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The Effects of AI Robot Service on Hotel Customer's Service Experience Satisfaction and Repurchase Intention

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Abstract:

The application of robotic service is expanding in hospitality industry rapidly and hotel managers are wondering how robotic service can improve the service quality and customer experience evaluation. On the basis of the cognitive appraisal theory, this study aims to fill the gap and develop a conceptual framework to examine how the robotic service influence experience evaluation from the perspective of customers' psycho-emotional level and subsequently identify the relationship between the robotic service and experiential quality, perceived value, overall satisfaction and repurchase intention of hotels. The finding identified performance expectancy, effort expectancy and subjective norm as the antecedents directly and positively impact on customers' experience quality and indirectly affect the customers' overall satisfaction, and the overall satisfaction positively impact on customers' repurchase intention, which provides a reference for the research on impact of technology service in hospitality.

Keywords: *Robot service, Hotel, Customer experience, Satisfaction, Cognitive appraise theory*

I. INTRODUCTION

A service robot refers to autonomous or semi-autonomous robotic devices that can provide a service [1]. These robots, empowered by artificial intelligence (AI) technology, have "a certain degree of autonomy, mobility, and sensory capabilities that allow them to perform intended tasks" [2]. In recent years, the use of artificially intelligent (AI) service robots is becoming popular as it is gradually being applied to various fields to deliver such services as catering, medical assistance, elderly care, retail, hospitality and tourism services, etc. [3].

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Service robots have been used to deliver hospitality services as early as 2014 with the deployment of Savioke's Relay robot by Starwood's Aloft Hotels to deliver amenities to hotel guests [4]. Later, Hilton Worldwide began to use Softbank's NAO robot concierge to inform guests on local attractions, restaurants, hotel amenities, etc. Henn-na Hotel in Japan was the first hotel to employ robots throughout its entire operations, from check-in at the front desk to automated luggage delivery and in-room companion [5], and the hotel deployed a functional trolley robot to escort hotel guests and carry their suitcases. Alibaba's future hotel "Flyzoo" opened in 2018 in China and there is no human employees where services are provided by robots. While Bowen and Morosan 2018 argues that around 25 percent of the "workforce" in the hospitality industry will be replaced by robot in the near future. While robots can perform repetitive simple tasks, presence of human employees will still be required to ensure the flawless delivery of services.

As a result of increases in the use of artificially intelligent robotic devices in service delivery, an increasing number of scholars have started examining the use of robots in service delivery utilizing a number of conceptual frameworks such as the technology acceptability model (TAM) [6]. Lu, Cai, and Gursoy (2019) developed a Service Robot Integration Willingness (SRIW) Scale to test consumers' long-term willingness to integrate artificial intelligence and service robots into regular service transactions [7]. Gursoy et al. (2019) argued that service robots empowered by AI technology can provide as good quality services as human employees if not better. Scholars further argued that the AI robotic technology used by hospitality firms can alter customers' evaluation of hospitality services [7].

However, only a few studies have examined the effect of robot service on customer experience and satisfaction. Chan & Tung (2019) investigated the effects of service delivery by robots on guest evaluations of hotel brand experience from the perspective of brand recognition utilizing experimental methodology [8]. They examined the influence of robot services on customers' sensory, behavioral, intellectual and affective evaluations from the perspective of brand recognition. Qiu, Li, Shu, & Bai (2019) investigated the influence of service robot attributes on customers' hospitality experience from the perspective of relationship building [9]. Tung & Au (2018) explored consumer experiences with robotic devices utilizing five crucial dimensions (i.e. embodiment, emotion, human-oriented perception, feeling of security and co-experience) of user experiences with Human-Robot Interaction (HRI). This study distinguished between the characteristics of robots and hotel employees utilizing thematic analysis to identify excerpts from the reviews and connect them to the five dimensions of user experiences in HRI [10].

While the above studies examined various aspects of service delivery by robots, broader

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concept of robot service and service types, and the effects of robot service on hotel customer's service experience assessment from the perspective of customers' psych-emotion during service encounters have not received much attention. Service experience is actually a complex process which will not only change with different service context, but also related to the service quality, service attitude as well as customers' expectations, subjective norms or motivations towards the services matter. Therefore, examination of customers' satisfaction with services delivered by service robots can enable us to further understand the relationship between robot service and customer experience. Scapin et al. (2012) argued that the customer experience can viewed as a consequence of a user's internal state, so the customers experience evaluation is ultimately expressed through emotions. To address this gap, this study develops a framework to identify the effects of robot service on hotel customers' service experience based on the cognitive appraise theory by investigating the relationship between robot service and hotel customer experience.

