The Impact of Artificial Intelligence Opportunities and the Perceived Risk of Unemployment on Employee Workplace Well-Being

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Based on the transactional theory of stress, people tend to adopt problem-oriented coping styles when they feel there are opportunities in the situation and can benefit from them. Positive effects of Artificial Intelligence (AI) on labor include increased income for certain management and skilled positions as well as the creation of new job opportunities. However, among its drawbacks are the jobs it replaces, which causes unemployment. According to resource conservation theory, concerns about job stability and persistence trigger the process of resource consumption, which wears people out emotionally (Xu, et.al., 2023). The study results provide the relationship among Artificial Intelligence (AI) opportunity perception, employees' workplace well-being (WWB) and Informal Learning in the Workplace (ILW).

Keywords: artificial intelligence opportunity perception, unemployment risk perception, employees' workplace well-being, informal learning in the workplace

INTRODUCTION

We define Artificial Intelligence (AI) as an extensive class of technologies that allow a computer device to perform tasks that a human required. It includes adaptive decision-making. On the other hand, human resource management (HRM) refers to the strategic and coherent approach to managing, nurturing, and supporting human resources and ensuring a positive workplace environment. Based on the transactional theory of stress, people tend to adopt problem-oriented coping styles, which positively affect their well-being, when they feel there are opportunities in the situation, and they can benefit from them. Positive effects of AI on labor include increased income for certain management and skilled positions as well as the creation of new job opportunities. However, among its drawbacks are the jobs it replaces, which causes unemployment. According to resource conservation theory, concerns about job stability and persistence trigger the process of resource consumption, which wears people out emotionally (Xu, et.al., 2023). So, Xu et al. (2023) were trying to explore the relationships between AI usage in the workplace and employees' workplace well- being. Our study conceptually reproduces the study by Xu et al. (2023) "The Relationship of Artificial Intelligence Opportunity Perception and Employee Workplace Well-Being: A Moderated Mediation Model". By conducting the comparative study, our research contributes to the "validation of the articles published in other journals so as a field we can be more confident in the advancement of science and increases the body of studies to enable better quality meta-analyses." (Dennis, et.al., 2015). Also, we adapt their research model (nomological network) to our study's context. We modified the relationships among some constructs thus achieved the architectural innovation in our study. By conceptually comparing prior study, we can confirm whether the prior findings generalize to the new context or that findings are closely tied to the original measures, analysis, etc. and don't generalize beyond them.

The study results provide strategies for organizations to leverage the positive side of AI (i.e., learning opportunity) and improve employees' workplace well-being. Also, it encourages inspiration on how to decrease the negative impact of AI unemployment risk.

Research Questions

1. What are the relationships between AI implementation and employees' Workplace Well-being?

2. How does the Unemployment Risk Perception impact employees' workplace well-being?

LITERATURE REVIEW

According to Tambe et. al (2019) HR has several issues where AI techniques can be applied, such as, the complexity of HR outcomes, large number of data observations, the consequences of hiring and firing decisions. The authors have mentioned the AI life cycle to overcome those challenges – operations, date generation, machine learning, and decision-making.

The challenges that Stone and Deadrick (2015) have mentioned in their article are: (1) Change from a manufacturing to a service economy (system based on buying and selling of services) and knowledge-based economy (use of information to generate value), (2) Rise in globalization (international, comparative, and cross-cultural environment), (3) Growing domestic diversity (such as, age, ethnicity), (4) emerging use of information technology.

According to De Cremer and Kasparov (2021), the article explores the evolving relationship between humans and machines in the workforce. While machines excel at repetitive tasks and become increasingly capable in cognitive work, humans possess unique qualities like intuition, emotion, and cultural sensitivity. The combination of these abilities, termed "Augmented Intelligence," holds promise for the future of work, where humans and machines collaborate synergistically rather than compete. Examples from chess illustrate how human-machine partnerships can outperform both humans and machines alone. The key lies in understanding and integrating AI strategically into organizations, fostering inclusive teams, and leveraging the strength of both humans and machines to enhance productivity and well-being. The article tells how humans and machines are shaking up the job scene. It points out that while machines are getting pretty good at doing tasks that used to be just for humans, like math and language, they're still missing some important human traits, like creativity and emotions. Instead of seeing it as a competition, it suggests teaming up both human and machine strengths. The study emphasizes the need for businesses to be smart about integrating AI, building teams that mix people and machines, and training leaders to handle them effectively. Ultimately, it's all about finding ways to make work better and more efficient while valuing what humans bring to the table. It highlights how AI, while adept at handling repetitive tasks and data analysis, lacks the human touch in areas like intuition and emotional intelligence. Instead of viewing AI as a threat to human jobs, the study also suggests a collaborative approach, where humans and machines work together to enhance productivity and efficiency. The authors argue for a strategic integration of AI into organizations. It underscores the importance of inclusive teams that combine human ingenuity with AI's analytical power, while also emphasizing the need for leaders who can navigate this new landscape effectively. The article advocates for a future where humans and machines collaborate harmoniously to achieve greater outcomes in the employees' workplace.

