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Predictors of Consumers' Intention to Dine at Robot Chef Restaurants: Anthropomorphism as Moderator

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ABSTRACT

Foodservice establishments are incorporating innovative technologies, such as robot chefs, to meet consumer demand for contactless dining experiences following the COVID-19 pandemic. Using Stimulus-Response theory, this study examined the drivers of customers' intentions to dine at robot-chef restaurants. Data was collected through a questionnaire administered using Qualtrics. The Partial Least Squares structural equation modeling (PLS-SEM) technique was applied to analyze 434 responses. Findings showed that performance expectancy, perceived food quality, and perceived hygiene positively affect customers' dining intentions at robot-chef restaurants. In addition, the positive effects of performance expectancy and perceived food quality become weaker when robot chefs are anthropomorphized. The findings of this study provide valuable insights for academics and foodservice industry practitioners to enhance consumer acceptance and ensure the successful adoption of capital-intensive robotic chef technologies.

Keywords: Robot chef; Performance expectancy; Perceived food quality; Perceived food hygiene; Anthropomorphism

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INTRODUCTION

The restaurant sector is widely recognized for its dynamic nature and its propensity for introducing innovative culinary techniques, tools, and equipment (Cifci & Alrawadieh, 2023). In 2025, the U.S. restaurant customer traffic was down from a year ago, and the Restaurant Performance Index (RPI) declined slightly, indicating continued contraction in restaurant industry activity (National Restaurant Association [NRA], 2025). Moreover, the National Restaurant Association (NRA) reported that restaurant operators in various states in the U.S. are facing the challenge of staffing shortages (NRA, 2025). Furthermore, the COVID-19 pandemic has heightened consumers' concerns about food safety and hygiene (Yang, 2021), which has resulted in increased demand for contactless dining experiences (Fusté-Forné, 2021).

In response to these challenges and emerging trends, players in the restaurant industry have begun turning to robotic chefs to enhance hygiene through contactless food handling (Chuah et al., 2022), reduce costs amid high inflation, and overcome labor shortages (Seyitoğlu et al., 2025). However, despite the growing need for robotic chefs in recent years, research on this topic is still in its early stages (Parvez, 2025), with little empirical work conducted in customer settings to examine the drivers of consumers' intentions to dine at robot-chef restaurants. Since the success of any new operational system requires initial customer support (Zhu, 2022), it is important to address this gap in the literature to reduce the risk of operational failure and the substantial capital waste associated with adopting this technology (Ivanov et al., 2025).

Earlier studies have examined attitudes toward robot chefs in different settings and from various perspectives. For example, Ivanov and Webster (2019) studied people's perceptions of using robots for different hospitality tasks, including restaurants settings. They found that the use of robots for cooking food was not considered appropriate. In contrast, Zemke et al. (2020) found that restaurant diners regarded robots as suitable for food preparation. In addition, Seyitoğlu et al. (2021) conducted semi-structured interviews to assess the perceptions of Turkish restaurant managers and customers regarding robot chefs. They found that customers generally hold positive attitudes towards robot chefs, whereas managers tend to have negative perceptions.

In another study, Fusté-Forné (2021) employed a qualitative research design to investigate tourists' perceptions of robot chefs in restaurants and identified potential advantages of incorporating robots into the hospitality and tourism industry. The findings of the study also revealed that tourists view the increasing presence of robots in food services as a means of dehumanizing the gastronomic experience. In three experiments conducted by Xiao and Zhao (2022), they examined factors influencing people's predictions of food quality in robot-cooked meals and found that participants anticipated food prepared by robotic chefs to be of above-average quality. Their findings also revealed that regardless of the complexity of the dishes, novel cues in chefs and food, or the level of anthropomorphism of the robotic chefs, participants consistently had lower expectations of food quality from robotic chefs compared to human chefs.

Moreover, the study conducted by Zhu and Chang (2020) explored the influence of imbuing robotic chefs with human-like traits, known as anthropomorphism, on the prediction of food quality and found that robotic chef anthropomorphism affects food quality prediction through the sequential mediators of warmth and competence. Furthermore, Zhu (2022) examined the effects of food quality, service quality, and perceived high-tech atmosphere in robotic-chef restaurants on customers' experience intention and patronage intention. The results indicated that perceptions of food quality directly impacts the intention to become a regular patron but it does not significantly influence the intention to have a particular dining experience. On the other hand, the perceptions of service quality and high-tech atmosphere positively influence experience intention and regular patronage intention through the mediator of interest in robot restaurants.

Taken together, earlier research indicates a growing positive attitude among consumers toward food prepared by robot chefs. However, the effects of perceived hygiene, perceived food quality, and performance expectancy of robot chefs on consumers' intentions to dine at robot-chef restaurants have received little attention in the current literature. Moreover, while previous studies have examined the influence of anthropomorphism on food quality prediction (Zhu & Chang, 2020), the moderating effect of anthropomorphism on the relationships between perceived hygiene, perceived food quality, and dining intention at robot-chef restaurants has not been extensively explored. To address these limitations, this study uses the Stimulus–Response (S–R) theory to examine the effects of performance expectancy,

perceived food quality, and perceived hygiene as stimuli that trigger responses in dining intention at robot-chef restaurants.

