individuals should defer to scientific authority and not elaborate on their notions about science, especially when claims are disputed or when controversies arise (Brossard & Nisbet, 2007; Lee & Scheufele, 2006). Akin et al. (2020) claim that this predisposition is a consistent predictor of attitudes to both general scientific issues and more distinct forms of emerging technology. Brossard and Nisbet (2007) contend that, regardless of context, "deference to scientific authority as a value predisposition serves as a strong and consistent opinion generator" (p. 30).

Political Ideology

Existing research shows a complex picture when it comes to the influence of political ideology on attitudes toward emerging technologies and agriculture. Broadly, when it comes to science, Pechar et al. (2018) refer to political ideology as an inconsistent predictor of attitudes. When it comes to emerging technologies, Calabrese et al. (2021) found that conservative ideology was negatively associated with general science attitudes. While this would suggest that conservatives would oppose emerging technologies, Brewer et al. (2023) determined that conservatives were more likely to oppose the banning of facial recognition technology and more likely to support the use of this technology by law enforcement. When it comes to agriculture, political ideology has been found to influence several areas. For example, Sanders et al. (2022) found that political ideology influences attitudes toward climate change, finding that liberal

ideology was associated with higher levels of climate change concern; a finding consistent with other studies (see Stanley & Wilson, 2019). Conversely, when looking more specifically at water-specific beliefs, Hundemer (2023) did not find that political ideology played a role in attitude formation. This suggests that specific agricultural applications may be impacted to different degrees by political ideology, making it an important value to consider in this study.

Religiosity

According to Brossard et al. (2009), individuals' levels of religiosity can act as perceptual filters that help in the formation of attitudes toward emerging technologies. For example, when it comes to emerging technologies such as genetic modification, Dawson et al. (2022) found that measures of religiosity (operationalized as how important religion was to someone's life) were significantly related to opposition to the adoption of the technology. While some studies have found that religiosity negatively impacts attitudes toward science (see McPhetres & Zuckerman, 2018), when it comes to agricultural attitudes, Karami and Mansoorabadi (2007) found that religious values predicted greater support for the environment and sustainable agriculture. These findings suggest that religiosity is an important value to consider when examining the convergence of science, technology, and agriculture. Considering evidence in extant literature of the potential influence of DSA, political ideology, and religiosity on attitudes about emerging technology and agriculture, the following research question was posed:

RQ2: How do value predispositions shape Californians' attitudes toward AI in agriculture?

Methods

This study used data obtained from an online survey of California residents. The survey instrument was designed and developed by the authors using Qualtrics and received Institutional Review Board approval before dissemination. The online survey was distributed by survey firm Centiment between February 7 and March 12, 2025. The survey took approximately 11 minutes to complete.

Participants for the study (N = 601) were recruited via the audience panel services provided by Centiment. For their audience panels, Centiment uses social media sites like Facebook and LinkedIn to recruit participants. According to Centiment, all respondents who qualify for a survey based on certain parameters (outlined by the authors) are notified once a survey becomes live. For this survey, only California residents (as determined by self-reported measures) were invited to take part in the survey. It is important to note that the sample from this study was not weighted, and the demographics of participants of this survey may not reflect California. Each participant for the survey was compensated $4.95 for completed responses.

Survey Instrument

A battery of questions was asked regarding demographics, media use, including general TV viewing, genre-specific media viewing, and news media viewing (see Appendix A). In addition to media use, participants were asked questions regarding partisanship, political ideology, and religious predispositions; all variables that have been noted as potentially influential concerning emerging technology (Brewer et al., 2022; Dawson et al., 2022).

Regarding the content and face validity of the survey instrument, questions related to media behavior and value predispositions were gathered from existing survey research (Appendix A; Brewer et al. 2022; Bingaman et al., 2024; Dawson et al., 2022). Each of these studies used similar measurements and wording for media behavior and value predistortions. As a preliminary check, content and face validity is important "for ensuring that the instruments and their measures (items, scales) are aptly designed, to capture and measure the constructs of interest" (Lim, 2024, p. 159). Regarding content validity, these questions were determined to be reflective of the constructs they encompass based on expert judgment (existing, peer-reviewed research). As for face validity, the subjective judgment of these measurements was deemed as appropriate by the authors. Given how closely the wording for the measurements in this study mirrors these existing studies, revalidation was deemed unnecessary. Relevant adaptions were made where necessary. For example, when asked how closely individuals followed news about specific topics, "agriculture" was included.