The idea of becoming good at defining the value of an employee can never really be measured because we're all humans who operate based on experience. Sometimes the true development of a company is from those dedicated employees who offer creative paths to make things run smoother due to their actual working in the environment to produce outcomes. Many times, the theories and the people who make up how the business should flow hardly ever have the experience of that said worker, they just make the plays and the rules. Cappelli (2020) depicts how scholars view the workforce and how it can be written that they know what is best? We have seen many instances where automation has been added to a production line without the deeper thoughts that what if this happens, and what will we do if this does not work the best. Managers and those who are in charge do not pay attention to the employee who simply must catch the box, palletize, and move at accelerated speeds. The loyal employee will stay there tired working non-stop for every second to obtain the job status that they can get done even if it causes them body damage. Chronologically the theories that have designed the workforce for the past 50 years have come from hierarchy. Rarely do we see developmental changes that come from the thoughts of employees who do the work. Right now, we see so many injustices in the production industry because companies hire more contract workers so that they do not have to offer any incentives, vacations, pensions, health care costs, and any other benefits offered because of policies that hold corporations accountable.

The article by De Cremer and Stollberger (2022), titled "Are People Analytics Dehumanizing Your Employees?" discusses how companies use data to identify new opportunities, make better decisions, and improve predictions. However, this focus on data has shifted attention away from the humans who do the work. Specifically, employee data is increasingly being used in human resources management (HRM) and people analytics (PA). There is a growing concern that employees are being reduced to mere data points, which can dehumanize them. To address this issue, experts recommend taking a more nuanced and thoughtful approach to people analytics. This can be achieved by emphasizing that people analytics is not a tool for automation, recognizing that it goes beyond efficiency, and refraining from reducing individuals to mere data sets. By adopting these strategies, companies can more effectively use people analytics to enhance their understanding of their employees without sacrificing their humanity.

People analytics should be implemented to enhance employees' abilities and performances. It should prioritize humans over machines. It is important to communicate clearly that using a performance analysis tool will not only be about predicting individual employee's performance. This approach can erode trust and infringe on employee privacy. Organizations should avoid framing performance as the goal, which can communicate that employees are merely a means to achieve that end. When it comes to motivating employees using performance appraisals, the language used plays a crucial role. To create a positive work environment, avoiding using language that dehumanizes employees is important. Specifically, HR should avoid using abstract language that refers to employees as numbers or objects. Terms like data, company assets, or investments that need to show a return on investment (ROI) can convey that employees are not valued as individuals who deserve respect and attention. It is essential to remember that employees bring their whole selves to work and treating them with appreciation for their unique qualities and values can make a significant difference in their level of engagement and motivation toward the organization's goals. Some organizations use people analytics strategies to collect employees' personal data to enhance transparency. However, this approach can create an empathy gap, where employees feel poorly understood despite the abundance of data collected. In such cases, people analytics may be perceived as treating employees like machines rather than fostering their growth and development. It is important to understand that collecting and analyzing employees' data can be useful and valuable to the organization if it is not primarily focused on making employees feel like quantifiable objects in a machine- driven context. Organizations should strive to use people analytics to create a positive and supportive work environment that fosters employee growth and development. This approach will help build a workforce that is engaged, motivated, and more likely to contribute to the organization's success.

In their article, Fuller et. al. (2019) highlights the often-underestimated adaptability of employees within organizations. They argue that despite common perceptions, employees can adjust to changing circumstances, technologies, and work environments. Drawing on examples from various industries, the article suggests that fostering adaptability among employees can lead to increased productivity, innovation, and overall organizational success. It emphasizes the importance of creating a culture that encourages learning, experimentation, and resilience. By investing in training, providing opportunities for skill development, and promoting open communication, employers can unleash their workforce's full potential and navigate the complexities of today's rapidly evolving business landscape.

In their article "Building Ethical AI for Talent Management," Chamorro-Premuzic, et. al (2019), discussed the role of artificial intelligence in transforming hiring within organizations. They highlighted the potential of AI to enhance hiring processes by more accurately predicting a candidate's work-related behaviors and performance potential compared to traditional recruitment methods. This predictive ability afforded by AI is based on analyzing extensive data sets and identifying patterns that might not be as apparent to human recruiters. The authors cautioned against the risks of bias within AI systems, which they explain can arise from biased training data sets or algorithms. These biases could exacerbate existing issues in hiring practices, like discrimination, unless carefully assessed and corrected. To leverage the benefits of AI in talent management while mitigating these risks, the article proposes a shift towards the development of more ethical AI systems. This involves the examination of AI algorithms for bias, educating candidates about the AI systems used to obtain their consent, and ensuring that AI systems are transparent and able to explain their predictions. The article emphasizes the importance of balancing fairness and accuracy in AI hiring and suggests that modern AI has the potential to overcome traditional trade-offs between these two goals. It advocates for open-source AI systems and third-party audits to hold companies accountable and ensure the ethical use of AI in talent management. Additionally, the authors argue that legal and ethical standards in traditional hiring should also apply to AI-driven hiring, particularly regarding the protection of candidate's personal information. In conclusion, the authors made the case that ethical AI can be used to improve organizational hiring practices by reducing bias and enhancing meritocracy in hiring. This would benefit individual organizations and contribute positively to the economy by expanding access to opportunities across a broad spectrum of socioeconomic backgrounds. The authors called for investments in AI technologies and human expertise to manage and mitigate the risks associated with AI in talent management.

THEORY AND HYPOTHESIS

The Transaction Theory of Stress explains how individuals process stress and the short-term and long-term effects of stress. When individuals believe there are opportunities in the situation and they can benefit from them, they tend to adopt problem-oriented coping styles, which positively impact their well-being. When individuals perceive that AI offers them opportunities, they will apply problem-oriented coping strategies, which will lessen their stress and improve their long-term well-being.

