Consequences of AI Induced Job Displacement

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Abstract: *Although artificial intelligence (AI) is bringing about good developments in a number of areas, there is a growing consensus that it poses a threat to job stability since it has the potential to replace some occupations. The aim of this project is to get a general understanding of the impact of artificial intelligence (AI) on employment, and how the integration of AI technologies affects the job market and the workforce. The population of our study comprises employees of Pharma industries. Total number of populations is one as we are only targeting Pharma industries employees. We have selected this population because we are analyzing the consequences of AI in Job displacement. Maximum sample size is 35*7 = 245 based on the number of respondents per variable. The study suggested that professional organizations who are willing to incorporate AI in their processes first should train and equip their workforce with the required skill set and focus on the skill development of the staff. Failing to keep up, the AI incorporating may lead them to be completely dependent on the AI for their everyday operations.*

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Introduction

The labor market is changing as a result of the introduction of new technology, producing winners and losers. Among these technologies, artificial intelligence (AI) is particularly significant as a disruptive force that raises concerns about job displacement while also improving productivity and living standards (Chen, Xie, Dong, & Wang, 2019; Makridakis, 2017). AI has proven to perform superhumanly in a variety of economically valuable tasks thanks to machine learning and algorithms (Kazi et al., 2020). Global businesses like retail, manufacturing, and entertainment are embracing breakthroughs in AI technology to increase productivity and effectiveness, as these technologies are developing quickly. But concerns about intelligent systems replacing humans in the workforce have grown as a result of the growing integration of AI, especially in industries like production and healthcare (Esmaeilzadeh, 2020; Postel-Vinay, 2002). This concern is of a larger public discussion on how AI will affect employment. Other concerns include the expectation of a gap in the economic system and worries that AI will completely replace the job market (Fatima, Jan, Khan, Javed, & Rashid, 2024; Mossavar-Rahmani & Zohuri, 2024).

Although artificial intelligence (AI) is bringing about good developments in a number of areas, there is a growing consensus that it poses a threat to job stability since it has the potential to replace some occupations and modify the character of others (Chen et al., 2019; Patrawala, 2019). Researchers who have long conjectured about the effects of AI on human labor, have predicted changes towards a world that is increasingly automated and may eventually employ fewer people (Kazi et al., 2020; Moradi & Levy, 2020; Patrawala, 2019).

Automation-related job displacement is not a recent issue. Researchers have cautioned about the rapid advancement of automation and its wide-ranging effects on various job classifications (Coelli & Borland, 2019; Krmac, 2011). The anxiety encompasses not just the loss of work but also the potential for automation to impede the emergence of new job prospects (Autor, 2015). Concerns about mass unemployment (Wisskirchen et al., 2017) and talks about how AI could improve hiring and onboarding, these are the two sides of the argument on AI's impact on employment (Reddy, Rani, & Chaudhary, 2019).

As AI systems are incorporated into society more and more, worries about prejudice, privacy, and moral quandaries have surfaced, necessitating a thorough analysis of their ramifications (Fatima et al., 2024; Kazi et al., 2020). It further draws attention to worries regarding pervasive data collecting and surveillance enabled by artificial intelligence systems (Signorini, 2014). Notion of contextual integrity is relevant for examining privacy issues around artificial intelligence (Nissenbaum, 2004). Ethical concerns arise when people have control over decisions made by AI systems. In order to guarantee equitable and just results, researchers present the idea of "fairness through awareness," arguing that biases in AI models should be addressed (Kheya, Bouadjenek, & Aryal, 2024).

Floridi presented the case for AI systems' accountability and transparency. Establishing accountability is essential because complicated algorithms provide ethical difficulties due to their lack of transparency (Floridi et al., 2018). The ethical terrain of artificial intelligence is characterized by obstacles that surpass technical factors. In talks of ethics, fairness, accountability, and transparency are at the forefront. As AI systems become more capable of making significant judgements, moral conundrums about their effects on people, society, and the autonomy of decision-making emerge (Esmaeilzadeh, 2020; Reddy et al., 2019).

The development of AI technology in recent years has resulted in extensive mechanization in a number of industries. These days, intelligent machines may do unusual duties like controlling manufacturing lines in heavy sectors and optimizing e-commerce projects (Hagendorff, 2020). Practical concerns are raised by this trend regarding the possible replacement of intelligent machine systems with humans in a variety of work roles. Jobs involving regular and technical duties are more likely to be replaced by technology (Fatima et al., 2024). Technology has an effect on more than just certain businesses; it also shapes the general field of study for important fields like economics, robotics, and anthropology. These technological factors will be very important in determining how governments and institutions around the world are shaped, which will have an impact on how society develops in the future (Makridakis, 2017).

Problem Statement

Artificial intelligence (AI) brings cool advancements, but it also raises worries about privacy, bias, lack of creativity, and ethics. These concerns can lead to a big problem: people losing their jobs due to AI privacy issues, biasness, lack of creativity in humans, and ethics concerning taking over certain tasks. Balancing innovation and ethical use of AI is crucial to avoid negative impacts on jobs while enjoying the benefits of these advancements.

Research Questions and Objectives

Following are the research questions that we highlighted in our throughout research according to our objective of research:

- Do ‘Ethical Dilemma in AI use’ and ‘Cost & Accessibility’ affect ‘Privacy Concerns’ for the consumers?
- Does ‘Privacy Concerns for the consumers’ affects ‘Environmental Impact’ and Job Displacement & Unemployment?
- Does ‘Ethical Dilemma in AI use’ affects ‘Environmental Impact’ and ‘Job Displacement & Unemployment?
- Does ‘Cost & Accessibility of AI’ affects ‘Environmental Impact’ and ‘Job Displacement & Unemployment’?
- Does ‘Biasness & Fairness’ affects ‘Environmental Impact’ and ‘Job Displacement & Unemployment’?
- Does ‘Lack of Creativity and Empathy’ affects Environmental Impact and Job Displacement & Unemployment?

The aim of this project is to get a general understanding of the impact of artificial intelligence (AI) on employment, and does the integration of AI technologies affects the job market and the workforce. Following are the key objectives set in this study:

- To investigate that Ethical Dilemma in AI use and Cost & Accessibility affect Privacy Concerns for the consumers.
- To investigate that Privacy Concerns for the consumers affects Environmental Impact and Job Displacement & Unemployment.
- To investigate that Ethical Dilemma in AI use affects Environmental Impact and Job Displacement & Unemployment
- To investigate that Cost & Accessibility of AI affects Environmental Impact and Job Displacement & Unemployment.
- To investigate that Biasness & Fairness affects Environmental Impact and Job Displacement & Unemployment.
- To investigate that Lack of Creativity and Empathy affects Environmental Impact and Job Displacement & Unemployment.

