Automation adoption decision: A snapshot of attitudes in the USA

Moncef Belhadjali
Norfolk State University

Sami Abbasi
Norfolk State University

Gary Whaley
Norfolk State University

ABSTRACT

Undoubtedly, automation has been increasingly becoming an integral part of our daily lives. This is abundantly clear in a variety of domains such as healthcare, transportation, banking, and education. This study uses data from a survey of 4,135 members of the Pew Research Center American Trends Panel. The purpose of this study is to assess individuals' decisions regarding driverless cars, robot caregivers, and computer programs that make hiring decisions. The results of three binary logistic regression models are reported. Each model includes one of the three automation decisions and the three demographic variables, age, sex, and education. The findings revealed that females are more likely to lean towards rejecting the three types of automation than would males. Also, older individuals are more likely to reject the driverless car and the hiring software. Finally, education is positively associated accepting the driverless car and the robot caregiver.

Keywords: automation, driverless vehicle, robot, attitudes, hiring, gender

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INTRODUCTION

Automation is "the application of technology, programs, robotics or processes to achieve outcomes with minimal human intervention." (https://www.ibm.com/topics/automation). The need for, and implementation of automation is evident in almost every aspect of our daily activities. It is a process that has been started, about a century ago, and cannot be stopped or undone. However, not everyone is willing to adopt any technological innovations resulting from automation. Particularly, the types of applications covered in this article, such as the autonomous vehicle (AV), the robot caregiver, and the computer program for hiring decision.

The public interest in adopting these new technologies has been mixed. A survey of Greek drivers found that their acceptance and willingness to obtain an AV is contingent upon cost, time, level of safety, and existence of GPS and parking assistant (Souris et. al., 2019). In addition, they concluded that Greek drives are concerned about safety, but have a positive attitude towards the AV. Gender plays a role in the acceptance of the AV. Females were more likely to use the AV than males, 78% and 59% respectively (Panagiotopoulos & Dimitrakopoulos, 2018). However, another study (Piao et. al., 2016) found that males (49%) were more likely to use the AV than females (39%). In general, perceived safety influences individuals' attitude to use an AV (Jones, 2020). A study of the public perception of the AV in Pakistan found that the decision to use an AV was significantly associated with age, education, job, and income (Ullah et. al., 2019). This study found that age was negatively associated with the AV acceptance, since the younger generation is more aware of the latest technologies. Also, education was found to be positively associated with the acceptance of the AV. Trust in the AV technology, and perceived benefits/risks impact the acceptance of AVs (Liu et. al., 2019).

The use of a robot to support caring for older individuals while residing in their own homes was explored in Japan through the "PARO" robot. This robot aims at improving the quality of life for individuals with dementia within the home context (Inoue et. al., 2021). In addition to Japan, PARO has been used in the USA and Canada. Over a three-months period, family members of seven households used PARO at least three times a week. Five out of the seven participants reported a positive reaction to PARO (Inoue et. al., 2021). The use of robots to provide home care to the elderly provided an alternative solution to the labor shortage problem, and the heavy reliance on migrant caregivers in Japan (Wright, 2019).

In the context of hiring and evaluating job candidates, a computer software could provide an objective tool to avoid biases, discrimination, and subjective judgment of the human recruiter (Knapp & Naber, 2021). These authors developed and implemented a computer-vision software that detects facial muscle activities and emotional expressions to predict a candidate's self-reporting motivation levels. The software was tested through an experiment involving 154 students as candidates for a job position. The software model outperformed the unreliable and biased recruiters' judgments (Knapp & Naber, 2021). As reported in (Rohr, 2018), more than 200 companies rely on an AI robot called "Robot Vera" that helps employers find candidates, 10 times faster than humans, by scanning CVs on the Internet and within customers' databases. Robot Vera conducts interviews by phone, taking up to 10,000 calls simultaneously, 24/7. In general, callers don't notice that they are talking to a robot.

METHODOLOGY

Data

The data used in the study was obtained from the Pew Research Center. The data was collected via an online survey developed by the Pew researchers and administered during the period of May 1-15, 2017. The respondents are members of the American Trends Panel (ATP), a pool of US citizens of age 18 and older. The total responses were 4,135. For the current study, three sets of cases were extracted. The first set contains all cases with valid responses to questions related to the driverless vehicle, and the demographic variables (N = 4,078). The second set contains all cases with valid responses to questions related to the robot caregiver, and the demographic variables (N = 2,038). The third set contains all cases with valid responses to questions related to the computer program for hiring decisions, and the demographic variables (N = 2,073). The demographic variables selected for this study are sex, age, and education.

Analysis and Results

The data in Tables 1, 2, and 3 (Appendix) from each of the three samples were analyzed through three binary logistic regression models using SPSS.