Artificial Intelligence (AI) refers to machines performing cognitive functions generally associated with human minds.

Informal Learning in the Workplace (ILW): There are two types of learning in the workplace: formal and informal learning. Formal learning refers to curricular behaviors and activities undertaken in a formally designated learning environment to acquire knowledge and skills. Informal learning refers to non-curricular behaviors and activities performed outside a designated learning environment to develop knowledge and skills. AI has an impact on the ILW. So, we come up with the following hypothesis:

Hypothesis 1. *Artificial Intelligence (AI) opportunity perception will be positively related to Informal Learning in the Workplace (ILW).*

Workplace Well-being (WWB): It refers to employees' perceptions and feelings about work satisfaction (Zheng, et.al., 2015). ILW can promote the satisfaction of psychological needs and enhance employees' WWB. Therefore, we propose the following hypothesis:

Hypothesis 2. *ILW will positively impact employees' perceptions of Workplace Well-being (WWB).*

From the above hypotheses, we found that Artificial Intelligence (AI) opportunity perception is positively related to Informal Learning in the workplace (ILW) and ILW is positively related to Workplace Well- being (WWB), so we can propose this hypothesis:

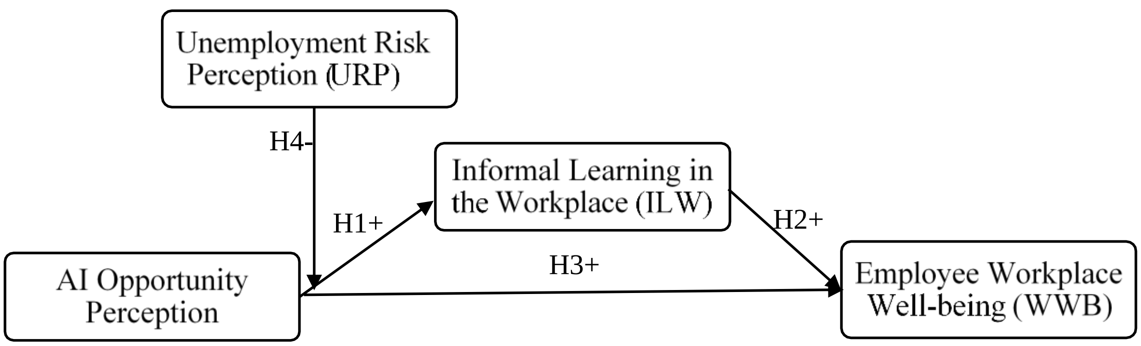
Hypothesis 3. *ILW plays a partial mediating role in the relationship between AI opportunity perception and employees' WWB.*

Resource conservation theory refers to the worries about job instability and persistence that activate the resource consumption process, leading to emotional exhaustion in individuals. The introduction of AI technology has two results: it will bring development opportunities to employees and employees will face the threat of unemployment. If Unemployment Risk Perception is not effectively controlled, employees will be emotionally exhausted and adopt defensive strategies to prevent the threat of losing resources.

Unemployment Risk Perception (URP): Perception is the critical link between humans and the world. Risk perception consists of a series of cognitive processes triggered by an individual's psychology, ultimately guiding their decision making. Therefore, unemployment risk perception is the employees' perceptions and understanding of various objective risks in the outside world that may lead to unemployment. It can negatively impact the relationship between AI opportunity perception and ILW. From this understanding, we propose the following hypothesis:

Hypothesis 4. *Unemployment Risk Perception (URP) negatively moderates the relationship between AI opportunity perception and ILW.*

FIGURE 1
THEORETICAL MODEL



METHODOLOGY

Participants

Employees from various occupations whose organization utilizes artificial intelligence (e.g., finance/auditing, management, technology/R&D, human resources management, production workers, clerical/office staff, administration/logistics staff, salespersons, customer service, lawyers, architects, healthcare workers, journalists, PR, educators, etc.). Xu et al.'s study sample was in China. We recruit a similar sample in the U.S.A.

Procedures

The study was deployed in CloudResearch (an online survey platform). The study specifies the recruitment information. Filters have also been applied to identify the qualified participants. The qualified participants can voluntarily opt-in to take the anonymous survey. After the data is collected, quantitative analysis (structure equation modeling, factor loadings, construct reliability, validity, etc.) applied to investigate whether there is any variation between the original and the replication study findings. Xu et al. used the survey platform Credamo (https://www.credamo.com) and sent out 300 questionnaires and the response rate was 89.3%. We are not sure about the difference in attrition rates between the two platforms (i.e., Credamo vs. MTurk) caused by survey incompleteness and attention check question failure. So, we have recruited 215 adult participants from CloudResearch to get a similar response rate. The participants are voluntarily self-enrolled. There are no restrictions on ethnicity, race, and age. However, participants need to be employees whose organizations use artificial intelligence.

Data Collection

We conceptually compare Xu et al.'s (2023) work on artificial intelligence's impact on employees' workplace informal learning and well-being. Firstly, the construct *Unemployment Risk Perception (URP)* only had three items in the original study. We added two items in case any original item is dropped during the factor loading process. The two items we adapted from Li et al. (2021) are "I am concerned about being laid off because of the development of artificial intelligence" and "I may face unemployment when enterprises apply artificial intelligence". Secondly, the sample in our study is different. Xu et al.'s (2023) adopted a Chinese data collection platform "Credamo" widely recognized by Chinese scholars to administer their survey. However, their participants' nationalities were not specified. Instead, we used CloudResearch as our data collection platform. Our participants were all located in the U.S. and are English speakers.