II. LITERATURE REVIEW

2.1 Robotic Service and Customer Behaviour

With the increase in customers' pursuit of personalised services, hoteliers began to look forward to the new experiences brought by robotic services. Therefore, it is a trend for hotels to use robotic services. The robotic service also covers the basic service functions of hotels, such as welcome, check-in, check-out, hotel internal guidance, room service, etc. More intelligent robots can also chat with hotel guests to meet their individual needs [11]. Technically, some robots may come with a user model to help them recognize human behaviour and respond appropriately, then provide corresponding services. In recent years, the research of robot hotel service has attracted the attention of academic scholars, mainly, including those from the United States and Hong Kong, China, who have determined the actual impact of robotic service. Murphy et al. (2017) not only discussed the design, management and training of service robots in hotel and tourism industry organisations, but also investigated customers' attitude, acceptance, satisfaction and evaluation of hotel robotic service. In addition to the above viewpoints, this study also solves some problems caused by robotic services, such as employee unemployment, operating cost and ethical issues [2]. Researchers try to explore the factors affecting customers' willingness to purchase robotic service from the perspective of robot performance. However, due to the influence of research conditions (i.e. a few hotels are currently served by robots), most of the studies mainly discussed the perception of customers through the experimental method. The actual impact of robotic service on hotel customers' purchase intention is still unknown. Understanding customers' purchase intention is helpful for hotels to accurately identify the target market and improve service quality.

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Behavioural intention refers to what the people intend to do under specific circumstances [12]. Purchase intention in this study refers to the customers who will revisit the same hotel after staying at a hotel with robotic services. On the other hand, Kim et al. (2007) argued that technology acceptance is a consumer consideration and determines these customers' intention of using the technology. Behavioural intention, which originated from psychology, is considered to be a kind of personal motivation that can accurately predict individual behavior. With the development of information and communication technology, the online platform for tourism and hotels has become a way for more tourists to choose tourist destinations and hotels, and the research on online customers' purchase intention and the factors influencing customers' purchase intention has also followed. For example, Berezina et al. (2012) suggests that hotel guests' perception of information security will have a negative impact on customers' purchase intention [13]. Casalo et al. (2015) studied the influence of online hotel information on hotel customers' purchase intention [14]. Although they simply looked at the factors that affect customers' purchase intention, they care and trust from the network adjustment, the investigation on customers' willingness to hotel reservation, the results showed that the customer to the hotel experience to comment on the Internet is important reference potential customers' purchase intention, the lower the evaluation of potential customers' purchase intention will be low, and vice versa. To sum up, the main factors that influence the RPI of hotels are information published on social media, such as Facebook, information security and hotel customer evaluation. However, the research ignores the impact of robot hotel services on customers' purchase intention, which is a new field and a trend of technology development for the future application of hotels. Much attention has focused on robots' service utilisation in the hotel industry in recent years. However, there are few studies investigating the effect of robotic service on the purchase intention from the perspective of customer experience, especially in the empirical study, which is almost a gap.

2.2 Robotic Service and Customer Experience

Creating guest experiences is one of the main competitive advantages of hotel companies (hotels, restaurants, bars, spas, conference and activity centres, etc.). The hotel attracts customers through various methods and technical applications, such as a strong theme atmosphere, technical innovation services, and the conceptualisation of specific experiences, such as the best experience, real experience, extraordinary experience and unforgettable experience. Hotels attempt to enhance the guest experience through the dimensions of the frameworks, such as the high-quality service, personalised service and improvement of deals, hybrids, amenities and so forth. Talwar (2015) until most goods and services will be produced (delivered) by robots, automation technologies and AI in an economic system called 'robotics economics' [2]. Ivanov and Webster (2017b) have even proposed that companies start treating social robots as customers

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because they will be able to perform all the activities that human customers do in regard to purchasing goods and services. Tung and Law (2017) proposed human-centred experiences under the robotics service in the hotel and identified the effect of presence and embodiment of service robots on customer experience.

As a new technology, service robots have been developed and applied in the tourism and hotel industry. Research shows how technologies can adjust and enhance tourism experiences by updating Robertson's tourism activities and interacting with Robertson's tourism destinations. As a matter of fact, many scholars have studied the customer experience related to technology. Festinger (1957) proposed cognitive dissonance theory (CDT) to describe a process model of individuals' behaviour in receiving technology services, including pre-usage expectations (beliefs) on technology, and experiences during usage overtime, and then post-usage perceptions of the technology. The inconsistency between the customers' original expectations and the observed performance is reflected in the non-confirmation construction. On the basis of CDT, Oliver (1980) suggests the expectation disconfirmation theory (EDT) or expectation confirmation theory, which has been applied to the adoption of marketing information technology (Bhattacherjee, 2001). EDT pays special attention to how and why user's reactions change with time. It is composed of four main structures: expectations, performance, inconsistency and satisfaction.