Model I: Driverless Vehicle: $Z_1 = B_0 + B_1\text{Age} + B_2\text{Sex} + B_3\text{Education}$

Model II: Robot Caregiver: $Z_2 = B_0 + B_1\text{Age} + B_2\text{Sex} + B_3\text{Education}$

Model III: Hiring Software: $Z_3 = B_0 + B_1\text{Age} + B_2\text{Sex} + B_3\text{Education}$

The results from the three regressions shown in Table 4 (Appendix) reveal that in model I, all variables have a statistically significant predictive power. In model II, only sex and education have a predictive power. In model III, only age and sex have a predictive power. Overall, sex is the only variable that has a statistically significant predictive power in the three models. The variable age is significant in models I and III. The variable education is significant in models I and II.

The results in Table 4 (Appendix) show negative coefficients for the variable sex, which could imply that females are more likely to lean towards rejecting the three types of automation than males. The negative coefficients for the variable age indicate that individuals in the fifty or higher age group are more likely to lean toward rejecting the driverless car and the hiring software. Finally, the positive coefficients for the variable education reveal that college graduates are more likely to lean toward accepting the driverless car and the robot caregiver. A series of Chi-square tests via SPSS support the results shown in Table 4 (Appendix). The decision regarding the robot caregiver, model II, is independent of age. The decision regarding the hiring software, model III, is independent of education.

CONCLUSION

It is a well-known fact that automation is no longer an option in many facets of our everyday lives. Automation has been adopted as a solution for creating more efficient tools to use in our daily lives. However, and fortunately, there are still few choices left that offer an opportunity to say no to automation. It is not clear as to for how long this will be the case. The current study reinforced the fact that, in general, females and males have different attitudes, in this case towards some aspects of the implementation of automation such as the driverless car,

the robot caregiver, and the hiring software. In addition, more educated individuals, specifically college graduates, are more likely to accept the driverless car and the robot caregiver. Finally, older individuals lean towards rejecting the driverless car and the hiring software. The data for the study were collected through a survey in May 2017. It would be beneficial to see the Pew Research center duplicating the survey annually. This is to offer snapshots of attitudes in the USA, taken at different years. The results could be used in future research to suggest strategies that facilitate the adoption of these three automation tools.

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APPENDIX

Table 1. Would you, personally, want to ride in a driverless vehicle if you had the opportunity?

	NO (2158; 53%)	YES (1920; 47%)	Total (4078; 100%)
Sex			
Female:	(1244; 60%)	(820; 40%)	(2064; 51%)
Male:	(914; 45%)	(1100; 55%)	(2014; 49%)
Age			
Under Fifty:	(706; 44%)	(915; 56%)	(1621; 40%)
Fifty or Higher:	(1452; 60%)	(1005; 40%)	(2457; 60%)
Education			
Non-College graduate:	(1179; 61%)	(744; 39%)	(1923; 47%)
College graduate:	(979; 45%%)	(1179; 55%)	(2155; 53%)

Table 2. Would you, personally, be interested in this type of robot caregiver for yourself or a member of your family?

	NO (1153; 57%)	YES (885; 43%)	Total (2038; 100%)
Sex			
Female:	(657; 62%)	(405; 38%)	(1062; 52%)
Male:	(496; 51%)	(480; 49%)	(976; 48%)
Age			
Under Fifty:	(439; 54%)	(368; 46%)	(807; 40%)
Fifty or Higher:	(714; 58%)	(517; 42%)	(1231; 60%)
Education			
Non-College graduate:	(633; 63 %)	(372; 37%)	(1005; 49%)
College graduate:	(520; 50%)	(513; 50%)	(1033; 51%)

Table 3. Would you, personally, want to apply for a job that used this type of computer program to make hiring decisions?

	NO (1576; 76%)	YES (497; 24%)	Total (2073; 100%)
Sex			
Female:	(804; 80%)	(207; 20%)	(1011; 49%)
Male:	(772; 73%)	(290; 27%)	(1062; 51%)
Age			
Under Fifty:	(576; 70%)	(251; 30%)	(827; 40%)
Fifty or Higher:	(1000; 80%)	(246; 20%)	(1246; 60%)

Education			
Non-College graduate:	(730; 78%)	(201; 22%)	(931; 45%)
College graduate:	(846; 74%)	(296; 26%)	(1142; 55%)

Table 4. Summary of Regression Results for the Three Models

	Model I		Model II		Model III	
	B_i	**Sig**	**B_i**	**Sig**	**B_i**	**Sig**
Constant	.224	.001	-.219	.026	-.785	.000
Age	-.635	.000	-.132	.154	-.567	.000
Sex	-.581	.000	-.440	.000	-.354	.001
Education	.621	.000	.504	.000	.204	.054