The demographic information of participants can be found in Table 1. A total of 373 participants joined the study, with 246 completing the survey. Fifteen participants did not pass the attention check, and sixteen participants did not meet the requirement for AI use in the workplace. So, we collected 215 valid responses eventually. Contrary to Xu et al.'s (2023) findings regarding gender distribution, our study has a higher percentage of male participants (63%). Participants older than 40 years account for more than those in Xu et al.'s study (30% vs. 13%). Master's and doctoral degree holders in our study are more than those in Xu et al.'s study (19% vs. 10%). We followed Xu et al.'s occupation category to sort our sample. Participants working in the technology and R&D fields are the most in both studies. The second highest occupation in our study is accounting, finance, and audit, followed by healthcare and customer service. While in Xu et al.'s study, it is management followed by admin/logistics staff and professionals. We also collected detailed demographic information unavailable in Xu et al. (2023). For example, the average length of employment for participants in our study is 8.5 years, while the average length of AI use in the workplace is 1.3 years. Non-management position employees in our study account for 48%. The size of the participants' organizations is presented in Table 1. Our study also included occupation length, organization size, and AI usage length as control variables besides gender, education level, and age.

TABLE 1
DEMOGRAPHIC INFORMATION

Data collection platform		CloudResearch	
Country		United States	
Gender	Male	135	63%
	Female	80	37%
	Total	215	
Age	18~29	78	36%
	30~39	74	34%
	40~49	36	17%
	50+	27	13%
	Total	215	
Education	High school	17	8%
	Some College or Associate Degree	39	18%
	Bachelor	118	55%
	Master	33	15%
	Ph.D.	8	4%
	Total	215	

Data collection platform		CloudResearch	
Country		United States	
Occupation	Technology/R&D	60	28%
	Management	9	4%
	Admin/Logistics staff	17	8%
	Professionals	7	3%
	Clerical / Office staff	3	1%
	Production	6	3%
	Marketing/Sales	18	8%
	Education	12	6%
	Accounting/Finance/audit	27	13%
	HR	5	2%
	Customer service	20	9%
	Public relationship	3	1%
	Healthcare	20	9%
	Others	8	4%
	Total	215	
	Occupation length (in years)	8.5 (M), 7.6 (SD), 0.5 (MIN), 44 (MAX)	
Position Ranking	Non-management position	103	48%
	Junior management	96	45%
	Senior management	16	7%
	Total	215	
Use	AI Usage length (in years)	1.3 (M), 1.1 (SD), 0.1 (MIN), 5 (MAX)	
Organization Size	1-49	45	
	50-99	25	
	100-499	44	
	500-999	30	
	1,000-4,999	36	
	5,000-9,999	9	
	More than 10,000	26	
	Total	215	

*M: Mean, SD: Standard Deviation, Min: Minimum Value, Max: Maximum Value

Although Xu et al. (2023) did not specify what type of AI the participants were using in their workplace, we asked our participants to provide the AI brand and the main functionalities they usually use in their workplace (see Table 2). CloudResearch also provided demographic profiling features to facilitate our sample recruitment and data collection. The detailed profiling information on CloudResearch can be found in Appendix Table B1. Meanwhile, we set up the filter to make sure that the AI systems are provided by participants' employers or are needed to use in their work environment. ChatGPT is the most popular AI tool used in our participants' work environments (37%). The main functionalities of ChatGPT used by participants in their workplace are programming, code analysis and troubleshooting, math problems, research, streamline workflow, customer support, writing and editing, etc. Our study's second popular AI system is Github Copilot, followed by Google Gemini, IBM Watson Health, and Microsoft Azure AI, etc.

TABLE 2
AI SYSTEMS AND MAIN FUNCTIONALITIES

AI system used in the work environment	**Summarized main functionalities of the AI system used inthe work environment**	**Number of users**
ChatGPT	Programming, code analysis and troubleshooting, math problems, research, streamline workflow, customer support, inventory and work scheduling management, idea/ content generation, draft correspondence, analyze and summarize data, writing and editing, etc.	79
Github Copilot	Code review/analyzing, code completion, Generating documentation	16
Google Gemini	Scheduling and organize notes, summarize documents and data, idea generation, problem solving, etc.	11
IBM Watson Health	Data analytics, diseases detection, patient diagnostic, treatment suggestion.	8
Microsoft Azure AI	Natural language processing, machine learning, speech recognition, etc.	6
Oracle Digital Assistant	Data analytics, customer support, service improvement.	4
OpenAI Codex	Programming, software development.	4
Bard	Running reports, generating ideas, data analysis, inventory management	3
Amazon Generative AI	Marketing research, inventory management, etc.	3
Midjourney	Text, images and video generation.	2
SAS Viya AI	Data analysis	2
Claude	Loan process	2
Einstein AI	Customer support	2
Alexa	Office scheduling	2
• Bellowing AI systems are categorized by their main functionalities since each AI system hasonly one unique brand.		
Main Functionalities of the AI Systems		**Number of users**
Marketing, sales, customer support		20
Robotic Process Automation		12
Healthcare and medical purpose		11
Programming, coding, and data analytics		9
Education and training		5
language processing and translation		4
Image creation		3
HR and recruiting		2
Editing and proofreading		2
Warehouse management		2
Agriculture		1
TOTAL NUMBER OF USERS		**215**

Common Method Variance

Harman's single-factor test was conducted using IBM SPSS Statistics (Version 29.0.1.0) to evaluate common method variance in our study. In the unrotated EFA setting, with the number of extracted factors set to one, the first factor explains 35% of the total variance. (see Appendix Table B2). This result is below the 50% threshold (Kock, 2021), leading us to conclude that common method bias is not a significant concern in our study.