2.3 Conceptual Framework

As above mentioned, the theory of emotion tells how motivation and cognition produce emotions in adaptationally relevant encounters [15] and the cognitive appraise theory framework is used to explain the multistep process that customers utilise in determining their revisiting robot-service hotel in this study [16]. In the framework of CAT, individuals have to go through several evaluation stages [16], including recognising the benefits and costs of receiving robotic service, which are based on performance expectancy (PE) and effort expectancy (EE), and customers' subjective norm (SN) which related social influence and personal attitude are also critical determinants of individuals' behavioural intentions in the primary evaluation. As shown in Table III, the EQ and PV are analysed in the secondary assessment, and positive emotions as satisfaction or negative emotion as dissatisfaction are generated in response to stimuli that lead to behavioural intentions [17].

On the basis of CAT and discussions from relevant literature (Section 2.5), the present study assumes that the hotel customer behaviour is determined by three appraisal states. The first evaluation is related to customers' motivation to experience robotic service, such as customers' PE, EE and SN. During the second evaluation stage, customers mainly consider the evaluation of

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EQ and overall PV from the perspective of the first motivation, and then form their own positive (satisfied) or negative (dissatisfied) feelings, which are combined with PV and finally related to their intention to revisit the robot hotel. Therefore, the secondary appraisal is an overall satisfaction evaluation based on customers' motivation in the form of PE, EE and SN toward the robotic service and formed their experiential assessment and PV. Moreover, the customers' decision related to the intention of revisiting the robot hotel is likely to be determined by customers' assessment of robotic service mediated by OS, which are generated through a complex multistage appraisal process [18]. Therefore, we proposed a conceptual framework to integrate seven structures: (1) PE, (2) EE, (3) SN, (4) EQ, (5) PV, (6) OS and (7) RPI. The details are shown in Figure 1.

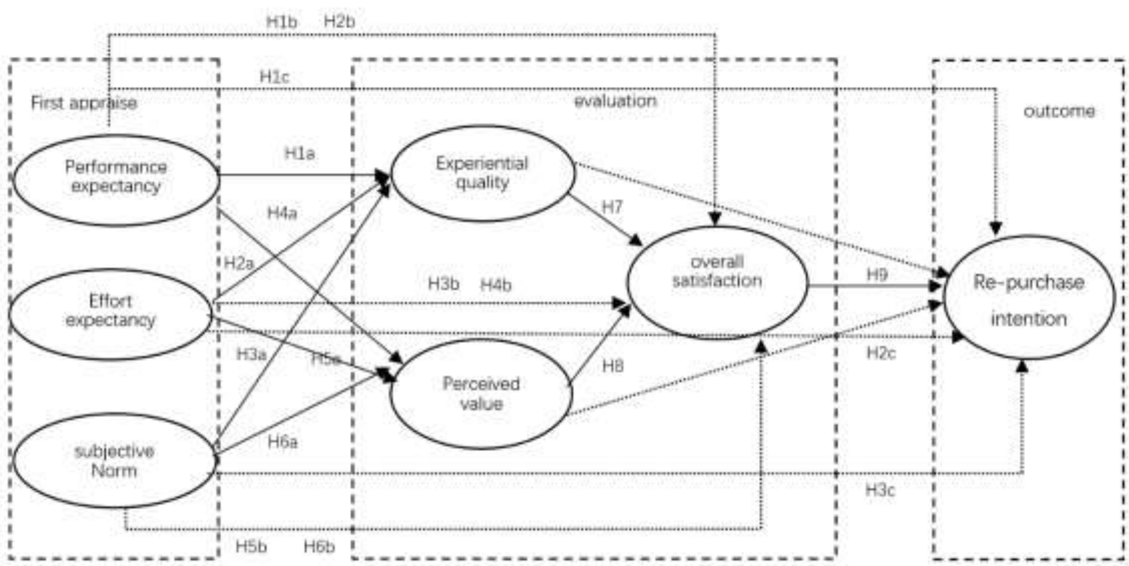

Fig 1: multi-stage process framework of robot service assessment

Base on the concept framework, this study proposed the following hypothesis.

H1a. The performance expectancy of robot has positive effect on hotel customer experiential quality.

H2a. The effort expectancy of robot has positive effect on hotel customer experiential quality.

H3a. The subjective norm of robot has positive effect on hotel customer experiential quality.

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H4a. The performance expectancy of robot has positive effect on hotel customer perceived value.

H5a. The effort expectancy of robot has positive effect effect on hotel customer perceived value.

H6a. The subjective norm of robot has positive effect on hotel customer perceived value.

H7. Experiential quality has a positive effect on hotel customers' overall satisfaction.

H8. Perceived value has a positive effect on hotel customers' overall satisfaction.

H9. Overall satisfaction has a positive effect on the repurchase intention of hotel customers.

H1b. The performance expectancy of robot has a positive indirect effect on hotel customer overall satisfaction through experiential quality.

H2b. The performance expectancy of robot has a positive indirect effect on overall satisfaction through perceived value.

