Customer Acceptance of Service Robots in the German Gastronomy Industry

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Dissertation written under the supervision of
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Dissertation submitted in partial fulfillment of requirements for the MSc in Management with specialization in Entrepreneurship, Strategy and Impact, at the Universidade Católica Portuguesa, 28.05.2026.

Abstract

This dissertation investigates customer acceptance of service robots in the gastronomy industry, employing a convergent mixed-methods design. Sixteen semi-structured expert interviews were conducted with gastronomy operators and technology providers across Germany and analyzed using a hybrid deductive-inductive coding scheme grounded in the Gioia methodology. A cross-sectional OLS regression model was applied to survey data from 210 respondents to test acceptance drivers derived from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT).

The quantitative findings identify Trust ($\beta = 0.268$, $p < .001$), Hedonic Motivation ($\beta = 0.209$, $p < .001$), and Social Influence ($\beta = 0.166$, $p < .05$) as significant drivers of Behavioral Intention, while Human Touch Preference ($\beta = -0.136$, $p < .01$) emerges as the dominant barrier. Perceived Usefulness did not reach statistical significance ($p = .076$), consistent with partial suppression by functionally adjacent constructs. The qualitative findings reveal that operator adoption is shaped by format fit, staff integration, and customer communication strategy rather than technological capability alone.

The study contributes an empirically grounded acceptance model for the gastronomy context and offers practical guidance for operators and technology providers navigating the deployment of robots. Structural pressures, including labor scarcity and rising operational costs, position service robots as a strategic investment rather than a novelty, yet acceptance remains contingent on trust, hedonic design, and effective human-robot complementarity.

Keywords: Service Robots, Customer Acceptance, TAM, UTAUT, Gastronomy, Hospitality, Trust, Hedonic Motivation, Mixed Methods

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Resumo

Esta dissertação investiga a aceitação do cliente aos robôs de serviço na indústria gastronómica, utilizando um desenho de métodos mistos convergentes. Realizaram-se dezasseis entrevistas semiestruturadas com operadores de gastronomia e fornecedores de tecnologia na Alemanha, analisadas através de um esquema de codificação híbrido dedutivo-indutivo fundamentado na metodologia Gioia. Aplicou-se um modelo de regressão OLS transversal a dados de inquérito de 210 respondentes, testando os determinantes de aceitação derivados do Modelo de Aceitação Tecnológica (TAM) e da Teoria Unificada de Aceitação e Uso de Tecnologia (UTAUT).

Os resultados quantitativos identificam a Confiança ($\beta = 0{,}268$, $p < 0{,}001$), a Motivação Hedónica ($\beta = 0{,}209$, $p < 0{,}001$) e a Influência Social ($\beta = 0{,}166$, $p < 0{,}05$) como determinantes significativos da Intenção Comportamental, enquanto a Preferência pelo Toque Humano ($\beta = -0{,}136$, $p < 0{,}01$) emerge como a principal barreira. A Utilidade Percebida não atingiu significância estatística ($p = 0{,}076$), consistente com supressão parcial por construtos funcionalmente adjacentes. Os resultados qualitativos revelam que a adoção é condicionada pela adequação ao formato, integração da equipa e estratégia de comunicação, não apenas pela capacidade tecnológica.

O estudo contribui com um modelo de aceitação empiricamente fundamentado para o contexto gastronómico e oferece orientação prática a operadores e fornecedores de tecnologia na implementação de robôs. Pressões estruturais como a escassez de mão-de-obra e os custos operacionais crescentes posicionam os robôs de serviço como investimento estratégico e não novidade, embora a aceitação permaneça dependente da confiança, do design hedónico e de complementaridade humano-robô eficaz.

Palavras-chave: Robôs de Serviço, Aceitação do Cliente, TAM, UTAUT, Gastronomia, Hotelaria, Confiança, Motivação Hedónica, Métodos Mistos

Título: Aceitação do Cliente de Robôs de Serviço na Indústria Gastronómica Alemã

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Acknowledgements

This dissertation marks the completion of an important stage in my academic journey, and I would like to thank those who supported me along the way.

My sincere thanks go to my supervisor, Prof. Peter V. Rajsingh, for his guidance, critical feedback, and consistent availability throughout this process. His engagement with my work contributed significantly to the quality of this thesis.

I am especially grateful to my parents, whose unconditional support made this academic path possible in the first place. Completing an international master's program was only possible because of their trust and commitment, and I do not take that lightly.

I would also like to thank my family and partner for their patience and encouragement, particularly during the more demanding phases of this project.

My thanks further extend to the sixteen industry experts who generously shared their time and knowledge with me, as well as to the survey participants and those who helped facilitate introductions and referrals.

Selected AI-supported tools were used for linguistic purposes only. All conceptual development, analysis, interpretation, and academic content were produced independently by the author.

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List of Abbreviations

AI	Artificial Intelligence
BI	Behavioral Intention
BP	Breusch-Pagan (test)
CO	Compatibility
df	Degrees of freedom
DOI	Diffusion of Innovations
HM	Hedonic Motivation
HTP	Human Touch Preference
M	Mean
n	Sample size
OLS	Ordinary Least Squares
OP	Operator
PE	Performance Expectancy
PEOU	Perceived Ease of Use
PI	Personal Innovativeness
PU	Perceived Usefulness
R^2	Coefficient of determination
RBT	Resource-Based Theory
SD	Standard Deviation
SI	Social Influence
SP	Supplier
TAM	Technology Acceptance Model
TAM2	Technology Acceptance Model 2 (Venkatesh & Davis, 2000)
TAM3	Technology Acceptance Model 3 (Venkatesh & Bala, 2008)
TR	Trust
UTAUT	Unified Theory of Acceptance and Use of Technology
UTAUT2	Unified Theory of Acceptance and Use of Technology 2 (Venkatesh et al., 2012)
VIF	Variance Inflation Factor
α	Cronbach's alpha
β	Standardized regression coefficient

1. Introduction

Dining out has always been about more than food. The experience carries social weight; a shared space, a human exchange, a ritual that goes beyond what is served on the plate. This is the context into which service robots are now being introduced. In a growing number of restaurants across Europe, East Asia, and North America, an autonomous wheeled platform navigates the floor with a tray of dishes, announces its arrival in a synthesized voice, and waits for the customer to unload. The interaction takes seconds. The question it raises is more complex.

The gastronomy sector is under compounding pressure. Labor scarcity has become structural across European markets. Hospitality repeatedly ranks among the sectors with the most unfilled vacancies, with turnover rates that make stable staffing a permanent management problem (Mingotto et al., 2021; Blöcher & Alt, 2021). Wage floors are rising. Recruitment is expensive. Against this backdrop, service robots have moved from a curiosity to a strategic option. The global market for professional service robots has expanded at a sustained pace, with gastronomy among the fastest-growing deployment contexts (Wirtz et al., 2018; Bowen & Morosan, 2018). The economic logic is compelling: a robot does not call in sick, does not require onboarding, and does not leave after two months for a competitor.

Throughout this study, "gastronomy" refers to the full range of food and beverage service formats including quick-service restaurants and snack counters, casual dining, fine dining, hotel restaurants, and cafés. Yet the economic logic is not the whole story. Japan's early robot restaurant deployments illustrated this sharply. Operators who invested in autonomous service systems encountered operational failures and, more telling, declining customer satisfaction (Reis et al., 2020). The robots worked technically. Customers still rejected them. What the robots could not replicate was the human element, namely the brief exchange with a server, the sense of being attended to, and the social legibility of a familiar service script. Customer acceptance, not technical performance, is the mechanism through which robotic deployments translate into business outcomes. The majority of empirical studies on service robot acceptance originate from Japan, China, and South Korea, markets characterized by cultural dispositions toward automation that differ substantially from those prevailing in Germany and broader Central European contexts. In these markets, hospitality robotics benefits from stronger institutional support and lower cultural resistance to service automation (Blöcher & Alt, 2021; Ivanov et al., 2019).

The technological picture has also shifted. Contemporary platforms integrate computer vision, autonomous navigation, and in an increasing number of deployments, large language model (LLM) interfaces that enable open-ended verbal interaction with customers (Rasheed et al., 2023). A robot that speaks and responds to questions triggers qualitatively different customer evaluations than a delivery trolley on wheels, with social and relational dimensions of acceptance becoming more salient as autonomy increases (Calleja, 2025).

In a sector where atmosphere, warmth, and human recognition are part of the product being consumed rather than merely a delivery mechanism for it, this matters. Evidence from multiple markets shows that customers evaluate service robots not only on functional performance but also on whether the interaction feels appropriate, reassuring, and socially readable (Wirtz et al., 2018; Figueiredo et al., 2025). A diner who finds a robot functionally adequate but socially unsettling will not return. Acceptance in gastronomy is not simply technology acceptance but service experience evaluation in which the agent happens to be non-human.

Research has developed a conceptual toolkit to explain these evaluations. The Technology Acceptance Model (TAM), with its core constructs of perceived usefulness and perceived ease of use (Davis, 1989), established the foundational framework. Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) extended this to consumer contexts, adding hedonic motivation, habit, and social influence as additional drivers (Venkatesh et al., 2012). Meta-analytic evidence confirms that functional utility, trust, and enjoyment are consistent predictors of service robot acceptance across settings (Blut et al., 2021). Yet these frameworks were not designed to capture the full complexity of acceptance in emotionally and socially rich service encounters, where a robot handling a customer's food activates social interpretation processes that go well beyond utility calculation.

A more specific gap is geographic and contextual. Germany, Europe's largest economy and a gastronomy market where personal service and a deeply embedded culture of hospitality carry particular social and commercial weight, has received virtually no dedicated empirical attention in this literature. German dining carries a distinct normative register: personal warmth, attentiveness, and the host-guest relationship function as embedded expectations rather than optional features of the experience (Ottenbacher et al., 2006). European consumers have demonstrated willingness to adopt self-service technologies in retail and banking (Weijters et al., 2007). Whether that pragmatic openness extends to restaurant contexts, where relational service norms are constitutive of the experience rather than incidental to it, is not resolvable from existing literature (Ghazali et al., 2025; Lin et al., 2020). Acceptance patterns established in Asian markets do not transfer straightforwardly to this cultural setting, and operators in Germany need evidence grounded in the market itself.

Four specific gaps converge on the same conclusion. The cultural transferability of established acceptance factors is untested for Germany. The practitioner perspective is largely absent from quantitative acceptance research. Context specificity within gastronomy, specifically which service tasks and dining formats are most and least amenable to acceptance, remains underdeveloped. Most consequentially, a theoretically grounded, mixed-methods study of service robot acceptance in German gastronomy does not yet exist. This study addresses that absence. Theoretically, it examines whether TAM, UTAUT2, and DOI generalize beyond the Asian markets in which the majority of prior research has been conducted, responding directly to the call by Blut et al. (2021) for primary data from additional country contexts. Empirically, it produces the first mixed-methods evidence base for the German market, combining consumer survey data with practitioner insight.

The primary research question driving this study is the following:

What factors drive customer acceptance of service robots in the gastronomy industry in Germany?

2. Literature Review

2.1 Service Robots

The literature review proceeds in five parts. The first two lay out the contextual groundwork: what service robots are, and what structural pressures the gastronomy sector currently faces. The third brings these together, examining how robots have been deployed in practice and what the evidence shows. The fourth works through the theoretical frameworks for consumer acceptance: TAM, UTAUT, and Diffusion of Innovations (DOI). The fifth applies management theory, providing the strategic lens through which operators navigate adoption decisions.

2.1.1 Definition, Classification and Evolution

Service robots are autonomous or semi-autonomous machines designed to perform service tasks in direct interaction with customers or staff, without continuous human operation. Wirtz et al. (2018, p. 909) define them as “system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organization’s customers.” This definition draws a functional boundary between industrial robots, which operate in controlled production environments, and service robots, which must navigate dynamic human settings and respond to unpredictable social cues.

Robots deployed in service settings resist simple categorization. One taxonomy organizes them by task type (delivery, greeting, concierge, entertainment, food preparation), but function captures only part of the picture. Human-likeness matters independently: an android design triggers different social expectations than a wheeled delivery trolley does. Autonomy level adds a further dimension, ranging from systems that follow pre-mapped routes to those capable of adapting in real time to unexpected obstacles or requests. These are not merely taxonomic distinctions. Human-likeness and perceived intelligence shape how customers actually evaluate their encounters with robots (Belanche et al., 2020). Historically, robotics in the hospitality sector was confined to back-of-house tasks such as automated dishwashing and conveyor systems for food preparation. The transition to customer-facing roles accelerated from the mid-2010s, enabled by falling hardware costs, advances in navigation algorithms, and greater processing capacity for real-time sensor fusion. The growing availability of commercial robot platforms marked the inflection point at which deployment became financially viable (Murphy et al., 2017). Robots subsequently entered restaurant floors, hotel lobbies, and delivery contexts across East Asia and, progressively, European and North American markets (Blöcher & Alt, 2021).

2.1.2 Technical Foundations and AI

A deployed service robot is the product of several interlocking technical layers. Mechanical actuators and a sensor suite (typically combining lidar, cameras, and infrared detectors) give the robot mobility and situational awareness. Onboard computing and connectivity tie the layers together. Increasingly, though, it is the Artificial Intelligence (AI) layer that determines what the robot can actually do. Computer vision enables person and object detection, speech recognition supports voice-based interaction, and path-planning algorithms manage real-time obstacle avoidance in dynamic environments (Rasheed et al., 2023). More recently, large language model integrations have begun to appear in front-of-house roles, allowing robots to engage with guests' open-ended questions rather than defaulting to pre-scripted responses.

