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SENTIMENTS AND ATTITUDES SHAPING AI ADOPTION: INSIGHTS FROM WORKING PROFESSIONALS IN CHINA

SENTIMENTOS E ATITUDES QUE INFLUENCIAM A ADOÇÃO DA IA: PERSPECTIVAS DE PROFISSIONAIS NA CHINA

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Abstract
This study explored how Chinese working professionals' attitudes toward AI can influence their intent to use and adopt the technology based on the Technology Acceptance Model (TAM). This study analyzed behavioral intentions for AI from 220 part-time Chinese graduate business (MBA) students. Positive and negative emotions were determined as major factors in the Chinese working professional's intent to use AI; positive emotions such as optimism and excitement increased the likelihood that working professionals would use AI while negative emotions such as fear and skepticism decreased this probability. Emotions were assessed by utilizing a culturally adapted version of the Positive and Negative Affect Schedule (PANAS) scale. Results indicated that emotions toward AI were better indicators of the potential to use AI than rational assessments of the technology and occurred prior to and subsequent to cognitive assessments. These results also suggest that organizations can support responsible adoption of AI in China by promoting positive perceptions of AI and addressing related fears.

Keywords: Artificial Intelligence (AI). Emotional Sentiments. Attitudes. Behavioral Intentions. China.

Resumo
Este estudo explorou como as atitudes dos profissionais chineses em relação à IA podem influenciar sua intenção de usar e adotar a tecnologia, com base no Modelo de Aceitação de Tecnologia (TAM). O estudo analisou as intenções comportamentais em relação à IA de 220 estudantes chineses de pós-graduação em administração (MBA) que cursam em regime de meio período. Emoções positivas e negativas foram identificadas como fatores principais na intenção dos profissionais chineses de usar IA; emoções positivas, como otimismo e entusiasmo, aumentaram a probabilidade de que os profissionais usassem IA, enquanto emoções negativas, como medo e ceticismo, diminuíram essa probabilidade. As emoções foram avaliadas utilizando uma versão culturalmente adaptada da escala Positive and Negative Affect Schedule (PANAS). Os resultados indicaram que as emoções em relação à IA eram melhores indicadores do potencial de uso da IA do que avaliações racionais da tecnologia e ocorriam antes e depois das avaliações cognitivas. Esses resultados também sugerem que as organizações podem apoiar a adoção responsável da IA na China promovendo percepções positivas da IA e abordando os medos relacionados.

Palavras-chave: *Inteligência Artificial (IA). Sentimentos Emocionais. Atitudes. Intenções Comportamentais. China.*

1 INTRODUCTION

AI has impacted on all aspects of daily life and employment (Brynjolfsson & McAfee, 2014). As such, both the government and industry in China encourage the development of smart technologies and, in turn, the integration of AI across nearly all sectors (Jarrahi, 2018). Even though the development of AI is expected to be influenced by both technological capabilities and user acceptance (Venkatesh & Davis, 2000), the emotional response (i.e., positive - enthusiastic, negative - apprehensive) users experience toward adopting new technologies is critical in determining whether new technologies are accepted or rejected (Bagozzi, Gopinath, & Nyer, 1999; Pereira, Silva, & Reis, 2020). Additionally, recent literature suggests that emotional responses to new technologies may occur before cognitive assessments and behavioral intentions toward new technologies (Meyer & Mark, 2009; Watson, Clark, & Tellegen, 1988). Therefore, an individual's degree of optimism and enthusiasm will positively impact his/her willingness to adopt AI. Conversely, anxiety and distrust will negatively affect an individual's willingness to engage with AI regardless of the perceived benefits of AI (Bagozzi, Gopinath, & Nyer, 1999). While there have been numerous studies regarding technology adoption, most studies have focused upon the practical and cognitive factors involved in the adoption process in western cultures (Venkatesh & Davis, 2000). However, there is still a need for further research concerning the emotional factor in technology adoption models, especially in the Chinese culture (Liu, Zhang, & Choi, 2018).

In addition to the fact that the vast majority of studies on technology adoption focus on consumer/technology expert populations, the present study seeks to identify the perspective of business professionals, specifically those in mid-career positions and working in rapidly developing environments, such as China. Identifying the perspectives of business professionals is crucial since business professionals and managers make strategic decisions regarding technology adoption for organizations. Examples may include MBA-level managers evaluating proposals to automate business processes using AI-powered solutions for customer services or proposing investments in new data analytics platforms that can alter organizational decision making. Strategic decisions made by business professionals and managers determine how organizations take advantage of emerging technologies and influence the rate of industry-wide adoption of emerging technologies. Since China is positioned at the forefront of the global AI market, it is essential to investigate both the affective and cognitive perspectives of mid-career professionals to facilitate widespread and effective AI adoption.

