ASSESSING STUDENT PERCEPTIONS OF ARTIFICIAL INTELLIGENCE WITHIN THE COMMUNITY COLLEGE SYSTEM

by

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Assessing student perceptions of artificial intelligence within the community college system

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Abstract

This study investigates student perceptions of artificial intelligence (AI). The study analyzed four independent variables – age, gender, school, and employment – to predict students' level of readiness to adopt AI within an educational setting. Using an instrument with two constructs, data was collected from a diverse, multicultural group of students within a community college in the northeastern U.S. The findings showed that age, gender, and school are significant predictors of readiness, while employment was not a significant predictor. Additionally, the findings showed no significant interaction effect between age and employment on readiness. The implications of the findings are discussed, and recommendations for further research are provided.

Keywords: ethics, artificial intelligence, community college, perceptions, readiness

Introduction

The arrival of artificial intelligence (AI) and large language learning models (LLMs) like ChatGPT are poised to transform the modern education system and society not seen since the invention of the printing press or the radio. As a technology, AI is fundamentally different in nearly every way since it can make decisions based on self-reinforcing algorithms, become more intelligent with use, and operate on a timescale beyond human capacity. What concerns most AI researchers is its ability to remove power and agency from humans within decision-making processes. This raises several important questions regarding safety, ethics, trust, and responsible usage within society. An educated (and re-educated) workforce will be necessary to utilize this technology within society effectively.

The emergence of AI from this perspective directly impacts higher education. Education and technology will become tightly integrated, mutually dependent, and mutually beneficial to students, teachers, and administrators. Research shows that AI will significantly impact the labor market, with 42% of all business processes being automated by 2027 (Forum, 2023). AI will create a new paradigm within the workplace as well. Many jobs will be replaced through automation while, at the same time, creating a new demand for skills within an AI-assisted workforce. Higher education faces several significant challenges in preparing the workforce. First, how should we retrain and upskill our existing workforce? Secondly, how should we train future practitioners? Finally, how should we transform educational processes regarding curriculum, student success, taxonomy, and outcomes?

Community colleges will be on the front lines of this educational transformation and remain an essential input to the workforce. Community colleges also represent important access institutions within the higher ed landscape, serving 39% of all undergraduates, including many African American, Latinx, and first-generation college students (Monaghan & Sommers, 2022). The challenge for the community college system will be adapting to this new reality and modifying traditional technology courses' instructional designs against solid headwinds of declining enrollment and limited resources.

Presently, there is a gap between what students understand or need to learn about AI and the types of AI curriculum and pedagogy to serve them. Researchers note that the design of AI curriculum is relatively unexplored (Lin et al., 2022). Researchers further note that what is needed to teach AI effectively must be better understood and that formal instructional planning approaches are limited (Chiu & Chai, 2020). Finally, research shows that education must evolve to meet these societal challenges (Alotaibi & Alshehri, 2023). The challenge in the community college system is that there is a wide variety of students, including traditional students, adult learners with full-time employment, part-time students, career changers, and online students. The types of AI curricula may be more than one-size-fits-all. With understanding student perceptions, there is a considerable risk of misaligning or incorrectly developing educational solutions that serve the students and the workforce. Moreover, with limited resources, community colleges must get it right. Therefore, this study aims to assess student perceptions and the impact of artificial intelligence on their education, careers, and readiness to adopt AI systems as part of their learning to help inform the development of curriculum, pedagogy, and faculty development. This research will answer the following questions:

RQ1: *Which predictor variables (age, gender, academic division, employment) are significant predictors of AI Readiness?*

RQ2: *Is there a significant interaction effect between the predictor variables of age and employment on AI readiness?*

Review of the Literature

People encounter AI technology in many ways on any given day, from organizing musical playlists on streaming applications to making financial decisions. From an education standpoint, the potential benefit of AI-assisted tools is the level of personalization they can provide (Hwang et al., 2020). The current approaches to AI education technology remain challenging for most educators and practitioners since AI is not limited to computer science students. Instead, it is cross-disciplinary, and how to deal with AI in an educational context still needs to be explored (Chen et al., 2022). Research shows that quality and efficiency are highly valued from the students' perspective, while concerns remain around accuracy (Burkhard, 2022). Additional research indicates that while students' level of understanding around AI remains moderately high (n=127, 77%), students' perceptions of how AI is being developed (n=127, 79%) and whether it will have a positive impact on their lives (n=127, 64%) remains moderately low (Jeffrey, 2020). Research shows a sobering effect on students' willingness to adopt and embrace AI in terms of assisted learning (Chiu & Chai, 2020).