The distinction between rule-based robotics and AI-enabled adaptive behavior is consequential for acceptance. Rule-based systems are predictable and consistent, which can reinforce trust, but they fail visibly when situations fall outside their programmed parameters. AI-augmented robots can handle greater ambiguity, but their behavior may become less predictable, introducing a different set of trust challenges. Customers form expectations about robot competence based on visible design cues and adjust their evaluations when robot behavior deviates from those expectations (Song & Kim, 2022).

2.1.3 Global Market Development

The global service robot market has grown considerably over the past decade, though the pace differs sharply from region to region (Grand View Research, 2024). Early projections had anticipated sustained compound annual growth in hospitality-adjacent sectors (Bowen & Morosan, 2018), and the evidence broadly bears that out. Between 2018 and 2023, deployment volumes in food and beverage service, hotel concierge, and retail expanded markedly, with East Asian markets setting the pace and European markets trailing at some distance (Blöcher & Alt, 2021). Hospitality is a sector where the enabling conditions for adoption (relatively standardized task structures and significant labor cost exposure) converged earlier than in many comparably sized service industries (McCartney & McCartney, 2020).

Progress within the sector has been uneven. Adoption has gone furthest in quick-service restaurants and hotel food delivery, where tasks repeat and the return on investment (ROI) case is straightforward. Full-service and fine-dining venues have held back. Their caution tracks worries about service ambience, customer expectations, and the relational dimension of dining (Bowen & Morosan, 2018). One pattern stands out across markets. The greater the cultural familiarity with technology-mediated interaction, the steeper the adoption curve, which implies that diffusion answers to demand-side social norms and not supply-side economics alone (Balaji et al., 2024).

2.2 The Gastronomy Industry

2.2.1 Current Trends and Digitalization

The gastronomy industry has undergone significant structural change over the past decade, driven by digital platforms, delivery infrastructure, and shifting consumer expectations. Buhalis et al. (2019) frame this as a broader process of "disruption," through which digital technologies decompose and reconfigure established value chains in ways that favor agile entrants over incumbent operators. In gastronomy, this materialized through the rapid scaling of food delivery platforms, digital ordering and payment systems, and data-driven personalization of the guest experience. The COVID-19 pandemic accelerated many of these trends, particularly contactless interfaces and remote ordering solutions, generating a cohort of consumers accustomed to digital mediation in what were previously unmediated service encounters (Kim et al., 2020).

Service robots are best understood within this broader digitalization trajectory rather than as a standalone development. Technological novelty in dining contexts operates atmospherically as well as instrumentally. The presence of a robot changes not just what happens at the table but the overall register of the experience (Spence, 2023). Deploying a robot is therefore a positioning statement as much as an operational decision. Whether the signal lands positively or negatively depends on how well the technology fits the service concept: a robot that reads as coherent in a fast-casual setting may feel incongruous in a context where personal hospitality is part of what guests are paying for.

2.2.2 Structural Challenges and Labor Shortages

Labor scarcity is the structural pressure that shapes everything else in this sector. Across European markets, front-of-house hospitality positions are among the most difficult to fill consistently. Turnover is high, seasonal volatility is built in, and fewer people are entering the workforce willing to take those jobs (Mingotto et al., 2021). Demographic trends are working against the sector. The supply of gastronomy-ready labor is contracting structurally, not just cyclically (Blöcher & Alt, 2021).

This structural pressure shapes the economic case for adopting robotics. Wirtz et al. (2018) argue that service robots become economically viable when the total cost of robotic deployment falls below the full cost of human labor for equivalent tasks, including wages, training, and turnover. As labor scarcity pushes wage floors higher and recruitment costs rise, this threshold is increasingly met for specific task categories. Delivery and transport tasks on the restaurant floor are among those identified in the literature as particularly suitable for robotic deployment (Murphy et al., 2017).

2.3 Service Robots in Gastronomy

2.3.1 Applications and Current Adoption

Service robots in gastronomy take on quite different roles depending on the setting. The most common application by far is food and beverage delivery (transporting dishes from the kitchen to the table), with reception, ordering, and floor-cleaning systems following at some distance (Garcia-Haro et al., 2021). Kuo et al. (2017) were among the first to document how customers respond to robots in restaurant settings, finding that both functional performance and the quality of human-robot interactions predicted customer satisfaction. That dual finding, functional and relational, has since become a recurring pattern in the literature.

Case evidence from Asian markets illustrates the range of adoption models. In one hospitality operation, robots were deployed across multiple service stages, and task allocation between humans and machines required continuous refinement as operational experience accumulated (Seyitoğlu & Ivanov, 2020). Hotel food and beverage settings tell a similar story. Effective integration there depended on a set of organizational adaptations, among them servicescape redesign, staff retraining, and the development of service recovery protocols for robot failures (Lu et al., 2020).

2.3.2 Opportunities and Strategic Potential

Operators who invest in service robots typically do so for overlapping reasons. Operational efficiency is the most straightforward. A robot running food to tables during the dinner rush does not tire, and its consistency frees human staff for the interaction-intensive parts of the job. Hygiene entered the calculation more explicitly during COVID-19, when eliminating human handling at certain delivery stages became not just an operational benefit but a visible guest-facing signal, and has remained relevant to consumer expectations since (Kim et al., 2020). Less obvious but equally real is the positioning dimension: deploying a robot communicates something about an operator's relationship to technology and innovation, with effects that vary considerably by customer segment (Wirtz et al., 2018).

Robotics adoption constitutes a strategic resource-allocation decision, with robots contributing to performance outcomes primarily through their effect on service quality as perceived by customers, making acceptance the central mechanism (Xiao & Kumar, 2019). Experimental evidence further shows that fit between the level of robot deployment and the service context (full-service vs. limited-service) shapes whether robots are experienced as enhancing or degrading the dining experience (Hu & Min, 2025). Strategic potential is real, but it is conditional on acceptance.

2.3.3 Key Challenges and Barriers

Deployment in gastronomy also surfaces challenges that purely technical or economic analyses understate. Milohnić & Kapeš (2019) identify several barriers to broader adoption, including the mismatch between the designed capabilities of robots and the dynamic complexity of real restaurant environments: uneven floors, moving obstacles, ad hoc customer behavior, and the unpredictability of dining group dynamics. These challenges reflect a fundamental tension between the structured environments in which robots perform best and the inherently unstructured nature of social dining.

Customer reactions add another layer of uncertainty. Discomfort and a perceived lack of warmth mediate negative service evaluations in robot-staffed restaurants, and not merely dissatisfaction with the task, but with the encounter itself (Choi et al., 2021). Design choices at the robot level matter considerably. Appearance and interaction style shape whether customers experience the robot as helpful or intrusive (Zemke et al., 2020). And when robots fail, which they sometimes do quite visibly, the consequences can reach beyond the immediate interaction. Negative spill-over effects from unexpected robot behavior extend to overall restaurant evaluations, suggesting that failure events are not contained but spread (Song & Kim, 2022).

Staff reactions add another layer of complexity. Service workers in robot-equipped restaurants frequently report uncertainty about where their responsibilities end and the robot's begin, and, predictably, about job security (Mingotto et al., 2021). Absent active management of those concerns, uncertainty tends to harden into resistance. The barriers to robot adoption are not purely technical; they are organizational and social in equal measure.

2.4 Consumer Acceptance

2.4.1 The Technology Acceptance Model and UTAUT

The Technology Acceptance Model, introduced by Davis (1989), established two constructs that have anchored acceptance research ever since: perceived usefulness (PU) and perceived ease of use (PEOU). The core argument is that people adopt a technology when they believe it improves their performance and does not demand excessive effort to operate. Both predictors, Davis found, jointly and independently shaped attitude toward use and actual behavior. TAM's parsimony (two constructs, a relatively clean causal chain) is what made it so generative, giving subsequent researchers a stable foundation to extend, qualify, and contest.

TAM2 (Venkatesh & Davis, 2000) expanded the original model by adding social influence processes (subjective norm, image, voluntariness) and cognitive instrumental processes (job relevance, output quality, result demonstrability) as antecedents of PU. TAM3 (Venkatesh & Bala, 2008) consolidated the antecedents of PEOU and PU into a single nomological network, integrating individual differences, system characteristics, social influence, and facilitating conditions. While TAM3 itself does not include trust as a core construct, parallel work has positioned trust as a key relational antecedent of adoption in contexts marked by behavioral uncertainty (Gefen et al., 2003; Pavlou, 2003). For service robots, this trust component is particularly relevant. Customers encounter robots whose behavior they cannot fully predict, and trust in robot competence mediates the relationship between functional evaluation and acceptance intention.

The Unified Theory of Acceptance and Use of Technology synthesized eight prior acceptance models into four core constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). UTAUT demonstrated substantially higher explanatory power than any of the constituent models individually. UTAUT2 (Venkatesh et al., 2012) extended the framework to consumer technology contexts by adding hedonic motivation, habit, and price-value perception. Hedonic motivation is of particular relevance in gastronomy, where the entertainment or novelty value of interacting with a robot can drive acceptance beyond functional utility.

When these constructs are brought to the restaurant context, the results are instructive. Blut et al.’s (2021) meta-analysis across 71 studies finds that perceived usefulness, trust, and hedonic motivation are the most consistent predictors of service robot acceptance, with PEOU showing a weaker and more context-dependent effect. A hospitality-specific sample confirms the pattern: perceived usefulness mediates the effect of robot interaction quality on use intention (Lin et al., 2020). Context matters, though. Performance expectancy weighs more heavily in full-service settings, while hedonic motivation becomes more prominent in limited-service formats where the novelty of the interaction is part of the appeal (Kao & Huang, 2023).

2.4.2 The Diffusion of Innovations

Rogers' (2003) Diffusion of Innovations theory approaches adoption from a fundamentally different angle than TAM. Rather than modeling what individuals privately calculate about usefulness, it traces how innovations actually move through social systems. The answer turns on five perceived properties of the innovation: how much relative advantage it offers over existing alternatives, how compatible it feels with users' existing habits and expectations, how complex the interaction is to navigate, whether the technology can be tried without full commitment (trialability), and how visible peer adoption is in the relevant environment (observability).

DOI also operates at the population level in a way that TAM does not. Rogers' bell-shaped adoption curve segments any adopting population into five groups (innovators, early adopters, early majority, late majority, laggards), each with different risk tolerances and relationships to social proof. Whether younger consumers systematically occupy earlier positions on this curve for robot-mediated restaurant service is an empirical question rather than an assumption. What DOI adds that TAM cannot is an account of how acceptance propagates, through observation, through peer influence, and through the gradual normalization that follows as robots become more visible in shared service spaces.

2.4.3 Trust, Affect and Social Presence

Trust sits at the center of service robot acceptance in a way that distinguishes it from most other technology adoption contexts. When a robot brings food to a table, guests are not merely evaluating task performance. They are deciding, often quickly and without explicit deliberation, whether the machine registers as a social actor they can engage with comfortably. A robot's perceived social competence, its capacity to signal warmth and attentiveness, mediates emotional reactions that feed into use intention largely independently of whether the delivery task itself was executed reliably (Mende et al., 2019).

Several studies document the affective dimension of robot encounters. Emotional responses to service robots mediate how cognitive evaluations translate into behavioral intention, so that positive affect strengthens the influence of perceived usefulness while negative affect dampens it (Huang et al., 2021). In gastronomy this channel probably carries more weight than in task-focused service, because the dining experience is emotionally and socially dense. Within dining contexts specifically, robot-induced enjoyment, rapport, and trust together drive engagement and revisit intention, particularly among younger guest segments (Ghazali et al., 2025).

Social presence, understood as the sense that a robot is a social actor capable of meaningful interaction, is a construct that bridges affective and cognitive acceptance pathways. Perceived social presence of a service robot strengthens trust and rapport, which in turn enhances satisfaction and loyalty intentions (Belanche et al., 2020). This effect is not uniform. Higher social presence expectations can also increase the salience of interaction failures, producing stronger negative reactions when the robot falls short.

2.4.4 Context, Barriers and Acceptance Drivers

Context moderates the strength and direction of acceptance effects. Across a large meta-analysis, Blut et al. (2021) find that service type moderates the outcome, with functional acceptance constructs carrying more force in task-oriented services and relational constructs mattering more in social ones. Gastronomy makes this especially clear, since it stretches from fast-food delivery at one end to formal dining at the other. Experimental findings sharpen the point. Acceptance turns on how well the level of robot deployment fits the type of restaurant, so that full-service venues with strong relational norms resist robots more than limited-service ones do (Hu & Min, 2025). The wording of the rollout counts as well. When guests read robots as a substitute for human relational service rather than a supplement to it, acceptance falls markedly (Chuah et al., 2021). Individual differences weigh alongside the setting. A guest's attitude to technology, prior digital experience, and personality each act as a steady moderator within the social psychology of robot acceptance (Savela et al., 2018). Age effects are real, yet conditional rather than absolute. Younger diners tend to arrive more open to robot-assisted service, but that openness recedes exactly where human contact feels most important (Figueiredo et al., 2025). How happy a guest feels during the encounter also helps carry robot performance through to overall satisfaction, a sign that the hedonic and functional sides are harder to separate than conventional acceptance models allow (El-Said, 2022).

What this body of research has not done is engage systematically with the German market. The constructs are established, the mechanisms reasonably well understood, and the contextual moderators documented, but the evidence base is drawn almost entirely from East and Southeast Asian samples. Germany is a different case: a gastronomy culture where the relational dimension of service carries more normative weight, and where assumptions about hospitality and human presence in dining contexts differ in ways that prior studies were not positioned to examine. That is the gap this study is designed to address.

2.5 Key Concepts of Management Theory

2.5.1 Disruptive Innovation

Disruptive innovation, in Christensen's original formulation (1997), begins with technologies that look modest by the standards incumbents care about. They perform on dimensions that established players have underweighted, improve iteratively, and eventually displace what came before. Digital platforms already put hospitality through one such disruption. Booking channels and delivery aggregators restructured the competitive environment in ways that most incumbents neither anticipated nor adapted to quickly (Buhalis et al., 2019). Whether service robots are following a similar arc is not yet settled, but their capability trajectory is not fixed.