Demographics

Several key demographic measures were captured as part of the survey, including *age* (*M* = 47.28, *SD* = 18.07; min = 18, max = 98); *gender* (female = 50% male = 48%; non-binary = 1%); *race* (White = 67%, Asian = 13%, Black = 12%, Native American = 5%); *ethnicity* (Hispanic = 26%); and *political party identification* (Democrat = 39%; Republican = 28%; Independent = 28%; Other = 5%). In addition to these demographic markers, education level was measured using a 7-point scale (from "less than High School" to "Doctorate Degree"; *M* = 3.72, *SD* = 1.40) and self-reported income using a 12-point scale (from "less than $10,000" to "more than $150,000"; *M* = 6.52, *SD* = 3.64). The only demographic measures used in the analyses below were age, gender, education, and income.

Media Use

For overall media viewing, respondents were asked to self-report how much time they spent watching television shows and movies (including on a computer or mobile device) using a five-point scale (from *"none"* to *"four hours or more"*; *M* = 3.80, *SD* = 1.16). In addition to overall media viewing, respondents were asked how often they watched different kinds of TV news using a four-point scale (from *"less often"* to *"nearly every day"*), including national network television news (such as ABC, CBS, or NBC), CNN, MSNBC, and The Fox News Channel. Given their high correlation, an index of network television, CNN, and MSNBC was created (*M* = 2.13, *SD* = .92). Regarding reliability, this index reached an acceptable Cronbach's alpha level (α = .78). The Fox News Channel remained as its own variable (*M* = 2.03, *SD* = 1.17). Moreover, respondents were further asked how closely they followed news about specific topics (four-point scale from *"not at all close"* to "*very closely*"), including technology (*M* = 2.71, *SD* = .94), agriculture (*M* = 2.30, *SD* = .92), politics (*M* = 2.9, *SD* = 1.00), and business (*M* = 2.53, *SD* = .96).

As determined by existing research on genre-specific cultivation effects associated with science fiction viewing and support for emerging technologies (see Bingaman et al., 2024; Brewer et al., 2024; Green, 2019; Hamilton, 2003; Nisbet & Goidel, 2007), respondents were asked how often they watched science fiction (four-point scale) ranging from "*less often*" to "*nearly every day*" (*M* = 1.98, *SD* = .93).

Value Predispositions

Consistent with how deference to scientific authority (DSA) has been measured in past surveys (see Akin et al., 2020; Brewer et al., 2022; Brossard & Nisbet, 2007; Dawson et al., 2022; Howell et al., 2020), respondents were asked how much they agreed with four statements (using a five-point scale from "*strongly disagree*" to "*strongly agree*". These statements included "scientists know best what is good for the public", "it is important for scientists to get research done even if they displease people by doing it", "scientists should do what they think is best, even if they have to persuade people that it is right", and "scientists should make the decisions about the type of scientific research done on artificial intelligence in agriculture". The responses to these four statements were indexed, with high levels of reliability (M = 3.56, SD = .86; α = .82). Political ideology was measured using a one-question, seven-point scale asking how respondents would describe their political views from "*very liberal*" to "*very conservative*" (M = 4.03, SD = 1.72; Liberal = 1, Conservative = 7). Religiosity was measured using a four-point scale ranging from "*not at all important*" to "*very important*" (M = 2.70, SD = 1.11).

Attitudes Toward AI

To begin with, attitudes toward AI needed to be analyzed. This study examined attitudes in four ways: general views of AI's effect on society, views of AI's effect on agriculture, support towards specific applications of AI, and trust in the development of AI by varying entities. For the first two of these, respondents were asked what effect they believed AI would have on (a) society as a whole (M = 2.59, SD = .95) and on agricultural (M = 2.72, SD = .89) on a four-point scale ranging from "*it will do a great deal of harm*" to "*it will do a great deal of good*". As for specific applications of AI in agriculture, respondents were asked (five-point scale from "*strongly oppose*" to "*strongly support*") how much they supported its use to monitor and manage crops (M = 3.69, SD = 1.12), animals (M = 3.54, SD = 1.21), water (M = 3.84, SD = 1.10), and supply chain (M = 3.71, SD = 1.15). Finally, using a five-point scale (from "*none at all*" to "*a great deal*"), respondents were asked how much they trusted the following entities to develop the use of AI in agriculture: government (M = 2.23, SD = 1.08), tech companies (M = 2.62, SD = 1.13), university researchers (M = 2.91, SD = 1.16), agricultural businesses and industry professionals (M = 2.87, SD = 1.11), and farmers and ranchers (M = 3.17, SD = 1.20).