This study is limited to part-time MBA students in Shanghai, who represent mid-career professionals attempting to balance their ongoing educational endeavors and their careers during a time when the use of advanced technologies is rapidly increasing. The primary objective of the study is to examine the views of mid-career professionals regarding AI, assess to what extent they are supportive or hesitant to implement AI, and assess the impact of emotional factors on their decisions to adopt AI. A well-designed survey instrument was used to assess the interaction between emotional and cognitive factors in the technology adoption decisions of mid-career professionals in a real world setting.

2 CONCEPTUAL BACKGROUND

While many believe that AI has the potential to solve complex societal problems and greatly enhance productivity, many others are fearful of job loss, violation of privacy rights, and/or unfairness. Many believe AI will assist them in their jobs; however, many others fear that they will lose their jobs. Examples of AI failures such as identifying wrong people through facial recognition software and/or failing to operate safely, further diminishes public trust and demonstrates both the 'can-do' attitudes toward AI, but also the 'reality-based' nature of the world we live in today. The ambivalence of the general public toward AI demonstrates the constant battle between the optimistic view of AI and the pessimistic view.

Business leaders similarly hold differing views about AI based upon whether they view AI as a positive tool to increase productivity, or if they see AI as a negative factor that may result in a loss of job. Managers and business leaders with greater experience in technology are generally more confident that AI will be able to positively impact their businesses and organizations than those with less experience. Thus, for business leaders and employees to use AI in the workplace, there must be a level of trust and an understanding of the AI system(s) being utilized. Demographic factors of age and gender and cultural background of an individual and/or a group also play significant roles in the perception of AI. Some countries view AI as a means to increase efficiency, while other countries view AI as a threat to job loss. Younger individuals, and those that are more frequent users of technology are generally more open to utilizing AI. Older individuals and/or less frequent users of technology tend to be more concerned. Trust in AI is diminished when an individual believes that the AI system is operating without transparency. Lack of transparency will generate skepticism about AI systems and reduce support for them.

2.1 Sentiments, attitudes, and behavioral intentions

Most researchers study the technological changes in organizations through many different theoretical models. Among them, the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) are among the most notable and have contributed to the understanding of what influences the utilization of new technologies. The TAM claims that beliefs concerning the ease of use and utility of an innovation are the determinants of whether or not the innovation is adopted (Venkatesh & Davis, 2000). The TPB claims that a user’s intention to engage in a particular behavior is influenced by three fundamental factors: the user’s attitude towards engaging in the behavior, the user’s subjective norms for engaging in the behavior, and the user’s perceived ability to control engagement in the behavior (Ajzen, 1991). A combination of both theories results in a model where the more favorably users perceive an innovation, the greater the probability that the users will utilize it. On the other hand, if users experience disorientation or trepidation concerning an innovation, the probability of utilizing the innovation diminishes.

Previous studies also show that when individuals feel enthusiastic about adopting a new technology, there is a greater chance of acceptance (Chung & Kwon, 2020; Pereira, Silva, & Reis, 2020). Conversely, the likelihood of acceptance of a new technology is diminished if the individual feels anxiety or frustration during the adoption process. According to the Theory of Planned Behavior, beliefs and feelings directly influence an individual’s behaviors (Ajzen, 1991; Ajzen & Fishbein, 2005). For example, when an employee believes that the implementation of AI will enhance their work and feels positively about it, the likelihood of implementing AI is enhanced (Hughes *et al*., 2018).

On the other hand, when an employee perceives risk, this negatively affects the employee's willingness to interact with AI. Additionally, the employee's positive beliefs about AI increase the likelihood of the employee implementing AI (Hughes *et al*., 2018).

A relevant concept is that affective reactions generally occur before a person evaluates a given circumstance logically (Watson & Clark, 1997; Watson, Clark, & Tellegen, 1988). In terms of the emergence of new technology, employees initially react to the new technology either positively (excitement) or negatively (anxiety) prior to assessing the technology objectively. The employees' initial emotional response to the new technology may potentially influence their subsequent attitudes and behaviors (Meyer & Mark, 2009). An example would be if an employee had a positive initial impression regarding the usability of AI, the employee is more likely to continue using AI (Pereira, Silva, & Reis, 2020). Consequently, the importance of being able to address an employee's initial emotional response to a new technology is critical to facilitating the successful implementation of technology within an organization.

