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Relationship between perceived threat of artificial intelligence and turnover intention in luxury hotels

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ABSTRACT

When artificial intelligence technology erodes employees' professional knowledge, they tend to feel highly anxious, and turnover intention is created. This study aimed to test the impact of the perceived threat of artificial intelligence on turnover intention through perceived organizational support and the perceived value of artificial intelligence. The method and procedure were as follow: construct a theoretical framework and propose hypotheses - collect questionnaires through voluntary sampling - use a two-step approach to test the model. This study has some findings. Theoretically, this study proposes a conceptual model of artificial intelligence perception. The combination of technology threat avoidance, organizational support, and perceived value theories applies to the research background of this study. Methodologically, the relationship between the perceived threat of artificial intelligence, perceived organizational support, perceived value of artificial intelligence, and turnover intention variables was studied together for the first time, and the perceived value of artificial intelligence as a new significant mediator between perceived organizational support and turnover intention is discovered. Managementarily, when facing the threats of artificial intelligence to employees, hotel managers should emphasize organizational support, especially in finance, career, and adjustment. This study has important implications for luxury hotel management. First, hotel employees' perceptions of artificial intelligence are dual. Second, luxury hotel managers should consider perceived organizational support to be a key variable.

1. Introduction

The hospitality industry significantly contributes to global GDP and employment [1]. However, statistics show that a voluntary turnover rate (estimated to be between 30 and 300%) is prevalent in the hotel sector worldwide and much higher than in other industries. For example, in China, the hotel sector's turnover rate is as high as 40%, whereas the average turnover rate for all industries is only 20% [1]. Thus staff turnover is a crucial issue in human resource management. In a similar study, labor turnover was a huge challenge facing the hotel industry. Holston-Okae stated that Okayh's employee turnover rate leads to a lack of success, inspiration, and attraction for outstanding employees [2]. In summary, the hotel industry has benefited from global GDP and employment. However, the high turnover rates cannot be ignored.

Over the last decade, there has been an increase in studies researching the evaluation of artificial intelligence applications, the social existence of artificial intelligence technology, and the impact of artificial intelligence applications on individuals and businesses [3]. Artificial intelligence technology is widely used in various hotel departments including catering, guest rooms, and marketing. For

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example, virtual assistants have been installed in hotel guest rooms, such as The Wynn Las Vegas and Aloft, to respond quickly to guests' needs. Problems related to emerging artificial intelligence technologies have become increasingly prominent in the news [4]. The benefits of new technologies to society have always been a concern.

Paradoxically, people also pay attention to the serious consequences of artificial intelligence technology, such as moral issues, criminal use, and unemployment. In addition, there have been concerns regarding how artificial intelligence, an emerging technology, affects human operation modes. Although the development of science and technology has shown exponential growth and benefits, it has also been associated with numerous adverse effects. This negative impact includes a highly negative work output, destroying the employment relationship, making employees feel extremely insecure at work, and impeding their future professional development [5]. Today, employees face tremendous pressure because of increasingly emerging technology, which, despite offering numerous benefits, poses an impending threat to them. Employees in today's work environment must endure the usual pressures of their daily work while dealing with the effects of technological advancement. When emerging technologies erode employees' original professional knowledge, they feel psychologically threatened, which leads to anxiety, sadness, and even depression [6]. Studies have shown that artificial intelligence awareness is significantly related to turnover intentions [5,7], and this increasing trend in technology usage has led to employment uncertainty and higher turnover intention among employees [8].

Fortunately, when employees receive organizational support, their reactions is involve psychological attachment and loyalty to the organization [5]. Studies have shown that perceived organizational support can be a potential moderating factor in the relationship between employees' perceived threat of artificial intelligence and turnover intention. This relationship weakens when employees experience higher levels of organizational support [7]. Another point that cannot be ignored is the perceived value of artificial intelligence, which is the opposite of its perceived threat. Research has shown that increasing customers' perceived value of artificial intelligence in marketing can help increase their willingness to purchase [9], and increasing employees' perceived value of artificial intelligence in human resources departments can help retain employees [10]. People prefer artificial intelligence technology to human decisions because artificial intelligence decisions seem fairer and reflect greater respect for employees [11]. Therefore, the research objective of this study is to validate the proposed theoretical model for the impact of the perceived threat of artificial intelligence on turnover intention in luxury hotels and to clarify the roles played by perceived organizational support and the perceived value of artificial intelligence.

The higher a hotel's star rating, the greater it's capacity and ability to implement artificial intelligence technology. Therefore, this study focuses on five-star rated luxury hotels. The empirical study process was as follows: constructing a theoretical framework and proposing hypotheses - collecting questionnaires through voluntary sampling - using a two-step approach to test the model. Few studies have examined the theoretical framework of the impact of the perceived threat of artificial intelligence on turnover intention through the perceived organizational support and the perceived value of artificial intelligence, which may be a research gap. At the same time, it also reflects the novelty of this study from the perspective of the double-sided perception of artificial intelligence technology. Its theoretical significance lies in the development of a theoretical model of artificial intelligence perception. Its practical significance lies for luxury hotels and their employees. For luxury hotels, the most direct benefit was increased employee retention. Good career growth is the most direct benefit for hotel employees.