Gastronomy is a sector where the structural conditions for disruption are accumulating, namely chronic labor scarcity, rising wages, task structures that are at least partially standardizable, and consumers increasingly accustomed to technology in service contexts (Bowen & Morosan, 2018). The counterargument is that disruption may be the wrong frame. Balaji et al. (2024) suggest that in many hospitality settings, robots are better described as process innovations, specifically improvements within an existing service model rather than replacements of its underlying logic. Which description proves correct depends on how quickly adoption accelerates and how consumer acceptance evolves.

2.5.2 Resource-Based Theory and Value Creation

Resource-Based Theory (RBT), as developed by Barney et al. (2021), frames the firm as a bundle of resources and capabilities whose configuration determines its capacity to create economic value. The central question is not which resources a firm possesses but how those resources are combined and deployed to produce superior value for customers. Barney et al. (2021) argue that sustained advantage arises from the co-specialization and complementarity of resources in combinations rivals cannot readily replicate.

For a restaurant adopting service robots, the RBT lens draws attention to what successful deployment actually requires. The robot hardware is only the starting point. Alongside it, operators need a servicescape that can accommodate autonomous navigation, including cleared pathways, reliable connectivity, and properly calibrated sensor environments. Staff capabilities matter equally. Operators need people who can collaborate with robots, manage the service recovery moments when the technology falls short, and sustain guest experience quality through a period of operational transition. Underlying both is something harder to see, namely the organizational routines, cultural norms, and institutional readiness that either enable or block effective integration. Treating the degree of robot adoption as a strategic variable formalizes this logic, with customer acceptance as the mechanism through which resource investments translate into value (Xiao & Kumar, 2019).

The RBT framing has a specific implication for this study. The value of service robots as a resource is not fixed by the technology itself but is activated or blocked by the acceptance or rejection of customers. A robot that performs reliably but fails to secure customer acceptance produces no value creation regardless of its technical specification. This places acceptance not as an incidental concern but as the central mechanism through which the resource bundle of robotic assets translates into economic outcomes. It is this theoretical positioning that motivates the present research focus on acceptance drivers rather than on technical performance alone.

2.5.3 Dynamic Capabilities

Dynamic Capabilities, as introduced by Teece et al. (1997) and elaborated by Eisenhardt and Martin (2000), extend RBT by addressing how firms change their resource configurations in response to environmental change. A firm's dynamic capabilities are its ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments. Teece et al. (1997) organize these capabilities around three analytical factors: processes (the coordinating routines through which firms integrate and combine activities), positions (current endowments of technological assets, intellectual property, and customer relationships), and paths (the strategic alternatives available to the firm, shaped by prior decisions and path dependencies). Barreto (2010) synthesizes the dynamic capabilities literature and proposes a four-dimensional model encompassing the propensity to sense threats and opportunities, seize opportunities, reconfigure resources, and make market-oriented decisions, a framework directly applicable to how gastronomy operators navigate robot adoption.

What this looks like for a gastronomy operator navigating robot adoption in practice is roughly as follows. Sensing means staying alert to competitor deployments, to shifts in what guests expect from automated service, to technical developments that change the economic calculation. Many operators in the German market have not yet developed this function systematically, which partly explains why adoption decisions often arrive late and reactively. Seizing is the harder step, namely committing resources, redesigning workflows, and training staff to work alongside machines. Reconfiguring comes after go-live, when accumulated operational experience and actual guest feedback begin to reveal what acceptance requires, and those requirements often differ substantially from what operators had anticipated.

Dynamic capabilities are path-dependent (Eisenhardt & Martin, 2000). Firms that have developed experience in managing technological transitions are better positioned to sense and seize robotics opportunities than those without such organizational history. This has implications for competitive dynamics in gastronomy. Chain operators and larger hospitality groups may develop robotics dynamic capabilities more rapidly than independent operators, not solely because of superior financial resources but because of a stronger organizational learning infrastructure. Yet the acceptance dimension is democratizing. Whether a robot deployment succeeds ultimately depends on how customers respond, regardless of the operator's size or sophistication. Understanding what drives that response among the most relevant customer segment is, therefore, both an academic and a practical imperative.

3. Methodology

3.1 Research Design

This study applied a mixed-methods research design grounded in the principles of the scientific method. The combination of qualitative and quantitative approaches allowed acceptance factors to be explored in depth before being tested at scale across a broader sample.

The research was data-driven, centered on a clearly specified dependent variable, service robot acceptance, examined through its drivers and moderators in the gastronomy industry. Methodological rigor was maintained through transparent construct operationalization, falsifiability, and replicability (Greener, 2008). The epistemological foundation combined inductive, deductive, and abductive reasoning. The deductive element formulated expectations from TAM, UTAUT2, and DOI, while the inductive element allowed additional insights to emerge from the expert interviews.

Abductive and retroductive reasoning, as described by Proudfoot (2022), supported an iterative process between empirical observation and theoretical refinement. Service robot acceptance represents a complex sociotechnical system shaped by multivariate influences, interaction effects, and genuine uncertainty; the research design explicitly accounted for this complexity. Mixed methods designs suit such settings because they allow multiple data sources to be integrated in ways that reduce single-method error and capture nonlinear relationships (Bazeley, 2021; Chen & Qi, 2023).

A convergent mixed methods design (QUAL + QUAN) was selected, allowing the qualitative and quantitative strands to be collected and analyzed in parallel before being merged through triangulation (Bazeley, 2021).

Figure 1

Research Design: Convergent Mixed Methods

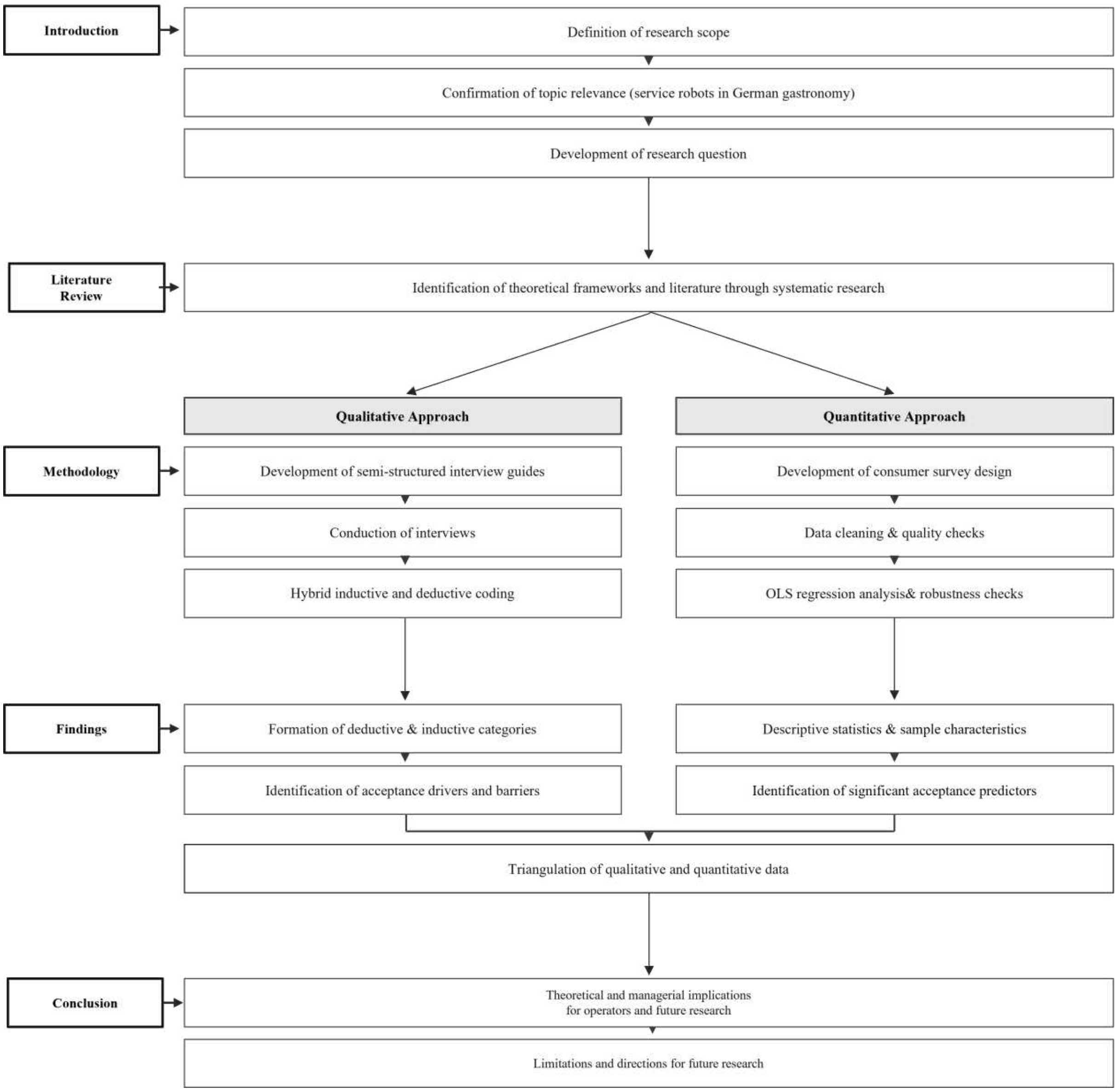


Figure 1 illustrates the convergent mixed-methods design used in this study. The qualitative strand (QUAL) and the quantitative strand (QUAN) were conducted largely in parallel, drawing on expert interviews and a consumer survey respectively, before being merged through triangulation. Although the strands ran in parallel, insights from the interviews also informed several concrete questions in the survey. The integration step enabled the systematic identification and discussion of areas of convergence and divergence.

3.2 Data Collection

Data collection consisted of three complementary components: (1) a structured secondary literature review, (2) primary qualitative interviews with industry experts, and (3) a primary quantitative survey of consumers in Germany. This multi-source strategy strengthened validity by drawing on different data types to illuminate the same phenomenon from distinct angles (Bazeley, 2021).

3.2.1 Secondary Data Collection

The secondary data collection followed a systematic and transparent literature review procedure. Academic databases including Web of Science, Scopus, and Google Scholar were searched using combinations of keywords: service robots, hospitality automation, technology acceptance, robot waiter, consumer acceptance, diffusion of innovations, and dynamic capabilities. The search was restricted to peer-reviewed journal articles, book chapters, and doctoral theses published in English. Backward and forward citation chaining were used to identify seminal papers and recent extensions.

The review served two purposes. First, it established the study's theoretical foundations by mapping existing empirical evidence on service robot acceptance and identifying the constructs used in prior research, including technology acceptance frameworks (Lin et al., 2020) and service encounter theory (Mende et al., 2019). Second, it informed the deductive coding of the qualitative analysis by clarifying operational definitions for constructs (Rashid et al., 2019).

3.2.2 Primary Data Collection: Qualitative Interviews

The qualitative component was based on semi-structured interviews with hospitality professionals who had direct operational experience with service robots. Participants included restaurant managers, technology consultants, robotics practitioners, and service designers. A total of sixteen interviews were conducted, in line with adequacy and saturation guidelines commonly applied in qualitative research (Guest et al., 2006; Nowell et al., 2017).

Participants were selected through purposive sampling to ensure diversity across organizational roles, market contexts, and levels of direct exposure to service robots. The interview guide followed a funnel structure (Brenner, 2006), opening with broader reflections on automation trends in gastronomy and progressively narrowing toward specific experiences of customer acceptance and rejection. All interviews were conducted remotely, recorded with participant consent, transcribed verbatim, and anonymized prior to analysis. Fifteen of the sixteen interviews were conducted in German. All German-language transcripts were subsequently translated into English before coding, ensuring consistency of language across the full dataset. Qualitative analysis followed a mixed inductive-deductive approach, grounded in Mayring's (2015) systematic qualitative content analysis. Deductive categories were derived a priori from the theoretical framework, specifically TAM, UTAUT2, and DOI, and applied to the interview transcripts. Inductive sub-categories emerged from the data, with participant responses introducing themes not fully anticipated by the framework. This dual coding strategy is consistent with methodological recommendations emphasizing reflexivity, transparency, and systematic coding (Braun & Clarke, 2022; Rowley, 2012; Nowell et al., 2017).

3.2.3 Primary Data Collection: Quantitative Survey

To complement and test the qualitative insights, a quantitative online survey was administered to consumers in Germany via Qualtrics, recruited through university mailing lists, social media channels, and online panels. From an initial 280 responses, a three-stage cleaning procedure removed incomplete submissions, attention-check failures, and non-German residents, producing a final analytical sample of 210 (see Appendix F, Table 9). No age restriction was applied, allowing for cross-generational comparison of acceptance attitudes.

The survey measured service robot acceptance using Likert-type scales adapted from established technology acceptance instruments (Lin et al., 2020; South et al., 2022). Constructs included perceived usefulness, effort expectancy, social influence, hedonic motivation, emotional comfort, perceived social fit, prior AI usage frequency, and situational acceptance across distinct gastronomic task types. Likert-scale construction followed methodological recommendations supporting the interval-scale properties of multi-item measures, which justify the use of parametric statistical techniques (Carifio & Perla, 2008). Items were pre-tested with a pilot group to evaluate clarity, item wording, and internal consistency.

The quantitative data provided the basis for descriptive and inferential statistical analysis, enabling the testing of relationships suggested by the qualitative findings. Analytical considerations regarding model fit, error terms, and overfitting were informed by methodological discussions of R^2, adjusted R^2, and cross-validated model performance (Chen & Qi, 2023).