Results

With these attitudes established, the two research questions were analyzed using a series of Ordinary Least Squares (OLS) regressions. All statistics were analyzed using Stata 19. Linear regressions are used to "analyze the relationship between an explanatory variable and an outcome variable while controlling for the effects of other variables" (Long & Freese, 2006, p. 4), with OLS regressions minimizing the sum of squares residuals. For this analysis, unstandardized coefficients were used (b).

When it comes to addressing how media viewing behavior influences attitudes toward AI in agriculture (RQ1), both Fox News viewing (b = .11, p < .01) and following technology news closely (b = .09, p < .05) were positively associated with the belief that AI would have a positive impact on agriculture. Conversely, following political news closely (b = -.13, p < .01) and

watching science fiction (b = -.11, p < .01) were both negatively associated with this attitude. For a full summary of OLS regression coefficients, see Appendix B.

When looking at media viewing behavior and attitudes toward specific applications of AI in agriculture (see Table 1), it appears that following technology news closely is positively associated with more supportive attitudes. Finally, regarding Californians' trust in different entities to develop AI in agriculture (see Table 2), media variables paint a nuanced picture. For example, those who watch a lot of media are much more likely to support both technology companies and agricultural businesses to develop AI, corroborating a cultivation effect. However, those more closely engaged with TV news (such as network television, CNN, and MSNBC) are more likely to support government-led efforts at developing AI. This specific difference could be supportive of a genre or programmatic-cultivation effect of media.

Diving more specifically into specific programs and genres, Fox News viewers and those who follow business news are more supportive of technology companies developing AI. Conversely, those who follow political news closely are less likely to support government or technology companies developing AI. Looking specifically at this relationship, a post-hoc analysis found that political news was positively correlated with both TV news viewing (r =.40, p < .001) and Fox News viewing (r = .25, p < .001), suggesting that political news is more strongly related to TV news such as network television programs, CNN, and MSNBC, than with Fox News. Finally, Californians who closely follow agricultural news are the most supportive of university researchers to develop AI.

Table 1.

Attitudes toward specific agricultural applications of AI

	Crops	Animals	Water	Supply Chain
Age	.002 (.003)	.004 (.003)	.005 (.002)	.002 (.003)
Gender (Fem = 1)	-.21 (.09)*	-.28 (.10)**	-.02 (.09)	-.33 (.09)**
Income	.03 (.01)*	.03 (.01)*	.03 (.01)*	.03 (.01)*
Education	.03 (.03)	.04 (.04)	.08 (.03)*	.01 (.04)
Political Ideology	.05 (.03)	.05 (.03)	.02 (.03)	.03 (.03)
Religiosity	.03 (.04)	.08 (.04)	.01 (.04)	.06 (.04)
Def. Sci. Auth.	.38 (.06)**	.35 (.06)**	.31 (.05)**	.36 (.06)**
Overall Media	-.01 (.04)	-.01 (.04)	.02 (.04)	.02 (.04)
TV News	-.04 (.06)	-.04 (.06)	-.06 (.06)	-.07 (.06)
Fox News	.06 (.05)	.10 (.05)*	.08 (.04)	.06 (.05)
Tech News	.12 (.06)*	.22 (.07)**	.18 (.06)**	.20 (.06)**
Ag News	.04 (.06)	-.02 (.07)	-.03 (.06)	-.08 (.06)
Political News	-.06 (.06)	-.13 (.06)	-.05 (.06)	-.02 (.06)
Business News	-.03 (.06)	-.03 (.07)	.03 (.06)	.02 (.06)
Science Fiction	.05 (.05)	.04 (.06)	.08 (.05)	.01 (.05)
Constant	1.48 (.33)**	1.21 (.36)**	1.33 (.33)**	1.53 (.34)**
R^2	.16**	.16**	.16**	.17**

Note. OLS regression coefficients, with standard error value in parentheses
**p < .01. *p < .05

When examining the influence of value predispositions (RQ2) across all three OLS regressions, it becomes apparent that DSA is a robust measurement that is strongly associated with support for AI in agriculture. DSA was positively associated with the beliefs that AI would be beneficial for both society (b = .30, p < .01) and agriculture (b = .30, p < .01). Likewise, DSA was strongly associated with all specific applications of AI in agriculture (Table 1), with crop and supply chain management having the strongest effect size (b = .38 and .36, respectively). As for trust in the development of AI (Table 2), DSA once again was strongly associated with all entities, with university researchers having the strongest effect size (b = .40). As for political ideology and religiosity, these value predispositions generally did not predict support for AI, except for religiosity as a positive predictor of support for government-led development.