In addition to influencing an employee's adoption of new technology in the workplace, emotions also have a considerable influence on how people make decisions. For example, if an employee views AI as beneficial or as decreasing stress, then the employee is more likely to implement AI (Hughes *et al*., 2018). However, if employees are concerned about privacy issues or fear that AI will replace their job, this could result in a reluctance to implement AI. Generally speaking, emotional considerations can influence an employee's decision to implement a new technology prior to objective consideration.

2.2 Positive and negative affect schedule (PANAS)

It is possible to classify people's emotional responses as either positive (e.g., excited, enthusiastic), or negative (e.g., sad, angry). The dual process model of emotion experience provides a way to experience both positive and negative emotions at the same time. By developing an understanding of what is meant by positive and negative affect researchers have been able to study mood fluctuations and develop predictive models of how users may react to emerging technology including AI. Researchers developed the Positive and Negative Affect Schedule (PANAS) as a means of measuring an individual's emotional state by assessing their levels of positive and negative affect (e.g., joy, pride; fear, guilt) (Watson *et al*., 1988). Over the course of its evolution, PANAS has continued to assess additional dimensions of an individual's emotional experience in increasing detail, thus providing researchers with useful information about the mood fluctuations that occur during a typical day (Watson and Clark, 1997). This body of research has greatly increased the role of emotions in decision making processes. As AI becomes increasingly prevalent in society, it is now essential to examine how users emotionally respond to AI, as well as how users cognitively evaluate AI. Using tools such as PANAS will provide researchers with more information about the variables most likely to affect user adoption of emerging technologies.

3 METHODS

To get honest answers from users about using AI, we used easy-to-answer questions that asked about users, perceptions of how much value they received from AI, how relevant AI was to their everyday lives, and how likely they would be to use it in either their jobs or personal life. The purpose of getting the users to express their perceptions was to find out how users truly emotionally reacted to AI instead of just what they said formally. This research studied how emotional reactions influenced people's actions when adopting AI by surveying working professionals in China. For the study, we used established psychological measures, like the PANAS, but modified them for the purposes of studying how people adopted AI at work and in their personal lives. This way, we could gain an overall view of how technology fit into peoples; daily routines and decision making processes.

We surveyed 220 part-time MBA students in Shanghai. Thus, they provide a snapshot of China's business industry as a whole. As part-time MBA students usually make the decisions regarding which technologies to adopt in their places of employment, the sample size appears to be representative of a diverse group of professionals, based upon age, position within organizations and educational background. However, since MBA students generally possess higher education and technology knowledge than workers on average, the results of the study may limit the extent to which the study's results can be generalized. It is essential to evaluate the study's conclusions while considering possible sampling bias. Additionally, since the study only targeted part-time MBA students, it is possible that the perspectives of new employees, non-management employees and those without high school diplomas or other post-secondary education/training, etc. who may not have had extensive exposure to modern digital technologies, are underrepresented. Consequently, the emotional responses and attitudes toward AI adoption demonstrated in this study may not provide a comprehensive and accurate portrayal of the diversity of opinions and behaviors in the workforce of China. Thus, future studies should provide a more balanced representation of occupational backgrounds, industries and education levels so that the generalizability of the study and a more complete understanding of how different demographic groups experience and react to AI adoption can be obtained.

After the surveys were completed, we analyzed the collected data to see if there were correlations between the emotional responses of the users and their decisions to implement technology. The quantitative data analysis involved conducting exploratory factor analysis to identify the underlying factors of emotional responses and then conducting multiple regression analysis to explore the predictive relationships among emotional responses, attitudes, and user behavior regarding AI implementation. The analysis looked at whether positive emotions (i.e., excitement), increased the likelihood of implementing AI and whether negative emotions (i.e., nervousness) acted as barriers to implementing AI. The study primarily investigated how attitudes and emotional responses influenced users to implement technology, as opposed to rational thinking.

4 RESULTS

Table 1 provides a detailed demographic overview of the study participants, offering key insights into their composition and experiences with AI. Participants were predominantly middle-aged to older adults who worked in business-related careers. They varied in terms of experience levels and career roles, providing a broad-based level of expertise concerning how AI functions in the real-world of business. According to many participants, AI is used in daily life (through smart speakers or LLM suggestions); however, fewer participants use it in their place of employment. Barriers to the use of AI at work included outdated computers, lack of training, and concern for appearing inexperienced. The difference between how participants viewed the use of AI at home vs. at work reflects the subjective nature of adopting new technologies and the varying natures of professional workplaces.