There is potential to bridge the gaps between student perceptions of AI and educators' ability to teach and leverage AI-assisted tools. Okewu et al. (2021) note that a large amount of data within higher education could enhance these processes using a data-driven approach. Despite the challenges, students and teachers regard AI as beneficial to the educational process because it delivers improved learning experiences and serves diverse populations (Chen et al., 2022). However, researchers note that students who regard technology as native to their lives are strong proponents of online education with a preference for independent learning styles (Kuleto et al., 2021). Research also shows anxiety around adopting these technologies and that student participation will depend on curriculum design (Chiu & Chai, 2020).

In an interview with Playboy Magazine, Canadian poet and philosopher Marshall McLuhan noted that media and the computer are extensions of man "that cause deep and lasting impressions in him and transform his environment" (McLuhan, 1969, p. 53). The extensions amplify certain senses or functions while insulating the shock of change by anesthetizing the conscious memory of the latter. McLuhan (1969) notes that it leads "precisely to the point where a new media-induced environment becomes all pervasive and transmogrifies our sensory balance, it also becomes invisible" (p. 54). In short, when something changes, something else is irrevocably lost, usually without notice. The education system sits in a similar precarious position. With the emergence of AI, there is potential to revolutionize the educational landscape (Kamalov et al., 2023). However, other researchers note that we must exercise caution as AI emerges from the laboratory and into the classroom (Schiff, 2021). We must ask the same questions about artificial intelligence in education: What is being lost, and what are the impacts of such decisions? (Treviranus, 2022).

New Paradigms of Learning

Researchers argue that the AI-learner relationship can be categorized into three paradigms (Ouyang & Jiao, 2021). In the first paradigm, the AI is the *director* of the learning, and the learner is the recipient. Learner behavior is augmented by outlining specific learning steps and sequences to lead the learner to correct performance. The second paradigm focuses on the AI as a *supporter* and the learner as a collaborator. This approach is based on cognitive and social constructivism, where learners personalize their learning through social interaction with people and technology. In the third paradigm, AI is *empowered* and made aware to navigate the complex relationships between learners, instructors, and the content. The learner retains agency through a deep learning approach by augmenting intelligence in real time that is transparent and effective.

Risks and Challenges of AI in Education

However, these approaches have considerable risks (George & Wooden, 2023). Researchers note that the most significant risks include perpetuating systemic bias and discrimination, perpetuating unfairness for students in marginalized populations, and amplifying racism and other injustices (Akgun & Greenhow, 2022). There are early warning signs. Researchers within the housing market have shown evidence of bias within datasets of machine learning algorithms used by home-buying agencies, causing disparate impacts on specific groups (Schneider, 2020). Akgun & Greenhow (2022) further note that data privacy and security are among the greatest ethical risks in this process.

Machine learning algorithms are only as good as the data they are trained on—the more robust the data, the more effective the algorithm. However, ubiquitous data collection in education potentially violates cybersecurity laws around personally identifiable information (Family Education Rights and Privacy Act, 2011). The more data collected and used, the greater the risk of compromising privacy, leading to AI-driven profiling and exploitation. Policies and regulations regarding transparency, governance, use, stewardship, and accountability are needed (Nguyen et al., 2023). Adams et al. (2023) note that international ethical guidance is swiftly developing for educators, including justice and fairness, non-maleficence, pedagogical appropriateness, agency, AI literacy, and teachers' well-being. There is a clear recognition of the need for algorithmic accountability as well. Without the ability to understand or clearly explain the results, there is a risk to student agency, freedom of choice, and autonomy (Bartoletti, 2022).