Table 2.

Trust in the development of AI technology in agriculture

	Gov.	Tech	Universities	Business	Farmers
Age	-.01 (.002)**	-.004 (.002)	-.002 (.002)	-.01 (.003)	-.003 (.003)
Gender (Fem = 1)	-.07 (.09)	-.02 (.09)	-.04 (.09)	-.05 (.09)	-.06 (.10)
Income	.03 (.01)	.01 (.01)	.02 (.01)	.05 (.01)**	.03 (.01)
Education	.05 (.03)	.03 (.04)	.04 (.04)	-.01 (.04)	.05 (.04)
Political Ideology	.02 (.03)	.04 (.03)	-.03 (.03)	-.01 (.03)	.03 (.03)
Religiosity	.13 (.04)**	.03 (.04)	.03 (.04)	.04 (.04)	.02 (.05)
Def. Sci. Auth.	.30 (.05)**	.34 (.06)**	.41 (.04)**	.22 (.06)**	.12 (.06)*
Overall Media	-.01 (.04)	.09 (.04)**	.04 (.04)	.12 (.04)**	.08 (.04)
TV News	.19 (.06)**	.03 (.06)	.05 (.06)	-.01 (.06)	-.05 (.07)
Fox News	.01 (.04)	.12 (.05)**	-.07 (.05)	.01 (.05)	-.01 (.05)
Tech News	-.02 (.06)	.10 (.06)	.01 (.06)	.05 (.06)	.08 (.07)
Ag News	.05 (.06)	-.04 (.06)	.18 (.06)**	.06 (.06)	.06 (.07)
Political News	-.15 (.05)**	-.14 (.06)*	-.04 (.06)	.002 (.06)	.05 (.06)
Business News	.04 (.06)	.15 (.06)*	.03 (.06)	.04 (.06)	.04 (.07)
Science Fiction	.02 .05)	-.001 (.05)	.02 (.06)	.01 (.05)	.05 (.06)
Constant	.64 (.32)*	.40 (.34)	.78 (.34)*	1.14 (.34)**	1.48 (.37)**
R^2	.18**	.16**	.18**	.12**	.08**

Note. OLS regression coefficients, with standard error value in parentheses
**p < .01. *p < .05

Discussion

Given the proliferation of AI in the agricultural sector (Kisliuk et al., 2023), as well as California's current reputation as both an agricultural and technological hub (Bauer, 2022; Glasner, 2024; West, 2023), this study sought to explore how media communication and value predispositions potentially influence Californians' attitudes about AI in agriculture. Grounded in

programmatic and genre-specific cultivation theory (Bingaman et al., 2024; Brewer et al., 2023; Calzo & Ward, 2009; Cohen & Weimann, 2000; Hawkins & Pingree, 1980, 1981; Lee & Niederdeppe, 2010; Stise et al., 2024), this study found significant relationships between various types of news media viewing behavior and attitudes about the use of AI in different agriculture contexts. Additionally, results from this study also show that deference to scientific authority is a robust value predisposition that helps predict positive attitudes. These findings, along with their implications, are discussed further below.

From a theoretical perspective, this study supports programmatic and genre-specific cultivation theory, which claims that specific media programs or genres can influence opinions, attitudes, or beliefs regarding a topic (Bingaman et al., 2024; Brewer et al., 2023; Calzo & Ward, 2009; Cohen & Weimann, 2000; Hawkins & Pingree, 1980, 1981; Lee & Niederdeppe, 2010; Stise et al., 2024). Unlike Brossard and Nisbet (2007), who found that news media did not influence support for agricultural biotechnology, this study finds that several types of media viewing behaviors were indeed associated with support for the use of AI in agriculture. For example, following technology-specific news closely was positively associated with support for AI in agriculture, including in the monitoring and management of crops, animals, water, and supply chain logistics. This result is unsurprising, as technology like AI is typically framed in news from a future-oriented, social-progress perspective (see Bingaman et al., 2021; Brewer et al., 2022; Olawuyi & Enuwah, 2025).