2. Literature review and hypotheses development

2.1. Perceived threat of artificial intelligence

Perceived threat (PT) is the recognition of danger or injury from the two dimensions of susceptibility and severity [12]. Artificial intelligence (AI) can realize complex mathematical algorithms and is defined as a set of extensive computer-aided systems that can efficiently solve problems and make decisions [13]. According to the definition of PT and AI, the perceived threat of artificial intelligence (PTAI) in this study refers to an individual's perception of the threat or harm caused by the application of AI technology. Perceived susceptibility refers to a person's belief in the risk of encountering threats, whereas perceived severity refers to a person's belief in the magnitude of encountering threats [14]. The perceived sensitivity of AI corresponds to knowledge and belief about AI applications. The perceived severity of AI is an assessment of personal beliefs regarding the individual suffering of the process and the intensity of the AI application.

2.2. Perceived organizational support

Perceived organizational support (POS) refers to the degree of perceived support by employees from their organization and the depth of the organization's concern for employees' well-being and contributions [15]. POS is measured by multiple dimensions, one of which is reflected in finance, career, and adjustment [16,17], namely FPOS, CPOS, and APOS. The FPOS measures how much employees perceive that their company cares about their financial needs; The CPOS is the degree to which employees care about the professional requirements of their organization; The APOS aims to help employees and their families adjust promptly to their current working and living environments [17].

2.3. Perceived value of artificial intelligence

Perceived value (PV) refers to the utility obtained by individuals from functional, product, or technical aspects of a technology or service [18] and is evaluated by utilitarian and hedonic [9]. Combining the definitions of PV and AI, the perceived value of artificial intelligence (PVAI) in this study refers to the utility that employees obtain by applying AI technology. Perceived utilitarian value is reflected in behavior or products, including saving time, costs, and convenience of use [19]. Perceived hedonic value reflects mental concentration and interest in the degree of the interactive process, expressed as arousal, curiosity, surprise [20], pleasure, and relaxation [21].

2.4. Turnover intention

Staff turnover is closely related to turnover intention. Employees' willingness to voluntarily leave a company is known as turnover intention (TI) [22]. It refers to the willingness to leave the organization for various reasons, to find a better alternative job, or to resign or stay in the current company [23].

3. Conceptual framework and hypothesis formulation

This study conceptualized the associations among PTAI, POS, PVAI, and TI. A relationship framework was developed between the PTAI and TI.

3.1. Perceived threat of artificial intelligence and turnover intention

Technology threat avoidance theory refers to the individual's perception of the threat or harm caused by information technology [24]. When the continuous development of AI technology erodes employees' professional knowledge and they perceive threats, they tend to become highly anxious [6]. According to the technology threat avoidance theory, if companies continue to use AI technology in the workplace, this may result in potentially high staff turnover rates across different industries. The study revealed that heightened AI awareness is negatively related to career satisfaction and positively related to turnover intention, cynicism, and depression [5]. The hotel industry is no exception, believing that the increasing trend in technology usage has led to uncertainty in employment and higher employee turnover intention [8]. Therefore, the following hypothesis was proposed:

H1. PTAI has a significant positive correlation with employees' TI in luxury hotels.

3.2. Perceived organizational support as a moderating role

Based on the social exchange theory and the principle of reciprocity, the organizational support theory was proposed [25]. According to the organizational support theory, POS makes employees think that they will receive help from the organization when they encounter difficulties. The support and resources provided by the organization make employees feel more capable and motivated to work [26]. In the era of AI technology development, POS provides employees with a supportive working environment, enabling them to build greater autonomy when encountering the negative impact of AI applications, to improve employees' overall well-being and satisfaction. POS can be considered as a potential moderating factor in the relationship between employees' perceived threat of AI and their turnover intention. When employees experience higher levels of organizational support, this relationship will weaken in the hotel industry [7]. Therefore, the following hypothesis was proposed:

H2. POS is a significant moderator between PTAI and TI in luxury hotels.

3.3. Perceived organizational support and turnover intention

Organizational support theory is based on the social exchange theory, and any organization's support will significantly impact employees, prompting them as a loyal to participate more in work [15]. The impact of POS on employee TI has always been a common area of study. It has been proven in different research fields [27,28]. Whether employees continue to stay in a company is positively related to the support level of the organization. The higher the organizational support level, the higher the employee retention. Therefore, the following hypothesis was proposed:

H3. POS has a significant negative correlation with employees' TI in luxury hotels.

3.4. Perceived organizational support and perceived value of artificial intelligence

According to organizational support theory, organizations provide various types of support to employees For instance, during the COVID-19 pandemic, employees considered organizational support crucial [29]. Similar to COVID-19, the rise of AI technology in the hotel industry poses a significant threat to some employees [30]. To combat the impact of COVID-19 and the rise of AI technology on employees, hotel management should provide employees with various types of support. Employees with management support can focus more on the value of AI technology than on its dangers. According to the interpretation of utilitarian value [19], if an organization provides management services related to AI technology to employees to improve their work efficiency, convenience, and save time, then employees will perceive the utilitarian value brought by AI technology. According to the definition of hedonic value [20], employees will experience hedonic value brought about by AI technology if the organization provides AI technology management services intended to make employees feel relaxed, surprised, and fun at work. Therefore, the following hypothesis was derived:

H4. POS has a significant positive correlation with PVAI in luxury hotels.