Table 2 presents a detailed overview of the organizational characteristics of the study participants, highlighting the diverse professional backgrounds and organizational contexts represented in the survey. Participants represented a vast number of different occupations, including non-technical employees, executives/managers, founders, technical experts, venture capitalists/investors, and professors/academics. The diversity of occupations represented indicates that AI is applicable to all business positions, not just technical positions. The participants were comprised of a wide variety of organizations, including small startup companies, medium-sized companies, and large corporations. It is significant that the size of the company is relevant when developing methods to encourage AI adoption due to the fact that methods developed for use with agile, fast-paced companies may not be successful for large, hierarchical organizations. Even though the process of AI adoption differs across different sizes of organizations, participants identified several common hopes and concerns regarding AI. Additionally, participants represented a diverse range of industries, including services, manufacturing, logistics, software development, and emerging markets. Given that businesses of all types will need to consider the impact of AI, participants continue to discuss the use of AI.

Table 1

Characteristics of the sample

Gender		Number	Percent
	Male	119	55%
	Female	98	45%
	Total	217	
Age		**Number**	**Percent**
	20s	5	2%
	30s	126	59%
	40s	78	37%
	50s	4	2%
	Total	213	
Used AI personally?		**Number**	**Percent**
	Yes	133	61%
	No	85	39%
	Total	218	
Used AI on job?		**Number**	**Percent**
	Yes	98	45%
	No	120	55%

Total	218

The general views expressed by the participants were overwhelmingly positive when it comes to AI, as shown in Table 3. All of the positive expressions used in this study had mean values greater than 3.0, which indicates that all of the participants expressed very high levels of interest in AI. In addition, other expressions such as 'excited,' 'strong,' and 'active' also support the notion that participants have a generally optimistic attitude toward AI and express confidence in their ability to perform. Furthermore, expressions such as 'inspired,' 'enthusiastic,' and 'proud' provide evidence of how motivated and proud the participants are of AI and reinforce the idea that the overall view is a positive one. On the other hand, expressions such as 'attentive' and 'determined' show a slightly different or weaker expression of engagement and suggest that while the participants are interested in AI, they do not necessarily have a deep emotional attachment to the subject. In addition, the expression 'alert,' which has the lowest mean value of all the positive expressions, shows that the participants are not as vigilant or prepared for new developments in AI as they are for other subjects.

Table 2

Organizational characteristics of the sample

Role		Number	Percent
	Executive	61	28%
	Founder/owner	32	15%
	Technical/IT	20	9%
	Non-technical	77	35%
	Investor	11	5%
	Academic/researcher	4	2%
	Other	13	6%
	Total	218	
Number of employees		**Number**	**Percent**
	1 - 50	52	24%
	51 - 200	45	21%
	201 - 1,000	41	19%
	1,001 - 5,000	43	20%
	5,001 - 20,000	17	8%
	Over 20,000	21	10%
	Total	219	
Product and service		**Number**	
	Software	26	10%
	Services	114	45%
	Physical products/goods	93	36%
	Other	23	9%
	Total	256[a]	

[a] Some organizations were involved in more than one product or service.

On the other hand, there is very little negative sentiment toward AI, and the descriptors of negative emotions used in this study had a mean value of less than 2.5. The two negative descriptors with the highest mean values were 'nervous' and 'distressed.' These descriptors indicate that a small percentage of participants are experiencing some apprehension or discomfort about AI. The negative descriptors 'jittery,' 'scared,' and 'upset,' although low, represent slight unease and are not widespread. The descriptors representing the weakest negative emotions (such as 'irritated,' 'hostile,' 'afraid,' 'ashamed,' and 'guilty') had the lowest mean values and represent a very small percentage of negative emotional reactions to AI. When comparing the positive and negative descriptors used in the study, the data clearly shows that the participants expressed much higher levels of positive sentiment toward AI than negative sentiment. The range of scores for the positive descriptors was between 3.3 and 3.9, whereas the range of scores for the negative descriptors was between 2.1 and 2.5. This large difference supports the conclusion that the participants have a generally positive and optimistic view of AI. The moderate standard deviation for both the positive and negative descriptors indicates that the participants varied somewhat in their response to the questions asked; however, the overall trends are still positive.