When it comes to attitudes regarding trust in various entities to develop AI in agriculture, the results suggest a more nuanced and complex picture. For example, overall media viewing – a classic cultivation effect (Gerbner, 1969, 1970, 1998) – was predictive of trust in technology and agricultural businesses to develop AI. Boyle and Kelly (2016) have noted the rise in business-oriented entertainment programming, which might help explain this cultivation effect among audiences who perceive business as the most trustworthy to further develop AI in agriculture. Looking more closely at news viewing, Californians that followed political news closely were less likely to trust the government or technology companies with the development of AI. Post-hoc analyses found that these individuals are more likely to get their news from network TV, CNN, or MSNBC. This could be reflective of the time period in which the survey was distributed; a post-2024 election that saw the Republican party take all three branches of government, along with tech company CEOs from Apple, Google, and Amazon attending President Trump's inauguration (see Swenson, 2025).

This also potentially aligns with the findings related to Fox News viewing and trust in tech companies to develop AI in agriculture. In addition to an ideological shift from prominent tech figures like Elon Musk and Mark Zuckerberg (Pasi, 2025), Republican lawmakers have proposed legislation that opposes AI regulation and instead focuses on innovation driven by the private sector (Bhuiyan, 2025). This dovetails with research that suggests that coverage of AI on Fox News has shifted more positively in the last few years (Eisenbeis & Elkins, 2024). This finding is further supported by the results that show that Fox News viewers are more likely to perceive the effects of AI as good for both agriculture and society. Considering the considerable support among "farming-dependent" – defined "as counties where 25% or more of average annual earnings were derived from farming" – counties for President Trump in the 2024 election (Felder, 2024, para. 4), these findings reinforce possible programmatic cultivation effects associated with Fox News viewing on support for AI in agriculture; an increasingly important policy position for Republican lawmakers (Shapero, 2025).

One final important finding when looking at trust relates to those who follow agriculture news closely. Following agricultural news closely, which could perhaps be seen as a proxy measurement of those more closely associated with the agricultural sector in some capacity, was positively associated with supporting university researchers to develop AI technologies. This level of trust could be the result of crucial extension efforts and partnerships between land-grant universities and the agricultural industry (see King et al. 2022). This also highlights that despite current federal opposition to funding research and higher education (see Knott, 2025), those who follow agriculture closely support and trust these institutions when it comes to the development of AI. These findings could be beneficial when advocating for research funding in higher education institutions.

A surprising finding from this study suggests that those who watch more science fiction are more likely to believe that AI will harm the future of agriculture. Not only does this result run counter to existing research (Bingaman et al., 2024; Brewer et al., 2024; Green, 2019; Hamilton, 2003; Nisbet & Goidel, 2007), but science fiction viewing did not influence attitudes about the effects of AI on society. One possible explanation for this finding could be related to science fiction portrayals of AI. In an experiment on visual framing of AI, Bingaman et al. (2021) found that negative portrayals of AI, like that of The Terminator, negatively influence individuals' attitudes toward the technology. This is important when thinking about the application of AI in agriculture, something closely aligned with food. When examining science fiction portrayals of food, Retzinger (2008) noted that in post-apocalyptic scenarios "hunger takes both literal and metaphorical form in science fiction films, arising from scarcity and uncertainty alike" (p. 12). Thus, it could be that science fiction viewers are more likely to perceive AI as associated with post-apocalyptic imagery, and therefore, detrimental to food production and agricultural processes.

When it comes to value predispositions, this study further strengthens existing research on the integral role that deference to scientific authority plays in attitude formation regarding emerging technologies (see Akin et al., 2020; Brewer et al., 2022; Brossard and Nisbet, 2007; Dawson et al., 2022; Howell et al., 2020). As demonstrated in this study, DSA remained a strong and positive predictor of support for the development of AI in agriculture. Specific to agriculture, these results reinforce findings from Brossard and Nisbet (2007) from nearly a decade ago on the influence of DSA on support for agricultural biotechnology.