3.5. Perceived value of artificial intelligence and turnover intention

Perceived value theory explains the utility individuals obtain from tangible products or intangible services [18]. In marketing, the perceived value obtained through AI is positively correlated with consumer purchase intentions [9]. In human resource management, AI has a positive perceived value that helps retain employees [10]. AI technology is expected to change the management direction of human resources departments because people prefer decisions made by AI technology to those made by humans. Especially in the service-intensive hotel industry, fairness and justice are important influencing factors of resignation and are highly valued by employees [31]. AI decisions seem fair and reflect respect for employees [11]. Therefore, the following hypothesis was derived:

H5. PVAI has a significant negative correlation with employees' TI in luxury hotels.

3.6. PVAI as a mediating role

Employees face new technological changes almost daily, but their attitudes are the opposite. Some employees welcome the changes brought about by the new technology, whereas others resist and take defensive measures [32]. Anxiety about future careers caused by huge changes in work culture and the environment brought about by new technology is the main reason for turnover intention [33]. With the rapid development of AI technology in the hotel industry, to reduce this anxiety, hotels must provide sufficient support to increase the perceived value of AI. It is necessary to fully consider the mediating factors of employees' perceived AI values between POS and TI. Therefore, the following hypothesis was formulated:

H6. PVAI is a significant mediator between POS and TI in luxury hotels.

3.7. Formulation of a conceptual framework

Based on the above research, this study proposes a conceptual framework for AI perception (Refer Fig. 1) that shows the impact of PTAI on TI in luxury hotels. PTAI is an independent variable and TI is a dependent variable. Between them, POS plays a moderating role. In addition, PVAI, the other side of PTAI, also plays a mediating role in the relationship between POS and TI.

4. Research methodology

4.1. Sample and procedure

This study investigated the relationships among PTAI, POS, PVAI, and TI. This study considers that the higher a hotel's star level, the more capable and financial it is to introduce AI technology. Therefore, this study focuses on five-star rated luxury hotels. According to information released by the Ministry of Culture and Tourism of the People's Republic of China, luxury hotels distributed across all 34 administrative regions of China by 2022. Due to geographical constraints and the convenience of the network, this study obtains data from the online platform "Sojump" (https://www.sojump.com). This study provided sample collection services for scholars and obtained data from 28 administrative regions in China. First, 30 employees were invited to conduct a pretest to improve the unreasonable aspects of the questionnaire. Then, under the guidance of two university professors, the wording of some items was revised to improve respondents' understanding. This study selected voluntary sampling and collected 628 questionnaires from June to August 2022. Respondents with missing values were eliminated, and the final efficacy rate was 83.3%. To obtain reliable results, the ratio of samples to independent variables (items) should be greater than 10:1 [34]. Therefore, a sample size of 523 was considered sufficient for this study. Table 1 presents the respondents' profile tables.

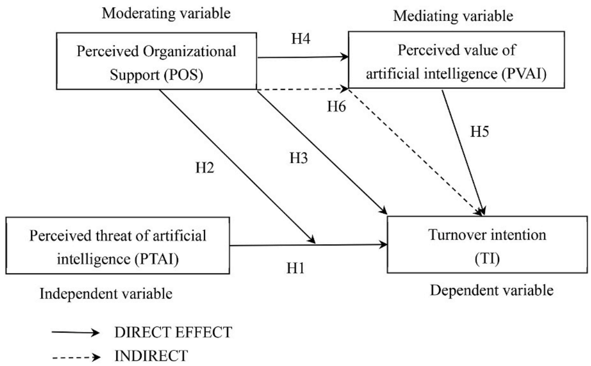

Fig. 1. AI perception model.

4.2. Measurement

The scale for the study was adopted from the existing literature and modified according to the context of this study. The measurement scale for the PTAI variables was adapted from a six-item scale created in previous studies [23]. The scale consists of two subscales (three items each) measuring perceived susceptibility (PSU) and perceived severity (PSE). POS was measured using a twelve-item scale developed in previous studies [26]. The scale has three subscales: Financial POS (FPOS), Career POS (CPOS), and Adjustment POS (APOS). Each subscale consisted of four items. A nine-item scale was used for the PVAI variable [16]. The first five items belong to perceived utility values (PUV), whereas the last four belong to perceived hedonic values (PHV). A five-item scale developed in previous studies [13] was used as the TI variable. For all 32 items, respondents were asked to evaluate on the 7-point Likert scale, ranging from "strongly disagree" to "strongly agree," represented by numbers 1–7. Finally, a complete questionnaire suitable for this study was developed.

4.3. Data analysis

The data was analyzed using Smart PLS (4.0 version), which is a suitable software for testing a conceptual model [35]. When the data is single-sourced, there is a significant probability of common method variance. Harman's one-factor test can be utilized to check for this possibility. After all 32 items participated in Harman's one-actor test, six unqualified items (FPOS2, FPOS4, PUV2, PHV1, PHV2, and TI5) were identified. After removing them, the KMO value is 0.93, the approximate χ^2 is 8552.71, the *df* value is 325, and the *P*-value is 0.000. The results are summarized in Table 2.