H1c. The performance expectancy of robot has a positive indirect effect on repurchase intention through experiential quality, perceived value and overall satisfaction.

H3b. The effort expectancy of robot has a positive indirect effect on hotel customers' overall satisfaction through experiential quality.

H4b. The effort expectancy of robot has a positive indirect effect on hotel customers' overall satisfaction through perceived value.

H2c. The effort expectancy of robot has a positive indirect effect on repurchase intention through experiential quality, perceived value and overall satisfaction.

H5b. The subjective norms of robotic service has a positive indirect effect on hotel customers' overall satisfaction through experiential quality.

H6b. The subjective norms of robotic service has a positive indirect effect on hotel customers' overall satisfaction through perceived value.

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H3c. The subjective norms of robot service has a positive indirect effect on repurchase intention through experiential quality, perceived value and overall satisfaction.

III. METHODOLOGY AND RESULT ANALYSIS

3.1 Research Design

The present study targets the relationship between the robot hotel service and customer experience evaluation and the influence of robotic service on customer satisfaction and RPI through developing a model to measure the relationship amongst them. In order to test and confirm the correlation relationship between these hypotheses, this study will adopt quantitative research methods based on the paradigm of positivism, mainly using the quantitative method of positivism. A questionnaire is designed according to the measurement items of each dimension in the research framework, and validity of each item is analysed. Before theinvestigation, the researchers conducted a pilot test before the questionnaires were officially distributed. The pre-test was conducted in the robot hotel of Shanghai, China, and 40 pre-test questionnaires were distributed to the customers of the robotic service in hotels. In using this method, researchers can adjust the survey according to the feedback of the questionnaire. Finally, the main survey was conducted through convenient sampling of robot hotel customers and data analysis was approached with the statistical analytic method of PLS-SEM.

3.2 Demography Information of Samples

In this study, a total of 400 questionnaires distributed to the targeted respondents and 331 questionnaires were collected in the main survey after elimination of invalid questionnaires. There are 331 respondents that were tested in this study, 42.3% were male and 57.7% were female. The most frequent age group was the 35-55 group, accounting for 59.21% of the sample. The majority of the respondents' income keep the 2001-5000 US dollars per month (59.52%) and next are 1001-2000 US dollars per month (21.15%), and a few respondents' income are above 5001 US dollars. In terms of education, 46.83% of the hotel employees had diploma from college, 24.47% had Bachelor's degrees and master degrees (16.31%), and only 2.42% are below the college. Most respondents (55.59%) take a travelling once a year and some respondents (27.29%) had traveling twice a year. Other respondents have more than three times travelling every year except some respondents (10.57%) do not have a travelling every year. As for the purpose for travelling, most respondents are for leisure & vacation (30.51%) and for entertainment (29.91%), and then for sightseeing (11.18%), for visiting relatives and friends (11.18%), For health recuperation (9.97%) and other purpose (7.25%). Finally, 54.38% interviewees stay in mid-scare hotel when they travel or be out for business, 34.14% stay in budget hotels, and 9.97% stay in

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luxury hotels and stay in other hotels.

3.3 Model Assessment

The measurement model assessment involves the evaluation of construct measures' reliability and validity. There are difference measures between the reflective construct and formative construct in assessment.[19] This research takes the assessment of reflective measurement models, which involves evaluating the measures' reliability (i.e. indicator reliability and internal consistency reliability) and the validity (i.e. convergent and discriminant validity). The indicator loadings should be larger than 0.7 to ensure indicator reliability. To establish internal consistency reliability, Cronbach's alpha and composite reliability (CR) should be higher than the threshold of 0.7. The average variance extracted (AVE), which should be larger than 0.5, allows assessing convergent validity (Ali, et al, 2017). For the validity, instead of using traditional methods for discriminant validity assessment, such as cross loadings and the Fornell- Larcker criterion, researchers should apply the heterotrait-monotrait (HTMT) criterion.

3.4 Reliability Analysis

During the research process, through smartpls3.0 software, Cronbach's α was used to test the reliability of the scale to ensure that the scale has good reliability and internal consistency reliability. It is generally believed that the Cronbach's α of the test result is greater than 0.70, and the measurement model has better reliability, and the larger the value of Cronbach's α, the higher the internal consistency as a measured observation variable. After the reliability analysis of the research sample data, the reliability test results are as follows (Table I). Cronbach's α are all greater than 0.7, indicating that the variables have good internal consistency, the measurement model has good reliability, the design is relatively reasonable, the survey data is reliable which can reflect the true degree of the measured feature, and can retain all items for the next data analysis.