As for other value predispositions, although existing studies were able to find that political ideology influenced attitudes—whether positively or negatively (see Brewer et al. 2023; Calabrese et al. 2021; Sanders et al. 2022)—toward emerging technologies, this study's findings did not find such a relationship. This could be consistent with research from Hundemer (2023) that highlight that political ideology did not influence attitude formation toward agricultural topics. While this paper specifically looked at AI, respondents could have been primed by the general topic of agriculture, thus nullifying any potential heuristic cues often driven by political ideology. Likewise, existing research has signaled that religiosity can influence attitudes toward both emerging technologies (see Dawson et al., 2022) or agriculture (Karami & Mansoorabadi, 2007). However, this study did not find that religiosity played much of a role in predicting attitudes toward the use of AI in agriculture.

Finally, from a practical perspective, these results provide a foundation for understanding audiences that may be helpful for strategic communication efforts centered around marketing AI in agriculture. For example, companies interested in marketing AI to industry professionals should look to university sponsorship or imagery, as those who closely follow agricultural news

support its development by universities. Moreover, university researchers could look to include farmers and ranchers in collaborative efforts. According to Pires et al., 2024, with a shift in agricultural progress in the U.S., farmers are generally willing and 40% more likely to adopt practices supported by universities conducting on-farm research than off-farm. Farmer involvement in AI research may help counterbalance public concerns by emphasizing transparency, equity, and community-centered development (Pires et al., 2024).

Beyond marketing opportunities, we believe that this data could be helpful for professionals in agricultural policy and/or advocacy when it comes to future development. As noted by Rasmussen et al. (2017), public support can often drive advocacy success. In the case of AI in agriculture, the results from this study show that Californians are generally supportive of the technology, with those that are willing to defer to scientific authority being particularly supportive. Given some of the past difficulties in establishing automation in California agriculture (see Baur & Iles, 2022), these results suggest that focusing on the science behind AI may be more influential than other types of framing. Despite the general support for the technology, there are some hesitations from Californians about the involvement of technology companies in developing AI in agricultural settings. Instead of technology companies, advocates could work more closely with farmers or university researchers to further the development of AI.

Limitations & Future Research

Despite the importance of these findings, the study also has several limiting factors that must be considered. First, this study uses survey methodology which relies on self-reported media viewing behavior. Although this is consistent with other studies of similar design (see Brewer et al., 2023; Dawson et al., 2022), self-reported measures may still lack accuracy. Moreover, survey methodology can only ever take a snapshot of a specific period of time. As this survey was conducted in February of 2025, these attitudes may shift as time goes on or as these technologies are further integrated into daily life. Likewise, this study relies on a sample of California residents and does not account for demographic weighting, potentially limiting the representativeness of the data.

In addition to the methodology, this study also relies on correlational analyses, providing challenges when trying to make causal inferences. One such opportunity for future research would be to explore the causal relationship between media content and attitudes (see Bingaman et al., 2021). For example, there could be an embedded experiment that examines various ways that AI can be framed within the context of agriculture to determine whether specific media content is driving differences in attitudes toward the technology and its use. Another possible avenue could be to conduct qualitative research to explore (a) what media coverage of AI in agriculture looks like, and (b) how this media coverage is interpreted by different audiences.

Finally, while this research was just focused on media and value predispositions, the results do point to several other important areas for researchers to continue studying. Specifically, the results point to potential gender differences among Californians, with women more likely to perceive AI as harmful to both agriculture and society. This could dovetail with research that shows nearly 25% of women feel like AI will upend their livelihood over the next decade (Roopaei et al., 2021). Future research in this area should look to explore how demographic factors such as gender can impact attitudes toward AI in agriculture.

Conclusion

With AI becoming more commonplace across several important societal sectors, understanding individuals' attitudes toward these technological advances becomes integral to future development, funding, and general acceptance. Not only do public perceptions of science and technology influence regulatory and policy initiatives from politicians (Malyska et al., 2016) but understanding these public attitudes can help agricultural professionals better understand and communicate with a general public that is increasingly disconnected from agricultural processes (Hill, 2020; Zimbelman et al., 1995). Specific to California, the country's biggest agricultural state and home to a burgeoning AI industry, this study provides a foundation to understanding the nuanced way that individuals feel about the adoption and development of AI in agriculture in the state. From a practical perspective, the findings from this study can act as an audience analysis that can better inform strategic communication and advocacy efforts between AI and agriculture – the future of farming in California and beyond.