For examining the common method bias [36], Harmon's one factor test was used to test the variables. In exploratory factor analysis, the number of factors was set to 1, and the results showed the cumulative % of Variance (Rotated) was 35.79 (below 40), indicating no significant common method bias in the study data. To consolidate this result, using confirmatory factor analysis to validate again, placing all items in a factor box. The results indicated that the fit indexes of the model cannot meet the standard (Chisq/df = 14.387, GFI = 0.514, RMSEA = 0.160, CFI = 0.524, NFI = 0.507, NNFI = 0.482), which once again indicates that there is no common method bias with the data.

After testing for common method bias, an updated Likert scale was administered. Descriptive statistics and normality tests are presented in Table 3. There are no outliers in the data. The absolute value of kurtosis was less than 10, and the absolute value of skewness was less than 3 [37], indicating that although the data did not have an absolutely normal distribution, it is approximately subject to normality.

5. Results

A correlation does not necessarily indicate causation with the intervention [38]. This study applies correlation-based methods (structural equation modeling) to survey data without intervention [39] to better understand the correlation between variables. A two-step approach is used to test the model. The first step was to test the validity and reliability of the measurement model. The second step was to test the hypotheses by analyzing the structural model (also called the inter-model) [40]. The statistical tool selects Smart PLS version 4.0 and uses partial least squares (PLS) modeling technology to test the conceptual framework. PLS-SEM is better for theory development and prediction purposes [40].

Table 1
Respondent profile table.

Items	Options	Count	Percentage	Items	Options	Count	Percentage
Gender	Male	228	43.6%	Educat-ion	Middle—high school	1	0.2%
	Female	295	56.4%		High school graduate	91	17.4%
Age	18–25	32	6.1%		Some college	406	77.6%
	26–30	213	40.7%		College graduate	23	4.4%
	31–35	202	38.6%		Post-college graduate	2	0.4%
	36–40	61	11.7%	Depart-ment	Front Office Department	83	15.9%
	41–45	12	2.3%		Housekeeping Department	112	21.4%
	46–50	2	0.4%		Food and beverage department	142	27.1%
	51–55	1	0.2%		Sale Department	101	19.3%
Salary level	2001–4000	6	1.1%		Recreation department	6	1.2%
	4001–6000	81	15.5%		Shopping department	22	4.2%
	6001–8000	138	26.4%		Public relations department	45	8.6%
	8001–10000	182	34.8%		Other departments	12	2.3%
	10001-	116	22.2%	Years of work in hotel industry	1–5	209	39.9%
Years of work in current hotel	1–5	377	72.1%		6–10	263	50.3%
	6–10	130	24.8%		11–15	37	7.1%
	11–15	13	2.5%		16–20	11	2.1%
	16–20	2	0.4%		21–25	2	0.4%
	21–25	1	0.2%		26–30	1	0.2%

Table 2
Total variance explained.

Component	Total	% of Variance	Cumulative %	Component	Total	% of Variance	Cumulative %
1	9.305	35.790	35.790	14	0.380	1.460	86.840
2	3.771	14.505	50.295	15	0.362	1.393	88.233
3	1.853	7.127	57.421	16	0.343	1.319	89.551
4	1.605	6.173	63.594	17	0.339	1.306	90.857
5	1.328	5.109	68.703	18	0.316	1.214	92.071
6	1.169	4.495	73.198	19	0.308	1.184	93.255
7	0.529	2.033	75.232	20	0.283	1.089	94.345
8	0.491	1.888	77.119	21	0.270	1.038	95.383
9	0.477	1.836	78.955	22	0.269	1.034	96.417
10	0.443	1.705	80.660	23	0.250	0.963	97.380
11	0.427	1.642	82.302	24	0.243	0.933	98.313
12	0.409	1.572	83.874	25	0.232	0.893	99.206
13	0.392	1.507	85.380	26	0.206	0.794	100

Table 3
The descriptive statistic and normality test.