Table I. Reliability Statistics

Construct	N of items	Cronbach's a
Performance expectancy	8	0.901
Effort expectancy	3	0.842
subjective Norm	7	0.934
Experiential quality	11	0.954
Perceived value	5	0.898
Re-purchase intention	4	0.854

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overall satisfaction	3	0.908

3.5 Validity Analysis

3.5.1 Convergent validity

It is generally considered that CR>0.7 and AVE >0.5, indicating that the latent variable has Ideal aggregation validity (Chin, 2010; Hair et al., 2017). In this paper, through the Smartpls3.0 software, the convergent validity results are shown in Table II. It can be seen that the factor loading are all greater than 0.5, indicating that all are significant; the combined reliability (CR) value is greater than 0.7, which proves the observation of the same dimension. The variables have good credibility, and the inherent quality of the model is ideal; the average variance extraction (AVE) is greater than 0.5, indicating that the observed variables can effectively reflect the potential characteristics of their common factor dimensions, and the convergent validity is good.

TABLE II. Assessment of measurement model

CONSTRUCT	ITEMS	LOADING	T VALUE	RHO_A	CR	AVE
PERFORMANCE EXPECTANCY	PE1	0.823	38.565	0.904	0.921	0.593
	PE2	0.821	44.659			
	PE3	0.742	22.259			
	PE4	0.811	33.636			
	PE5	0.746	26.044			
	PE6	0.743	23.232			
	PE7	0.704	22.673			
	PE8	0.762	23.902			
EFFORT EXPECTANCY	EE1	0.894	66.421	0.843	0.905	0.760
	EE2	0.887	69.984			
	EE3	0.834	43.260			
SUBJECTIVE NORM	SN1	0.799	37.882	0.935	0.947	0.718
	SN2	0.867	45.820			
	SN3	0.874	63.405			
	SN4	0.870	55.712			
	SN5	0.873	62.447			
	SN6	0.885	64.736			
	SN7	0.754	25.654			
EXPERIENTIAL QUALITY	EQ1	0.810	34.429	0.954	0.96	0.68

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	EQ2	0.828	41.916		0	4
	EQ3	0.847	49.116			
	EQ4	0.794	29.834			
	EQ5	0.803	28.594			
	EQ6	0.806	36.505			
	EQ7	0.828	41.164			
	EQ8	0.840	40.346			
	EQ9	0.850	49.592			
	EQ10	0.831	38.771			
	EQ11	0.857	50.330			
	PV1	0.874	60.941			
	PV2	0.849	49.336			
PERCEIVED VALUE	PV3	0.814	30.028	0.900	0.92 5	0.71 1
	PV4	0.850	48.674			
	PV5	0.828	31.648			
	OS1	0.876	53.937			
	OS2	0.896	68.745			
OVERALL SATISFACTION	OS3	0.878	62.321	0.909	0.93 6	0.78 4
	OS4	0.892	69.903			
	PI1	0.890	71.012			
RE-PURCHASE INTENTION	PI2	0.897	73.829	0.859	0.91 1	0.77 4
	PI3	0.853	28.545			

Note: Performance Expectancy (PE), Effort Expectancy(EE), Subjective Norm(SN), Experiential Quality(EQ), Perceived Value(PV), Perceived Value(PV), Overall Satisfaction(OS), Re-purchase Intention(PI)

3.5.2 Discrimination validity

Discriminant validity is the extent to which each LV is distinct from other constructs in the model (Chin, 2010; Hair et al., 2017). Discriminant validity assessment has become a generally accepted prerequisite for analyzing relationships between latent variables. Here, Fornell-Larcker criterion approaches were employed.

Fornell-Larcker criterion: Discriminative validity refers to the degree of discrimination between variables (Chin, 2010; Hair et al., 2017). Generally, the square root of AVE and the correlation coefficient are used to test. When the square root of AVE of a variable is greater than the correlation coefficient of the variable and other variables, it means that the internal

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correlation of the variable is greater than the external correlation, indicating that the variables have good discrimination validity. It can be found from the Table III that the square root of the AVE of each variable is greater than the correlation coefficient between this variable and other variables, indicating that the discrimination validity between the variables in this study meets requirements.

TABLE III. Fornell-Larcker criterion

CONSTRUCT	EE	EQ	PV	PE	RPI	OS	SN
EE	(0.872)						
EQ	0.717	(0.827)					
PV	0.653	0.819	(0.843)				
PE	0.720	0.785	0.737	(0.770)			
RPI	0.589	0.808	0.785	0.724	(0.880)		
OS	0.657	0.816	0.802	0.732	0.827	(0.885)	
SN	0.672	0.708	0.622	0.659	0.631	0.619	(0.847)

3.6 Assessment of Structure Model

The study uses GoF, R^2, and Q^2 to test the goodness of fit and predictive power of the model. GoF is an important indicator to measure the goodness of the PLS model. There are three levels for the GoF indicator: GoF low = 0.1, GoF medium = 0.25, GoF high=0.36. The GoF of this model is 0.695, indicating that the model has a good degree of fit, and the R^2 value represents the ability of exogenous latent variables to explain changes in endogenous latent variables. The R^2 of Experiential quality, Perceived value, Overall satisfaction, Re- purchase intention are 0.698, 0.590, 0.719, 0.764, indicating that the model has a better explanatory ability. In addition, the Q^2 values of Experiential quality, Perceived value, Overall satisfaction, and Re-purchase intention are all greater than 0, which meets the requirements of predictive ability.