Literature Review

Theoretical Background

The theory of technological unemployment assumes that a decline in the need for human labor may result from technical advancements, especially in automation and artificial intelligence. According to this theory, there may be job displacement and a fall in total employment as technology advances and becomes more adept at carrying out tasks that have historically been performed by humans. Technological unemployment is based on the observation that, although automation might boost output and efficiency, it has the potential to displace particular skill sets or jobs (Kapeliushnikov, 2019; Postel-Vinay, 2002). Variables selected in this study based on theoretical groundings are discussed as under:

Job Displacement and Unemployment

Job displacement happens for many reasons where people lose their jobs. AI is one of the reasons for job displacement. When artificial intelligence and automation technologies were introduced, work which was normally done by humans was taken over by machines resulting in a drop in need for human labor in particular occupations. According to previous research it has been noticed that AI has a massive impact on the job market (Brynjolfsson & McAfee, 2014). It is also stated that “AI not only has an impact on job displacement but employment opportunities as well" (Tiwari, 2023). But scholars stress that the effects are not just bad because AI is also causing a change in the nature of work. Researches address ethical issues and emphasize the necessity for responsible AI implementation to reduce undesirable societal effects, such as job displacement (Esmaeilzadeh, 2020; Kheya et al., 2024).

Bias and Unfairness:

AI systems that frequently favor or disfavor particular people or groups based on traits like race, gender, and ethnicity are said to have produced biased decisions. Research on bias in AI found that bias can result in unfair results that increase existing gaps and can be caused by historical or societal inequalities found in training (Leavy, O'Sullivan, & Siapera, 2020; Pagano et al., 2023). Another research on unfairness in AI found that Unfairness can lead to unequal treatment, create societal inequities, and give rise to moral dilemmas (Langer, König, Back, & Hemsing, 2023; Pandey & Caliskan, 2021). Furthermore, researchers offer insights into the difficulties in holding AI systems responsible for biases and advocates for greater understanding, transparency and transparency in order to reduce unfair results (Esmaeilzadeh, 2020; Pagano et al., 2023).

Privacy Concerns

Artificial intelligence (AI) raises privacy concerns because it collects, analyzes, and uses enormous amounts of personal data. Large datasets are frequently used by AI systems to train and enhance their functionality; however managing sensitive data presents serious privacy concerns. An article mentioned about serious crimes and risks occurred due to AI and recommendations to avoid it (Floridi et al., 2018). Many studies have shown the disadvantages of AI when it comes to privacy (Barthelmess et al., 2017). In their discussion of the privacy consequences of big data analytics, Barocas and Selbst highlight how the systematic gathering and examination of enormous datasets—a crucial part of artificial intelligence (AI) systems—may unintentionally result in injustice and violation of privacy. The authors stress the importance of carefully weighing the privacy and ethical ramifications of using AI in decision-making processes.

Ethical Dilemma

Artificial intelligence (AI)-related ethical dilemma occurs when the use or implementation of AI systems puts opposing moral beliefs, values, or interests at conflict. An article mentioned that "Using AI to make decisions in situations where there is a chance of harm to people creates ethical issues and raises the question of what values these systems should take precedence over" (Lin, P., Abney, K., & Bekey, G. A. (Eds.). (2014)). Another study discussed the issues on spreading misinformation or creating realistic fake videos (Brundage et al., 2018). The difficulties of integrating moral values into AI systems are examined in (Wallach and Allen, 2009). The writers talk about how hard it is to programme complex moral decision-making procedures and what might happen if AI systems start making unethical decisions.

Cost and Accessibility

Artificial Intelligence can be very expensive and time-consuming. AI is very expensive since it requires the newest hardware and software to function and stay current with requirements. Research shows that "The costs of an AI system include those for data collecting, software, hardware, expert labor, and continuous updates and support" (Jordan, M. I., & Mitchell, T. M. (2015)) also "Cost, ease of use, and removing obstacles that could prevent widespread adoption are all factors in AI systems" (Brynjolfsson & McAfee, 2014; Brynjolfsson, Rock, & Syverson, 2018).

Lack of Creativity and Empathy

Lack of creativity and empathy due to AI involve the limitations and challenges associated with replicating these human qualities in machines. AI is not capable of thinking out of the box. It can learn things which are pre-fed data but creating something new would be a challenge for it. AI can execute tasks based on data and patterns, they can find it difficult to come up with creatively and with the range of options and innovation that identify human creativity (Colton & Covert, 2007). Another study says that "although AI can replicate emotional reactions using already programmed principles, it might not be able to understand or feel emotions in the same way that humans do (Vogeley, K., & Newen, A. (2007)).

Environmental Impact

The impacts that the development, implementation, and utilization of artificial intelligence systems have on the environment are referred to as their environmental impact. This effect can take many forms, therefore it's critical to weigh the advantages and disadvantages. An article was published referring to "advice on how to create AI systems that are environmentally friendly" (Schwartz, Dodge, Smith, & Etzioni, 2020). Another article was published on the same mater "the importance of designing AI systems that are not only effective but also environmentally friendly" (Henderson, P., Islam, R., Bachman, P., Pineau, J., Precup, D., & Meger, D. (2018, April)). The resource usage of AI systems and its possible impact on the world's energy consumption (Amodei et al. 2016). The accuracy of AI algorithms is discussed in the study, and it makes the point that badly developed systems might result in needless computing demands, which consequently increase their environmental impact.