Factor Loadings

We used SPSS to perform principal component extraction and apply varimax rotation for the factor analysis. The result showed that the constructs *Informal Learning in the Workplace* (ILW) item 5 and item 6 loaded on one separate factor (see Table 3). ILW item 4 and construct AI opportunity item 2 have borderline loadings. So, these four items were excluded from further analysis. All the other items met the cutoff value for the factor loading threshold (Hair, et.al., 2021).

TABLE 3
FACTOR LOADINGS

Rotated Component Matrix					
	Component				
	1	2	3	4	5
WWB_3	0.894	-0.119	0.165	0.042	0.073
WWB_6	0.853	-0.071	0.137	0.197	0.138
WWB_2	0.84	-0.076	0.133	0.183	0.138
WWB_5	0.822	-0.087	0.223	0.147	0.021
WWB_1	0.812	-0.11	0.069	0.185	0.158
WWB_4	0.79	-0.081	0.264	0.156	-0.045
URP_4	-0.085	0.93	0.027	-0.159	-0.068
URP_5	-0.099	0.913	-0.028	-0.115	-0.03
URP_2	-0.081	0.908	0.005	-0.174	-0.016
URP_1	-0.088	0.907	0.068	-0.149	-0.02
URP_3	-0.126	0.904	0.016	-0.184	-0.014
ILW_2	0.25	-0.111	0.785	0.115	0.009
ILW_9	0.103	0.118	0.77	0.15	0.137
ILW_7	0.035	0.04	0.769	0.224	0.163
ILW_1	0.272	0.012	0.741	0.166	0.039
ILW_3	0.196	-0.023	0.69	0.139	0.062
ILW_8	0.115	0.027	0.621	0.284	0.153
ILW_4	0.06	0.067	0.604*	0.032	0.512
AI Opportunity_4	0.201	-0.136	0.174	0.875	0.133
AI Opportunity_5	0.198	-0.185	0.179	0.855	0.008
AI Opportunity_3	0.156	-0.197	0.234	0.844	0.049
AI Opportunity_1	0.218	-0.263	0.218	0.784	0.064

AI Opportunity_2	0.133	-0.152	0.344	0.559*	-0.051
ILW_5	0.138	-0.005	0.275	0.037	0.829*
ILW_6	0.171	-0.136	0.122	0.082	0.816*
Extraction Method: Principal Component Analysis.					
Rotation Method: Varimax with Kaiser Normalization.					
a Rotation converged in 6 iterations.					

* Indicates that the item was removed from further analysis.

Measurement Model Assessment

SmartPLS (version 4.1.0.3) was used to calculate each construct's Cronbach's alpha, composite reliability, and average variances extracted (AVEs). Then, we used SPSS to calculate the correlations among the latent variables (see Table 4).

Cronbach's alpha scores range from 0.872 to 0.962 (see Table 4), which satisfies the criteria to proceed to the next phase of the study (Taber, 2018). The composite reliability scores range from 0.903 to 0.967, exceeding the 0.7 threshold value (Hair et al., 2021). Therefore, the criteria for internal consistency reliability have been satisfied. Convergent validity is confirmed with average variances extracted for the constructs between 0.61 and 0.855 since these values are all above the 0.5 cutoff (Hair et al., 2021). The Fornell-Larcker criterion was also met, as the square root of the AVE (shown on the diagonal of Table 4) is greater than the correlations between the focal construct and all other constructs. Meanwhile, Table 3 shows that cross-loadings are not a threat. Based on a minimum difference of 0.2 between each factor loading and its corresponding cross-loading, none of the items exhibited any issues. Moreover, the heterotrait-monotrait ratio matrix presented in Table 5 indicates that all values are below the cutoff of 0.85 (Hair, et.al., 2021). In conclusion, the construct discriminant validity was satisfied.

TABLE 4
CONSTRUCT RELIABILITY, CORRELATION, AND AVERAGE VARIANCE EXTRACTED

	Cronbach's alpha	**Composite reliability**	**AI Opportunity**	**Employee Work-place Wellbeing**	**Informal Learningin the Work-place**	**Unemployment Risk Perception**
AI Opportunity	0.936	0.954	**0.917**			
Employee Workplace Wellbeing	0.939	0.951	.456***	**0.875**		
Informal Learning in the Workplace	0.872	0.903	.528***	.488***	**0.781**	
Unemployment Risk Perception	0.962	0.967	-.405***	-.256***	- 0.043	**0.925**
		AVE	0.84	0.765	0.61	0.855

Note: Bold values are the square root of Average variance extracted (AVE). Correlation is significant at the * 0.05 level, ** 0.01 level, *** 0.001 level (2-tailed).

TABLE 5
HETEROTRAIT -MONOTRAIT RATIO (HTMT) MATRIX – EWWB MODEL (N = 215)

	AI Opportunity	Employee Workplace Wellbeing	Informal Learning in the Workplace	Unemployment RiskPerception
AI Opportunity				
Employee Workplace Wellbeing	0.456			
Informal Learning in the Workplace	0.518	0.466		
Unemployment Risk Perception	0.402	0.242	0.078	

We also used SmartPLS to conduct the variance inflation factors (VIF) analysis. VIF scores for the constructs ranged from 1.02 to 1.46 (see Table 6), which is below the cutoff value of 10 (Cohen, et.al., 2015). So, multicollinearity is not an issue to our study.