3.7 Predictive Poerr of Model

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3.7.1 Direct effect test results

This study uses the Bootstrapping algorithm in the SmartPLS3.0 software to select a resampled sample test with a capacity of 5000 for the original data to analyze the direct path results of the model. The hypothesis test results are shown in the following Table IV:

TABLE IV. Results of the direct effect hypotheses

HYPOTHESES	**PATH RELATIONSHIP**	PATH COEFFICIENT	**T**	**P**	**CONFIDENCE INTERVAL (97.5%) BIAS CORRECTED**
H1A	Performance expectancy→ Experiential quality	0.462	6.653	0.000	[0.335,0.605]
H2A	Effort expectancy → Experiential quality	0.206	3.540	0.000	[0.091,0.317]
H3A	Subjective Norm→ Experiential quality	0.266	4.842	0.000	[0.158,0.371]
H4A	Performance expectancy → Perceived value	0.490	6.494	0.000	[0.347,0.644]
H5A	Effort expectancy→ Perceived value	0.182	2.706	0.007	[0.044,0.311]
H6A	subjective Norm→ Perceived value	0.177	2.751	0.006	[0.054,0.310]
H7	Experiential quality→ overall satisfaction	0.484	5.336	0.000	[0.312,0.660]
H8	Perceived value → overall satisfaction	0.405	4.384	0.000	[0.222,0.576]
H9	overall satisfaction→	0.827	26.962	0.000	[0.762 ,0.88

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Re-purchase intention	1]

It can be found from the table that the path coefficient of Performance expectance to Experimental quality is 0.462 (t=6.653, P<0.01), indicating that Performance expectance has a significant positive impact on Experimental quality, H1a is Supported; The path coefficient of Effective to Experimental quality is 0.206 (t=3.540, P<0.01), indicating that Effort expectancy has a significant positive effect on the Experimental quality, H2a is Supported; the path coefficient of Subjective Norm to the Experimental quality is 0.266 (t=4.842, P<0.01), It shows that Subjective Norm has a significant positive impact on the Experimental quality, H3a is Supported; the path coefficient of Performance expectance to the Performed value is 0.490 (t=6.494, P<0.01), which shows that Performance expectance has a significant positive impact on the Performed value. H4a is Supported; the path coefficient of Effort expectancy to the Perceived value is 0.182 (t=2.706, P<0.01), which indicates that Effort expectancy has a significant positive effect on the Perceived value, H5a is Supported; the path coefficient of Subjective Norm to the Perceived value is 0.177 (t=2.751, P<0.01), indicating that Subjective Norm has a significant positive impact on the Perceived value, H6a is Supported; the path coefficient of Experiential quality to overall satisfaction is 0.484 (t=5.336, P<0.01), indicating that Experimental Quality has a significant positive effect on overall satisfaction, H7 is Supported; the path coefficient of Perceived value to overall satisfaction is 0.405 (t=4.384, P<0.01), indicating that Perceived value has a significant positive effect on overall satisfaction, H8 Supported; Overall satisfaction The path coefficient of overall satisfaction to Re-purchase intention is 0.827 (t=26.962, P<0.01), indicating that Overall satisfaction has a significant positive impact on Re-purchase intention, H9 is Supported.

3.7.2 Indirect effect test results

The indirect relationship in the study is mainly realized through PLS and Bootstrapping. The path coefficient of the indirect effect test is shown in the Table V. From the table, it can be found that the indirect effect of Performance expectancy on overall satisfaction through Experimental quality is 0.223, and the confidence interval does not contain 0, indicating H1b is supported; the indirect effect of Performance expectancy on overall satisfaction through the Performed value is 0.199, and the confidence interval does not contain 0, indicating H2b is supported; the indirect effect of Performance expectancy on Re-purchase intention through Experiential quality and overall satisfaction is 0.185, and the confidence interval does not include 0, and the indirect effect of Performance expectancy on Re-purchase intention through Performed value and overall satisfaction is 0.164, and the confidence interval is not Contains 0, indicating H1c is supported.