3.3 Analytical Approach and Triangulation

Qualitative and quantitative data were analyzed independently and subsequently integrated through methodological triangulation to minimize single-method bias (Bazeley, 2021). The qualitative material was examined using the hybrid inductive-deductive thematic analysis framework (Mayring, 2015; Braun & Clarke, 2022), with attention to systematic data handling and analytic transparency (Rashid et al., 2019).

Quantitative data were analyzed using descriptive and inferential statistics to test the relationships between acceptance and its proposed drivers. Regression models were used, with model fit evaluated using adjusted R^2 and cross-validation procedures to guard against overfitting (Chen & Qi, 2023).

Integration of the two strands occurred through iterative comparison: qualitative themes informed the interpretation of quantitative patterns, while quantitative results corroborated or challenged qualitative insights. Cross-case comparison of interview findings, structured through a thematic matrix, was used to identify systematic patterns across participant accounts. Conclusions were treated as validated when all three sources converged; where divergence was observed, it was addressed explicitly. As this study follows an exploratory mixed-methods design, no formal hypothesis structure was adopted. The regression serves as a triangulation instrument rather than a hypothesis-testing tool, assessing whether quantitative patterns corroborate the qualitative findings.

4. Findings

4.1 Qualitative Findings

Sixteen expert interviews produced a dataset spanning eight operators (OP) and eight suppliers (SP) or consultants active in the German gastronomy and service robotics market (see Appendix B, Table 5). Three operators had deployed service robots in live settings, two were in an active evaluation phase, and three had assessed the technology and declined adoption. This contrast proved analytically productive, since the rejection cases sharpened the boundary conditions for adoption. Suppliers contributed cross-case pattern recognition that individual operators could not access in isolation. Six aggregate dimensions emerged from combined deductive-inductive coding (Mayring, 2015), presented below in order of explanatory weight. Section 4.2 reports the quantitative consumer survey results. Triangulation is developed in Section 4.3. The section addresses the research question directly: what factors drive customer acceptance of service robots in the gastronomy industry? Operator and supplier accounts show that consumer acceptance results from an adoption infrastructure constructed through deliberate decisions about context, communication, and rollout sequencing.

4.1.1 Functional Drivers and Economic Triggers

Structural labor shortage emerged as the primary adoption trigger across ten of sixteen interviews. "We simply couldn't find staff, that was the real reason we started looking at the robot" (OP-01). The same pressure surfaced in different forms. At one restaurant, five unfilled service positions coincided with a trade journal article about a successful deployment in Düsseldorf, and consideration turned into action. "We couldn't fill five positions, at the same time applications just dried up, it was really frustrating" (OP-04). Another operator framed the calculation in terms of operational reliability rather than cost reduction. "If a robot can help me run the operation more reliably, then it's worth a serious look" (OP-05). The shortage ran sector-wide across collective catering, where conventional recruitment channels were exhausted. "Skilled workers in the entire canteen area are missing everywhere" (SP-04). Perceived usefulness extended the argument into direct efficiency arithmetic. A robot-integrated kitchen required two operators where eight workers once stood (SP-06), and across 41 gastronomy projects, staff walking distances fell by an average of 20 to 25 percent (SP-07).

4.1.2 Social Proof, Guest Appeal, and the Novelty Ceiling

Social influence (Venkatesh et al., 2003) shaped adoption consideration ahead of economic assessment in several cases. OP-05, before any supplier negotiation, visited a restaurant in Cologne that had deployed a robot specifically to verify whether the atmosphere she feared losing was intact. The observation that human staff remained the visible service layer resolved her concern. OP-02 tracked competitor deployments at trade fairs; SP-06 framed the modernized canteen as an employer branding signal, arguing that organizations competing for talent communicate forward-looking values through digitalized service environments. Guest reactions at deployment were consistently positive, but interviewees drew a sharp distinction between the initial novelty response and sustained engagement. OP-04 stated the transition plainly: “After two months the photo-taking stopped, now it’s just a trolley that drives around.” Van Doorn et al. (2017) and Ghazali et al. (2025) confirm that novelty appeal erodes with repeated exposure and sustained acceptance requires functional utility. OP-06’s experience showed that proactive guest communication two weeks before first operation reduced surprise and improved initial comfort ratings.

4.1.3 Barriers: Human Touch, Inertia, and Technical Constraints

Human touch preference was the most structurally persistent barrier. OP-08, operating an upscale restaurant in northern Germany, articulated the position systematically. The three-hour experience, the sommelier's narrative, and the server who recalls a guest's preferences after two years constitute the product guests purchase. Fifteen of twenty regular customers she informally surveyed found the robot interesting elsewhere but unwelcome at their table. Wirtz et al. (2018) establish that robots encounter systematic resistance where empathy is constitutive of the service encounter. A distinct second barrier was the persistent misconception that adoption requires immediate staff reduction. SP-03 described operators who sent away a staff member on the day the robot arrived, triggering the operational deterioration that the complementarity model prevents; SP-07 attributed three project terminations in his consulting portfolio to this single root cause. Technical and spatial constraints formed a third cluster. OP-07's 85-square-meter dining room proved too compact during peak service. This format-level limitation reflects the boundary between process enhancement and wholesale disruption that Balaji et al. (2024) identify.

4.1.4 Enabling Conditions: Trust, Leasing Models, and Trialability

Trust in operational reliability was earned through observable performance rather than assumed from specifications. The threshold was around two hundred consecutive tables without failure before skepticism gave way to integration (SP-01). A comparable progression unfolded during a two-week pilot, with confidence functionally established by the third day of continuous operation (OP-01). The leasing model emerged as the single most consequential structural enabler. Its commercial logic removed the capital commitment that prevents smaller operators from attempting a trial (SP-05). The typical breakeven fell at 14 to 18 months, and operators who reviewed this projection adjusted their risk perception significantly (SP-07). Exposure-based trials substantially increase adoption intention, operationalizing Rogers's (2003) concept of trialability through the reversible financial structure the leasing model provides (Figueiredo et al., 2025).

4.1.5 Contextual Moderators: Business Type, Culture, and Scale

Business type was the primary contextual moderator. SP-01 and SP-05 drew the same boundary. Volume-oriented casual dining and high-throughput formats suit robot deployment, whereas formats where the service experience constitutes the core value proposition do not. OP-08 operationalized this from the operator perspective. Technology that operates in the guest's field of vision must justify itself within the restaurant's stated identity. Limited-service environments show substantially higher robot acceptance than full-service counterparts (Kao & Huang, 2023). Cultural context moderated viability beyond format. SP-03 reported that operators without German professional socialization displayed markedly lower resistance in initial sales conversations. SP-06 observed that German operators expect years of documented evidence before committing, whereas the same robot in China functions as an innovation signal. OP-06's hotel breakfast area with 70 percent international guests illustrated the gradient empirically. Asian guests were almost uniformly enthusiastic, German and Swiss guests were reserved, and American guests were open. Scale set an independent threshold. SP-01 placed the minimum viable deployment at 80 covers, while SP-04 placed it at 500 meals per day in collective catering.

4.1.6 From Rollout to Market: Implementation Realities and Diffusion Stage

Positioning the robot as a complement to human labor rather than a substitute was the dominant strategic framing across the dataset. "It carries the dishes; my team talks to the guests. Everyone is happier" (OP-01). This framing managed resistance from operators, staff, and guests simultaneously, matching the optimal human-robot configuration where robots execute high-volume routine tasks while humans concentrate on interactions requiring empathy and relational judgment (Wirtz et al., 2018). OP-06 described the transformation in operational detail. A designated robot attendant role emerged organically in the first weeks of deployment. Without it, efficiency gains did not materialize. This progression maps onto Teece et al.'s (1997) reconfiguration capability. Operators who integrate robots into existing service routines (retasking staff rather than reducing headcount) demonstrate the dynamic capability that distinguishes sustained deployments from failed ones (see Section 2.5.3).

At the market level, the German gastronomy sector remained in an early-adopter phase at the time of fieldwork. SP-01 still conducted outbound acquisition calls as the primary sales channel. SP-06 estimated the deployment landscape would look substantially different within three years. The six dimensions together describe an adoption pathway rather than a list of independent variables. Labor scarcity provides the structural entry condition; perceived utility converts pressure into a deployment decision. Social proof accelerates initial consideration, but the novelty ceiling means operational performance determines whether adoption persists beyond the trial period. Barriers, from human touch preference in emotionally intensive formats to spatial constraints to the staff communication failures that ended three of SP-07's projects, are surmountable when trust, trialability, and internal preparation are in place.

4.1.7 Operator Uncertainty About Customer Reactions

A recurring theme was operator uncertainty about how guests would respond. Non-adopters framed this as a principal adoption barrier. OP-07, a multi-site operator in the evaluation phase, articulated the concern shared by several interviewees. "Our main concern is actually that customers will not accept it; that some customers will have a problem with being partly served by robots, or even just seeing a robot in the restaurant. That is really our biggest concern: how people will react. Especially older customers" (OP-07). "That is a question we ourselves are also asking, and I wish I could answer it, but I cannot. We will probably need to run a pilot first and see how people actually react in the end" (OP-07). Operators with active deployments offered a direct counterpoint. Multiple accounts (including OP-01 and several supplier interviewees) reported that older guests adapted to robot service more readily than anticipated, often after brief initial hesitation. This informational asymmetry is the demand-side knowledge gap that Section 4.2 addresses directly.

4.2 Quantitative Findings

This section reports results from the quantitative consumer survey. The analysis proceeds in seven subsections: sample characteristics, experience and perception with service robots, regression analysis, measurement quality, regression results, robustness checks, and acceptance patterns across restaurant types. All computations were performed in R (version 4.3.2).

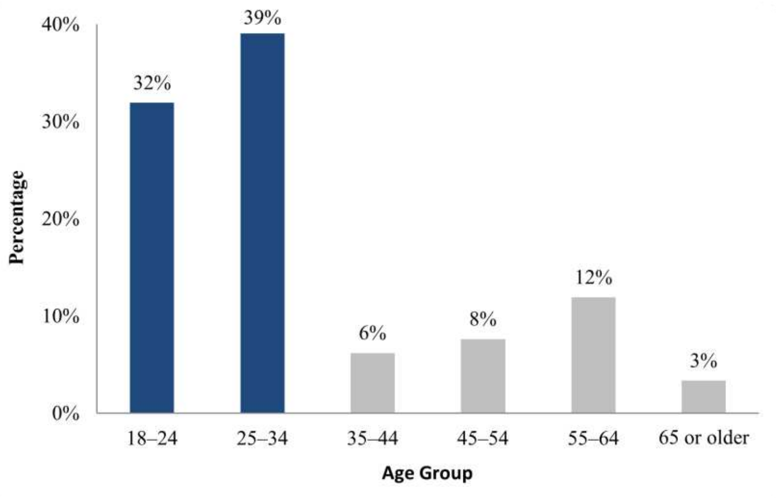
4.2.1 Sample Characteristics

A total of 210 valid responses were collected from consumers residing in Germany who regularly dine at restaurants. Respondents were recruited via an online questionnaire distributed through personal networks and social media channels. The survey was accessible for four weeks during the data collection period. Respondents outside Germany or with incomplete core responses were excluded, yielding a final sample of 210.

Figure 2 displays the age and gender distribution of the sample. The respondent base skewed toward younger age groups: 32% were aged 18 to 24 years and 39% were aged 25 to 34, together accounting for 71% of the sample. The 35–44 and 45–54 cohorts contributed 6% and 8% respectively, while respondents aged 55 to 64 accounted for 12% and those 65 or older for 3%.

Figure 2

Age distribution of survey respondents (n=210)



In terms of gender, 55.2% of respondents identified as female, 44.3% as male, and 0.5% as non-binary as seen in Figure 3.

Figure 3

Gender distribution of survey respondents (n=210)

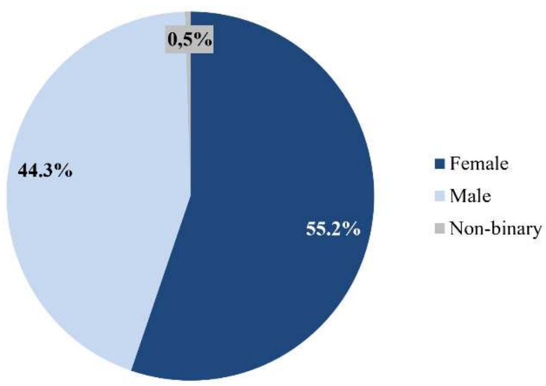


Figure 4 displays the restaurant visit frequency of respondents. The majority visited restaurants regularly: 38% went 3–4 times a month and 36% 1–2 times a month, together representing 74% of the sample. A further 16% dined out more than once a week, while 10% visited less than once a month.