The Importance of Algorithmic Fairness for Protected Groups

Research is accelerating to establish measures for algorithmic fairness to mitigate risks of systemic bias and discrimination (Madaio et al., 2022). Fairness has always been the cornerstone of education, and the principle of fairness within algorithms ensures that protected and marginalized groups are protected (Pedro et al., 2019). Mehrabi et al. (2021) note that algorithmic bias occurs when the algorithm adds bias to the input data based on the choices applied within regression models. This can disproportionately affect certain groups or subgroups, which can bias the outcome. That is the challenge. AI learning algorithms are developed to discover correlations between independent variables, then distilled into a singular target or dependent variable. The target variable is important because it encodes and optimizes the algorithm's output. It will only be as robust as the selection of measurement criteria and only partially capture the complexity as it only seeks statistical fit. Larger sample sizes can create better models, but a representative population is still required to ensure model predictions are fair and trustworthy. Although establishing algorithmic fairness is complex, it is an important requirement for marginalized community college populations and should be considered when selecting AI tools.

Kizilec & Lee (2022) note that statistical fairness can be established around independence, separation, sufficiency, similarity, and causality. Statistical independence is based on group fairness and demographic parity. Statistical separation, on the other hand, focuses on equal opportunity and equal odds. Separation improves independence by avoiding disparate treatment and including conditional outcomes, which are ignored when using statistical independence. This is a better choice for merit-based outcomes that allocates resources to qualified individuals. Statistical sufficiency is used for improving fairness through calibration within groups. Statistical similarity is fairness through unawareness, where the similar protected attributes are quantified between individuals directly. Finally, causal fairness is grounded in the belief that the algorithm's prediction is fair if the prediction remains unchanged using a counterfactual scenario. The notion of algorithmic fairness and associated complexity highlight the importance of careful decision-making when selecting AI tools. One must understand the situation and context in which to apply to ensure fairness. It is not one size fits all. Kizilec & Lee (2022) further note that statistical independence should be prioritized in education because it aims to allocate resources equally regardless of background or the group's qualifications. To assist with these challenges, the industry is stepping up.

With fairness becoming increasingly concerning, industry leaders are producing toolkits to help researchers and software developers leverage common frameworks to mitigate bias in models (Bellamy et al., 2019). With each model revision, programmers can perform unit testing for each code segment to ensure the model behaves as designed – an important step to establish transparency. Holstein & Doroudi (2022) agree and call for internal auditing and codesign teams between students, educators, and developers. There is also a call to regulate AI algorithms in the same manner as pharmaceuticals to ensure safety and ethics (Kaminski, 2023). Above all, algorithms must be carefully selected and continuously tested to ensure they are fair, build trust, and meet rigid quality standards.

The Future of Work

As AI tools gain traction within society, the impact on the future workforce becomes self-evident. A recent study between Harvard Business School partners and Boston Consulting Group (BCG) noted that among 758 consultants given 18 realistic business tasks, those using AI (ChatGPT-4) completed 12.2% more tasks 25.1% faster and produced 40% higher results versus those who did not (Dell'Acqua et al., 2023). Authors noted that those consultants who performed negatively blindly adopted outputs without comprehensive interrogation, raising questions for AI designers and companies. While ChatGPT-4 can produce superior content, blind trust can lead to more homogenized outputs (Dell'Acqua et al., 2023). That is the inherent risk of using machine learning models. The model tends to regress to the status quo (80%) rather than embrace the diversity of thought within the outliers (20%). History shows that outliers are often where society's most useful innovations are created. In education, this can paradoxically mean scaling up poor pedagogical approaches, suppressing innovation, and reducing human agency - the opposite of what AI tools are intended to do (Bartoletti, 2022).

Throughout history, education has been the path by which better lives are possible, and humans can reach their unique human potential. Despite long-established, entangled, complex processes within education, AI is rapidly pressing forward to address the challenges. Although there is promise, there are risks and challenges for students, particularly community college students, for whom the most significant impact is likely to be felt.