Conceptual Framework and Hypotheses

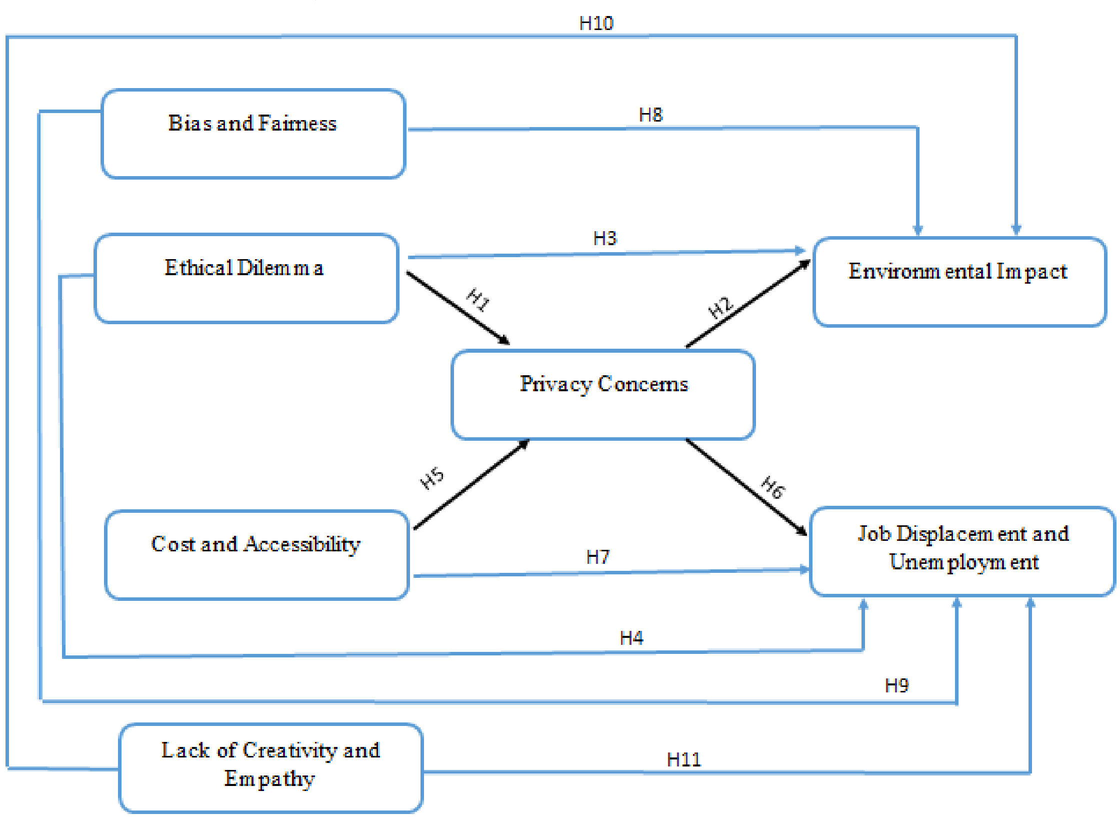

Figure 1: Conceptual Model

- HI: Ethical Dilemma in AI use causes Privacy Concerns for the consumers.
- H2: Privacy Concern in AI use affects the Environmental Impact of AI.
- H3: Ethical Dilemma has the direct effect on the Environmental Impact of AI use.
- H4: Ethical Dilemma of AI has direct effect on Job Displacement & Unemployment.
- H5: Cost & Accessibility of AI causes Privacy Concerns for the users.
- H6: Privacy Concern in AI use affects the Job Displacement & Unemployment.
- H7: Cost & Accessibility of AI has a direct effect on Job Displacement & Unemployment.
- H8: Biasness & Fairness directly affects Environmental Impact of AI.
- H9: Biasness & Fairness has a direct effect on Job Displacement & Unemployment.
- H10: Lack of Creativity and Empathy due to AI has a direct effect on the Environmental Impact of AI.
- H11: Lack of Creativity and Empathy due to AI has a direct effect on Job Displacement & Unemployment.

Methodology

Since Artificial Intelligence is a subject of study that is rapidly expanding, it is important to examine the literature from the standpoint of the study's nature to understand how it adds to it. It tells if the study is designed to identify problems with use of AI in organizational operations and suggest appropriate solutions, or, as in certain instances, whether researchers are prescribing solutions based on their experience and knowledge.

By classifying the publications as having a positivist research, quantitative methodology is used to analyze the hypotheses derived in this study (Godwin et al., 2021; Peters, Işik, Tona, & Popovič, 2016). On the other hand, normative approaches are those that address the concerns in a prescriptive manner by making recommendations for what a person should do in a certain risk situation (Moradi & Levy, 2020).

Sampling Technique

Because a sampling frame is not available, i.e., personal questions were not used in surveys i.e. name, email etc. probability sampling cannot be employed for this study; instead, convenience sampling provides the basis for the research (Saunders, Lewis, & Tornhill, 2007). Convenience sampling facilitates the ease of data gathering at low cost financial resources (Malik, Ghafoor, & Iqbal, 2013).

This research follows the deductive research approach. Deductive approach is the movement from a general aspect to specific. A deductive approach is concerned testing an existing theory through quantitative data analysis, and then designing a research strategy to test the hypothesis (Ansari, Khalid, Jalees, & Ramish, 2017; Arora & Agarwal, 2019; Qureshi, Ramish, Ansari, & Bashir, 2022). The research model of this research is constructed with the help of Technological Unemployment theory. To further test the hypothesized model quantitative data is collected. Profile of the Respondents

An online survey was constructed to operationalize the conceptual model. The survey method is considered the most typical and convenient method of data collection (Nooruddin, Ramish, Munir, Ahmed, & Ansari, 2022; Yasir, Bashir, & Ansari, 2021). Our survey had many similar measurement items to previous researches as the constructs were adopted from such researchers who operationalized similar constructs. Our research utilized previously constructed and tested questionnaires by previous researchers. Data collected from the online survey is coded to allow data analyses using software such as (Smart-PLS, V.4 & SPSS). Software is utilized to perform regression analyses. PLS is especially helpful in scenarios involving complex models, small sample numbers, and potential multicollinearity between predictor variables. PLS is preferred since it is made for simple interactions and ideal for data that is not normally distributed.

Sampling Size

The population of our study comprises employees of Pharma industries. Total number of populations is one as we are only targeting Pharma industries employees. We have selected this population because we are analyzing the consequences of AI in Job displacement. Maximum sample size is 35*7 = 245 based on the number of respondents per variable (Ansari, 2020; Onwuegbuzie, Johnson, & Collins, 2009; Sekaran, 2003).

Scale and Measure

In order to conduct a quantitative study, surveys are mostly based on questionnaires. The questionnaire for this study was created by modifying the constructs that had already been established in earlier research. Strongly Agree to Strongly Disagree were the answers available on the 5-point Likert scale used in the survey. Measured on a scale ranging from 1='Strongly agree' to 5= 'Strongly disagree'. Previous investigations had already proved the constructs' reliability.

\Results

Profile of Respondents

Among the 250 respondents, half were males (125 individuals, 50%), and the remaining half were females (125 individuals, 50%). The predominant age group among participants was 26 to 35 years, accounting for 49.2%, while 32% were in the 25 and below age category.