Figure 4

Restaurant visit frequency of survey respondents (n=210)

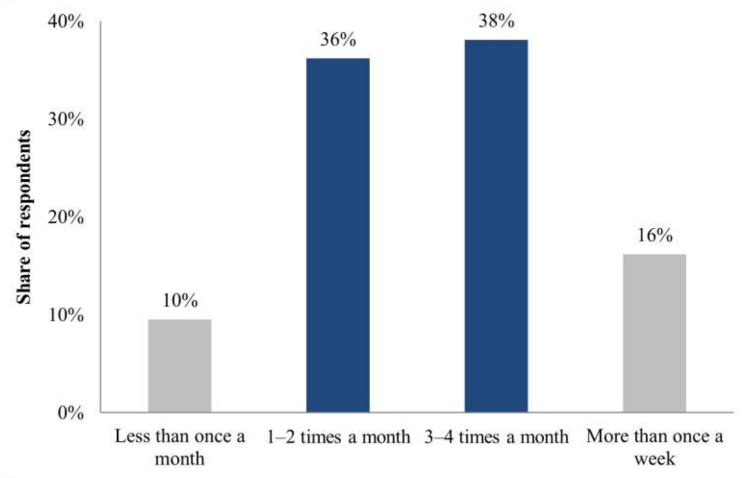
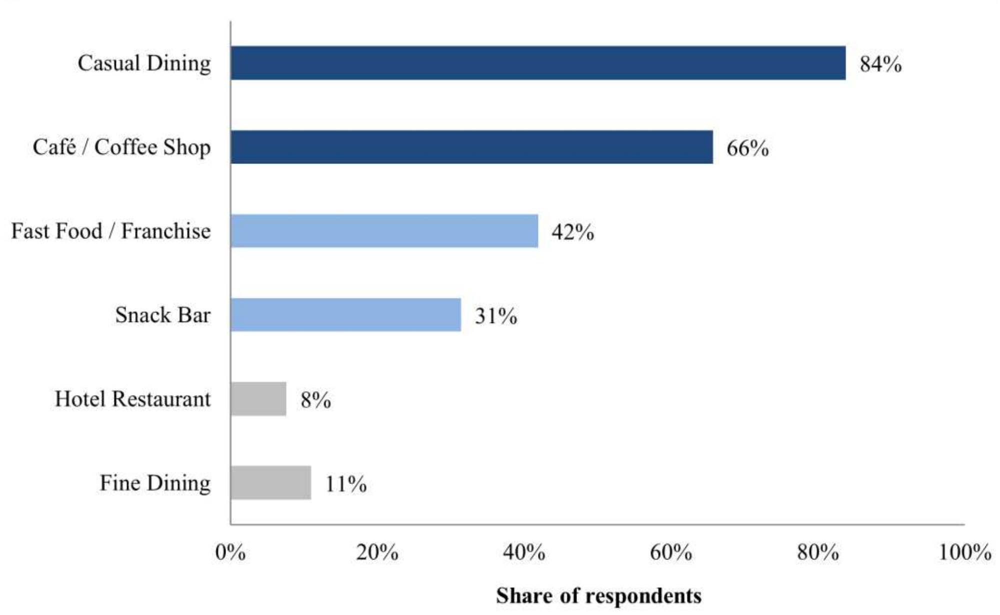


Figure 5 illustrates the types of restaurants visited most frequently, with multiple responses permitted. Casual dining establishments were by far the most common setting, selected by 84% of respondents. Cafés and coffee shops ranked second at 66%, followed by fast food and franchise restaurants (42%) and snack bars (31%). Fine dining was chosen by 11% and hotel restaurants by 8%.

Figure 5

Restaurant types visited most frequently (n=210; multiple responses permitted)



4.2.2 Experience and Perception with Service Robots

Figure 6 summarizes prior exposure to service robots in restaurants and the ratings assigned by those with direct experience. A majority of respondents (58%) had previously encountered a service robot in a restaurant setting, while 38% had not and 4% were uncertain. Among the 121 respondents who reported prior exposure, evaluations were predominantly positive: 11% rated the experience as very positive and 32% as positive, with an additional 24% rating it as rather positive. Neutral ratings were provided by 21%, while 7% responded rather negatively and 5% negatively or very negatively. Taken together, 67% of respondents with direct robot experience reported a net positive impression.

Figure 7 breaks down these ratings in detail. The distribution is skewed toward the positive end of the scale: 67% of respondents fell into the three positive categories (very positive, positive, rather positive), 21% reported a neutral impression, and only 12% rated their experience negatively across the three lowest categories combined. Notably, only 2% of respondents rated the experience as very negative, suggesting that strongly adverse reactions remain rare. This pattern indicates that direct exposure tends to reinforce rather than reduce acceptance.

Figure 6

Prior experience with service robots among survey respondents (n=210)

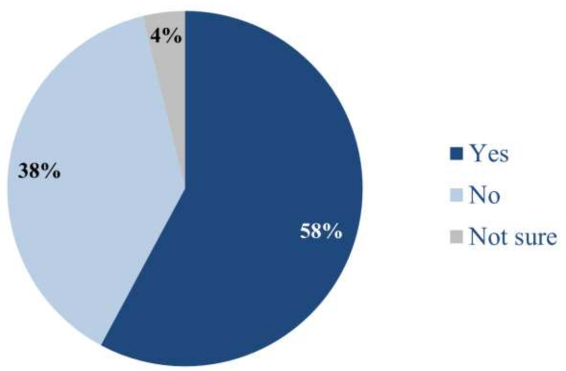


Figure 7

Experience ratings of service robots (n=121)

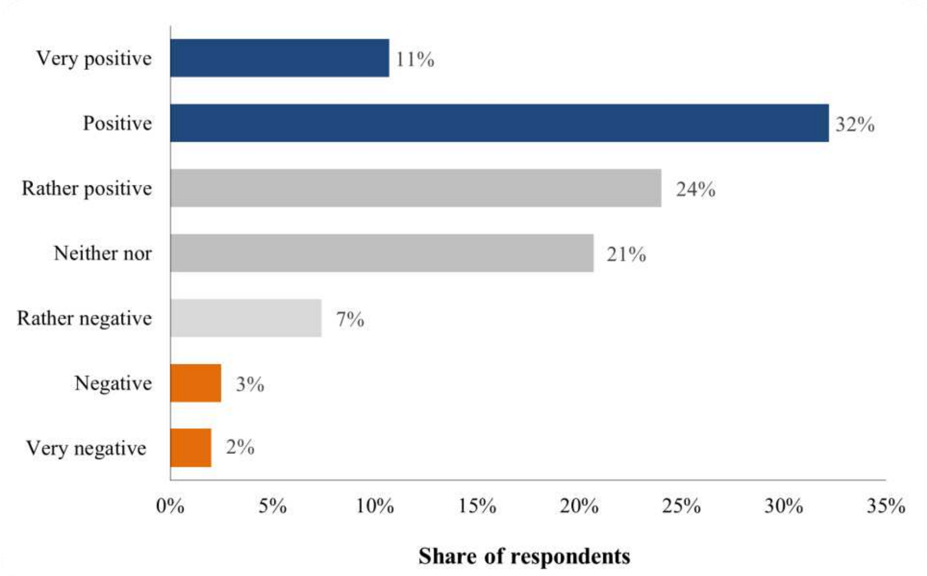


Figure 8 presents respondents' perceptions of which tasks service robots are best suited to perform. Food delivery to the table was identified as the most appropriate application by 73% of respondents, followed by clearing plates and glasses (54%), ordering food and drinks (47%), and payment processing (44%). Guest welcoming and instructions were seen as suitable by 25%. Only 10% selected none of the above, suggesting broad acceptance of robots across multiple service functions.

Figure 8

Tasks perceived as suitable for service robots (n=210)

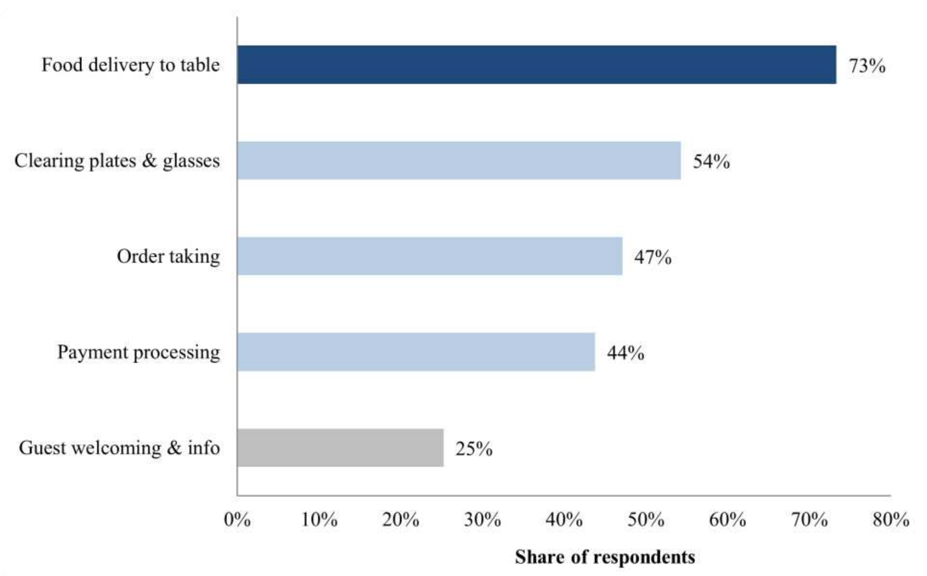
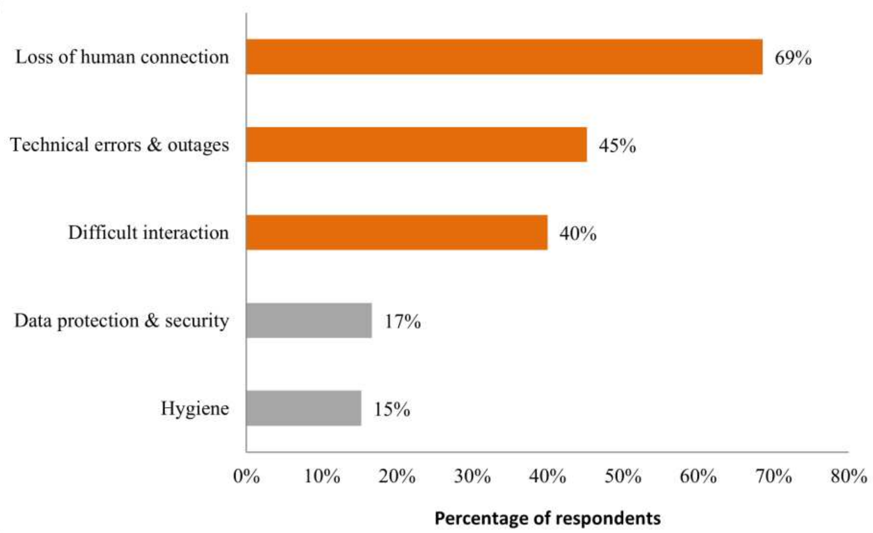


Figure 9 shows the concerns respondents associated with service robots in restaurants, again with multiple responses permitted. The most frequently cited concern was the loss of human connection in customer service, selected by 69% of respondents, reflecting the continued importance of interpersonal interaction in gastronomy contexts. Technical errors and outages were cited by 45%, and difficulty of use or interaction by 40%. Data protection and security issues were raised by 17%, and hygiene concerns by 15%.

Figure 9

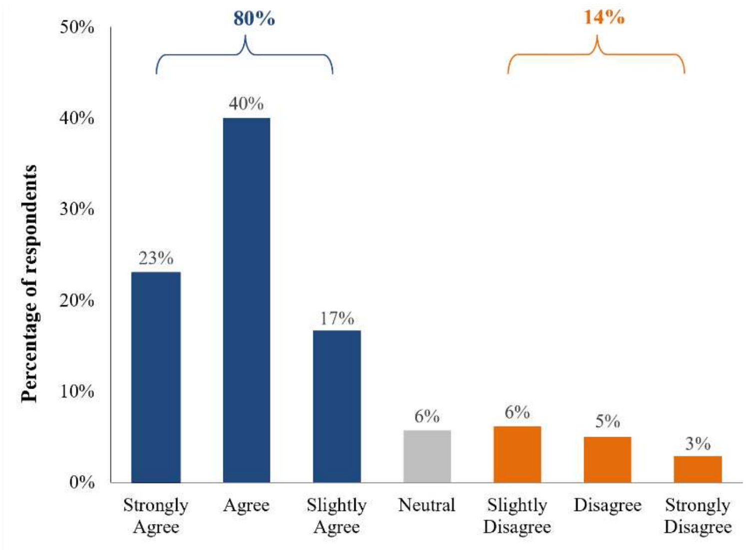
Concerns regarding service robots (n=210; multiple responses permitted)



Before examining the regression model and gastronomy-type-specific differences, it is useful to establish the overall acceptance baseline across the full sample. Figure 10 displays the distribution of responses to the item "I would be fine with being served by a service robot the next time I go to a restaurant" (n = 210, seven-point Likert scale). 80% of respondents agreed at a score of 5 or above (most common: 6, at 40%); only 14% scored 3 or below. The mean score of 5.47 (SD = 1.52) confirms a broadly favorable baseline orientation, even before controlling for construct-level heterogeneity in the regression model.

Figure 10

Overall service robot acceptance (n=210)



4.2.3 Regression Analysis

Eight constructs were operationalized to measure the distinct factors theorized to drive customer acceptance of service robots in restaurant settings. Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) represent the core cognitive evaluation dimensions from TAM (Davis, 1989). Social Influence (SI), Hedonic Motivation (HM), and Compatibility (CO) extend the framework to social and experiential drivers, as conceptualized in UTAUT2 (Venkatesh et al., 2012). Trust (TR) was included as a relational antecedent of acceptance, following TAM3 (Venkatesh & Bala, 2008). Human Touch Preference (HTP) captures domain-specific resistance: preference for human-delivered service as a structural barrier to robot adoption (Lin et al., 2020). Personal Innovativeness (PI) served as an individual-differences control. Behavioral Intention (BI), the dependent variable, was operationalized as the unweighted mean of items BI1, BI2, and BI3; item BI4 was excluded because it measures a conditionality of acceptance rather than intention itself.

Each latent construct was operationalized as the arithmetic mean of its constituent Likert-scale items, yielding a continuous composite score for each respondent (see Table 10 in the Appendix for the full item-to-construct mapping). The eight construct scores and five control variables (age, gender, education, restaurant visit frequency, and prior robot experience) were entered simultaneously into an OLS regression with Behavioral Intention as the dependent variable.