Table 3

Descriptive statistics of sentiment items

Positive sentiment				Negative sentiment			
	N	Mean	Std. dev.		N	Mean	Std. dev.
Interested	217	3.87	1.089	Nervous	211	2.45	1.083
Excited	212	3.59	1.042	Distressed	213	2.45	1.066
Strong	213	3.59	1.008	Jittery	210	2.40	1.064
Active	208	3.58	0.945	Scared	211	2.35	1.077
Inspired	211	3.55	0.996	Upset	207	2.28	1.046
Enthusiastic	213	3.48	0.914	Irritable	209	2.26	1.053
Proud	212	3.41	0.996	Hostile	210	2.23	1.088
Attentive	210	3.37	0.951	Afraid	212	2.22	1.004
Determined	207	3.31	0.946	Ashamed	210	2.13	1.114
Alert	212	2.73	1.035	Guilty	208	2.11	1.085

Table 4 presents the results of factor analysis, identifying two primary components that represent distinct dimensions of participants’ emotional responses toward AI. The first dimension of negative sentiment, which is comprised of the most strongly loaded (high loadings > .75) emotion words ‘distressed,’ ‘hostile,’ ‘irritated,’ and ‘afraid,’ represents a range of emotions including guilt, anxiety, fear, and discomfort. The word ‘upset’ has the largest loading in this category, followed by ‘ashamed’ and ‘jittery.’ Also included in this category were ‘alert’ and ‘distressed,’ both of which had smaller loadings than those listed above but still contributed to the overall negative sentiment of this group. These findings indicate that a large number of respondents experience a certain level of unease when interacting with AI.

The second dimension of positive sentiment was made up of emotions with loadings ranging from .73 to .82 and included the emotion words ‘excited,’ ‘enthusiastic,’ ‘proud,’ and ‘active.’ Collectively these emotion words relate to engagement and motivation and the emotion words ‘excited’ and ‘enthusiastic’ had the largest loadings in this category. In addition, the emotion words ‘attentive’ and ‘determined’ also were identified as part of this category, although their loadings were somewhat smaller, indicating a focus or a cognitive type of positive emotion rather than one based on enthusiasm. Additionally, there were several instances where emotion words had multiple loadings, i.e., they were identified in more than one category. The emotion word ‘alert’ is an example of this phenomenon and indicates that for many respondents the use of AI elicits a neutral or ambivalent response. The factor analysis found that respondents' emotional experiences can be divided into two separate categories: the first being a negative sentiment related to distress and unease, and the second being a positive sentiment related to engagement and optimism. Understanding how to address negative emotional responses while fostering positive emotional responses will ultimately result in improved levels of acceptance and adoption of AI technology.

Table 4

Factor analysis of sentiment items

	Component	
	1	2
Excited	-0.039	**0.823**
Enthusiastic	-0.031	**0.820**
Proud	0.050	**0.816**
Active	-0.008	**0.815**
Strong	0.019	**0.806**
Interested	-0.071	**0.776**
Inspired	-0.092	**0.773**
Determined	0.065	**0.737**
Attentive	0.059	**0.732**
Alert	**0.625**	0.174

Distressed	**0.691**	0.058
Hostile	**0.738**	0.029
Irritable	**0.771**	0.011
Jittery	**0.804**	0.000
Afraid	**0.778**	-0.010
Scared	**0.767**	-0.043
Nervous	**0.797**	-0.050
Guilty	**0.772**	-0.067
Ashamed	**0.806**	-0.073
Upset	**0.820**	-0.109

Table 5 presents an overview of the means, standard deviations, and Cronbach's Alpha of the four constructs examined in this study (positive sentiment, negative sentiment, attitude, and intention). The four constructs examined represent an important component to assess participant's beliefs and engagement with AI. In addition to providing descriptive information related to each of the constructs analyzed in the study, the statistical information presented in Table 5 includes measures of the central tendency, variability, and internal consistency of each construct through use of mean scores, standard deviations, and Cronbach's Alpha. For example, based upon data collected as part of this research, participants exhibited moderate-high levels of positive sentiment toward AI; with an average score of 3.53, and a relatively small standard deviation of .158. This represents an overall optimistic, enthusiastic, and interested view of AI among the sample. Furthermore, the Cronbach's Alpha value of .923 for the positive sentiment scale, represents an extremely high level of internal consistency, and reliability, for the measurement.