TABLE 6
COLLINEARITY STATISTICS (VARIANCE INFLATION FACTORS) – INNER MODEL LIST

	VIF
AI Opportunity -> Employee Workplace Wellbeing	1.333
AI Opportunity -> Informal Learning in the Workplace	1.241
Age -> Employee Workplace Wellbeing	1.461
Education -> Employee Workplace Wellbeing	1.07
Gender -> Employee Workplace Wellbeing	1.075
Informal Learning in the Workplace -> Employee Workplace Wellbeing	1.384
Occupation length -> Employee Workplace Wellbeing	1.349
Org size -> Employee Workplace Wellbeing	1.023
Unemployment Risk Perception -> Informal Learning in the Workplace	1.188
Usage length -> Employee Workplace Wellbeing	1.015
Unemployment Risk Perception x AI Opportunity -> Informal Learning in the Workplace	1.106

Structural Model Assessment

Instead of using hierarchical regression as in Xu et al. (2023), we used PLS-SEM path analysis in our study. Firstly, Xu et al. (2023) employed confirmatory factor analysis instead of exploratory factor analysis in their study, indicating that they tested their hypothesized structure based on existing theories. In this study, we focus on examining the validity of the relationships among the latent variables in a new context. Secondly, the dependent variable, Employees' Workplace Well-being (WWB), is constructed from six items and measured on a seven-point Likert scale, rather than a continuous or discrete variable. So, technically, the path analysis is more suitable for our study.

The estimates of the path coefficients and the explained variance were assessed using the bootstrapping resampling method in SmartPLS. A total of 5,000 subsamples were used, and the test was conducted as a two-tailed test at a 5% significance level.

Artificial Intelligence (AI) *opportunity perception* is significantly and positively associated with *informal learning in the workplace* (β = 0.525, T-value = 8.462, P < .001) and *Employee* Workplace Wellbeing (WWB) (β = 0.292, T-value = 3.285, P = .001) (see Table 7). *Informal learning in the workplace* is positively associated with *Employee Workplace Wellbeing* (β = 0.298, T-value = 3.261, P = .001). So, the partial mediating effect of *informal learning in the workplace* is significant between *AI opportunity perception* and *employee workplace wellbeing*. This is consistent with the original study. However, Unemployment Risk Perception (URP) does not significantly moderate the relationship between *AI opportunity perception* and *informal learning in the workplace* (β = 0.005, T-value = 0.105, P = 0.916) (please see Table 7 and Figure 2).

TABLE 7
PATH ANALYSIS

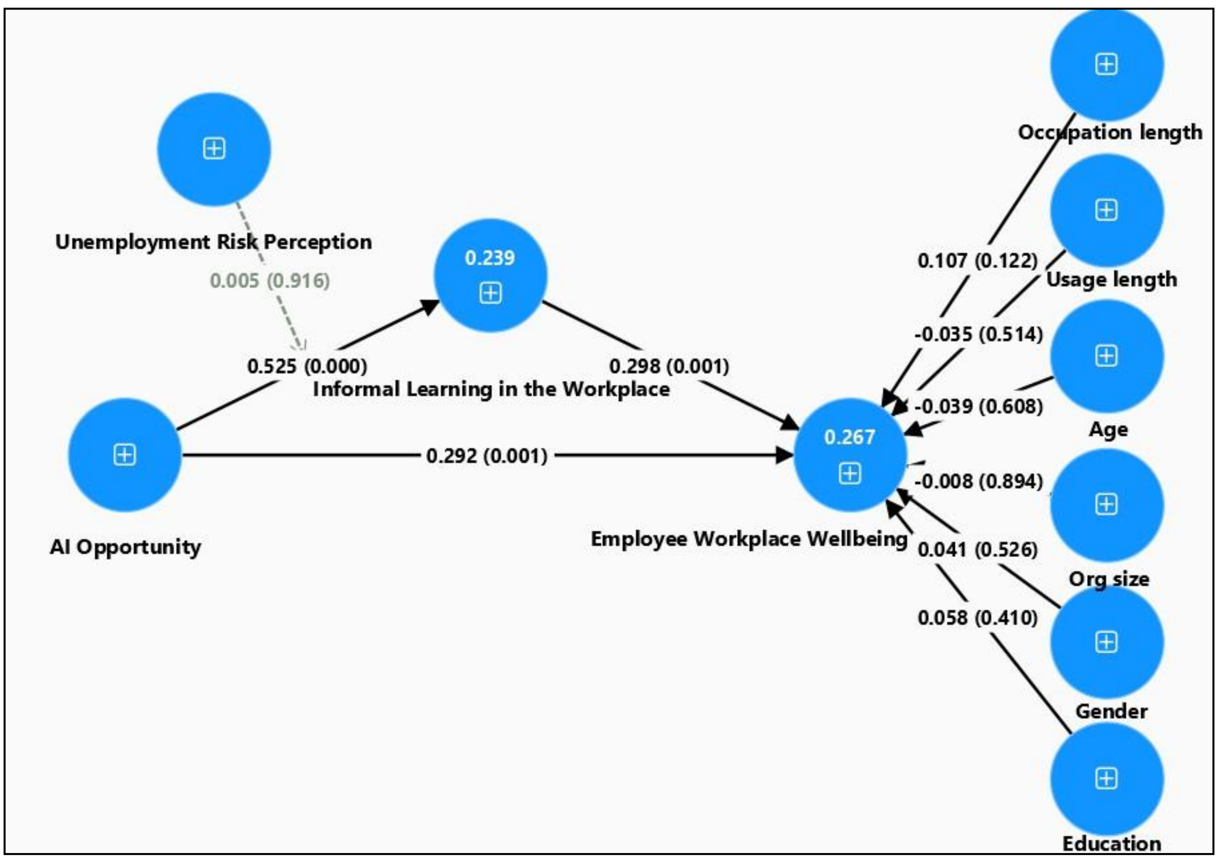
	Original sample	Sample mean	Standard deviation	T statistics	P value
AI Opportunity -> Employee WorkplaceWellbeing	0.292	0.297	0.089	3.285	0.001
AI Opportunity -> Informal Learning in theWorkplace	0.525	0.525	0.062	8.462	0
Informal Learning in the Workplace ->Employee Workplace Wellbeing	0.298	0.297	0.092	3.261	0.001
Unemployment Risk Perception -> InformalLearning in the Workplace	0.149	0.15	0.087	1.719	0.086
Unemployment Risk Perception x AI Opportunity -> Informal Learning in theWorkplace	0.005	0.009	0.05	0.105	0.916
Usage length -> Employee Workplace Wellbeing	-0.035	-0.035	0.053	0.653	0.514
Occupation length -> Employee WorkplaceWellbeing	0.107	0.126	0.069	1.546	0.122
Org size -> Employee Workplace Wellbeing	-0.008	-0.01	0.058	0.133	0.894
Age -> Employee Workplace Wellbeing	-0.039	-0.061	0.076	0.514	0.608
Education -> Employee Workplace Wellbeing	0.058	0.059	0.071	0.824	0.41
Gender -> Employee Workplace Wellbeing	0.041	0.043	0.065	0.635	0.526