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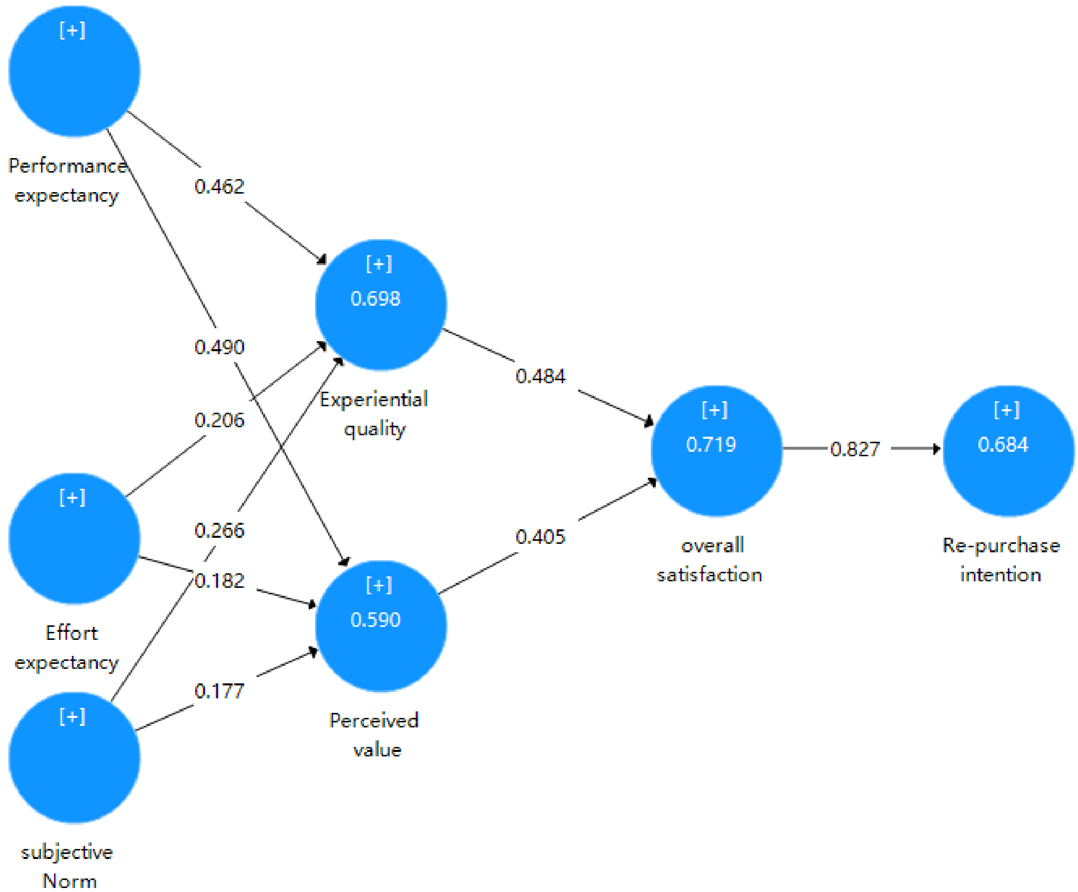

Fig 2: Structural model diagram

The indirect effect of Effort expectancy on overall satisfaction through Experimental quality is 0.099, and the confidence interval does not contain 0, indicating H3b is supported; the indirect effect of Effort expectancy on overall satisfaction through Perceived value is 0.074, the confidence interval does not contain 0, indicating H4b is supported; the indirect effect of Effort expectancy on Re-purchase intention through Experimental quality and overall satisfaction is 0.082, and the confidence interval does not contain 0 The indirect effect of Effort expectancy on Re-purchase intention through Perceived value and overall satisfaction is 0.061, and the confidence interval does not contain 0, indicating H2c is Supported.

The indirect effect of Subjective Norm on overall satisfaction through Experimental quality is 0.128, and the confidence interval does not contain 0, indicating H5b is supported; the indirect effect of Subjective Norm on overall satisfaction through Perceived value is 0.072, the confidence interval does not contain 0, indicating H6b is supported; the indirect effect of Subjective Norm con Re-purchase intention through Experiential quality and overall

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satisfaction is 0.106, and the confidence interval does not contain 0 , the indirect effect of Subjective Norm on Re-purchase intention through Perceived value and overall satisfaction is 0.059, and the confidence interval does not contain 0, indicating H3c is Supported.

TABLE V. Results of the indirect effect hypotheses

HYPOTHESES	PATH RELATIONSHIP	INDIRECT EFFECT	T	CONFIDENCE INTERVAL (97.5%) BIAS CORRECTED	SUPPORTED
H1B	PE→ EQ→ OS	0.223	3.987	[0.125,0.344]	Yes
H2B	PE→ PV→ OS	0.199	3.405	[0.097,0.327]	Yes
H1C-1	PE→ EQ → OS→RPI	0.185	3.899	[0.102,0.287]	Yes
H1C-2	PE → PV→ OS →RPI	0.164	3.337	[0.079,0.272]	Yes
H3B	EE → EQ → OS	0.099	2.865	[0.039 ,0.174]	Yes
H4B	EE→ PV→ OS	0.074	2.220	[0.016,0.146]	Yes
H2C-1	EE → EQ → OS →RPI	0.082	2.824	[0.032,0.146]	Yes
H2C-2	EE → PV → OS →RPI	0.061	2.210	[0.013,0.121]	Yes
H5B	SN→ EQ → OS	0.128	3.302	[0.060,0.212]	Yes
H6B	SN→ PV → OS	0.072	2.220	[0.020,0.144]	Yes
H3C-1	SN→ EQ → OS →RPI	0.106	3.261	[0.050 ,0.177]	Yes
H3C-2	SN→ PV → OS →RPI	0.059	2.196	[0.016 ,0.121]	Yes