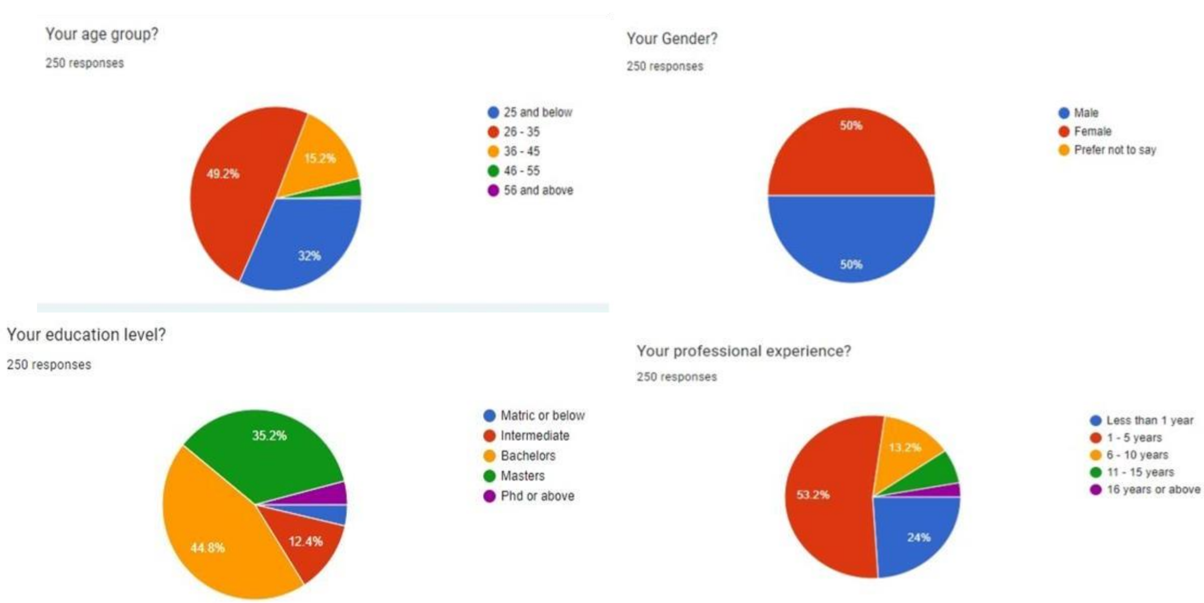

Figure 2: Demographics of the Respondents

Descriptive Statistics

It has been used to assess the univariate normality of the data obtained from respondents through the use of questionnaires. Measures of central tendency, skewness, and kurtosis are examples of descriptive results (Kline, 2011). The descriptive statistical findings also include variance and standard deviation. If the range of skewness and kurtosis falls between -2.0 and +2.0, which is the sufficient condition of univariate normality; outliers are found using descriptive results (George & Mallery, 2003).

Table 1: Descriptive Statistics

	Mean	Std. Deviation	Skewness	Kurtosis
JDU	2.136	.752	.760	-.068
EI	2.047	.735	.890	.868
PC	2.038	.764	1.196	1.674
ED	2.018	.723	1.067	1.415
CA	2.068	.742	1.015	1.160
BUF	2.140	.745	.881	.628
LCE	1.993	.722	1.050	1.048

Normality of the data was ensured by assessment of skewness and kurtosis of all items. The skewness and kurtosis of all the variables lie in the range of ± 3 to be accepted as normally distributed (Kline, 2011). Table 2 displays the skewness and kurtosis results. In terms of Skewness values, PC has the highest value at 1.196 (Mean = 2.0386, SD = .764), while JDU has the lowest value at 0.76 (Mean = 2.13, SD = .75). Kurtosis has a maximum value of 1.67 of PC (Mean = 2.0386, SD = .764) and a minimum value of -0.06 of construct JDU (Mean = 2.13, SD = .75). Thus, according to scholars, every concept satisfies the condition of univariate normality (George & Mallery, 2003). According to the given skewness values, all of the variables (JDU, EI, PC, ED, CA, BUF, and LCE) have positive skewness, indicating that their distributions are right-skewed. The majority of the data points in these distributions are concentrated on the left side, while the right tails are longer. Greater skewness values indicate that the corresponding distributions are more significantly skew.

Reliability Analysis

In this study, the internal consistency of the data is measured using Cronbach's alpha that is how closely related a set of items are as a group. If the constructs' Cronbach alpha values are higher than 0.6, they are regarded to be reliable (Sekaran & Roger, 1997). Additionally, reliability analysis is utilized to lessen researcher biases and data inaccuracies (Bryman & Bell, 2012). Cronbach's alpha value greater than 0.7 implies that the instrument is acceptable (Santos, 1999). Therefore, based on the results, the variables are judged to be reliable.

Table 2: Interpretation of Constructs Reliability

Constructs	Cronbach's alpha	No. of items	Mean	Std. Deviation	Composite reliability (rho_a)	Composite reliability (rho_c)
BUF	0.811	4	2.1407	.75778	0.819	0.875
CA	0.862	5	2.0685	.74273	0.865	0.901
ED	0.863	5	2.0181	.72329	0.864	0.901
EI	0.862	5	2.0472	.73531	0.862	0.901
JDU	0.841	6	2.1365	.75295	0.843	0.883
LCE	0.866	5	1.9937	.72273	0.866	0.903
PC	0.846	5	2.0386	.76438	0.849	0.891

The constructs with the highest reliability (α=.86) are the LCE (M=1.99, SD=.72) and the lowest reliability (α=.81) are the BUF (M=2.14, SD=.75). Cronbach's alpha as a whole is 0.85. (Hair et al. 2010), all Cronbach's Alpha values found were more than.70, indicating good data reliability. Composite Reliability measure can be used to check how well a construct is measured by its assigned indicators. Hence, composite reliability greater than 0.5 is considered tobe reliable (Hair Jr., Hult, Ringle, & Sarsedt, 2017).