Methodology

Instrument

The instrument for this study was designed by (Buabbas et al., 2023). For the purposes of this study, two constructs from this instrument were used. The constructs are 1) student perceptions toward AI - 8 items and 2) the impact of AI on student education - 4 items. The items from the instrument were taken from two previous validated studies, Sit et al. (2020) and Moxley-Wyles et al. (2020), respectively. To ensure the validity and reliability of the survey, Buabbas et al. (2023) revised the instrument using a qualified academic team to ensure the instrument matched the study's objectives. The instrument was empirically examined and reviewed for clarity of wording, removing ambiguous statements and bias. Buabbas et al. (2023) tested the instrument against a pilot study of 20 students to examine suitability and reliability. The instrument was measured using a test-retest technique on different days and times. The correlation of the scores indicated a correlation value of 0.984, indicating very high correlation and excellent reliability. The constructs with their associated items are as follows:

Student Perceptions Toward AI

1. AI will play an important role in my chosen field.
2. AI will replace some specialties in my lifetime.
3. I understand the basic principles of AI.
4. I am comfortable with AI terminologies.
5. I understand AI limitations.
6. AI teaching will benefit my career.
7. All students should receive AI teaching.
8. At the end of my degree, I will possess the knowledge needed to work with AI in my intended major.

Impact of AI on Student Education

1. AI systems will have a positive impact on my education.
2. Incorporating AI into my education would ease the learning process.
3. Using AI in my education training will prepare me for professional employment.
4. I am willing to use AI in my education.

The instrument used a 5-point Likert-type scale with the following scoring strategy: 5 = strongly agree, 4 = agree, 3 = neutral, 2 = disagree, 1 = strongly disagree.

Subjects and Procedure

A Microsoft Office 365 survey tool, i.e., Microsoft Forms™, was used to acquire and review the data. Convenience sampling was used to administer the survey to 1,358 subjects via email. The survey was completed with 339 subjects (N=339) for an overall response rate of 25%. Before administering the survey, IRB (Institutional Review Board) authorization was obtained to use human subjects. The subjects for this study were community college students enrolled in a degree or certificate program from a single institution in the northeastern U.S. Subjects were males, females, and non-binaries between the ages of 18 and 60 and employed working between 1 and 40 hours per week. All subjects signed a consent form to participate in the study. No incentives were provided. Confidentiality and anonymity were assured. Institutional information security policies were strictly followed to secure all data.

Results

Reliability Analysis of Instrument

The reliability analysis of the scale, based on responses from 339 participants (*N*=339), indicated a high level of internal consistency, with Cronbach's alpha α = .889 for the overall scale and α = .885 when based on standardized items. These values suggest that the scale items are highly reliable in measuring the construct of AI Readiness. The scale consisted of 12 items, with individual item means ranging from *M* = 2.96 to *M* = 3.75, indicating variability in responses contributing to a comprehensive construct assessment. This high level of reliability supports the scale's use in further research and practical applications related to evaluating AI Readiness among individuals.

RQ1: *Which predictor variables (age, gender, academic division, employment) are significant predictors of AI Readiness?*

To answer this question, a multiple regression analysis was used to understand how age, gender, school level, and employment status predict AI Readiness. Table 1 shows the results of a multiple regression analysis for the predictor variables and the dependent variable. The analysis, based on 339 observations, revealed that the model significantly predicted AI Readiness, $R^2 = .144$, $F(4,334) = 14.095$, $p < .001$, indicating that approximately 14.4% of the variance in AI Readiness can be explained by the predictor variables. Specifically, gender ($\beta = -.416$, $p <. 001$) and school level ($\beta =.080$, $p = .003$) were significant predictors, with gender having a negative relationship and school level a positive relationship with AI Readiness. Age showed a positive association ($\beta = .069$, $p = .039$), though its impact was relatively smaller. Employment status was not a significant predictor ($\beta = -.006$, $p = .809$).

Table 1.
Multiple Regression Analysis Predicting AI Readiness (Dependent Variable)

Predictor	Model					
	B	SE	β	*t*	*p*	95% CI for B
Constant	3.442	.182		18.913	<.001	[3.084, 3.799]
Age	.069	.033	.108	2.077	**.039**	[.004, .135]
Gender	-.416	.066	-.323	-6.294	**<.001**	[-.546, -.286]
School	.080	.027	.152	2.987	**.003**	[.027, .132]
Employment	.006	.023	-.013	-.242	.809	[-.051, .040]

Note: *N*=339. CI = confidence level. $R = .380$, $R^2 = .144$, Adjusted $R^2 = .134$. ANOVA $F(4, 334) = 14.095$, $p < .001$.