IV. CONCLUSION AND DISCUSSION

4.1 Conclusion of Results

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The results of this study support the proposed model, which demonstrates the relationships between seven structures related to RPI of customers. The results show that in the robotic service in hotels in China, the scale used can effectively and reliably measure these seven constructs. Both internal reliability and construct validity of each latent construct were found to be satisfactory. Moreover, the model fit indices validated a good fit between the measurement model and the dataset. The equivalent results of cross-validation between the two parts of the dataset further demonstrated the generalizability of the measurement model. The multi-group invariance analysis also established that the measurement models are comparable across different groups of samples. The structural model was also fit with the obtained data. Therefore, the measurement model and structural model are satisfactory, effective and reliable in measuring structures and estimating their relationships.

The eighteen proposed hypotheses in this study model are supported. PE, EE and SN directly and positively affect customer EQ and PV of hotels, and they are also found to indirectly and positively affect customers' OS mediated by EQ and PV. Two direct effects from EQ and PV to customer satisfaction were found to be significant. Besides, the indirect relationships between PE of robotic service and RPI were found to be significant and were proven to be mediated by EQ and OS. At the same paths, EE and SN both influence the RPI separately mediated by EQ and OS. The influence of SN was not as strong as the previous assumptions.

4.2 Theoretical and Practical Contributions

As one of the few overall studies in the hotel industry regarding the determinants and results of robot customers' experience evaluation, this research filled the research gap between theoretical and practical contributions. Firstly, this study proposed a seven-structure model to test the influence of robotic service on hotel customer service experience evaluation, customer satisfaction and RPI behaviour through a complex multistage evaluation process. The research framework developed in the current study provides a psychological perspective for the research of service robots, and forms a new theoretical framework model to test the customers' experience evaluation under the background of robotic service in hotels, which is a useful supplement to the research of robotic service experience. In addition, the finding of this study confirmed that there is a relationship between robotic service evaluation and hotel customers' EQ, hotel overall PV, hotel OS, and RPI of hotels in this framework. Secondly, on the basis of the relevant literature review (Oliver, 1980; Chen and Tsai, 2007), the finding of this study provides PE, EE and SN as the direct antecedents of influencing customer experience and PV in the background of robotic service in hotel, and these antecedents affect the OS and RPI of the hotel through the EQ evaluation and PV. All these dimensions in the conceptual model can

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be used in future research related to service experience, satisfaction and loyalty of robotic service or AI new technology. Finally, this study also focuses on the broader concept of robotic service, and evaluates the mediating role of EQ, overall PV and OS between robotic service evaluation and RPI of hotels through an empirical test of the conceptual model. This further promotes the research on the relationship amongst the customer experience, satisfaction and RPI in the field of smart hotels, and this study provides a reference for studying the influence of technical service application on hotels.

This study can be valuable in terms of service robot application in the hospitality industry by combining constructs as customer expectancy, SN, EQ and OS and RPI. Hoteliers, service robot design and customers are the major stakeholders. Good application of robotic service in the hospitality industry will benefit them all. Therefore, the practical implications can be of major use to Hoteliers, service robot design and sales companies, and customers. Based on the finding of this study, hoteliers should ensure that their robotic service can meet customers' PE, such as providing more accurate and consistent information, making less error during the service encounter, supporting more dependable and predictable service, and so on. Hotel managers should conduct several trials to ensure the performance of all robotic services running normally. On the other hand, from the perspective of customer consumption expectations, robot designers should pay more attention to enhance the service efficiency, stability and intelligence level during the designing process. In terms of efficiency and stability, strengthening the stability of the intelligent service robot and reducing the failures in the service process are the prerequisites to ensure the service efficiency and stability.

4.3 Limitation

The current study has some limitations. In the present study, the sample was collected in a hotel in China. Most respondents in the investigation are Chinese customers and customers from other countries are limited, especially the data collection during the COVID-19 pandemic, and foreign tourists are rare. Therefore, the research results are favourable to Chinese customers but not universal. Besides, Cognition refers to the understanding and evaluation of what happens when people encounter adaptability in life. Human cognition is based on knowledge and experience to evaluate the importance of what happens when people contact the environment [17]. Different individuals have certain differences in cognition of the same thing, including gender differences, which illustrate that group differences can be used as coordination variables for the following research. Therefore, it is necessary to subdivide different groups, which is more conducive to judging the accuracy of the results of this study.

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