Confirmatory factor analysis (CFA)

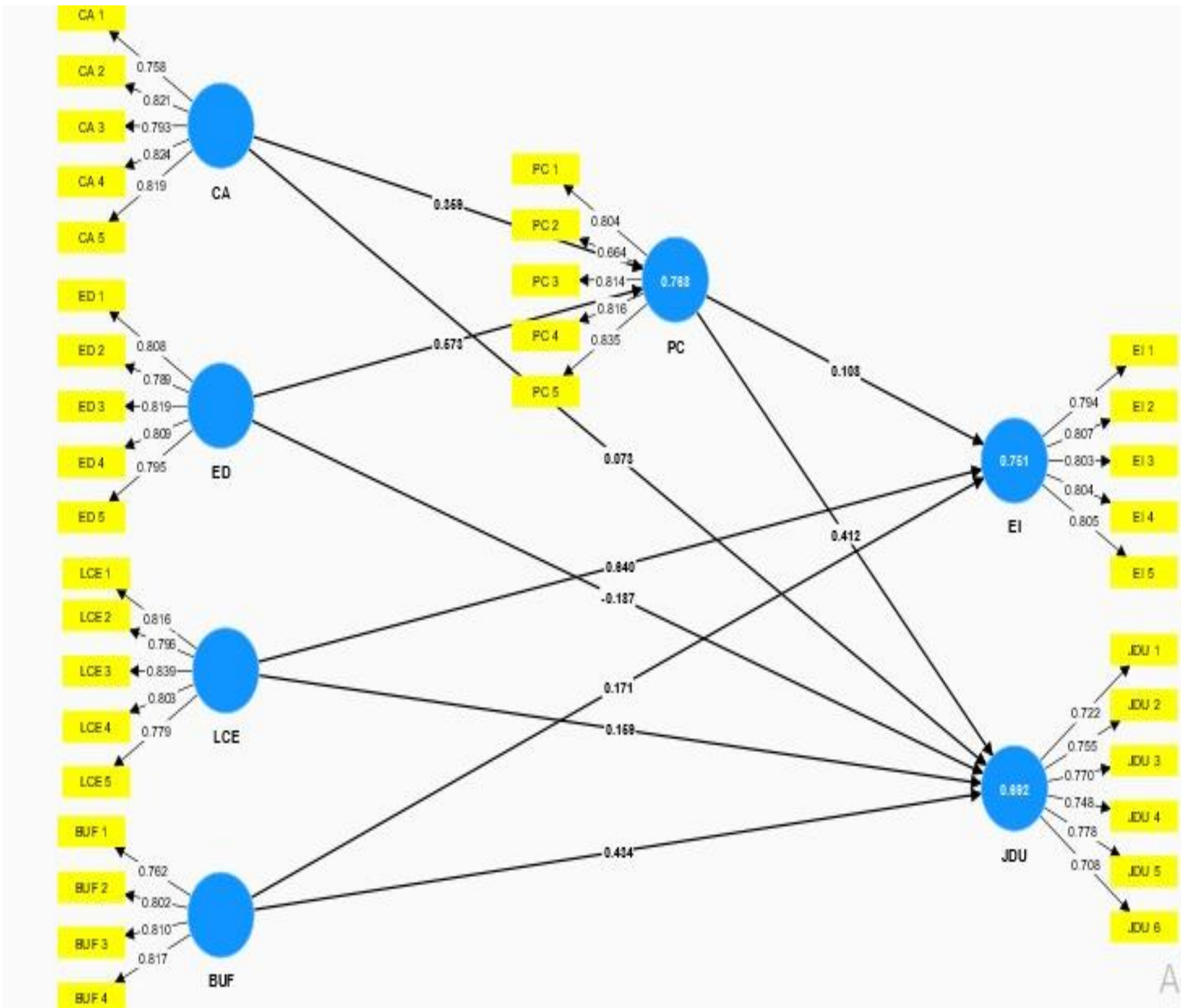

Figure 3: SEM Model conducted using PLS SEM

A multivariate statistical technique called confirmatory factor analysis (CFA) is used to assess how well the measured variables represent the number of components. Similar procedures are used in confirmatory factor analysis (CFA) and exploratory factor analysis (EFA) (Aertssen, Ferguson, & Smits-Engelsman, 2016; Kline, 2015). In EFA, data is simply investigated and information about the number of factors needed to reflect the data is obtained. Every measured variable in an exploratory factor analysis has a relationship with every latent variable (Ansari, 2020). However, confirmatory factor analysis (CFA) allows researchers to identify which latent variable is associated with which measured variable as well as the number of factors that must be present in the data (Kumar, 2012; Schreiber, 2006). One method to support or refute the measurement theory is confirmatory factor analysis (CFA). As all variable's factor loading is 0.6, it indicates that there is a strong correlation between it and the underlying factor (Garson, 2016).

Table 3: Interpretation of Constructs Reliability

	BUF	CA	ED	EI	JDU	LCE	PC
BUF 1	0.762						
BUF 2	0.802						
BUF 3	0.810						
BUF 4	0.817						
CA 1		0.758					
CA 2		0.821					
CA 3		0.793					
CA 4		0.824					
CA 5		0.819					
ED 1			0.808				
ED 2			0.789				
ED 3			0.819				
ED 4			0.809				
ED 5			0.795				
EI 1				0.794			
EI 2				0.807			
EI 3				0.803			
EI 4				0.804			
EI 5				0.805			
JDU 1					0.722		
JDU 2					0.755		
JDU 3					0.770		
JDU 4					0.748		
JDU 5					0.778		
JDU 6					0.708		
LCE 1						0.816	
LCE 2						0.796	
LCE 3						0.839	
LCE 4						0.803	
LCE 5						0.779	
PC 1							0.804
PC 2							0.664
PC 3							0.814
PC 4							0.816
PC 5							0.835

Correlation Analysis

The Karl Pearson Correlation test can be used to determine the relationship among several construct (Altuna & Konuk, 2009; Joseph F Hair, Black, Babin, & Anderson, 2006). The correlation coefficient's value indicates the relationship's strength and weakness. A correlation coefficient number around one (either +1 or -1) indicates a significant link between the variables, whereas a value near zero indicates no association at all (Bryman & Bell, 2011).

Table 4: Interpretation of Correlation

Constructs	BUF	CA	ED	EI	JDU	LCE	PC
BUF	1						
CA	0.752	1					
ED	0.749	0.754	1				

Constructs	BUF	CA	ED	EI	JDU	LCE	PC
EI	0.738	0.810	0.738	1			
JDU	0.777	0.72	0.662	0.685	1		
LCE	0.761	0.846	0.767	0.853	0.726	1	
PC	0.741	0.791	0.844	0.726	0.756	0.769	1

The positive associations between different constructs are indicated by the Karl Pearson correlation coefficients. Notably, at the confidence level of 95%, there are strong correlations between CA and ED (0.754), LCE and EI (0.853), and PC and ED (0.844). Some correlations, like the one between BUF and LCE (0.761) and JDU (0.777), are moderate. Furthermore, there is a weak association (0.662) between JDU and ED. Because all bi-variate interactions have values between.30 and.90, this indicates that there is no problem with multi-co-linearity and that the constructs are different and unique.