4.2.4 Measurement Quality

Cronbach's alpha (α) was computed for all multi-item constructs to assess internal consistency. Three constructs exceeded the conventional .70 threshold comfortably: Behavioral Intention (α = .827), Hedonic Motivation (α = .817), and Perceived Usefulness (α = .812). Perceived Ease of Use (α = .762), Trust (α = .785), and Compatibility (α = .753) met the threshold without qualification. Social Influence (α = .644) and Human Touch Preference (α = .691) fell marginally below .70; both consist of two items only, a structural constraint that tends to yield lower alpha estimates independent of genuine item coherence (South et al., 2022). Inter-item Pearson correlations were therefore computed as a supplementary reliability check. All two-item constructs showed significant positive inter-item correlations: Hedonic Motivation (r = .692, $p < .001$), Trust (r = .648, $p < .001$), Perceived Ease of Use (r = .616, $p < .001$), Compatibility (r = .604, $p < .001$), Human Touch Preference (r = .539, $p < .001$), and Social Influence (r = .475, $p < .001$). These values confirm adequate convergence within each construct, and all eight were retained for subsequent analysis. Full reliability and inter-item correlation statistics are reported in Appendix F, Table 12.

Table 1

Cronbach's Alpha Reliability Coefficients

Construct	Items	α	Interpretation
Perceived Usefulness (PU)	3	0.812	Good
Perceived Ease of Use (PEOU)	2	0.762	Acceptable
Social Influence (SI)	2	0.644	See note
Hedonic Motivation (HM)	2	0.817	Good
Compatibility (CO)	2	0.753	Acceptable
Human Touch Preference (HTP)	2	0.691	See note
Trust (TR)	2	0.785	Acceptable
Behavioral Intention (BI)	3	0.827	Good

Note. α = Cronbach's alpha. Conventional threshold: α ≥ .70. SI and HTP fell below threshold due to two-item scale structure; supplementary inter-item correlations are provided in Table 12.

Construct means were computed as unweighted item averages on the seven-point Likert scale (1 = strongly disagree, 7 = strongly agree). Human Touch Preference registered the highest mean (M = 5.44, SD = 1.26), indicating a pronounced preference for human-delivered service that sits in direct tension with the other acceptance constructs. Trust followed (M = 5.26, SD = 1.27), and Behavioral Intention occupied the upper-moderate range (M = 4.93, SD = 1.26). Social Influence (M = 4.75, SD = 1.33) and Perceived Usefulness (M = 4.45, SD = 1.39) fell in the moderate range. Hedonic Motivation (M = 4.13, SD = 1.67), Compatibility (M = 4.10, SD = 1.61), and Personal Innovativeness (M = 4.14, SD = 1.80) clustered near the scale midpoint, with PI showing the widest individual dispersion. The pattern is meaningful. Respondents on average expressed moderate-to-positive acceptance intentions while simultaneously recording the highest score on a barrier construct, signaling that acceptance competes with an active relational preference rather than simply overcoming neutral resistance. Descriptive statistics for all constructs are reproduced in Appendix F, Table 11. Bivariate correlations between construct mean scores (Appendix F, Figure 14) confirm the expected directional relationships. Trust, Hedonic Motivation, and Social Influence correlate positively with Behavioral Intention, while Human Touch Preference correlates negatively, consistent with its hypothesized barrier role.

4.2.5 Regression Results

The eight constructs were entered simultaneously into an OLS regression with BI as the dependent variable. OLS was appropriate given the continuous scale of the composite mean and the absence of floor or ceiling effects in the BI distribution. Five control variables were included to partial out demographic and behavioral variance including age, gender, education level, restaurant visit frequency, and prior experience with service robots. Listwise deletion on missing values reduced the analytic sample from n = 210 to n = 187; 23 cases were excluded due to incomplete control responses. Full regression output, including all standardized and unstandardized coefficients, is presented in Table 2.

The model fit was strong: $R^2 = .759$, adjusted $R^2 = .741$, $F(13, 173) = 42.02$, $p < .001$ (South et al., 2022; Chen & Qi, 2023). The high adjusted R^2 confirms that explanatory power withstands penalization for model complexity and that the construct battery captures the dominant structural drivers of acceptance. Four constructs reached statistical significance (see Table 2). Trust was the strongest predictor ($\beta = 0.268$, $p < .001$). Respondents who perceived robots as operationally reliable and safe expressed markedly higher acceptance intention, confirming the TAM3 proposition that trust functions as a primary relational antecedent of adoption (Venkatesh & Bala, 2008). This finding aligns directly with the operator accounts in Section

4.1, where trust in robot performance was described as the threshold condition for guest-facing deployment. Hedonic Motivation was the second-largest contributor (β = 0.209, $p < .001$), corroborating UTAUT2's inclusion of enjoyment and novelty as core acceptance drivers in consumer contexts (Venkatesh et al., 2012). Where the service interaction itself carries experiential value, robots that generate positive arousal benefit from that dynamic.

Social Influence was also significant (β = 0.166, $p < .05$). Respondents who perceived robot service as socially normative in their reference group expressed higher acceptance, consistent with UTAUT's normative pressure mechanism (Venkatesh et al., 2003). The effect is smaller than Trust and HM, suggesting that experiential evaluations outweigh peer norms as drivers of acceptance in this sample. Human Touch Preference exerted a significant negative effect (β = −0.136, $p < .01$). As preference for human service delivery increased, Behavioral Intention declined, confirming HTP as a domain-specific resistance barrier. Guests who associate service quality with interpersonal warmth evaluate robots unfavorably regardless of their functional utility. The finding is particularly notable because HTP recorded the highest descriptive mean in the sample (M = 5.44), meaning this barrier is not only statistically significant but structurally widespread. Perceived Usefulness approached but did not reach the conventional threshold (β = 0.111, p = .076); partial suppression by functionally adjacent constructs such as HM and TR is a plausible account given the inter-construct correlations. Perceived Ease of Use produced a near-zero coefficient (β = 0.027, n.s.), a finding that warrants interpretation rather than dismissal. In a restaurant context, guests interact with the robot only at the brief moment of service delivery, making effort expectations largely irrelevant to acceptance. Compatibility, Personal Innovativeness, and all five control variables were likewise non-significant.

Taken together, these findings provide a clear empirical answer to the central research question: customer acceptance of service robots in gastronomy is driven primarily by trust, hedonic motivation, social influence, and resistance to human touch substitution. Technologically receptive consumers who find robot interaction enjoyable and perceive it as socially normative exhibit the strongest behavioral intentions to use service robots. Conversely, consumers with pronounced human service preferences report lower acceptance, confirming that HTP functions as a structural barrier rather than mere indifference. The strong model fit ($R^2 = .759$, adjusted $R^2 = .741$) confirms that the UTAUT2-based construct battery captures the dominant structural drivers of acceptance in this context. These results carry direct implications for technology deployment strategies and consumer communication, which are developed in Chapter 5.

Table 2

OLS Regression Results: Predictors of Behavioral Intention (n=187)

	Dependent variable: **Behavioral Intention (BI)**
Perceived Usefulness (PU)	0.111 (0.062)
Perceived Ease of Use (PEOU)	0.027 (0.055)
Social Influence (SI)	0.166* (0.065)
Hedonic Motivation (HM)	0.209*** (0.056)
Compatibility (CO)	0.115 (0.067)
Human Touch Preference (HTP)	−0.136** (0.049)
Trust (TR)	0.268*** (0.066)
Age	−0.034 (0.048)
Gender	−0.058 (0.118)
Education	−0.012 (0.029)
Dining Frequency	0.016 (0.053)
Robot Experience	−0.069 (0.117)
Personal Innovativeness (PI)	0.039 (0.041)
Constant	1.261* (0.575)
Observations	187
R^2	0.759
Adjusted R^2	0.741
Residual Std. Error	0.711 (df = 173)
F Statistic	42.019*** (df = 13, 173)

Note. *p < .05; **p < .01; ***p < .001. Standard errors in parentheses. Control variables: Age, Gender, Education, Dining Frequency, Robot Experience, Personal Innovativeness.

4.2.6 Robustness Checks

Two diagnostic checks verified OLS assumptions. Variance inflation factors fell below 5.0 for all predictors, with Compatibility recording the maximum (VIF = 4.28), ruling out problematic multicollinearity (see Appendix G, Table 13). Homoscedasticity was assessed via the Breusch-

Pagan test: BP = 17.981, df = 13, p = .158. The result provides no evidence against constant error variance, confirming that OLS standard errors are valid (see Appendix G, Table 14).

4.2.7 Acceptance by Gastronomy Type

The regression model treats gastronomy type as a background control, but the descriptive data warrant a more focused reading. Respondents rated the fit of service robots across five restaurant categories on a seven-point scale, producing a pronounced gradient that tracks directly with service formality. This section examines those differences and connects them to the moderating role of context identified by expert informants in Section 4.1.

Figure 11

Perceived fit of service robots across restaurant types (n=210)

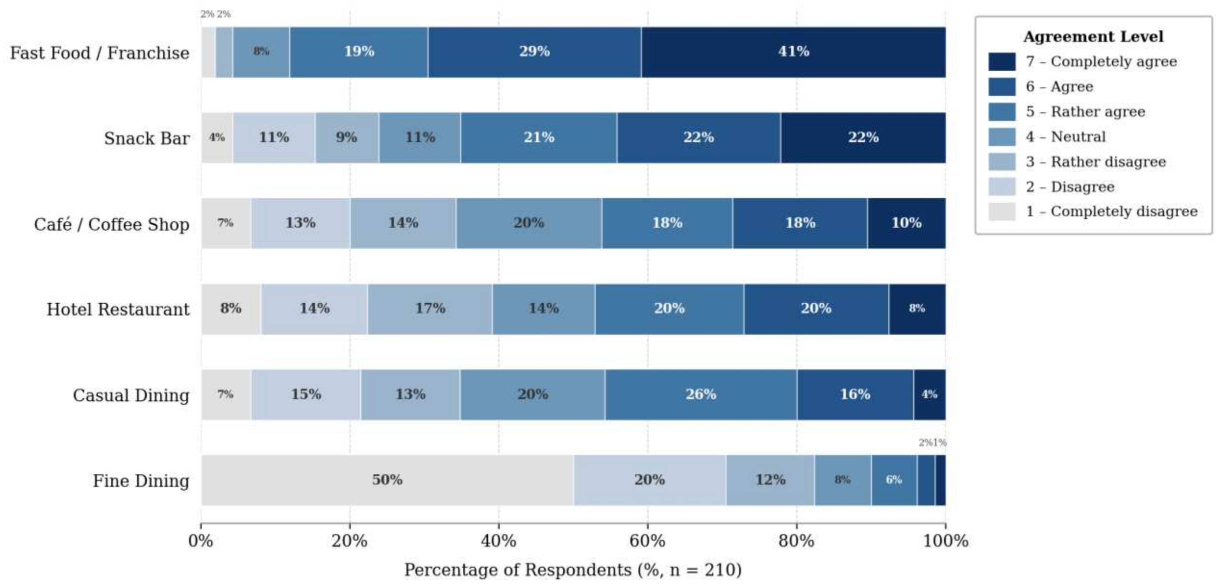


Figure 11 illustrates respondents' assessments of how well service robots fit into different restaurant types, rated on a seven-point Likert scale from 1 (completely disagree) to 7 (completely agree). Fast food and franchise restaurants received the strongest endorsement (M = 5.90), with 41% of respondents fully agreeing that robots fit this context. Snack bars (M = 4.89) and cafés (M = 4.24) also received moderately positive assessments. In contrast, fine dining establishments were perceived as the least suitable context (M = 2.12), with 50% completely disagreeing. These findings align with the qualitative expert data, which consistently identified service formality and relational service expectations as key moderators of robot acceptance.

The gradient is steep. Fast food and franchise settings recorded a mean of 5.90, with 41% of respondents fully endorsing robot deployment, and snack bars followed at 4.89. These contexts share low service formality and high operational throughput, where speed and consistency are the primary value drivers and interpersonal warmth is a secondary expectation at best. Cafés fell in the moderate range ($M = 4.24$), a finding consistent with their dual positioning as both transactional and social spaces. The pattern reverses sharply for fine dining: a mean of 2.12 with 50% completely disagreeing signals near-categorical rejection in contexts where relational service and expressive hospitality define the value proposition. This gradient replicates qualitative expert accounts from Section 4.1, where adoption decisions clustered precisely along the formality axis. The implication is that gastronomy type does not merely moderate robot acceptance at the margins. For fine dining, it constitutes a structural ceiling. Operators in mid-segment contexts face the more tractable design problem of calibrating robot involvement to service register, while fast food operators face a straightforward acceptance landscape where robot fit is already presumed by most guests.

4.3 Triangulation

Triangulation across the three data sources converges on a consistent structural pattern with one substantive divergence. The literature review, the expert interview dataset, and the consumer survey all confirm that gastronomy type is the primary moderator of acceptance. Operators reported smooth adoption in low-formality, high-throughput settings. The survey yielded a pronounced acceptance gradient from fast food ($M = 5.90$) to fine dining ($M = 2.12$) and prior research consistently identifies service formality as a boundary condition for robot-mediated service (van Doorn et al., 2017; Wirtz et al., 2018). Trust emerged as the dominant individual-level predictor in the regression ($\beta = 0.268$, $p < .001$), with qualitative accounts consistently identifying operational reliability as the threshold condition for guest-facing deployment. Hedonic Motivation ranked second ($\beta = 0.209$, $p < .001$), confirming the relevance of experiential value in consumer adoption, consistent with UTAUT2 (Venkatesh et al., 2012). Perceived Usefulness did not reach statistical significance in the regression model, though qualitative informants framed functional utility as the primary economic justification for deployment.