We further analyzed moderated mediation relationship proposed by Xu et al. (2023), the indirect effect between *AI opportunity perception* and *Employee Workplace Wellbeing* via *Informal Learning in the Workplace* was still not significant (β = 0.002, T-value = 0.1, P = 0.92) (see Table 8). This result is inconsistent with the findings of Xu et al. (2023). We discuss alternative explanations in the next section.

TABLE 8
MODERATED MEDIATION - SPECIFIC INDIRECT EFFECTS

	Original sample	Sample mean	Standard deviation	T-Statistics	P-value
Unemployment Risk Perception x AI Opportunity -> Informal Learning in the Workplace -> Employee Workplace Wellbeing	0.002	0.003	0.016	0.1	0.92
Unemployment Risk Perception -> Informal Learning in the Workplace -> Employee Workplace Wellbeing	0.045	0.044	0.03	1.493	0.135
AI Opportunity -> Informal Learning inthe Workplace -> Employee Workplace Wellbeing	0.157	0.155	0.05	3.126	0.002

FIGURE 2
EMPIRICAL MODEL TEST RESULT



Altogether, *AI opportunity perception* and *informal learning in the workplace* explained 27% of the variance in *employee workplace wellbeing* (see Table 9). *AI opportunity perception* explains 24% of the variance in *informal learning in the workplace.* According to Cohen (1988) (p. 413), the independent variable(s) in our study successfully explains large variance in the dependent variable(s).

TABLE 9
R-SQUARE

	R-square	R-square adjusted
Employee Workplace Wellbeing	0.267	0.239
Informal Learning in the Workplace	0.239	0.229

DISCUSSION

The current study is an effort to explicitly examine the impact of Artificial Intelligence opportunities and the perceived risk of unemployment on employees' workplace well-being. In keeping with the hypotheses, results show that there is a positive relationship between Artificial Intelligence (AI) opportunity perception and Informal Learning in the Workplace (ILW) and between ILW and employees' perceptions of Workplace Well-being (WWB). So, we can say that ILW is mediating in the relationship between AI opportunity perception and employees' WWB. From the above results we have found that ILW plays both full and partial mediation, as AI opportunity perception is also directly and positively related to WWB.

From the above result, we couldn't find any significant moderating effect of Unemployment Risk Perception (URP) on the relationship between AI opportunity perception and ILW. There can be several reasons, some of them are: (a) Societal level– The U.S. companies may have not implemented AI vigorously in the relevant fields that it can take lots of employees' job positions and may cause significant unemployment issue (b) Organizational level- Employees of the organization are not very aware of AI opportunities, and they may perceive it as a challenge. Integrating AI into their current IT infrastructure could incur significant managerial and technical costs (c) Individual level – The employees are very eager to learn in the workplace to help cope with the stress brought on by AI. In other words, most of our samples adopted problem-oriented coping strategies when they encounter AI in their workplace. They tend to gather information, seek advice, engage in informal learning, summarize experiences, and ultimately solve problems. According to the transactional theory of stress, our sample believed there were more opportunities associated with AI in the situation, and that they could benefit more from them.

Practical and Theoretical Implications

An organization should understand the opportunities of Artificial Intelligence transformation for their career development. An organization should take measures from now and establish new career development paths for their employees so that their employees will not lose their jobs due to the development of AI. Contextualize transactional theory of stress, SDT, and Resource conservation theory in the Artificial Intelligence and employees' Workplace Well-being scenario.