The findings of this study contribute to the literature by advancing understanding of the underlying factors that influence customer decision-making and intention formation in the context of robot-chef contactless dining experiences. In practice, the findings help restaurant operators by highlighting that robot-chef restaurants must simultaneously communicate a clean food preparation process, high quality of the final food product in terms of taste, variety, and aesthetics, and high consistency and accuracy of operation to attract customers.

LITERATURE REVIEW

Stimulus–Response (S–R) Theory

Developed in the early 20th century, the stimulus–response (S–R) theory, which combines psychological and sociological perspectives, was first proposed by Watson (1913). He argued that human behavior can be understood as a combination of stimuli and corresponding responses, the two essential components of the framework (Guo et al., 2025). Stimulus (S) encompasses both internal (individual) and external (environmental) factors that trigger a response, while response (R) refers to the behavioral actions exhibited by humans in reaction to these interconnected stimuli, which may be positive or negative (Zhang et al., 2022). The theory has been used to study consumer behavior in previous studies (Agostini et al., 2021; Chen & Li, 2020; Yang et al., 2024). A stimulus can lead to various responses, such as intentions, decisions, or changes in behavior (Guo et al., 2022). This study proposes that the functional attributes of robot chefs (e.g. performance expectancy) and the attributes of food cooked by robot chef (e.g., perceived food quality and hygiene) serve as stimuli that trigger customers' reactions, specifically their intention to dine at a robot-chef restaurant.

Performance Expectancy

Performance expectancy refers to the extent to which robots can deliver reliable and consistent service to consumers (Lu et al., 2019). In this study, performance expectancy is defined as the extent to which robot chefs cook food with consistency, accuracy, and precision. The importance of performance expectancy in the adoption of emerging technologies (Venkatesh et al., 2012), particularly robots, has been shown in previous studies (Gursoy et al., 2019; Lin et al., 2020). For example, Lu et al. (2019) demonstrated that performance expectancy influences consumers' inclination to utilize service robots. Similarly, Subero-Navarro et al. (2022) found a positive influence of performance expectancy on customers' intention to use service robots in retail settings. Additionally, Lee et al. (2021) identified performance expectancy as a factor shaping guests' intention to use hotel robot assistants. While previous studies have conceptualized performance expectancy in service-robot settings, the current study suggests that consumers may also consider the functional aspects of robot chefs when deciding to dine in a robot-chef restaurant context. For example, they may evaluate whether the food prepared by robot chefs consistently matches what is described on the menu. Given that performance expectancy functions as a functional stimulus (Zhang et al., 2022), it is likely to influence customers' intentions to dine at robot-chef restaurants. Therefore, this study proposes the following hypothesis:

H1. Performance expectancy has a positive influence on customers' intention to dine at a robot chef restaurant.

Perceived Food Quality

The core competency of a restaurant resides in its food, and it is the quality of that food that defines its performance (Zhu & Chang, 2020). Customers attach great importance to food quality and often prioritize it over other attributes when choosing a restaurant (Lu & Gursoy, 2017). Perceived food quality refers to

consumers' overall evaluation of the excellence of food in terms of its nutritional value and desirability (Liu et al., 2022). In this study, perceived food quality is defined as consumers' overall assessment of the taste, nutritional value, and aesthetics of the food prepared by robot chefs.

According to prior research, the primary factor affecting consumers' behavioral intentions in restaurant settings is the food quality (Zhu & Chang, 2020). For instance, Ryu and Han (2010) discovered that food quality holds the greatest predictive power for consumer behavioral intentions in quick-casual dining establishments. Ha and Jang (2012) also found that customers who positively evaluate food quality in a restaurant are more likely to visit the restaurant in the future. Similarly, Mohamad et al. (2022) showed that perceived food quality is a significant predictor of consumers' behavioral intentions in the street food context. In addition, Zhu (2022) found that food quality perceptions affects consumers' patronage intentions in robot-chef restaurants in China. Given that prior studies have underscored the role of consumers' perceptions of food quality in shaping decision-making (Baiardi et al., 2016), this stimulus may influence consumers' behavioral intentions toward food prepared by robot chefs. Hence, this study proposes the following hypothesis:

H2. Perceived food quality has a positive influence on customers' intention to dine at a robot chef restaurant.

Perceived Food Hygiene

Hygiene practices in the food preparation process involve maintaining food cleanliness, ensuring proper sanitation procedures, and preventing contamination from various sources, including chemicals, physical substances, and microorganisms (Chandimali et al., 2025). In this study, perceived hygiene refers to the extent to which consumers believe that robot chefs maintain cleanliness and ensure proper sanitation during the food preparation process, rather than focusing on the attributes of the final food products. In light of the COVID-19 pandemic, customers have shown a growing awareness of hygiene (Kazancoglu & Demir, 2021). They have become more attentive to food hygiene (Eslamdoust et al., 2024; Francioni et al., 2022) and have begun prioritizing it over cost and convenience (Liu et al., 2022) when selecting restaurants. This heightened attention is primarily driven by their increased concerns that inadequate hygiene practices may lead to food contamination with viruses or foodborne illnesses such as food poisoning (Shim et al., 2021).