Construct Validity

When variables/constructs are opted in research, their validity is to be assured on the basis of variance that can be differentiated because of industry and demographics. Construct utilized in the research were already utilized in past examinations too, so controlling them as per the Pakistani industry might influence the results. Subsequently, to keep up with the uniformity of the study, determining the validity of the respondents' data was required. Construct validity is determined by conducting the tests of “convergent validity” and “discriminant validity” (Fornell & Larcker, 1981). The test of convergent validity can be found out by actually through AVE (average variance explained), the upsides of which should be greater than 0.40 (Hair, Ringle, & Sarstedt, 2011; Hair et al., 2006). Since every one of the upsides of AVE in this examination are more than 0.4, it implies that the information satisfies the prerequisites of the united legitimacy (Ansari, 2020).

Convergent Validity

This shows whether a test that is designed to assess a particular construct correlates with other tests that assess the same construct. It is measured through Average Variance Extracted (AVE). It says that AVE should be greater than 0.5. Hence, the items have strong correlation because all of the study's constructs meet the convergent validity requirement (Hair Jr. et al., 2017).

Table 5: Interpretation of Convergent Validity

Constructs	Cronbach's alpha	Mean	Std. Deviation	Average variance extracted(AVE)
BUF	0.811	2.140	.757	0.637
CA	0.862	2.068	.742	0.766
ED	0.863	2.018	.723	0.747
EI	0.862	2.047	.735	0.744
JDU	0.841	2.136	.752	0.558
LCE	0.866	1.993	.722	0.651
PC	0.846	2.038	.764	0.622

Discriminant Validity

Square of AVE should be greater than correlation of a variable with other variables (Ab Hamid, Sami, & Mohmad Sidek, 2017). It indicates the extent to which a given construct is different from other constructs (John Hulland, 1999). It follows the rule that “items should have a higher correlation with the latent variable that they are supposed to measure than with any other latent variable in the model (Chin, 1998). In other words, it defines the similarity between the constructs.

Table 6: Interpretation of Fornell Larcker Criteria

Construct s	BUF	CA	ED	EI	JDU	LCE	PC
BUF	0.798						
CA	0.752	0.875					
ED	0.749	0.754	0.864				
EI	0.738	0.810	0.738	0.863			
JDU	0.777	0.720	0.662	0.685	0.747		
LCE	0.761	0.846	0.767	0.853	0.726	0.807	
PC	0.741	0.791	0.844	0.726	0.756	0.769	0.789

Structural Model Assessment

B, p-value, t-value and CI .Since, p values of CA -> JDU, LCE -> JDU and PC -> EI are greater than 0.05. Therefore, H7, H11 and H2 hypothesis are rejected. Other than that, all hypothesis is accepted

Table 7: Direct and Indirect Effects

Effects	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
BUF -> EI	0.172	0.173	0.074	2.311	0
BUF -> JDU	0.438	0.448	0.096	4.554	0
CA -> JDU	0.075	0.066	0.111	0.673	0.500
CA -> PC	0.359	0.356	0.071	5.074	0
ED -> JDU	-0.193	-0.185	0.095	2.024	0
ED -> PC	0.573	0.575	0.065	8.767	0
LCE -> EI	0.642	0.644	0.071	9.029	0
LCE -> JDU	0.16	0.162	0.097	1.653	0.100
PC -> EI	0.105	0.102	0.083	1.260	0.200
PC -> JDU	0.412	0.403	0.105	3.927	0
CA -> EI	0.000	0.000	0.000	1.200	0.200
CA ->JDU	0.100	0.100	0.000	3.300	0
ED -> EI	0.100	0.100	0.100	1.200	0.200
ED -> JDU	0.200	0.200	0.100	3.500	0

Coefficient of Determination

Coefficient of determination can be assessed as substantial if $R^2 \geq 0.26$, moderate for $R^2 \geq 0.13$ and weak for $R^2 \geq 0.02$. R2 of EI, JDU and PC is much higher than 0.26. This means the model fits the data (Garson, 2016; Nwaneri, 2015). Table given below depicts the r-square result.

Table 8: Interpretation of R2

	R-square	R-squareadjusted
EI	0.751	0.748
JDU	0.694	0.688
PC	0.768	0.766

Discussion and Conclusions

A detailed understanding of the effects of Artificial Intelligence on opportunities for employment and job displacement is offered by the research that was consulted for this analysis. Some research points to a possible loss of the labor market due to automation of repetitive work (Brynjolfsson et al., 2018; Floridi et al., 2018; Langer et al., 2023). This study included statistical analysis, calibration, and a variety of question formats. Although Artificial

Intelligence has brought so many benefits for us in making our lives easy day by day, but it also affected many people by its disadvantages (Fatima et al., 2024; Pagano et al., 2023).

This current study makes several contributions like outer loading which determines the construct related question that is how much of the construct is well describing the questions. Majority of the values in our study are more than the threshold value the item PC2 has the outer loading less than 0.708, this item has been deleted. In discriminant validity all constructs are discriminated and differentiated with each other as their threshold value is < or equal to 0.85 except between EDU & JD. It explains that most of the constructs are well represented by itself. On the other hand, in path coefficient direct effect, p values of CA -> JDU, LCE -> JDU and PC -> EI are greater than 0.05. Therefore, H7, H11 and H2 hypothesis are rejected. Other than that, all hypotheses are accepted.

Furthermore, the indirect effect of Cost accountability and Ethical Dilemma on Environmental Impact determines the two hypotheses are non-supported since P value is greater than 0.05 and T states is less than 1.645. As our data is not normal so we performed PLS analysis. Composite reliability denotes all values greater than 0.07, which are greater than its threshold value, indicating that it is reliable and consistent. AVE indicates that the majority of the values are greater than 0.5, hence constructs have strong correlation and that the variances are converging to represent the construct.

Conclusion

According to the respondents, although AI may boost productivity and open up new job prospects, they may also result in a large loss of jobs. With their increasing intelligence, machines are expected to eventually outperform humans in many areas. This research was done to investigate what are the elements that are affected by Artificial Intelligence and how. After getting responses on our survey, we ran tests and results showed that 8 out of 11 hypotheses were accepted indicating that Artificial Intelligence does have a major impact on job displacement and other elements.

Theoretical implications

According to the survey's findings, the main detrimental effects of AI in companies could be the displacement of the conventional workforce, while it will open new opportunities and create new jobs, the skill requirement of the average worker will have to be upgraded to keep up the technological advancements and escape redundancy.