Table 5

Reliability statistics of research constructs

Construct	N of items	Mean	Std. dev.	Cronbach's Alpha
Positive sentiment	9	3.530	0.158	0.923
Negative sentiment	10	2.261	0.127	0.926
Attitude	5	4.094	0.173	0.915
Intention	5	4.071	0.032	0.938

Conversely, the scores associated with the negative sentiment construct indicate that although participants have experienced some degree of mild negative emotions toward AI, those emotions do not appear to be extreme. Based on the mean of 2.261, and the standard deviation of .127, it appears that participants have little-to-no fear, or anxiety, toward AI. Moreover, the Cronbach's Alpha value of .926, for the negative sentiment construct, demonstrates that the scale used to measure negative sentiment is highly reliable. Overall, the relatively weak negative sentiment expressed by the participants suggests that the fears associated with AI are present, but not insurmountable, and therefore not an impediment to the eventual adoption of AI.

Participants' attitudes toward AI represent an extremely positive overall evaluation of the technology, as indicated by the mean score of 4.09, and the standard deviation of .17, suggesting a relatively uniform assessment of the technology's potential benefits in professional settings. Furthermore, the Cronbach's Alpha value of .91 for the attitude construct, provides additional support for the reliability of the attitude scale, and thereby strengthens the validity of the findings. Finally, the results of the behavioral intention construct reveal a high degree of willingness to adopt AI, as evidenced by the mean score of 4.07, and the very low standard deviation of .03, indicating a high degree of homogeneity among participants, regarding their desire to incorporate AI into their work environments. Also, the Cronbach's Alpha value of .93, for this construct, reinforces the reliability of the scale used to measure behavioral intention. Collectively, the findings of the three constructs demonstrate a progression from positive affective responses toward AI, to favorable attitudes toward AI, and finally, toward a strong intention to adopt AI. Although negative sentiment was evident among participants, it does not compare to the overwhelmingly positive perception of AI, and thus, may serve as a barrier to widespread adoption of AI technology, depending on how the concerns are addressed.

The results of the regression analyses presented in Tables 6, 7, and 8 demonstrate that 'positive sentiment' and 'negative sentiment' are both significant predictors of participants' views of AI. In essence, as sentiment (both positive and negative) increases or decreases, so do participants' views of AI. The significance of emotional responses in determining participants' views of AI supports their influence. The data analysis demonstrates that positive emotional responses have a substantially greater effect on participants' views of AI than do negative emotional responses. Thus, it is reasonable to believe that by encouraging positive emotional responses, one can significantly increase the likelihood of acceptance and usage of AI.

The results of the hierarchical regression in Tables 9, 10, and 11 demonstrated that in Model 1, ‘intentions’ is the dependent variable and ‘positive sentiment’ and ‘negative sentiment’ are the independent variables. On the other hand, in Model 2, ‘intentions’ is the dependent variable and ‘positive sentiment,’ ‘negative sentiment,’ and ‘attitudes’ are the independent variables. Hierarchical regression was used instead of structural equation modeling (SEM), as hierarchical regression is best used to assess the increased amount of variance in the dependent variable that can be accounted for by each set of predictors entered into the regression in order (Cohen *et al*., 2003; Tabachnick & Fidell, 2019). As such, hierarchical regression permits an examination of the unique amount of variance in the dependent variable that is accounted for by introducing additional predictors (i.e., ‘attitudes’) once the prior predictors have been entered (Aiken & West, 1991). Thus, hierarchical regression is most closely aligned with this research’s objectives to determine if ‘attitudes’ make a unique contribution to participants’ ‘intentions,’ beyond their positive or negative sentiments.

Hierarchical regression also provides greater clarity of interpretation and transparency in testing direct relationships between observed variables than does SEM. In particular, in studies with relatively smaller sample sizes (Field, 2018), hierarchical regression provides a simpler and more robust way of testing hypothesized relationships compared to SEM. In addition, SEM typically requires larger sample sizes and assumes knowledge of the relationship between latent constructs and the measurement model, whereas hierarchical regression does not assume such knowledge (Cohen *et al*., 2003; Hair *et al*., 2019). As a result, the use of hierarchical regression increases the validity of the results, as they clearly demonstrate the additional predictive capability of ‘attitudes’ in predicting participants’ ‘intentions’ to use AI.