Findings from recent studies show that perceived hygiene plays an important role in shaping individuals' decision-making and purchase intentions (Francioni et al., 2022; Pillai et al., 2021). For example, Al Amin et al. (2021) found that ensuring proper hygiene in food delivery had a positive influence on customers' intention to continue using mobile food delivery applications amid the COVID-19 pandemic. Similarly, Shim et al. (2021) observed a positive link between perceived hygiene and customers' inclination to purchase coffee services. Likewise, the study conducted by Francioni et al. (2022) revealed that customers' perceptions of hygiene related to online food delivery services (OFDS) had a positive impact on their intention to continue using them. While prior studies have demonstrated the significant effect of hygiene on food-related decisions, they have conceptualized perceived hygiene in the context of food preparation by human chefs rather than robot chefs. Since perceived hygiene plays an important role in food preparation (Mohamad et al., 2022), this external stimulus within the S–R framework may also shape consumers' decision-making when the process is carried out by robot chefs. Hence, this study proposes that:

H3. Perceived hygiene has a positive influence on customers' intention to dine at a robot chef restaurant.

The Moderating Effect of Robot Anthropomorphism

Anthropomorphism has been defined as "people's tendency to attribute human traits to non-lifelike artifacts" (Duffy, 2003, pp. 199-200). Spatola and Wudarczyk (2021) defined robot anthropomorphism as the attribution of human-like characteristics to non-human agents such as robots. Anthropomorphism can produce both positive effects (Calahorra-Candao & Martín-de Hoyos, 2024) and negative effects (Gong, 2025; Grazzini et al., 2023), yet little research has explored its interaction with food-related perceptions. Thus, it is important to examine how anthropomorphism moderates the relationship between consumers' perceptions of robot chefs' functional and food attributes and their intention to dine at such restaurants. Consumers often view robot chefs as machines (Xiao & Zhao, 2022); hence, they evaluate performance primarily based on accuracy, precision, and consistency rather than on creativity or the capacity to cook aesthetically pleasing dishes. However, when robot chefs are anthropomorphized, consumers' evaluations of performance shift toward human-like skills such as creativity in cooking (Kazakova et al., 2025). Consequently, anthropomorphism may weaken the impact of performance expectancy on consumers' intention to dine at robot-chef restaurants because robot chefs lack the artisanal qualities associated with human craftsmanship (Nozawa et al., 2022). Therefore, we hypothesize:

H4. Anthropomorphism moderates the relationship between performance expectancy and intention to dine at robot chef restaurant, such as the positive relationship (H1) is weaker for higher level of anthropomorphism.

Food prepared by robot chefs is often viewed as machine-made, which is perceived as less natural, less appealing, and less artisanal by consumers compared to food prepared by human chefs (Abouab & Gomez, 2015; Fuchs et al., 2015). Additionally, human chefs believe that robots transform dishes into ordinary, fabricated products, which they perceive as being of lower quality compared to food cooked by humans (Bucak & Yiğit, 2021). Hence, adding human-like features to robots may weaken the effect of perceived food quality on consumers' intention to dine at robot-chef restaurants. This occurs because consumers evaluate food prepared by anthropomorphized robot chefs based on human standards, and in many cases, robot chefs may underperform relative to human chefs due to their lack of tacit knowledge and culinary skills (Seyitoğlu et al., 2021). Therefore, we hypothesize:

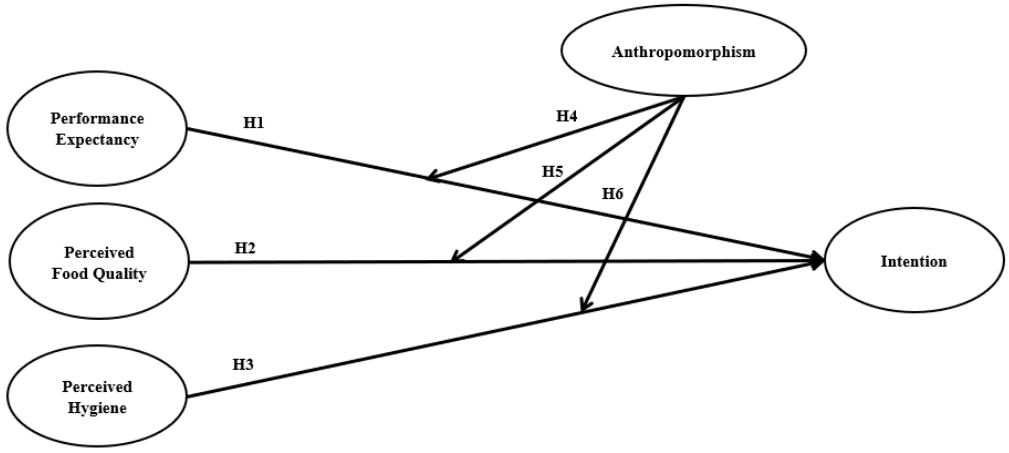
H5. Anthropomorphism moderates the relationship between perceived food quality and intention to dine at robot chef restaurant, such as the positive relationship (H2) is weaker for higher level of anthropomorphism.