Practical Implications

The study suggested that professional organizations who are willing to incorporate AI in their processes first should train and equip their workforce with the required skill set and focus on the skill development of the staff. Failing to keep up, the AI incorporating may lead them to be completely dependent on the AI for their everyday operations.

Limitation and Future Research

Artificial intelligence is a diverse, broad, and dynamic field including an array of technologies. The pharmaceutical industry in Karachi was the main focus of this study, but there is room to expand in the future; various sectors might be investigated throughout Pakistan. Seven variables total—four independent, two dependents, and one mediator—were included in this study. Demographic characteristics, which were not examined in this study's parameters, may be included in future research. The concepts used in this work were derived from research that mainly evaluated the effects of artificial intelligence on job displacement.

The study's findings suggest that developing new conceptual frameworks for the consequences of artificial intelligence may provide further understanding of the topic. Furthermore, adding innovative contracts on the effects of AI-led job displacement could provide insightful viewpoints for further research. Also, the same study in different industry can be performed to check the results in different populations.

References

Ab Hamid, M. R., Sami, W., & Mohmad Sidek, M. H. (2017). Discriminant Validity Assessment: Use of Fornell & Larcker criterion versus HTMT Criterion. *Journal of Physics: Conference Series*, *890*(1). https://doi.org/10.1088/1742-6596/890/1/012163

Aertssen, W. F. M., Ferguson, G. D., & Smits-Engelsman, B. C. M. (2016). Reliability and structural and construct validity of the functional strength measurement in children aged 4 to 10 years. *Physical Therapy*, *96*(6), 888–897. https://doi.org/10.2522/ptj.20140018

Altuna, O. K., & Konuk, F. A. (2009). Understanding Consumer Attitudes Toward Mobile Advertising and its impact on consumers behavioral intentions: A Crossmarket Comparison of United States and Turkish Consumers. *International Journal of Mobile Marketing*, *4*(2), 43–51.

Ansari, J. (2020). *Measuring Religio-Spiritual Insights that Influence Attitude towards Advertising during Religious Festivals*. Institute of Business Management.

Ansari, J., Khalid, F., Jalees, D. T., & Ramish, M. S. (2017). Consumer's Attitude towards Ramadan Advertising. *South Asian Journal of Management Sciences*, *11*(1), 14–31. https://doi.org/10.21621/sajms.2017111.02

Arora, T., & Agarwal, B. (2019). Empirical Study on Perceived Value and Attitude of Millennials Towards Social Media Advertising: A Structural Equation Modelling Approach. *Vision*, *23*(1), 56–69. https://doi.org/10.1177/0972262918821248

Brundage, M., Avin, S., Clark, J., Toner, H., Eckersley, P., Garfinkel, B., … others. (2018). The malicious use of artificial intelligence: Forecasting, prevention, and mitigation. In *arXiv preprint arXiv:1802.07228*.

Bryman & Bell. (2012). *Business Research Methods* (3rd ed.). Oxford University Press.

Bryman, A., & Bell, E. (2011). *Business Research Methods* (3rd Editio). Oxford: Oxford University Press.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton \& Company.

Brynjolfsson, E., Rock, D., & Syverson, C. (2018). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. The economics of artificial intelligence: An agenda. *University of Chicago Press. Https://Doi. Org/10*, *3386*, w24001.

Chen, G., Xie, P., Dong, J., & Wang, T. (2019). Understanding Programmatic Creative: The Role of AI. *Journal of Advertising*, *48*(4), 347–355. https://doi.org/10.1080/00913367.2019.1654421

Chin, W. W. (1998). *The partial least squares approach to structural equation modeling.*

Coelli, M. B., & Borland, J. (2019). *Behind the headline number: Why not to rely on Frey and Osborne's predictions of potential job loss from automation*.

Colton, D., & Covert, R. W. (2007). *Designing and Constructing Instruments gor Social Research and Evaluation*. John Wiley & Sons, Inc.

Esmaeilzadeh, P. (2020). Use of AI-based tools for healthcare purposes: A survey study from consumers' perspectives. *BMC Medical Informatics and Decision Making*. https://doi.org/10.1186/s12911-020-01191-1

Fatima, H., Jan, S. M. H. A., Khan, A. K., Javed, S., & Rashid, M. (2024). EFFECT OF ARTIFICIAL INTELLIGENCE ON THE HUMAN WORKFORCE. *International Journal of Contemporary Issues in Social Sciences*, *3*(1), 1197–1203.

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., … others. (2018). AI4People—an ethical framework for a good AI society: opportunities, risks, principles, and recommendations. *Minds and Machines*, *28*, 689–707.

Fornell, C., & Larcker, D. F. (1981). SEM with Unobservable Variables and Measurement Error: Algebra and Statistics. *Journal of Marketing Research*, Vol. 18, pp. 1–16.

Garson, G. D. (2016). *Partial Least Square (PLS-SEM)*. NC: Statistical Associates Publishing. Retrieved from www.statisticalassociates.com

George, D., & Mallery, P. (2003). SPSS for Windows Step by Step: A Simple Guide and Reference, 11.0 Update. In *Boston, MA: Allyn y Bacon.[Links]*. https://doi.org/10.1177/1073191112446654

Godwin, A., Benedict, B., Rohde, J., Thielmeyer, A., Perkins, H., Major, J., … Chen, Z. (2021). New Epistemological Perspectives on Quantitative Methods: An Example Using Topological Data Analysis. *Studies in Engineering Education*. https://doi.org/10.21061/see.18

Hagendorff, T. (2020). The ethics of AI ethics: An evaluation of guidelines. *Minds and Machines*, *30*(1), 99–120.

Hair, Joe F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202

Hair, Joseph F, Black, W. C., Babin, B. J., & Anderson, R. E. (2006). *Multivariate Data Analysis*. Pearson.

Hair Jr., J. F. K., Hult, G. T. M. H., Ringle, C. M., & Sarsedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2nd ed.). Los Angeles: SAGE Publications Ltd.

John Hulland. (1999). Use of partial least squares (PLS) in strategic management research: A review of four recent studies. *Strategic Management Journal*, *20*(2), 195.

Kapeliushnikov, R. (2019). The phantom of technological unemployment. *Russian Journal of Economics*, *5*(1), 88–116.