Table 6

Model summary

Model	R	R square	Adjusted R square	Std. error of the estimate
1	.701[a]	0.491	0.485	0.51849

Table 7

ANOVA[a]

Model		Sum of squares	df	Mean square	F	Sig.
1	Regression	46.9420	2	23.4710	87.31	<.001[b]
	Residual	48.6578	181	0.2688		
	Total	95.5998	183			

a. Dependent variable: attitude
b. Predictors: (Constant), negative sentiment, positive sentiment

Table 8

Coefficients[a]

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.
		B	Std. error	Beta		
1	(Constant)	2.1348	0.2213		9.6472	0.0000
	Positive sentiment	0.6308	0.0503	0.671	12.5473	0.0000
	Negative sentiment	-0.1145	0.0466	-0.132	-2.4586	0.0149

a. Dependent variable: attitude

The ANOVA in Table 10 also provided supplementary support for the superiority of Model 2. Specifically, in Model 1, the regression sum of squares was 39.6148 and represented the proportion of variability in ‘intentions’ that was explained by the independent variables ‘positive sentiment’ and ‘negative sentiment.’ Additionally, the F-value of 58.96 with a p-value < 0.001 supported the model’s statistical significance. Conversely, the inclusion of ‘attitudes’ in Model 2 increased the regression sum of squares to 72.7766 and increased the explanatory power. Further, the F-value for Model 2 increased to 159.02 with a p-value of less than 0.001, again supporting the model’s superior capacity to explain the variability in ‘intentions.’ Lastly, the residual sum of squares decreased to 27.3060 and the mean square for residuals decreased to 0.1525, providing support for the notion that the inclusion of ‘attitudes’ enhanced the model’s fit and predictive accuracy. Collectively, the results presented here provide substantial support for the conclusion that Model 2 represents a significantly superior explanation of ‘intentions’ than Model 1.

Table 9

Model summary

Model	R	R square	Adjusted R square	Std. error of the estimate	Change statistics				
					R square change	F change	df1	df2	Sig. F change
1	.629[a]	0.396	0.389	0.5796	0.396	58.963	2	180	0.000
2	.853[b]	0.727	0.723	0.3906	0.331	217.386	1	179	0.000

a. Predictors: (constant), positive sentiment, negative sentiment
b. Predictors: (constant), positive sentiment, negative sentiment, attitude

Table 10

ANOVA[a]

Model		*Sum of squares*	*df*	*Mean square*	*F*	*Sig.*
1	Regression	39.6148	2	19.8074	58.96	<.001[b]
	Residual	60.4678	180	0.3359		
	Total	100.0826	182			
2	Regression	72.7766	3	24.2589	159.02	<.001[c]
	Residual	27.3060	179	0.1525		
	Total	100.0826	182			

a. Dependent variable: intention
b. Predictors: (constant), positive sentiment, negative sentiment
c. Predictors: (Constant), positive sentiment, negative sentiment, attitude

Collectively, the results suggest that the single most influential factor determining an individual's intention to use AI is his/her attitude toward AI. Once an individual establishes a positive attitude toward AI, the initial emotional responses that he/she experienced become less relevant. Developing a positive attitude toward AI may represent one of the key factors that will encourage individuals to adopt AI.

Table 11

Coefficients[a]

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.
		B	Std. error	Beta		
1	(Constant)	2.3018	0.2476		9.2955	0.000
	Positive sentiment	0.5746	0.0562	0.5973	10.2169	0.000
	Negative sentiment	-0.1191	0.0521	-0.1335	-2.2835	0.024
2	(Constant)	0.5405	0.2052		2.6335	0.009
	Positive sentiment	0.0537	0.0518	0.0558	1.0357	0.302
	Negative sentiment	-0.0248	0.0357	-0.0278	-0.6940	0.489
	Attitude	0.8256	0.0560	0.8068	14.7440	0.000

a. Dependent variable: intention

5 DISCUSSION

The majority of Chinese professionals involved in the survey felt positively toward AI and believed it would have a positive impact on their jobs. The majority of respondents expressed a positive outlook with respect to AI, while also expressing a sense of hopefulness and a feeling of being ‘all in this together.’ Professionals’ first impressions of AI can provide initial positive evaluations of AI; these evaluations can eventually become less significant as they develop their own personal opinions regarding AI. Ultimately, a professional’s final opinion of AI will be determined by the development of an attitude toward AI. Positive attitudes toward AI will generally result from positive emotions such as optimism and enthusiasm. On the other hand, fear and anxiety will likely hinder the adoption of AI, while optimism and enthusiasm will likely motivate the acceptance of AI. As a whole, this study demonstrates that emotions can significantly influence the behavior of individuals and sometimes may even be more influential than factual information. To promote the adoption of AI, equal emphasis should be placed on generating feelings of pride and enthusiasm in addition to providing technical information.