Robot chefs are often viewed as mechanical systems (Sochacki et al., 2024) that cook food with consistent sanitary precision (Parvez, 2025) and provide a touchless dining experience by eliminating human contact (Gong et al., 2025). However, as robot chefs become more humanlike, consumers may begin to question whether they maintain the same hygienic advantages they expect from machines, such as a reduced cross-contamination (Seyitoğlu et al., 2025). The anthropomorphism of robot chefs may evoke hygiene concerns that are typically reserved for human chefs (Koch et al., 2021), such as a greater likelihood of contamination, thereby weakening the impact of perceived hygiene on consumers' dining intentions in robot-chef restaurants. Hence, we hypothesize that:

H6. Anthropomorphism moderates the relationship perceived hygiene and intention to dine at robot chef restaurant, such as the positive relationship (H3) is weaker for higher level of anthropomorphism.

Figure 1 illustrates the conceptual model of this study.

Figure 1
Conceptual Model of the Study



Source: Authors' Work

METHODS

Survey Instrument Development

The survey questionnaire was developed via Qualtrics and included images of two different robot chefs, one humanized and one nonhumanized, each shown in a different kitchen setting preparing different food items, accompanied by a brief explanation of the robot chefs' functions. The questionnaire also contained items measuring research constructs as well as demographic questions. Participants were asked to review the explanations and images, imagine dining at a robot-chef restaurant, and respond to the questionnaire.

The measurement items were developed using established scales from the existing literature (Table 1). All construct items were measured using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). A pilot study with 40 respondents recruited via Prolific, was conducted to ensure the clarity and readability of the scale. No unclear or ambiguous sentences were identified by participants, confirming the face validity at this stage. Screening questions were included to ensure data quality. Examples include: "Are you over 18 years old?" and "Have you dined at a restaurant within the past year?" Respondents who did not meet the eligibility criteria were screened out, and no data were collected from them. In addition to these screening questions, one attention-check question was added to the survey to ensure response quality.

Data Collection

This study complied with Institutional Review Board (IRB) requirements. Informed consent was obtained from participants, and their participation was anonymous and voluntary. Each participant received $2 for completing the survey. Participants were recruited through Prolific Academic Ltd., an online research platform for collecting high-quality survey data. This platform was chosen because of its rigorous participant screening, which enables researchers to collect high-quality data (Douglas et al., 2023).

Sample

The study's inclusion criteria required participants to be at least 18 years old, currently residing in the United States, and to have dined at a restaurant in the past 12 months. Following the 10-times rule of

Table 1: Demographic profile of the participants			
Variable	Category	*n*	%
Gender	Male	203	46.8
	Female	215	49.5
	Prefer not to mention	16	3.7
Age	18 – 25	71	16.1
	26 – 35	152	35.5
	36 – 45	106	24.5
	46 – 55	51	11.8
	56 – 65	40	9
	66 – 75	13	2.5
Ethnicity	White or Caucasian	313	72.1
	Black or African	31	7.1
	Hispanic or Latino	31	7.1
	American Indian or Alaskan Native	2	0.5
	Asian	34	7.8
	I consider myself to be of multiple ethnicities/races	17	3.9
	Prefer not to respond	6	1.4
Education	Less than high school	5	1.1
	High school graduate or GED	67	15.3
	Some college	101	23.1
	Associate degree	37	8.5
	Bachelor's degree	170	38.9
	Graduate degree (Masters or Doctorate)	46	10.5
	Professional degree	8	1.8
	Prefer not to respond	3	0.7
Income	Less than $20,000	42	9.7
	$20,000 to $39,999	95	21.9
	$40,000 to $59,999	72	16.6
	$60,000 to $79,999	55	12.7
	$80,000 to $89,999	25	5.8
	$90,000 to $99,999	21	4.8
	$100,000 and above	124	28.6
Marital status	Single	252	58.1
	Married	158	36.4
	Others	18	4.1
	Prefer not to respond	6	1.4

thumb, which suggests that the minimum sample size should be at least ten times the maximum number of structural paths pointing to any latent variable in the model (Hair et al., 2021), the target sample size was 450. Responses that failed the screening or attention-check questions, or were incomplete, were removed prior to analysis. After applying these data-quality measures, the final dataset consisted of 434 valid responses.

RESULTS

Partial Least Squares structural equation modeling (PLS-SEM) technique, through SmartPLS 4, was used to analyze the data and assess the proposed hypotheses of the study. PLS-SEM was used as the data analysis tool because the main goal of the study was prediction and explanation (Charmchian Langroudi et al., 2025; Hair & Alamer, 2022). The model was assessed in two steps: assessing the measurement (outer) model and the structural (inner) model.

Common Method Bias (CMB)

In behavioral research, it is important to examine data for common method bias (CMB), as it can affect observed relationships between constructs, resulting in misleading conclusions, which affect the validity of research findings (Podsakoff et al., 2024). To test for CMB, Harman's single-factor test was used (Kock et al., 2021). As the total variance explained by all variables was 41%, it can be argued that CMB is not an issue in this study.