The divergence concerns the magnitude of general consumer receptivity. Operators in the evaluation phase consistently expressed uncertainty about whether guests would accept the technology at all (Section 4.1.7). The survey data, by contrast, recorded a mean Behavioral Intention of 4.93 on a seven-point scale ($SD = 1.26$), with 80% of respondents agreeing at a score of 5 or above on the overall acceptance item. Realized acceptance exceeded operator anticipations across all restaurant types where comparison was possible. This gap constitutes a substantive finding in its own right: informational asymmetry between the supply and demand sides of the adoption decision may suppress deployment rates below what consumer preferences would support, reinforcing Blöcher and Alt’s (2021) characterization of the European market as vendor-driven rather than demand-led. Taken together, the three data sources support a positive and differentiated answer to the research question. Customer acceptance of service robots in the gastronomy industry is driven primarily by trust and hedonic motivation, moderated structurally by gastronomy type, with social influence as a secondary driver and human touch preference as a significant barrier.

5. Conclusion

5.1 Discussion of Main Findings

This study combined a systematic literature review, sixteen expert interviews, and a consumer survey of 210 respondents to investigate what factors drive customer acceptance of service robots in German gastronomy. A consistent structural answer emerged across all three strands, alongside one substantive divergence.

Trust emerged as the dominant predictor of behavioral intention ($\beta = 0.268$, $p < .001$), confirmed by both the regression model and the qualitative strand, in which operators described reliability and safe physical operation as the threshold condition for deployment. Hedonic Motivation was the second-largest contributor ($\beta = 0.209$, $p < .001$), indicating that enjoyment and novelty drive acceptance beyond mere utility calculation, consistent with UTAUT2 (Venkatesh et al., 2012). Social Influence contributed positively ($\beta = 0.166$, $p < .05$), confirming that peer norms shape acceptance stances as UTAUT predicts. Perceived Ease of Use did not reach significance, consistent with Blut et al. (2021).

Human Touch Preference constitutes the study's most structurally significant finding. Registering the highest descriptive mean in the sample ($M = 5.44$) alongside a significant negative regression coefficient ($\beta = -0.136$, $p < .01$), HTP reflects a widespread baseline preference for interpersonal service delivery that competes with acceptance regardless of a robot's functional quality. This is not a segment phenomenon but a structural condition of the German gastronomy market that no deployment strategy can safely ignore.

The most consequential divergence between the data strands concerns operator uncertainty. Interviewees in the evaluation phase consistently expressed doubt about whether guests would accept the technology. The survey recorded a mean behavioral intention of 4.93, with 67% of those with prior robot experience reporting a net positive impression. Consumer openness exceeded operator anticipations across every restaurant type. This informational asymmetry may be suppressing deployment rates below what consumer preferences would support (Blöcher & Alt, 2021). The age-specific concern is a case in point. The regression shows age was non-significant, and adopters reported that older guests adapted well in practice.

The simultaneous occurrence of high Human Touch Preference (M = 5.44) and broad acceptance of robot service resolves an apparent paradox. These two findings describe a complementarity principle: consumers accept robots for transactional functions, including food delivery, order routing, and greeting, while maintaining a clear preference for human staff in relational service moments. Service robots are not substitutes for human hospitality but complements to it. Deployment strategies that treat robots as replacements for front-of-house staff misread the demand structure this study identifies.

The qualitative strand reframes the Trust finding. Operators did not describe trust as a competitive advantage but as a prerequisite, the minimum operational standard below which customer-facing deployment does not occur. Trust does not add incrementally once perceived as adequate. It enables the remaining acceptance drivers to operate.

A productive tension between the qualitative findings and DOI theory concerns the adoption sequence. Rogers (2003) positions relative advantage as the primary adoption trigger, implying rational utility assessment drives initial consideration. Several operators in this study, however, investigated robots after observing competitor deployments before any formal utility calculation. Social proof triggered consideration and economic justification followed. In low-information markets, peer observation functions as a heuristic substitute for deliberate assessment. Early-stage diffusion in German gastronomy appears observation-triggered rather than advantage-triggered, a sequence inversion not captured by DOI's staged adoption logic.

German consumers display moderate-to-high acceptance levels, with Behavioral Intention exceeding the scale midpoint (M = 4.93). This challenges the assumption that Western European markets are structurally less receptive than East Asian markets (Blut et al., 2021; Lin et al., 2020). Adoption barriers in Western markets appear driven more by operator hesitancy and deployment scarcity than by fundamental consumer resistance.

5.2 Theoretical Contributions

This study makes seven contributions to the acceptance literature. First, it confirms that the UTAUT2 construct battery generalizes to a Central European gastronomy context, extending a literature concentrated in Asian markets (Blut et al., 2021; Lin et al., 2020). Trust and Hedonic Motivation replicate as dominant drivers; Perceived Usefulness carries less weight when hedonic and relational constructs are included simultaneously.

More specifically, the non-significance of both PU ($\beta = 0.111$, $p = .076$) and PEOU ($\beta = 0.027$, n.s.), TAM's two foundational constructs, warrants a structural interpretation beyond partial suppression. TAM was developed for utilitarian contexts in which cognitive utility evaluation dominates (Davis, 1989), such as software systems and productivity tools. Gastronomy represents a categorically different setting, where the service encounter is fundamentally social and affective rather than instrumental. The dominance of Trust and Hedonic Motivation over PU and PEOU suggests that TAM's cognitive evaluation model encounters a boundary condition in high-affect service contexts. Acceptance in this domain is determined less by whether guests calculate that a robot will be useful than by whether they trust it and whether interacting with it generates positive affect. Acceptance frameworks for social service technology require relational and hedonic constructs as primary components rather than optional extensions to a utilitarian baseline.

Second, Human Touch Preference is established as a domain-specific resistance construct operating independently of standard acceptance drivers. Its high mean and significant negative coefficient confirm that gastronomy acceptance research requires a resistance term conventional TAM and UTAUT formulations do not supply, adding empirical specificity to calls by Ghazali et al. (2025) and Figueiredo et al. (2025) for relational and emotional dimensions in high-contact service acceptance frameworks.

Third, the operator-consumer informational asymmetry is an original empirical observation. The gap documents a sensing failure (Teece et al., 1997). Operators systematically misread consumer demand, suppressing deployment below consumer-supported levels.

Fourth, gastronomy type functions as a structural moderator that realigns the entire acceptance profile, not merely a control variable. The acceptance gradient from fast food ($M = 5.90$) to fine dining ($M = 2.12$) is categorical rather than incremental. Acceptance research aggregating across gastronomy types risks producing findings that describe no specific segment accurately.

A fifth contribution concerns the conceptual framing of robot-human service relationships in acceptance models. Prior frameworks, including standard TAM and UTAUT formulations, treat service robots as objects consumers either accept or reject at the encounter level, without accounting for the social scripts and interaction expectations Novak and Hoffman (2019) identify as central to consumer encounters with AI-powered physical agents. The complementarity principle identified here requires a more differentiated framing: consumers simultaneously accept robots for specific service functions and resist them for others within the same encounter.

A sixth contribution connects acceptance research to product design through the Hedonic Motivation finding. With $\beta = 0.209$, Hedonic Motivation ranks second among all predictors, evidence that affective interaction quality is a primary acceptance determinant, not a secondary product attribute. The dominant engineering paradigm's focus on efficiency and error reduction is misaligned with the acceptance drivers identified here; hedonic design should be integrated from the earliest development stages.

Seventh, the study operationalizes the management theory frameworks reviewed in Section 2.5. Labor-driven deployment decisions confirm RBT's resource complementarity logic (Barney et al., 2021). The robot's value as a physical asset is activated by customer acceptance rather than guaranteed by technical performance, as Section 4.1.1 demonstrates. The operator sensing failure documented in Section 4.1.7, specifically the systematic underestimation of consumer openness, maps onto the dynamic capabilities framework (Teece et al., 1997), which Barreto (2010) operationalizes across sensing, seizing, and reconfiguring dimensions. Accurate demand sensing is a prerequisite for timely seizing, and its absence constitutes a capability deficit constraining market development. The format-specificity of adoption across Sections 4.1.5 and 4.2.7 confirms the integration-over-disruption trajectory Balaji et al. (2024) distinguish. Robots extend the existing service model in viable formats, and acceptance collapses where adoption would require reconstituting the fundamental service logic.

5.3 Practical Implications

For gastronomy operators, the findings support a trust-first, context-matched deployment logic. Robots introduced with transparent communication about their function, operational limits, and safety generate higher acceptance than those without contextual framing. The novelty curve identified across interviews is real but manageable through staged rollout, beginning in high-throughput, low-formality settings where guests are most receptive (Hu & Min, 2025). Fine dining operators should treat the survey gradient as a structural signal: current consumer preferences do not support robot deployment in formal service contexts at scale.

For suppliers and manufacturers, the HTP finding identifies a communication design problem more than a technical one. Robots that signal attentiveness through appearance and feedback behaviors reduce the relational deficit driving resistance without requiring full replication of human interpersonal dynamics.

The complementarity principle has direct operational implications for staffing and service design. Operators should not frame robot deployment as a labor substitution strategy: consumer acceptance is conditioned on perceiving robots as additions to the service experience, not replacements for the human contact that remains part of it. Deployment models that keep human staff in relational moments while assigning delivery and routine tasks to robots align with what consumers in this study prefer. Operators who frame robots primarily as labor cost reduction tools risk triggering the Human Touch Preference resistance this study identifies as a structural feature of the gastronomy acceptance landscape.

The informational asymmetry documented in Section 5.1 represents the most immediately addressable finding for industry stakeholders. If operators systematically underestimate consumer readiness, the highest-return intervention is not consumer education but operator information provision. Industry associations, trade publications, and gastronomy robotics suppliers are positioned to publish structured deployment outcome data from operational pilots, including customer response metrics, staff impact assessments, and repeat visit rates, that close the perception gap between operator anticipations and actual consumer reports.

For hardware developers and system integrators, the primacy of Hedonic Motivation in the consumer acceptance model identifies a product development priority that efficiency-oriented engineering alone does not address. Robots perceived as enjoyable to interact with, generating positive affective responses through appearance, motion design, and feedback behavior, will be adopted faster than functionally equivalent but affectively neutral alternatives. This is not a secondary consideration to be addressed after core functionality is delivered: in the gastronomy context, affective interaction quality is a primary acceptance driver, and investment in interface and motion design is, in quantitative terms, investment in customer acceptance.

The Social Influence finding carries a timing implication for investors and market strategists. Its current significance ($\beta = 0.166$) reflects a market that has not yet reached the critical mass at which peer norm effects become self-reinforcing. Once robot deployment in fast-casual and mid-range restaurant segments reaches the density at which guest exposure becomes routine, the same mechanism that currently produces a modest positive effect will accelerate adoption across the late majority. Actors who enter before this inflection point are positioned to capture the benefits of early presence before competitive density reduces differentiation opportunities (Teece et al., 1997).

5.4 Limitations

Several limitations constrain the scope and generalizability of this study. First, the survey sample skewed sharply toward younger respondents: 71% were aged 18 to 34, consistent with online convenience sampling but likely overstating population-level acceptance. Older cohorts, representing a demographically significant portion of German dining patrons, are underrepresented and may hold more pronounced HTP and lower behavioral intention. Second, all constructs relied on self-reported measures subject to social desirability bias and retrospective distortion. The dependent variable is behavioral intention rather than observed behavior, and the gap between stated intentions and actual conduct in live service encounters cannot be addressed within a cross-sectional survey design. Third, the cross-sectional design captures attitudes at a single point in a rapidly evolving landscape; longitudinal variation, including the effect of repeated exposure to service robots, could not be examined. Fourth, the geographic scope is an explicit constraint. Findings are anchored in the German market and cultural transferability to other European contexts cannot be assumed. Fifth, the Human Touch Preference scale was operationalized with two items, producing a Cronbach's alpha below the conventional .70 threshold; this constrains the precision with which HTP's independent effect can be isolated. Sixth, the triangulation inference that operators underestimate consumer openness rests on a cross-strand comparison between qualitative operator assessments and quantitative consumer data: instruments measuring different constructs through different methods. Finally, the expert interview sample, though consistent with data saturation evidence (Guest et al., 2006), was concentrated in Germany and subject to survivorship bias: all interviewees were engaged with robot adoption, and operators who had categorically rejected the technology were not captured.

5.5 Future Research

Four directions emerge directly from the study's findings and limitations. Longitudinal research tracking the same respondent panel across multiple robot encounters would establish whether HTP diminishes with familiarity or persists as a stable preference, a distinction with fundamental implications for the adoption trajectory. Fine dining deserves dedicated investigation: an acceptance score of 2.12 suggests near-categorical resistance, but the mechanisms remain unspecified. A cross-national replication comparing Germany with Japan or South Korea would directly test whether the Trust-HTP construct hierarchy is consistent across cultural contexts. Experimentally, the operator-consumer asymmetry is a tractable design problem: what evidence formats most effectively close the perception gap is a question with direct managerial application and high practical return for the industry.

5.6 Final Conclusion

The research question driving this study asked what factors drive customer acceptance of service robots in the German gastronomy industry. The evidence points to a clear, ranked answer. Trust in operational reliability is the dominant predictor of behavioral intention, followed by hedonic motivation and, to a lesser extent, social influence. A pronounced human touch preference operates as the principal structural barrier, and gastronomy type sets the frame within which all of these forces operate. Acceptance is therefore neither uniform nor purely technological. It is conditioned on trust, affect, and contextual fit, and it differs sharply across formats, from fast food, where robots are presumed to belong, to fine dining, where consumer preferences foreclose deployment at scale.

Two findings carry particular weight. Operators systematically underestimate consumer readiness, which suggests that the binding constraint on diffusion in Germany sits on the supply side rather than the demand side. Consumers, in turn, accept robots as complements to human service rather than substitutes for it. Operators who build the enabling conditions for acceptance through transparent communication, contextual fit, and an accurate reading of consumer demand are not simply adopting a technology. They are reconfiguring the terms of the service encounter itself.