Kazi, A. M., Qazi, S. A., Ahsan, N., Khawaja, S., Sameen, F., Saqib, M., … Stergioulas, L. K. (2020). Current challenges of digital health interventions in Pakistan: Mixed methods analysis. *Journal of Medical Internet Research*, *22*(9), 1–14. https://doi.org/10.2196/21691

Kheya, T. A., Bouadjenek, M. R., & Aryal, S. (2024). The Pursuit of Fairness in Artificial Intelligence Models: A Survey. In *arXiv preprint arXiv* (Vol. 1). Association for Computing Machinery. Retrieved from Association for Computing Machinery website: http://arxiv.org/abs/2403.17333

Kline, R. B. (2011). Principles and practice of structural equation modeling. In *The Guilford Press* (3rd ed.). New York, NY: The Guilford Press. https://doi.org/10.1038/156278a0

Kline, R. B. (2015). *Principles and practice of structural equation modeling*. Guilford publications.

Krmac, E. V. (2011). Intelligent Value Chain Networks: Business Intelligence and Other ICT Tools and Technologies in Supply/Demand Chains. *Supply Chain Management - New Perspectives*. https://doi.org/10.5772/799

Kumar, K. (2012). A Beginner's Guide to Structural Equation Modeling, 3rd edn. In *Journal of the Royal Statistical Society: Series A (Statistics in Society)* (Vol. 175). https://doi.org/10.1111/j.1467-985x.2012.01045_12.x

Langer, M., König, C. J., Back, C., & Hemsing, V. (2023). Trust in Artificial Intelligence: Comparing trust processes between human and automated trustees in light of unfair bias. *Journal of Business and Psychology*, *38*(3), 493–508.

Leavy, S., O'Sullivan, B., & Siapera, E. (2020). Data, power and bias in artificial intelligence. *ArXiv Preprint ArXiv:2008.07341*.

Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. *Futures*, *90*, 46–60.

Malik, M. E., Ghafoor, M. M., & Iqbal, H. K. (2013). Impact of Brand Image and Advertisement on Consumer Buying Behavior. *World Applied Sciences Journal*, *23*(1), 117–122. https://doi.org/10.5829/idosi.wasj.2013.23.01.824

Moradi, P., & Levy, K. (2020). *The Future of Work in the Age of AI: Displacement or Risk-Shifting?(2020)*.

Mossavar-Rahmani, F., & Zohuri, B. (2024). Artificial Intelligence at Work: Transforming Industries and Redefining the Workforce Landscape. *Journal of Economics \& Management Research. SRC/JESMR-284. J Econ Managem Res*, *5*(2), 2–4.

Nissenbaum, H. (2004). Privacy as contextual integrity. *Wash. L. Rev.*, *79*, 119.

Nooruddin, U. M., Ramish, M. S., Munir, N., Ahmed, S., & Ansari, J. (2022). ADOPTION AND COMMITMENT TO ONLINE BANKING IN PAKISTAN uSING THE TECHNOLOGY ACCEPTANCE MODEL. *Banking and Bank Systems*.

Nwaneri, C. E. (2015). The Impact of Corporate Social Responsibility (CSR) on Organization Profitability. *International Journal of Business and Management*, *10*(9), 60. https://doi.org/10.5539/ijbm.v10n9p60

Onwuegbuzie, A. J., Johnson, R. B., & Collins, K. M. T. (2009). Call for mixed analysis: A philosophical framework for combining qualitative and quantitative approaches. *International Journal of Multiple Research Approaches*, *3*(2), 114–139. https://doi.org/10.5172/mra.3.2.114

Pagano, T. P., Loureiro, R. B., Lisboa, F. V. N., Peixoto, R. M., Guimarães, G. A. S., Cruz, G. O. R., … others. (2023). Bias and unfairness in machine learning models: a systematic review on datasets, tools, fairness metrics, and identification and mitigation methods. *Big Data and Cognitive Computing*, *7*(1), 15.

Pandey, A., & Caliskan, A. (2021). Disparate impact of artificial intelligence bias in ridehailing economy's price discrimination algorithms. *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society*, 822–833.

Patrawala, R. (2019). The Artificial Intelligence Era its Seismic Potential to Create a Job Displacement Conundrum. *IIBM'S Journal of Management Research*, 112–129.

Peters, T., Işik, Ö., Tona, O., & Popovič, A. (2016). How system quality influences mobile BI use: The mediating role of engagement. *International Journal of Information Management*, *36*(5), 773–783.

Postel-Vinay, F. (2002). The dynamics of technological unemployment. *International Economic Review*, *43*(3), 737–760.

Qureshi, M. A., Ramish, M. S., Ansari, J., & Bashir, M. A. (2022). Leader's Toxicity at Workplace: How Leader's Decadence Affect Employees? A Pakistani Perspective. *SAGE Open*, *12*(2), 21582440221096424.

Reddy, A. J. M., Rani, R., & Chaudhary, V. (2019). Technology for sustainable HRM: An empirical research of health care sector. *International Journal of Innovative Technology and Exploring Engineering*. https://doi.org/10.35940/ijitee.A9108.119119

Santos, J. R. A. (1999). Cronbach's alpha: A tool for assessing the reliability of scales. *Journal of Extension*, *37*(2), 1–5.

Saunders, M., Lewis, P., & Tornhill, A. (2007). Research Methods for Business Students. In *Pearson Education Limited 2*.

Schreiber, J. B. (2006). *Modeling and Confirmatory Factor Analysis Results : A Review*.

Schwartz, R., Dodge, J., Smith, N. A., & Etzioni, O. (2020). Green ai. *Communications of the ACM*, *63*(12), 54–63.

Sekaran, U. (2003). Research Methods for Business:A Skill Building Approach. In *John Wiley & Son*. Hoboken, NJ: John Wiley & Sons. https://doi.org/10.1017/CBO9781107415324.004

Sekaran, U., & Roger, B. (1997). *Research Methods for Business: A Skill Business Approach*. Signorini, A. (2014). Use of social media to monitor and predict outbreaks and public opinion on health topics. *ProQuest Dissertations and Theses*, 128. https://doi.org/10.1007/s13398-014-0173-7.2

Tiwari, R. (2023). The impact of AI and machine learning on job displacement and employment opportunities. *Interantional Journal of Scientific Research in Engineering and Management*, *7*(01).

Wisskirchen, G., Biacabe, B. T., Bormann, U., Muntz, A., Niehaus, G., Soler, G. J., & von Brauchitsch, B. (2017). Artificial intelligence and robotics and their impact on the workplace. *IBA Global Employment Institute*, *11*(5), 49–67.

Yasir, M., Bashir, M. A., & Ansari, J. (2021). Technological Antecedents of Organizational Agility: PLS SEM Based Analysis Using IT Infrastructure, ERP Assimilation, and Business Intelligence. *Market Forces*, *16*(1).