Demographics of the Participants

The participants consisted of 49.5% females (n = 215), 46.8% males (n = 203), and the remainder preferred not to identify their gender. Moreover, the majority of respondents were young, with those aged 26 to 35 forming the largest group at 35.5% (n = 152). Furthermore, 72.1% (n = 313) of the respondents were White, 58.1% (n = 252) were single, and 38.9% (n = 170) held a bachelor's degree (Table 1).

Measurement Model

To assess the measurement model, the measures' reliability as well as the convergent and discriminant validity of the constructs were examined. Except for items A3, PFQ3, and PFQ5 (with loadings of 0.677, 0.698, 0.688 respectively), all the other items had loadings higher than the accepted threshold of 0.7. These items were retained because removing them reduced the AVE and reliability measures. All constructs had composite reliability and Cronbach's alpha of above 0.7, and average variance extracted (AVE) values above 0.5 (see Table 2), which established the measurements' reliability and convergent validity (Hair et al., 2022). The square root of the AVE for every construct was greater than the inter-construct correlation values (Fornell & Larcker, 1981), and the Heterotrait-Monotrait Ratio (HTMT) values were below the 0.9 threshold (Hair et al., 2021). Even though the A-I construct pair's HTMT value is lower than their correlation, the value is acceptable since lower HTMT values can occur in models with conceptually distinct constructs designed to capture different theoretical domains. This reflects strong discriminant validity rather than measurement weakness (Franke & Sarstedt, 2019; Voorhees et al., 2016). Moreover, HTMT is used to detect absence of discriminant validity when the values exceed the accepted thresholds (typically > 0.85-0.90) (Hair et al., 2022). As anthropomorphism is differentiated from other constructs in the model, and the HTMT values involving anthropomorphism are below the accepted thresholds, these lower HTMT values are consistent with both theoretical expectations and established SEM guidelines. Thus, discriminant validity was established (see Table 3).

Structural Model

The guidelines recommended by Hair et al. (2022) were followed in testing the hypothesized conceptual model (Table 5). The structural model was evaluated using Partial Least Squares Structural Equation

Table 2: Measurement model of the study		
Construct and measurement items	Factor Loading	Adapted from
Perceived food hygiene (Cronbach's α: 0.953, CR: 0.966, AVE: 0.878)		Francioni et al. (2022)
PH1. The foods cooked by Robot chefs are clean and hygienic to consume.	0.958	
PH2. The foods cooked by robot chefs are hygienic.	0.958	
PH3. The foods cooked by robot chefs are clean to consume.	0.959	
PH4. Sanitation of ingredients used to cook the foods by robot chefs is well managed.	0.871	
Perceived food quality (Cronbach's α: 0.821, CR: 0.874, AVE: 0.582)		Zhu and Chang (2020)
PFQ1. The foods cooked by robot chefs look tasty	0.849	
PFQ2. The foods cooked by robot chefs are safe to consume	0.803	
PFQ3. The foods cooked by robot chefs have wide variety	0.698	
PFQ4. The foods cooked by robot chefs are visually attractive	0.765	
PFQ5. The foods cooked by robot chefs are good for my health	0.688	
Performance expectancy (Cronbach's α: 0.938, CR: 0.951, AVE: 0.764)		Lin et al. (2020)
PE1. Robots are more accurate than human beings in cooking food	0.874	
PE2. Robots are more accurate with less human errors in cooking food	0.888	
PE3. Robots provide more consistent cooking than human beings	0.910	
PE4. Robots are more consistent in cooking food	0.898	
PE5. Robots are more dependable than human beings in cooking food	0.863	
PE6. Robots are more predictable than human beings in cooking food	0.807	
Anthropomorphism (Cronbach's α: 0.867, CR: 0.897, AVE: 0.638)		Zhu and Chang (2020)
A1. I think about the robotic chef as a person.	0.866	
A2. The robotic chef has own personalities.	0.851	
A3. The robotic chef has own intention.	0.677	
A4. The robotic chef has own consciousness.	0.739	
A5. The robotic chef feels like a person.	0.843	
Intention (Cronbach's α: 0.966, CR: 0.978, AVE: 0.937)		Yoo et al. (2018)
I1. I would dine at robot chef restaurants.	0.956	
I2. Dinning at robot chef restaurants is something I would do.	0.946	
I3. I could see myself dine at robot chef restaurants.	0.962	