RQ2: *Is there a significant interaction effect between the predictor variables of age and employment on AI readiness?*

To answer this question, a univariate ANOVA was performed for the predictor variables (age and employment) and the dependent variable AI Readiness. Levene's Test indicated no significant violations of the homogeneity of variances assumption ($F = 1.405$, $p = .095$). Table 2 shows the descriptive statistics. The descriptive statistics from the univariate analysis examined AI Readiness across different age groups and employment statuses. The analysis shows variability in AI readiness mean scores across age groups, with older groups generally indicating higher AI Readiness.

Table 2.
Descriptive Statistics for Predictor Variables

Age	Employment (Hrs)	Mean	Std. Deviation	N
18-20	Not working	3.1636	.81502	27
	1-10	2.7500	.59900	7
	11-20	3.1090	.64755	26
	21-30	3.1597	.61773	24
	31-40	3.2847	.54871	12
	40 or more	2.6667	.11785	2
	Total	3.1233	.67193	98
21-29	Not working	3.0787	.73067	18
	1-10	3.2604	.80109	8
	11-20	2.9625	.65699	20
	21-30	2.9375	.94470	20
	31-40	3.3056	.83176	24
	40 or more	3.3287	.89364	18
	Total	3.1366	.81542	108
30-39	Not working	3.1726	.78137	14
	1-10	3.7500	.	1
	11-20	3.3417	.97218	10
	21-30	3.2167	.83041	5
	31-40	3.2812	1.00916	16
	40 or more	3.2576	.94418	22
	Total	3.2623	.89467	68
40-49	Not working	3.6458	.50149	8
	1-10	4.0417	.76603	2
	11-20	3.0370	.82086	9
	21-30	3.3611	.54220	3
	31-40	3.0208	.65427	8
	40 or more	3.5486	.64692	12
	Total	3.3671	.69480	42
50 or older	Not working	3.0833	.45644	5
	11-20	4.0000	.	1
	21-30	2.5833	2.00347	2
	31-40	3.3333	.38188	3
	40 or more	3.5486	.58975	12
	Total	3.3551	.71959	23
Total	Not working	3.1921	.73964	72
	1-10	3.1759	.78168	18
	11-20	3.1035	.72737	66
	21-30	3.0725	.80649	54
	31-40	3.2606	.78624	63
	40 or more	3.3649	.81148	66
	Total	3.2013	.77451	339

Table 3 shows the results of the univariate ANOVA for the predictor variables (age and employment) and the dependent variable, AI Readiness. The analysis showed no significant interaction effect between age and employment on AI readiness ($F(19, 310) = .810$, $p = .696$), suggesting that the combined impact of these variables does not significantly influence AI Readiness. Given the lack of significant interaction, post-hoc analyses were not performed.

Table 3. Univariate ANOVA
Test of Between-Subject Effects

Source	Type III Sum of Squares	*df*	Mean Square	F	*p*	ηp2
Corrected Model	14.441a	28	.516	.849	.689	.071
Intercept	1271.927	1	1271.927	2093.856	<.001	.871
Age	3.889	4	.972	1.601	.174	.020
Employment	1.372	5	.274	.452	.812	.007
Age * Employment	9.344	19	.492	.810	.696	.047
Error	188.312	310	.607			
Total	3676.993	339				
Corrected Total	202.752	338				

Discussion

Theoretical Implications

This research contributes significantly to the literature by establishing that age, gender, and school are significant predictors of AI Readiness. This supports the work of Hu & Ortagus (2019), who show that gender is a significant predictor of STEM success. Furthermore, the type of academic division (or school) within a college institution is also a significant predictor of AI Readiness, underlining the importance of early college pathways for traditional students into STEM. This finding supports the work of Fink et al. (2021), which shows that pathways into STEM supported with calculus and non-math science, technology, or engineering courses are reliable predictors of STEM success across a wide range of disciplines, including artificial intelligence. The evidence also shows that employment, regarding the number of hours worked per week, was not a significant predictor of AI Readiness. This finding is notable as it does not support the literature, namely Zhang & Yang (2020), who show that there is a negative effect on student success based on the number of hours worked.

The study also reports no interaction effect between the predictor variables age and employment on AI Readiness. The finding indicates that AI Readiness is higher for older individuals, but when considering employment, the effect on AI Readiness is not significant. Given the two constructs in the instrument, namely student perception and impact, the number of hours a student works does not significantly impact an individual's readiness.