With regard to intentions, the study found that attitude played a major role. There was a highly significant positive relationship between attitudes and intentions. Thus, the more positive an individual’s attitudes toward AI, the stronger they reported their behavioral intentions to either adopt or utilize AI. These findings indicate the significance that attitudes have in influencing behavioral intentions. Additionally, positive sentiment did exert a positive effect on behavioral intentions; however, the effects of positive emotions were less than that of the overall attitude toward AI. Hence, while positive emotions do contribute to an individual’s behavioral intentions, they do not contribute as much as the total attitude toward AI. Conversely, negative sentiment exhibited a relatively minor detrimental effect on behavioral intentions, which indicates that negative attitudes toward AI can inhibit an individual’s desire to adopt or utilize AI. Nevertheless, the degree to which negative attitudes toward AI impede behavioral intentions is less than the combined effects of both attitude and positive sentiment. Beyond the quantitative data collected, it is apparent that both logic and emotions influence the adoption of new technologies. Generating excitement for new technologies and promoting their benefits are two of the key drivers of change. Even though there may be some uncertainty, developing strong positive emotions is essential to successfully adopting new technologies such as AI.

This research contributes to existing theory in three ways. First, the research supports the Technology Acceptance Model (TAM) by incorporating the affect model of Watson *et al*. (1988) into the TAM, thus expanding the scope of the TAM by including emotional aspects of attitudes (Watson, Clark, & Tellegen, 1988; Venkatesh & Davis, 2000). Second, the research illustrates how emotions influence behavioral intentions by demonstrating how sentiments act as precursors to attitudes and intentions, thereby empirically supporting the affective-cognitive-behavioral pathway (Bagozzi, Gopinath, & Nyer, 1999). Finally, the research expands its applicability to real-world contexts by highlighting the importance of cultural and professional environments in AI adoption, specifically through the illustration of the importance of a Chinese professional environment that has previously been underrepresented in the literature (Liu, Zhang, & Choi, 2018).

6 CONCLUSION

The main conclusion of this research was that emotions contribute significantly to whether individuals accept AI in the workplace. This study demonstrated that individuals who have positive sentiments toward AI such as 'hope' and 'interest' will be more likely to engage with AI, whereas individuals with concerns will have less impact than those with enthusiasm and optimism when implementing AI. In addition to its theoretical implications, this research has contributed to existing theory in several ways. First, this study provided empirical evidence supporting the Technology Acceptance Model (TAM) through the inclusion of specific emotional elements within TAM. Much of the research regarding technology adoption focuses solely on the cognitive evaluation of technology, and therefore, this study addressed a previously identified gap in this area of research. Second, this study examined the degree to which both positive and negative sentiment act as antecedents of attitude and intention, which empirically validated the affective-cognitive-behavioral sequence in user decision-making. Third, this study increased the body of contextually relevant knowledge through an examination of a Chinese business population, a large yet relatively under-represented group in current AI research. Thus, the theoretical findings of this study were grounded in a rapidly changing, increasingly digital socio-economic environment.

Based on the findings of this study, companies and policy makers should consider the following recommendations to improve the user experience with AI. Companies and governmental agencies must clearly communicate with users; concerns regarding AI and provide adequate training and support to users. Users must be given access to resources, such as FAQs, peer mentoring, or AI ambassadors who can serve as easily accessible points of contact. Companies and organizations can also develop targeted interventions to encourage positive emotions and ultimately increase adoption. For example, companies and organizations can develop training programs that allow employees to become confident users of AI tools, develop internal communications that highlight the successes and accomplishments of other employees who successfully utilized AI in their daily work, and provide easy-to-access information and resources, such as online tutorials, FAQs, and peer mentoring. Furthermore, organizations can host workshops and simulations that allow employees to interact with AI in a real-time manner, which may help reduce anxiety and fear associated with AI and replace them with excitement and enthusiasm. Organizations can also recognize and celebrate the small successes of AI applications in daily work processes, which will reinforce positive attitudes toward AI and encourage continued usage. Overall, the success of AI implementation will depend on fostering emotional engagement and linking an individual's professional use of AI to their personal use.

There are many opportunities for future research in this area of study. One opportunity for further research is to explore different perspectives across regions and industries, and time to better understand how individuals' emotional responses to AI change over time. Therefore, the most effective AI adoption strategies will require both emotional and rational elements. If an organization fosters positive emotions and attitudes toward AI, employees will be more likely to adopt and continue to utilize AI. Understanding the importance of emotional engagement will assist in the development of more successful AI implementations.

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