Limitations and Future Directions

In this study, we have collected data only from the U.S. That can be why we didn't get any significant moderating effect of Unemployment Risk Perception (URP) on the relationship between AI opportunity perception and ILW. Moreover, due to time constraints, it was impossible to find out the long- term effect and relationship of these variables.

In the future we can do a longitudinal study for at least five years to see the differences. We can also develop a target sample into more stratified categories (e.g., healthcare, manufacturing, marketing, geography).

CONCLUSION

The research has identified the relationship among Artificial Intelligence (AI) opportunity perception, employees' workplace well-being (WWB) and Informal Learning in the Workplace (ILW). AI as an emerging technology has highlighted the tension between employers and employees. How to leverage the

AI is critical in the socio-technical progress. Our research will contribute to the new dimension in AI and HRM research.

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APPENDIX 1: QUESTIONNAIRE

Demographics

What is your gender:

- Male
- Female
- Non-Binary

What is your age:____(in years) What is the highest degree or level of school you have completed?

- High school graduate, diploma or the equivalent
- Some college credit, no degree
- Associate degree
- Bachelor’s degree
- Master’s degree
- Doctorate degree

What is your occupational title in your organization? (e.g., staff, manager, team leader, supervisor, associate director, director, executive officer, etc.):

____

What is your primary functional work area? (e.g., accounting, finance, supply chain, healthcare,education, journalism, research & development, customer service, etc.)

____

How many years have you worked in this field?

____

Please provide the name of the proprietary AI systems offered by your organization that you are using in your daily work environment.

____

Please provide the main functionalities of the proprietary AI systems offered by your organization thatyou are using in your daily work environment.

____

How many years have you used this artificial intelligence (AI) application at your work environment?

____

What is the approximate total number of employees your organization has?

____

Measurement items of key variables:

Artificial Intelligence (AI) Opportunity Perception

To what extent do you agree with the following statement:

1. The adoption of artificial intelligence by enterprises is beneficial to me;
2. The influence of enterprises applying artificial intelligence on me can be controlled;
3. The application of artificial intelligence by enterprises can increase the likelihood of my personalsuccessful career development;
4. It is an opportunity for me that enterprises apply artificial intelligence;
5. It is possible for me to gain more than lose when enterprises apply artificial intelligence.

Strongly disagree ~ Strongly agree

Informal Learning in the Workplace (ILW)

How often did you participate in the following activities during a typical working week in the past threemonths?

1. Reflecting about how to improve my performance.
2. Experimenting with new ways of performing my work.
3. Using trial and error strategies to learn and perform better.
4. Interacting with a mentor.
5. Interacting with my supervisor.
6. Interacting with my peers.
7. Reading professional magazines and vendor publications.
8. Searching the Internet for job-relevant information.
9. Reading management books.

Never ~ Always

Workplace Well-being (WWB)

To what extent do you agree with the following statement:

1. I am satisfied with my work responsibilities.
2. I feel basically satisfied with my work achievements in my current job.
3. I find real enjoyment in my work.
4. I can always find ways to enrich my work;
5. Work is a meaningful experience for me;
6. In general, I feel fairly satisfied with my present job.

Strongly disagree ~ Strongly agree

Unemployment Risk Perception (URP)

To what extent do you agree with the following statement:

1. I am likely to lose my job because of the development of artificial intelligence.
2. I am worried about losing my job because of the development of artificial intelligence.
3. Compared with other people in the same profession, the development of artificial intelligence ismore likely to cause me to lose my job.
4. I am concerned about being laid off because of the development of artificial intelligence.
5. I may face unemployment when enterprises apply artificial intelligence.

Strongly disagree ~ Strongly agree

APPENDIX 2: SUPPLEMENTARY INFORMATION AND DETAILED ANALYSIS

TABLE B1
DEMOGRAPHIC PROFILING FEATURES PROVIDED BY CLOUDRESEARCH

AI Experience Which of the following have you used AI for? Select All
Creating or editing images and art.
Writing or editing text, such as emails, articles, or creative writing.
Generating or enhancing music and sound effects.
Data analysis and visualization for research or business insights.
Virtual assistants for scheduling, reminders, or information retrieval.
Language translation or learning tools.
Playing or creating video games.
Educational purposes, such as tutoring or interactive learning modules.
Health
Social media management, like content creation or audience engagement.
Customer service, through chatbots or automated responses.
Financial planning or investment advice.

TABLE B2
COMMON METHOD VARIANCE

Harman Single Factor analysis						
Total Variance Explained						
Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.964	37.926	37.926	7.36	35.048	35.048
2	4.106	19.553	57.479			
3	2.486	11.838	69.317			
4	1.526	7.265	76.582			
5	0.883	4.204	80.786			
6	0.556	2.647	83.432			
7	0.535	2.549	85.981			
8	0.408	1.941	87.923			
9	0.353	1.679	89.602			
10	0.342	1.631	91.232			
11	0.243	1.159	92.391			
12	0.231	1.101	93.492			
13	0.219	1.041	94.533			
14	0.196	0.935	95.469			
15	0.171	0.814	96.282			
16	0.165	0.783	97.066			
17	0.154	0.735	97.801			
18	0.141	0.67	98.47			
19	0.125	0.594	99.064			
20	0.114	0.543	99.608			
21	0.082	0.392	100			
Extraction Method: Principal Axis Factoring.						