Items	Min.	Max.	Mean	S.D.	Median	Skewness	Kurtosis	Kolmogorov-Smirnov Test	
								D-value	p
FPOS1	1	7	5.273	1.043	5	−0.535	0.497	0.199	0.000**
FPOS3	1	7	4.88	1.33	5	−0.445	−0.156	0.182	0.000**
CPOS1	1	7	5.13	1.299	5	−0.674	0.296	0.183	0.000**
CPOS2	1	7	5.22	1.352	5	−0.792	0.452	0.193	0.000**
CPOS3	1	7	5.382	1.208	6	−0.8	0.585	0.204	0.000**
CPOS4	1	7	5.291	1.332	5	−0.798	0.415	0.202	0.000**
APOS1	1	7	4.43	1.46	5	−0.214	−0.492	0.155	0.000**
APOS2	1	7	4.516	1.6	5	−0.386	−0.64	0.175	0.000**
APOS3	1	7	5.335	1.255	5	−0.938	1.155	0.2	0.000**
APOS4	2	7	5.327	1.212	5	−0.537	−0.128	0.192	0.000**
UV1	2	7	5.816	0.925	6	−0.781	1.195	0.248	0.000**
UV3	1	7	5.92	0.995	6	−1.139	2.468	0.238	0.000**
UV4	1	7	5.654	1.099	6	−1.013	1.571	0.237	0.000**
UV5	1	7	5.822	1.097	6	−1.241	2.473	0.251	0.000**
HV3	1	7	5.325	1.122	5	−0.6	0.595	0.191	0.000**
HV4	1	7	5.767	1.138	6	−1.226	2.136	0.241	0.000**
PSU1	1	7	3.306	1.528	3	0.461	−0.579	0.191	0.000**
PSU2	1	7	3.159	1.631	3	0.571	−0.556	0.181	0.000**
PSU3	1	7	3.48	1.665	3	0.278	−0.846	0.16	0.000**
PSE1	1	7	2.847	1.384	3	0.476	−0.418	0.189	0.000**
PSE2	1	7	2.901	1.558	3	0.776	−0.023	0.189	0.000**
PSE3	1	7	3.375	1.699	3	0.36	−0.93	0.177	0.000**
TI1	1	7	3.411	1.604	3	0.489	−0.424	0.152	0.000**
TI2	1	6	2.398	1.214	2	0.801	0.305	0.219	0.000**
TI3	1	7	2.291	1.259	2	1.091	1.158	0.23	0.000**
TI4	1	7	2.12	1.205	2	1.378	2.24	0.238	0.000**

5.1. *Measurement model test*

Validity is the ability of instrument to measure what it supposed to be measured for a construct. There are three types of validity required for each measurement model [41].

5.1.1. *Convergent validity*

The outer loading (should be ≥ 0.7) is to evaluate the reflection measurement model, the composite reliability (CR) (should be ≥ 0.7) is to evaluate the internal consistency, and the average variance extracted (AVE) (should be ≥ 0.5) is to evaluate the convergent validity [40].

The loadings, AVEs, and CRs of the items listed in Table 4 qualified. PSU and PSE were used to measure the independent variable, PTAI. The moderating variable, POS, was measured using the FPOS, CPOS, and APOS. The mediating variable PVAI was measured using PUV and PHV.

5.1.2. *Construct validity*

It is recommended that the use of at least one fitness index from each category of model fit [41]. The value of Root Mean Square of Error Approximation (RMSEA) should be < 0.08. The values of Goodness of Fit Index (GFI), Comparative Fit Index (CFI), and Normed

Table 4
Summary for the constructs.

Constructs	Items	Loadings	CR	AVE
PSU	PSU1	0.902	0.889	0.819
	PSU2	0.910		
	PSU3	0.903		
PSE	PSE1	0.891	0.858	0.779
	PSE2	0.885		
	PSE3	0.871		
PTAI	PSU	–	0.922	0.720
	PSE	–		
FPOS	FPOS1	0.932	0.845	0.866
	FPOS3	0.929		
CPOS	CPOS1	0.869	0.878	0.733
	CPOS2	0.878		
	CPOS3	0.826		
	CPOS4	0.850		
APOS	APOS1	0.849	0.873	0.724
	APOS2	0.855		
	APOS3	0.844		
	APOS4	0.854		
POS	FPOS	–	0.857	0.541
	CPOS	–		
	APOS	–		
PUV	PUV1	0.823	0.858	0.701
	PUV3	0.852		
	PUV4	0.847		
	PUV5	0.828		
PHV	PHV3	0.908	0.785	0.823
	PHV4	0.906		
PVAI	PUV	–	0.902	0.672
	PHV	–		
TI	TI1	0.875	0.888	0.748
	TI2	0.892		
	TI3	0.841		
	TI4	0.850		

Fit Index (NFI) should all be > 0.9. The value of Chi- Square/Degree of freedom (Chisq/df) should be < 5.0.

In Absolute Fit, the value of RMSEA was 0.064 (less than 0.08). In the Incremental Fit, the NFI value was 0.895 (close to 0.9), and all other indexes were within the standard range. In the Parsimonious Fit, the Chisq/df value was 3.149 (less than 5.0). The above indicated that all values of fitness indexes for the model have achieved the required level (Refer Table 5).

5.1.3. *Discriminant validity*

Furthermore, this study used the HTMT criterion for validity assessment to test the discriminant validity. HTMT value should be $\leq$ 0.85 [42]. As shown in Table 6, the HTMT values were acceptable. Therefore, the respondents understood that all the structures were distinct.

5.2. *Results from the structural equation model*

5.2.1. *Multicollinearity*

When the Variance Inflation Factor (VIF) value is ≤ 3, there is no multicollinearity problem between indicator variables [43]. The results of the inner model were summarized in Table 7.

5.2.2. *Path coefficients*

This study used 5000 re-sample bootstrapping procedures to assess the PLS path modeling, T-statistics is used to estimate path coefficients [40]. The β-value represents the path coefficient. BCILL and BCIUL do not span 0, indicating a significant path coefficient

Table 5
Summary for fitness indexes.