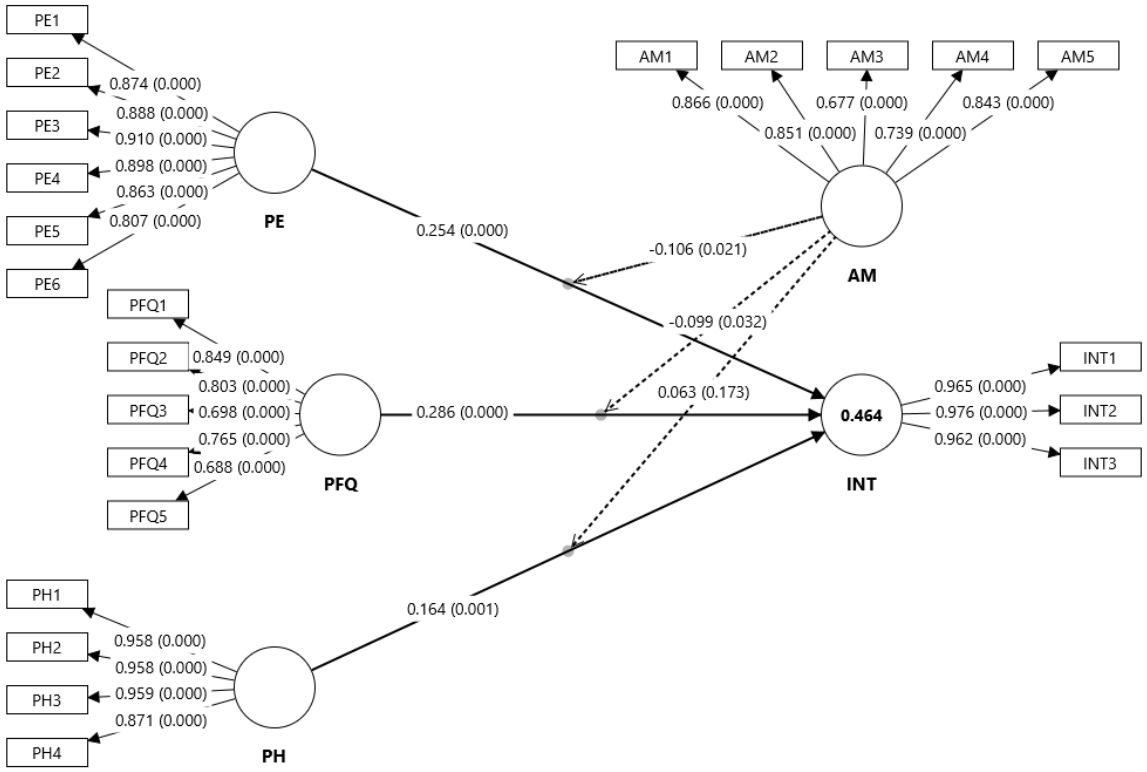
Table 3: Discriminant validity (Fornell–Larcker Criterion)					
	PH	PFQ	PE	A	I
PH	**0.937**				
PFQ	0.667	**0.763**			
PE	0.557	0.557	**0.874**		
A	0.058	0.185	0.071	**0.799**	
I	0.513	0.590	0.548	0.240	**0.968**

Notes. PH = perceived hygiene; PFQ = Perceived food quality; PE = performance expectancy; A = anthropomorphism; I = intention.

Values below the diagonal represent inter-construct correlations; Bold diagonal values are the square roots of the AVE.

Modeling (PLS-SEM) with a bootstrapping procedure of 5,000 subsamples and a 95% confidence interval (Figure 2). Multicollinearity was not a concern, as all the Variance Inflation Factor (VIF) values were below the recommended threshold of 5.

Figure 2. Structural Model of the Study



Source: Authors' Work

The direct effect analyses showed that performance expectancy significantly and positively influenced intention to dine at a robot-chef restaurant ($\beta = 0.239$, $t = 5.156$, $p < 0.001$), supporting H1. Similarly, perceived food quality ($\beta = 0.296$, $t = 6.351$, $p < 0.001$) and perceived hygiene ($\beta = 0.266$, $t = 3.500$, $p < 0.001$)

had significant positive effects on intention to dine at a robot-chef restaurant supporting H2 and H3, respectively.

Examining the moderating effect of robot anthropomorphism, the interaction between performance expectancy and anthropomorphism was negative and significant for intention to dine at a robot-chef restaurant ($\beta = -0.106$, $p < 0.05$), thus supporting H4. Similarly, the interaction between perceived food quality and anthropomorphism had a significant negative effect on intention to dine at a robot-chef restaurant ($\beta = -0.099$, $p < 0.05$), supporting H5. The interaction between perceived hygiene and robot anthropomorphism did not have a significant effect on intention to dine a at robot-chef restaurant ($\beta = 0.063$, $p = 0.173$). Therefore, H6 was not supported.

The R^2 value for intention = 0.464 indicates a significant effect of the independent variables on the dependent variable. Generally, R^2 values of 0.75 show a strong effect, values around 0.5 indicate a moderate effect, and values of 0.25 or lower show a weak effect on the dependent variable. The predictive relevance of the model was examined using the Q^2 statistic. The result was above zero (intention = 0.444), indicating strong predictive relevance of the model (Hair et al., 2021). The standardized root mean square residual (SRMR) value was 0.061, which is lower than the accepted threshold of 0.08, highlighting the suitability of the model for the observed data.