Practical Implications

Community college students come in many shapes and sizes and have different needs. Since age, gender, and academic division have been shown to be significant predictors of AI readiness, increasing readiness across these three predictors will take innovative approaches. Community college students can be classified into adult learners (25 or older) and traditional students (recent graduates from post-secondary schools). Learners will arrive with either an associate degree (or higher) or little or no college-level coursework. The context in which an individual arrives at the community college has practical implications on how curriculum and support systems should be designed. The following points are offered.

Coursework in artificial intelligence requires strong mathematical skills in several subject areas typically covered in high school math and physics courses. Research shows that the main pillars for teaching machine learning encapsulate four domains: regression, dimensionality reduction, density estimation, and classification (Deisenroth, Faisal, & Ong, 2020). These four domains encompass key topic areas, including vector calculus, probability and distributions, optimization, linear algebra, geometry, and matrix decomposition. This presents unique challenges for community colleges to upskill and re-educate a workforce. Research shows that 59% of students who enroll at community colleges are referred to developmental math courses. Of that group, only 20% complete their first math course (Schudde & Keisler, 2019). In addition, the coursework needed to complete these math subjects is concentrated in upper-level degree programs, making it difficult for an upskilling adult learner to gain new skills in AI.

Fortunately, researchers note that new approaches are emerging to teach data science focused on a mix of mathematics, statistics, linear algebra, machine learning, data mining, and data imaging (Gürsakal et al., 2020). As such, this new paradigm opens new opportunities for innovative pedagogical approaches. For example, Schudde & Keisler (2019) note that corequisite math models where students take the development math component along with the principal topic have been shown to increase successful student outcomes by 16%. Corequisite models accomplish this by combining two courses into a single 6-credit course within a single semester. The 6-credit course is underpinned by wrap-around services to support student success. The use of high-impact practices may also be beneficial. High-impact practices include internships, capstone courses, collaborative assignments, and undergraduate research. Each of these practices mutually benefits students and employers in the field of artificial intelligence. Studies show that students who participate in high-impact practices tend to have better learning outcomes than those who do not and that learning outcomes increase with more than one practice (An & Loes, 2023).

Beyond mathematics, teaching programming languages could be examined as well. Researchers also note that programming languages, including Python, R, and SQL-related subjects, should be taught at every opportunity within the educational process (Gürsakal et al., 2020). In addition, how we teach programming leading to text-based languages is also essential. Studies have shown that teaching simple graphical programs such as Scratch as a first step reduces the difficulty and increases the speed of learning text-based languages (Armoni et al., 2015).

Finally, studies show that AI can help bridge the gap in mastering foundational subjects. The potential of personalized learning systems is clear. Personalized learning systems are based on the concept that each learner is taught and assessed individually. Researchers note that delivering personalized content to a learner based on the individual's particular needs for AI subjects could be an extremely effective learning system (Murtaza et al., 2022). However, researchers note that the dangers of using AI in an educational context remain and require further investigation (Kamalov et al., 2023).

Conclusion

This study investigated which predictor variables (age, gender, academic division, employment) are significant predictors of AI Readiness. In addition, the study investigated whether there was a significant interaction effect between age and employment. Results show that age, gender, and academic division are significant predictors of AI Readiness but that employment, specifically the number of hours worked, is not a significant predictor of AI Readiness. Furthermore, the results showed no significant interaction effect between age and employment.

This study highlights the importance of understanding the changing workplace, assessing readiness to adopt AI technology, and the need for clear pedagogical pathways to help community colleges educate, re-educate, and upskill the existing workforce. The limitations of this study include a small sample size of a single community college located in the northeastern U.S. It is recommended that the sample size include different community colleges within different geographical areas to understand the predictor variables in a larger context. Secondly, the finding of employment does not support the literature. Further research should be conducted to understand why the number of hours worked does not affect student perceptions of AI Readiness. Third, the survey instrument was modified slightly to meet IRB requirements. It is recommended that the survey instrument undergo piloting testing to reaffirm the reliability of the instrument following best practices (Collins, 2003). In terms of future research, it is recommended that exploratory factor analysis be conducted to identify underlying relationships among the variables to gain deeper insights into the results (Wold et al., 1987).

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