Name of category	Name of index	Index value	Comments
Absolute fit	RMSEA	0.064	Achieved the required level
Incremental fit	GFI	0.900	Achieved the required level
	CFI	0.926	Achieved the required level
	NFI	0.895	Achieved the required level
Parsimonious fit	Chisq/df	3.149	Achieved the required level

Table 6
Discriminant validity.

Variables	PSU	PSE	FPOS	CPOS	APOS	PUV	PHV	TI
PSU	–							
PSE	0.719	–						
FPOS	0.098	0.103	–					
CPOS	0.192	0.141	0.373	–				
APOS	0.218	0.211	0.312	0.462	–			
PUV	0.274	0.281	0.438	0.623	0.530	–		
PHV	0.222	0.278	0.516	0.637	0.574	0.769	–	
TI	0.386	0.364	0.474	0.534	0.487	0.694	0.713	–

[44]. The p-value <0.05 or the 95% confidence interval will achieve significance [40]. In all paths except PTAI * POS - > TI, the path coefficients were shown to be significant. The results were shown in Table 8.

Among all direct relationships, PTAI was positively related to TI ($t = 5.444$, $p < 0.001$), POS was negatively related to TI ($t = 5.848$, $p < 0.01$), and POS was positively related to PVAI ($t = 27.000$, $p < 0.001$). Thus H1 and H3-H5 were supported.

For the moderation test, PTAI did not play a moderating role between PTAI and TI ($t = 0.026$, $p > 0.05$). Thus H2 was rejected.

For the mediation test, the relationship POS - > PVAI - > TI ($t = 8.861$, $p < 0.001$) is significant, and a negative relationship is found. To compensate for the deficiency in the significance test, the mediating effect size should be reported in the statistical analysis results. Further calculations showed that the mediating effect size was 49.54% (indirect effect was −0.268, direct effect was −0.273, and total effect was −0.541), corresponding to partial mediation [45]. Thus, H6 was accepted.

5.2.3. Explanatory power, effect size, and the predictive correlation

R-squared (R^2) is the variance of the endogenous variables that explains the interpretation of the exogenous variables. The R^2 value is 0–1. The explanatory power of the model changed positively with R^2. The R^2 values of 0.25, 0.50, or 0.75 for endogenous latent variables can be respectively described as weak, moderate or substantial [46]. F-Square (F^2) is the change in R^2 when an exogenous variable is removed from the model. F^2 is effect size (≥ 0.02 is small; ≥ 0.15 is medium; ≥ 0.35 is large) [47]. The predictive correlation is expressed as a Q-squared (Q^2) to evaluate the model's predictive ability. Q^2 is greater than 0 (≥ 0 is small; ≥ 0.25 is medium; ≥ 0.50 is large), indicating that the exogenous constructs have predictive relevance for the endogenous construct under consideration [40]. The relevant data were listed in Table 9.

The R^2 value of TI was 0.482, which shows that all predictors explained 48.2% of the turnover intention. FPOS has the lowest explanatory power for the model ($R^2 = 0.320$), but it is also sufficient. The F^2 values of TI were 0.063 (small level), 0.080 (small level), and 0.175 (medium level), corresponding to PTAI, POS, and PVAI, respectively, whereas the other F^2 values were at a large level. The Q^2 values of all variables were above 0; among them, FPOS, APOS, and TI were at a medium level, and all others were at a large level. Overall, this model can well reflect the predictive correlation.

5.2.4. Structural equation model

Based on the two-step approach, the structural model was obtained. As shown in Fig. 2. The numbers in the blue circles represent R^2. The route of the outer model is indicated by green, and the values outside and inside the brackets are path coefficients, respectively (β-Value) and T-value. The route of the inner model is shown in black, and the values outside and inside the brackets are the loadings and T-values.

6. Discussion

6.1. Results and comparison

This study proposes an AI perception model that includes PTAI, POS, PVAI and TI variables for luxury hotel employees in China. The results are as follows: PTAI has a significant positive effect on TI (H1), POS does not play a significant moderator between PTAI and TI (H2), POS has a significant negative effect on TI (H3) and has a significant positive effect on PTAI (H4), PVAI has a significant negative effect on TI (H5), and PVAI plays a significant partial mediator between POS and TI (H6).

The theoretical model proposed in this study was designed from two opposing perspectives on AI perception, which differs from previous models. However, the related hypotheses in previous studies were supported, while H2 in this study was rejected. This is worth discussing.

This study rejects H2 ($t = 0.026$, $p > 0.05$), which contradicts previous relevant results. This study considered two typical previous studies for comparison. Respondents in the first comparative object (Ref. No. 7) were from five-star rated luxury hotels, as in this study.

Table 7
Inner model and its VIFs.

Relationships	PTAI- > TI	POS- > TI	PVAI- > TI	PTAI*POS- > TI
VIF	1.107	1.794	1.820	1.040

Table 8
The results of hypothesis testing.