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Appendix A

Survey Flow

In general, do you usually think of yourself as a…

- Democrat
- Republican
- Independent
- Other

In general, how would you describe your political views?

- Very Liberal
- Liberal
- Somewhat Liberal
- Middle of the Road
- Somewhat Conservative
- Conservative
- Very Conservative

How important is religion in your life?

- Not at all important
- Not too important
- Somewhat important
- Very important

How old are you?

[Open Numerical Response]

How do you identify?

- Male
- Female
- Non-binary/third gender
- Prefer to self-describe
- Prefer not to say

What is the highest level of education you have completed?

- Less than high school
- High school graduate
- Some college
- 2-year degree
- 4-year degree
- Professional degree
- Doctorate

Do you identify as…

- Hispanic/Latino
- Not Hispanic/Latino

Which of the following do you identify as… (please check all)

- White
- Black or African American
- American Indian or Alaska Native
- Asian

- Native Hawaiian or Pacific Islander
- Not Listed

Which of the following best describes your yearly household income?

- Less than $10,000
- $10,000 - $19,999
- $20,000 - $29,999
- $30,000 - $39,999
- $40,000 - $49,999
- $50,000 - $59,999
- $60,000 - $69,999
- $70,000 - $79,999
- $80,000 - $89,999
- $90,000 - $99,999
- $100,000 - $149,999
- More than $150,000

On the average day, how much time do you spend watching television shows and movies (including on a computer or mobile device)?

- None
- One hour or less
- Two hours
- Three hours
- Four hours or more

How often do you watch each of the following (less often, a few times a month, a few times a week, nearly every day):

- National network television news on ABC, CBS, or NBC
- CNN
- MSNBC
- The Fox News Channel

How often do you watch science fiction?

- Less often
- A few times a month
- A few times a week
- Nearly every day

How closely do you follow news about… (not at all closely, not too closely, somewhat closely, very closely):

- Technology
- Agriculture
- Politics
- Business

How often do you agree or disagree with the following statements (strongly disagree, somewhat disagree, neither disagree nor agree, somewhat agree, strongly agree):

- Scientists know best what is good for the public
- It is important for scientists to get research done even if they displease people by doing it
- Scientists should do what they think is best, even if they have to persuade people that it is right
- Scientists should make the decisions about the type of scientific research done on artificial intelligence in agriculture

What effect do you think artificial intelligence will have on… (it will do a great deal of harm, it will do about equal amounts of harm and good, it will do moderate amount of good, it will do a great deal of good)

- Society as a whole
- Agriculture as a whole

How much do you support or oppose each of the following uses of artificial intelligence to monitor and manage… (strongly oppose, somewhat oppose, neither oppose nor support, somewhat support, strongly support):

- Crops (e.g., automatic spraying, nutrient detection, and harvesting)
- Animals (e.g., feeding, disease diagnosis, and tracking)
- Water Usage (e.g., irrigation systems)
- Supply Chain (e.g., packaging, transportation, and distribution)

How much do you trust each of the following to manage the development and use of artificial intelligence in agriculture… (none at all, a little, a moderate amount, a lot, a great deal):

- Government entities
- Technology companies
- University researchers
- Agricultural businesses and industry professionals
- Farmers and ranchers

Appendix B

Table of OLS regression coefficients

Attitudes about effects of AI on agriculture and society

	Society	Agriculture
Age	-.002 (.002)	-.001 (.002)
Gender (Fem = 1)	-.35 (.07)**	-.40 (.07)**
Income	.03 (.01)*	.02 (.01)*
Education	.01 (.03)	.03 (.03)
Political Ideology	.03 (.02)	.03 (.02)
Religiosity	.06 (.03)	.03 (.03)
Def. Sci. Auth.	.30 (.05)**	.30 (.04)**
Overall Media	.02 (.03)	.03 (.03)
TV News	.04 (.05)	.06 (.04)
Fox News	.09 (.04)*	.11 (.03)**
Tech News	.10 (.05)*	.09 (.05)*
Ag News	.01 (.05)	.02 (.05)
Political News	-.11 (.05)**	-.13 (.04)**
Business News	.03 (.05)	.06 (.05)
Science Fiction	.02 (.04)	-.11 (.04)**
Constant	.81 (.27)**	1.10 (.25)**
R^2	.22**	.25**

Note. OLS regression coefficients, with standard error value in parentheses
**$p < .01$. *$p < .05$