DISCUSSION

This study investigated the effects of perceived performance expectancy, perceived food quality, and perceived hygiene on consumers' intention to dine at a robot-chef restaurant, using S-R theory. It also examined the negative moderating effect of robot anthropomorphism on these relationships. The results show significant direct effects of performance expectancy, perceived food quality, and perceived hygiene on consumers' intention to dine at robot-chef restaurants. Performance expectancy and perceived food quality exerted strong positive influences, while perceived hygiene contributed meaningfully to intention. These findings are consistent with previous literature. Research on technology adoption in the hospitality industry underscores the vital role of service-quality perceptions and the functional benefits of adoption (Ivanov & Webster, 2021; Parasuraman et al., 1988; Tussyadiah & Park, 2018; Venkatesh et al., 2012). The outcomes of this study reinforce previous findings, showing that even in a highly novel dining environment, , consumers' behavioral intentions are grounded in their evaluation of quality attributes and tangible performance aspects (Jones & Alimohammadirokni, 2024). The results showing the positive effect of perceived hygiene also align with research illustrating increased consumer concern about food hygiene in post-pandemic dining (Jiang & Wen, 2020), suggesting that minimized human handling and contactless food preparation are effective drivers of adoption.

Table 4: Discriminant validity (HTMT Criterion)

	PH	PFQ	PE	A	I
PH	-	0.738	0.589	0.070	0.534
PFQ		-	0.616	0.201	0.647
PE			-	0.093	0.575
A				-	0.225
I					-

Notes. PH = perceived hygiene; PFQ = Perceived food quality; PE = performance expectancy; A = anthropomorphism; I = intention.

All values on the upper-right triangle represent the Heterotrait–Monotrait Ratio (HTMT).

Table 5: Structural model assessment results								
Relationship	*M*	*SD*	*β*	*t*-statistics	*p*-value	R^2	95% CI	
							LL	UL
H1: PE → I	0.254	0.046	0.254	5.549	0.000	0.464	0.162	0.345
H2: PFQ → I	0.288	0.047	0.286	6.033	0.000	0.464	0.196	0.380
H3: PH → I	0.162	0.047	0.164	3.380	0.000	0.464	0.065	0.257
H4: PFQ * A → I	-0.105	0.048	-0.106	2.304	0.021	0.464	-0.193	-0.014
H5: PE * A → I	-0.102	0.047	-0.099	2.150	0.032	0.464	-0.195	-0.012
H6: PH * A → I	0.062	0.046	0.073	1.362	0.073	0.464	-0.029	0.152

Notes. PH = perceived hygiene; PFQ = Perceived food quality; PE = performance expectancy; A = anthropomorphism; I = intention.

The findings show a significant negative moderating effect of robot anthropomorphism on the relationship between performance expectancy and intention, as well as between perceived food quality and intention. This highlights the impact of higher levels of robot anthropomorphism on the way consumers process robot-chef performance and quality information. Studies show that as the human-likeness of robots increases, so do consumers' expectations about the functional and cognitive abilities of the robot, expectations that might not always be met (Grazzini et al., 2023; Qian & Wan, 2024). These heightened expectations can result in an appearance-function mismatch which can lead to less favorable evaluations of a robot's functional performance. Moreover, higher levels of anthropomorphism in a robot can result in elevated cognitive load. This can weaken the effect of functional cues such as performance expectancy and food quality, distract attention from task performance, and affect the evaluation of a robot's functional capabilities (Gong, 2025).

Lastly, the non-significant interaction between perceived hygiene and robot anthropomorphism on consumer intention indicates that hygiene perceptions operate independently of anthropomorphic cues. This finding aligns with previous research showing that environmental cues and observable protocols have a greater effect on consumers' sanitation and cleanliness judgments than the service agent's appearance (Magnini & Zehrer, 2021). Overall, the current findings suggest that in the context of robot-chef restaurants, enhancing functional benefits such as performance and quality remains critical, but the way robots are designed visually and behaviorally can alter their effectiveness. Overly human-like designs may dilute the persuasive impact of core service attributes, while hygiene perceptions appear resistant to such design effects.

Theoretical Implications

This study makes several theoretical contributions to the literature on human-robot interaction (HRI) and consumers' intention toward robotic dining. First, the findings indicate that consumers apply additional evaluative criteria, such as perceived hygiene, beyond the functional factors like performance expectancy emphasized in traditional technology acceptance models (e.g, TAM and UTAUT) in experiential consumption contexts. These findings highlight the need for technology-specific extensions of traditional technology acceptance models. This is particularly important in food-related HRI settings in which usefulness perceptions can include sensory, contamination-related, and sanitary evaluations that are not captured by traditional models.

Second, the findings empirically show that consumers engage in risk-benefit trade-offs when forming decisions and intentions regarding emerging robotic technologies. Perceptions of food quality and performance expectancy show the benefits of adopting robotic dining, while perceptions of hygiene and

contamination risk represent the risk dimensions. In addition, the moderating role of anthropomorphism demonstrates that design cues can shift the perceived balance between these benefits and risks.

Third, this study contributes to the growing body of research on HRI by showing that human-robot interaction in foodservice is multi-dimensional. Consumers do not evaluate food prepared by robot chefs solely based on technological competence, such as accuracy and precision; rather, they integrate sensory expectations into their evaluations. This underscores that consumer responses to food-preparing robots are influenced by both functional and experiential dimensions, indicating that HRI models should account for multi-attribute evaluation processes in hedonic and sensory contexts. Fourth, this study contributes to conceptual clarity by distinguishing between perceived hygiene and perceived food quality in food prepared by robot chefs, and by empirically validating their distinct effects on consumers' adoption of emerging food technologies such as robot chefs.