Hypothesis	Relationship	β-Value	Path coefficient	T-value	SD	p-value	BCI LL	BCIUL	Result
H1	PTAI- > TI	0.190	0.190	5.444	0.035	0.000	0.123	0.261	Accept
H2	PTAI*POS- > TI	−0.001	−0.001	0.026	0.034	0.370	−0.068	0.065	Reject
H3	POS- > TI	−0.273	−0.273	5.848	0.047	0.000	−0.365	−0.180	Accept
H4	POS- > PVAI	0.661	0.661	27.000	0.024	0.000	0.612	0.707	Accept
H5	PVAI- > TI	−0.406	−0.406	9.668	0.042	0.000	−0.486	−0.322	Accept
H6	POS- > PVAI- > TI	−0.268	–	8.861	0.030	0.000	−0.327	−0.210	Accept

Note: It used a 95% confidence interval with a bootstrapping of 5,000.

Table 9
The results of R^2, F^2, and $Q.^2$.

Variables	Sub-variables	F^2	R^2	Adjusted-R^2	Q^2 (=1-SSE/SSO)
PTAI	PSU	9.710	0.907	0.906	0.737
	PSE	8.593	0.896	0.896	0.693
POS	FPOS	0.470	0.320	0.318	0.268
	CPOS	2.273	0.694	0.694	0.503
	APOS	1.713	0.631	0.631	0.450
PVAI	PUV	17.073	0.945	0.944	0.658
	PHV	5.192	0.839	0.838	0.686
TI	TI	0.063 (PTAI) 0.080 (POS) 0.175 (PVAI)	0.482	0.478	0.355

Note: SSE = the sum of the squared observations; SSO = the sum of the squared prediction errors.

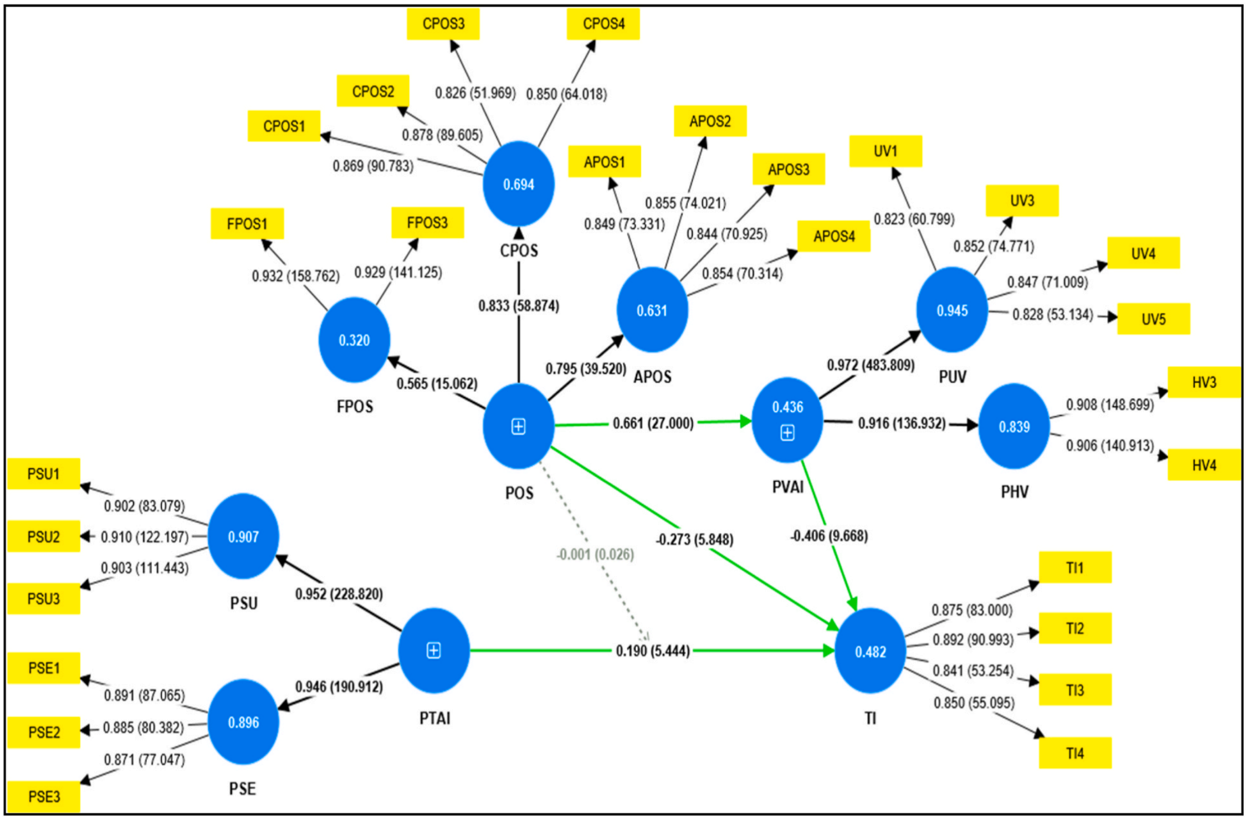

Fig. 2. Structural model.

However, the results were different, which may be related to the research scope and POS scale. The research scope of this study is all over China, whereas the first comparative object focuses on only one province in China. For the POS scale, this study uses 12 items developed in 2004 and 2017 [16,17], whereas the first comparative object uses 8 items developed in 1986 [15]. Some differences were observed between the second comparative object (Ref. No. 5) and this study on respondents (employees of the service sector), research scope (New Zealand), and sample size (only 120). In addition, the TI variable in the comparative study was measured with a 4-item scale developed in 1999 [48]. While this study was measured with a 5-item scale developed in 2019 [7] while considering the same context of the increasing development of AI technology. In these two previous studies, the scale of the variables was proposed for a long time. Therefore, the improved scales of the POS and TI variables used in this study are more suitable for the research needs of modern society with the development of AI technology. Other hypotheses (H1, H3-H6) in this study were supported and achieved consistent results compared to previous studies. H1, based on the technology breakthrough avoidance theory, is supported by the conclusions of previous studies. Previous research fields such as the service sector (Ref. No. 5) have also been validated, indicating that employees' perception of the threat posed by new technology will lead to turnover intention in multiple research fields. For H3-H5, this was common in previous related studies and was successfully supported in this study. Regarding H6, many scholars verified the existence of meaningful mediators between POS and TI. Few studies have considered PVAI as a mediator; however, it was validated based on the perceived value theory in this study. Compared to previous studies, the similarity lies in the presence of significant mediators, whereas the difference lies in validating a new mediator in this study.

6.2. Implications

This study has important implications for luxury hotel management. First, hotel employees' perceptions of AI are dual. Employees have different perceptions of AI owing to their different life experiences. Suppose hotel managers focus on enhancing employees' perceived value of AI and dispel concerns about the threats posed by AI technology through education and training. In this case, the employees' turnover intentions changed. Second, luxury hotel managers should consider POS to be a key variable. Although POS has not yet been validated as a moderating variable between PTAI and TI, there are signs of a weakening relationship between POS and PTAI. More importantly, POS directly and significantly affects TI and PVAI, respectively. Therefore, if hotel managers can provide high-level support to employees in terms of changing management policies and leadership styles when hotel employees are facing AI threats, they will feel more satisfied and loyal to their hotels.

6.3. Theoretical and practical contribution

The theoretical significance lies in the development of a theoretical model that can fill this research gap. This theoretical framework combines technology threat avoidance theory, organizational support theory, and perceived value theory, which reflect the impact of the perceived threat of AI on turnover intention through perceived organizational support and perceived value of AI in luxury hotels in China.

Its practical significance lies for luxury hotels and their employees. With the gradual application of artificial intelligence technology in luxury hotels, this study provides recommendations for hotel management to address the threat of artificial intelligence technology, namely providing high-level organizational support to employees, psychologically helping them reduce their willingness to leave luxury hotels due to significant changes in the work environment and the anxiety of future careers caused by artificial intelligence threats. For luxury hotels, the most direct benefit was increased employee retention. Indirect benefits include saving recruitment and education costs, improving service quality, and increasing creativity. The most direct benefit for hotel employees is good career growth, whereas the indirect benefits are acquiring new skills used by AI, increasing the sense of achievement, and so on.

6.4. Limitations and future research

This study has some limitations. First, this study used cross-sectional data, which may have affected the relationships. In future research, panel data, which combines cross-sectional data with time series data, will be used to make the data analysis results more convincing. Second, it should have considered whether the respondents' organizational environments have already introduced AI systems. In future research, it will be necessary to classify whether luxury hotels have applied AI systems to reflect respondents' feelings more accurately. Third, questionnaire development and research instruments must be adjusted to include hotel-specific items. As few scholars have developed questionnaires on the PTAI and PVAI, the items in this study were adapted from previous questionnaires. Therefore, adjusting hotel-specific items to a level recognized by academia is a future research direction. Fourth, PTAI and PVAI were proposed based on two different theories, and this study did not initially consider the relationship between them. PTAI and PVAI should have a correlation by their definitions. In future research, this relationship will be necessary to verify to increase the completeness of this model.

7. Conclusion

The aim of the study is to examine the relationship between the perceived threat of artificial intelligence and turnover intention through perceived organizational support and perceived value of artificial intelligence. The data consists of employees of luxury hotels in China. This study proposes a conceptual model of artificial intelligence perception and six hypotheses. After verification, the findings were as follows: The perceived threat of artificial intelligence directly affects turnover intention; Perceived organizational support directly affects the perceived value of artificial intelligence and turnover intention, respectively; The perceived value of artificial intelligence directly affects turnover intention and plays a significant partial mediator (effect size is 49.54%) between perceived organizational support and turnover intention. These findings are reflected in the theory, methods, and hotel management in the context of the increasing development of artificial intelligence technology in hotels and high turnover rate of hotel employees. Theoretically, this study proposes a conceptual model of artificial intelligence perception. The combination of technology threat avoidance, organizational support, and perceived value theories applies to the research background of this study. This not only expands the application scope of this theoretical combination, but also finds suitable supporting theories for this study. Methodologically, the relationship between the perceived threat of artificial intelligence, perceived organizational support, the perceived value of artificial intelligence, and turnover intention was studied together for the first time, and the perceived value of artificial intelligence was discovered as a new significant mediator between perceived organizational support and turnover intention. With regard to the threat of artificial intelligence to employees, the perceived organizational support of hotel managers should be emphasized, especially in the areas of finance, career, and adaptation.

Production notes

Author contribution statement

Yanan LI: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Data availability statement

No data was used for the research described in the article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e18520.

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