Lastly, the findings add to the theories of anthropomorphism in the design of robots indicating that anthropomorphism operates as a context-dependent design cue. Research shows that the increase of anthropomorsim in robots often triggers elevated expectations of their functional, social, or cognitive capabilities, expectations that may not be met in highly task-oriented contexts such as robotic food preparation (Grazzini et al., 2023; Qian & Wan, 2024; So et al., 2024). Building on these findings, the results of this study show that higher robot anthropomorphism can redirect evaluative attention of consumers toward human-like expectations, which can weaken the effect of key functional factors such as food quality and performance. This contributes to theoretical understanding by showing that the effects of anthropomorphism is not uniform across domains. Instead, it interacts with the specific expectations of each domain, and in settings that rely on precision, such as robot-chef restaurants, it can reduce rather than increase acceptance (Gong, 2025; Song & Kim, 2022; Song et al., 2024).

Practical Implications

The findings of this study provide several practical insights. Considering that performance expectancy, perceived food quality, and perceived hygiene had significant positive effects on consumer intention, communicating reliable performance, consistent high-quality food output, and verifiable hygiene practices of robot chefs should become a priority when adopting this technology in restaurants. To operationalize these elements, restaurant operators can offer transparent preparation processes by making the robot chefs' food-preparation activities visible to diners through transparent kitchen designs, adopting robot chefs with self-sanitation features, or using real-time performance dashboards that display cooking accuracy, such as timing precision.

The findings suggest that food quality, hygiene, and performance are key drivers of intention; however, the anthropomorphic design of robot chefs can affect how consumers evaluate these factors. Higher levels of anthropomorphism might lead consumers to form human-like expectations of robots' abilities, which could negatively affect the functional capabilities of a robot if the expectations are not met. From a practical standpoint, this means designers should balance the anthropomorphic features of a robot to match its actual capabilities and purpose. Aligning the degree of a robot's human-like and anthropomorphic cues in a way that clearly communicates its purpose without overshadowing its functional strengths can result in more favorable consumer evaluations in robot-chef restaurant environments.

The non-significant moderation effect for hygiene suggests that hygiene communication should remain robust, and foodservice operators should invest in hygiene-focused messaging, such as showing sterilization procedures or contactless preparation by robot chefs (Pillai et al., 2021). For example, restaurant operators can incorporate timed hygiene demonstrations by having robot chefs perform a visible automated cleaning and sanitation cycle every hour. In addition, they can use digital signage

screens that play pre-recorded videos of cleaning, self-sanitation, and food preparation process of robot chefs to reinforce hygiene perceptions.

Robot chef vendors can offer different models tailored to specific restaurant types, such as quick-service or upscale dining, based on customer expectations and operational needs. Moreover, marketing teams of these kinds of restaurants should customize their communication strategies and marketing messages accordingly. For quick-service restaurants, marketing messages may emphasize speed and rapid preparation of food that is consistent in taste and portion. In contrast, full-service or upscale restaurants may highlight the reduction of cross-contamination by using QR codes on menus that link to live or recorded videos of the robot-chef food-preparation process to strengthen hygiene messaging.

Policymakers and regulatory bodies should establish standardized guidelines and clear regulations for robot-chef-prepared food to ensure transparency in data logs, such as sanitation cycles. In addition, audit procedures for automated cleanliness cycles should be in place for robot-chef restaurants, and policymakers should create required certifications for robot-chef hygiene protocols

Limitations and Future Studies

In spite of meaningful insights, this study has some limitations. While the structural model reveals meaningful relationships, experimental and longitudinal studies are recommended to further investigate the dynamics of consumer perceptions and behavioral intentions toward robot chefs. Moreover, anthropomorphism was treated as a unidimensional construct in this study. However, in recent years, multidimensional views of the construct have emerged that identify facets of robot anthropomorphism beyond physical appearance cues, such as social and behavioral cues (e.g., emotion display, gaze, and voice) and mind perception (e.g., agency). Future studies can use validated multidimensional measurements (Chi et al., 2025; Kim & Im, 2023) to investigate which specific facets of anthropomorphism help or hinder acceptance of robot chefs.

This study only examined the moderating effect of anthropomorphism on the relationship between perceived performance expectancy, perceived food quality, and perceived hygiene and consumers' intention to dine at a robot chef restaurant. Future studies should explore other factors, such as trust, perceived creepiness, and gender, to better understand their impact on these relationships. Moreover, this study was conducted in a single cultural context. As cultural factors can affect how consumers interpret robot characteristics like anthropomorphism, future studies should replicate this study across diverse cultures. Another limitation of this study is its scenario-based design, in which participants were asked to imagine a dining experience rather than evaluate an actual one. Since anticipated perceptions may differ from real-world experiences, future research should conduct studies in actual robot-chef restaurant settings to validate these findings in a real-world context.

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