References

Balaji, M. S., Jiang, Y., Walsh, S. P., Behl, A., & Jain, K. (2024). A contingency-based approach to service robot design: Role of robot capabilities and personalities. *Technological Forecasting and Social Change, 201*, 123257. https://doi.org/10.1016/j.techfore.2024.123257

Barney, J. B., Ketchen, D. J., & Wright, M. (2021). Resource-Based Theory and the Value Creation framework. *Journal of Management, 47*(7), 1936–1955. https://doi.org/10.1177/01492063211021655

Barreto, I. (2010). Dynamic capabilities: A review of past research and an agenda for the future. *Journal of Management, 36*(1), 256–280. https://doi.org/10.1177/0149206309350776

Bazeley, P. (2021). *Integrating analyses in mixed methods research*. SAGE Publications.

Belanche, D., Casaló, L. V., & Flavián, C. (2020). Frontline robots in tourism and hospitality: Service enhancement or cost reduction? *Electronic Markets, 31*, 477–492. https://doi.org/10.1007/s12525-020-00432-5

Blöcher, K., & Alt, R. (2021). AI and robotics in the European restaurant sector: Assessing potentials for process innovation in a high-contact service industry. *Electronic Markets, 31*, 529–551. https://doi.org/10.1007/s12525-020-00443-2

Blut, M., Wang, C., Wünderlich, N. V., & Brock, C. (2021). Understanding anthropomorphism in service provision: A meta-analysis of physical robots, chatbots, and other AI. *Journal of the Academy of Marketing Science, 49*, 632–658. https://doi.org/10.1007/s11747-020-00762-y

Bowen, J., & Morosan, C. (2018). Beware hospitality industry: The robots are coming. *Worldwide Hospitality and Tourism Themes, 10*(6), 726–733. https://doi.org/10.1108/WHATT-07-2018-0045

Braun, V., & Clarke, V. (2022). *Thematic analysis: A practical guide*. SAGE Publications.

Brenner, M. (2006). Interviewing in educational research. In J. L. Green, G. Camilli, & P. B. Elmore (Eds.), *Handbook of complementary methods in education research* (pp. 357–370). Lawrence Erlbaum.

Buhalis, D., Harwood, T., Bogicevic, V., Viglia, G., Beldona, S., & Hofacker, C. (2019). Technological disruptions in services: Lessons from tourism and hospitality. *Journal of Service Management, 30*(4), 484–506. https://doi.org/10.1108/JOSM-12-2018-0398

Calleja, D. L. (2025). *Dancing with robots: Consumer acceptance of service robots in the hospitality industry* [Doctoral thesis]. Eindhoven University of Technology.

Carifio, J., & Perla, R. (2008). Resolving the 50-year debate around using and misusing Likert scales. *Medical Education, 42*(12), 1150–1152. https://doi.org/10.1111/j.1365-2923.2008.03172.x

Chen, J., & Qi, L. (2023). How much should we trust the adjusted R^2 in identifying reliable predictors? *Quantitative Psychology Research*. https://doi.org/10.1080/15140326.2023.2207326

Choi, S., Mattila, A. S., & Bolton, L. E. (2021). To err is human(-oid): How do consumers react to robot service failure and recovery? *Journal of Service Research, 24*(3), 354–371. https://doi.org/10.1177/1094670520978798

Christensen, C. M. (1997). The innovator's dilemma: When new technologies cause great firms to fail. *Harvard Business School Press.*

Chuah, S. H.-W., Aw, E. C.-X., & Cheng, C.-F. (2021). A silver lining in the COVID-19 cloud: Examining customers' value perceptions, willingness to use and pay more for robotic restaurants. *Journal of Hospitality Marketing & Management*. Advance online publication. https://doi.org/10.1080/19368623.2021.1926038

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? *Strategic Management Journal, 21*(10–11), 1105–1121.

Eisinga, R., Grotenhuis, M. T., & Pelzer, B. (2012). The reliability of a two-item scale: Pearson, Cronbach, or Spearman-Brown? *International Journal of Public Health*, *58*(4), 637–642. https://doi.org/10.1007/s00038-012-0416-3

El-Said, O. A. (2022). Are customers happy with robot service? Investigating satisfaction with robot service restaurants during the COVID-19 pandemic. *Heliyon, 8*(2), e08986. https://doi.org/10.1016/j.heliyon.2022.e08986

Figueiredo, I. G., Moutinho, P. F., Duarte, P. O., & Macedo, A. C. (2025). Customers' Intentions to Use Restaurants with Robot Waiters: An Extension of the Technology Acceptance Model. *Journal of the Knowledge Economy*, *17*(2), 3687–3713. https://doi.org/10.1007/s13132-025-02827-1

Garcia-Haro, J. M., Oña, E. D., Hernandez-Vicen, J., Martinez, S., & Balaguer, C. (2021). Service robots in catering applications: A review and future challenges. *Electronics, 10*(1), Article 47. https://doi.org/10.3390/electronics10010047

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly, 27*(1), 51–90. https://doi.org/10.2307/30036519

Ghazali, E. M., Mutum, D. S., & Cheah, J.-H. (2025). Dining with robots: An integrated perspective on functional, emotional and relational dimensions of customer experience. *Electronic Markets, 35*, 57. https://doi.org/10.1007/s12525-025-00797-5

Gioia, D. A., Corley, K. G., & Hamilton, A. L. (2013). Seeking qualitative rigor in inductive research: Notes on the Gioia methodology. *Organizational Research Methods, 16*(1), 15–31. https://doi.org/10.1177/1094428112452151

Grand View Research. (2024). Service robotics market size, share & trends analysis report, 2024–2030. https://www.grandviewresearch.com/industry-analysis/service-robotics-industry

Greener, S. (2008). Business research methods. *BookBoon.*

Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough? An experiment with data saturation and variability. *Field Methods, 18*(1), 59–82. https://doi.org/10.1177/1525822X05279903

Hu, Y., & Min, H. (2025). Crossing the innovation chasm: When and how to deploy service robots and facilitate customer adoption at restaurants. *Journal of Hospitality and Tourism Technology*. https://doi.org/10.1108/JHTT-11-2024-0777

Huang, D., Chen, Q., Huang, J., Kong, S., & Li, Z. (2021). Customer-robot interactions: Understanding customer experience with service robots. *International Journal of Hospitality Management, 99*, 103078. https://doi.org/10.1016/j.ijhm.2021.103078

Ivanov, S., Gretzel, U., Berezina, K., Sigala, M., & Webster, C. (2019). Progress on robotics in hospitality and tourism: A review of the literature. *Journal of Hospitality and Tourism Technology*. https://doi.org/10.1108/JHTT-08-2018-0087

Kao, W., & Huang, Y. (2023). Service robots in full- and limited-service restaurants: Extending technology acceptance model. *Journal of Hospitality and Tourism Management, 54*, 220–234. https://doi.org/10.1016/j.jhtm.2022.11.006

Kim, S., Kim, J., Badu-Baiden, F., Giroux, M., & Choi, Y. (2020). Preference for robot service or human service in hotels? Impacts of the COVID-19 pandemic. *International Journal of Hospitality Management*, *93*, 102795. https://doi.org/10.1016/j.ijhm.2020.102795

Kuo, C.-M., Chen, L.-C., & Tseng, C.-Y. (2017). Investigating an innovative service with hospitality robots. *International Journal of Contemporary Hospitality Management, 29*(5), 1305–1321. https://doi.org/10.1108/IJCHM-08-2015-0414

Lieberman, M. B., & Montgomery, D. B. (1998). First-mover (dis)advantages: retrospective and link with the resource-based view. *Strategic Management Journal*, *19*(12), 1111–1125. https://doi.org/10.1002/(SICI)1097-0266(1998120)19:12<1111::AID-SMJ21>3.0.CO;2-W

Lin, H., Chi, O. H., & Gursoy, D. (2020). Antecedents of customers' acceptance of artificially intelligent robotic device use in hospitality services. *Journal of Hospitality Marketing & Management, 29*(5), 530–549. https://doi.org/10.1080/19368623.2020.1685053

Lu, L., Zhang, P., & Zhang, T. (2020). Leveraging "human-likeness" of robotic service at restaurants. *International Journal of Hospitality Management*, *94*, 102823. https://doi.org/10.1016/j.ijhm.2020.102823

Mayring, P. (2015). Qualitative Inhaltsanalyse: Grundlagen und Techniken (13., überarbeitete Auflage). Beltz.

McCartney, G., & McCartney, A. (2020). Rise of the machines: Towards a conceptual service-robot research framework for the hospitality and tourism industry. *International Journal of Contemporary Hospitality Management, 32*(12), 3835–3851. https://doi.org/10.1108/IJCHM-05-2020-0450

Mende, M., Scott, M. L., van Doorn, J., Grewal, D., & Shanks, I. (2019). Service robots rising: How humanoid robots influence service experiences and elicit compensatory consumer responses. *Journal of Marketing Research, 56*(4), 535–556. https://doi.org/10.1177/0022243718822827

Milohnić, I., & Kapeš, J. (2019). Barriers to implementing and using robots in the hospitality industry. In V. Bevanda & S. Gručić (Eds.), *6th International Scientific Conference on*

Recent Advances in Information Technology, Tourism, Economics, Management and Agriculture (pp. 189–196). ITEMA.

Mingotto, E., Montaguti, F., & Tamma, M. (2021). Challenges in re-designing operations and jobs when introducing AI and robotics in services: Findings from a case in the hospitality industry. *Electronic Markets, 31*, 493–510. https://doi.org/10.1007/s12525-020-00439-y

Murphy, J., Hofacker, C., & Gretzel, U. (2017). Dawning of the age of robots in hospitality and tourism: Challenges for teaching and research. *European Journal of Tourism Research, 15*, 104–111.

Novak, T. P., & Hoffman, D. L. (2019). Relationship journeys in the internet of things: A new framework for understanding interactions between consumers and smart objects. *Journal of the Academy of Marketing Science, 47*, 216–237. https://doi.org/10.1007/s11747-018-0608-3

Nowell, L. S., Norris, J. M., White, D. E., & Moules, N. J. (2017). Thematic analysis: Striving to meet the trustworthiness criteria. *International Journal of Qualitative Methods, 16*(1). https://doi.org/10.1177/1609406917733847

Ottenbacher, M., Gnoth, J., & Jones, P. (2006). Identifying determinants of success in development of new high-contact services. *International Journal of Service Industry Management*, *17*(4), 344–363. https://doi.org/10.1108/09564230610680659

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce, 7*(3), 101–134. https://doi.org/10.1080/10864415.2003.11044275

Porter, M. E. (1985). Competitive advantage: Creating and sustaining superior performance. *Free Press*.

Proudfoot, S. (2022). Inductive and deductive research approaches. In M. Allen (Ed.), *The SAGE encyclopedia of communication research methods*. SAGE Publications.

Rasheed, H. M. W., Warraich, M. A., Ahmad, A., Malik, M. I., & Ul-Haq, J. (2023). Exploring interaction between humans and AI-enabled service robots: Findings and future research directions. *Technological Forecasting and Social Change, 192*, 122555. https://doi.org/10.1016/j.techfore.2023.122555

Rashid, Y., Rashid, A., Warraich, M. A., Sabir, S. S., & Waseem, A. (2019). Case study method: A step-by-step guide for business researchers. *International Journal of Qualitative Methods, 18*. https://doi.org/10.1177/1609406919862424

Reis, J., Melao, N., Salvadorinho, J., Soares, B., & Rosete, A. (2020). Service robots in the hospitality industry: The case of Henn-na hotel, Japan. *Technology in Society, 63*, 101423. https://doi.org/10.1016/j.techsoc.2020.101423

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Rowley, J. (2012). Conducting research interviews. *Management Research Review, 35*(3/4), 260–271. https://doi.org/10.1108/01409171211210154

Savela, N., Turja, T., & Oksanen, A. (2018). Social acceptance of robots in different occupational fields: A systematic literature review. *International Journal of Social Robotics, 10*(3), 317–329. https://doi.org/10.1007/s12369-017-0452-5

Seyitoğlu, F., & Ivanov, S. (2020). Understanding the robotic restaurant experience: a multiple case study. *Journal of Tourism Futures*, *8*(1), 55–72. https://doi.org/10.1108/jtf-04-2020-0070

Song, C. S., & Kim, Y.-K. (2022). The role of the human-robot interaction in consumers' acceptance of humanoid retail service robots. *Journal of Business Research, 146*, 489–503. https://doi.org/10.1016/j.jbusres.2022.03.087

South, L., Saffo, D., Vitek, O., Dunne, C., & Borkin, M. A. (2022). Effective use of Likert scales in visualization evaluations: A systematic review. *Computer Graphics Forum*, *41*(3), 43–55. https://doi.org/10.1111/cgf.14521

Spence, C. (2023). Robots in gastronomy: Psychological and financial considerations. *International Journal of Gastronomy and Food Science*, *32*, 100707. https://doi.org/10.1016/j.ijgfs.2023.100707

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

van Doorn, J., Mende, M., Noble, S. M., Hulland, J., Ostrom, A. L., Grewal, D., & Petersen, J. A. (2017). Domo Arigato Mr. Roboto: Emergence of automated social presence in organizational frontlines and customers' service experiences. Journal of Service Research, 20(1), 43–58. https://doi.org/10.1177/1094670516679272

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences, 39(2)*, 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157–178. https://doi.org/10.2307/41410412

Weijters, B., Rangarajan, D., Falk, T., & Schillewaert, N. (2007). Determinants and outcomes of customers' use of Self-Service Technology in a retail setting. *Journal of Service Research*, *10*(1), 3–21. https://doi.org/10.1177/1094670507302990

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: Service robots in the frontline. *Journal of Service Management, 29*(5), 907–931. https://doi.org/10.1108/JOSM-04-2018-0119

Xiao, L., & Kumar, V. (2019). Robotics for customer service: A useful complement or an ultimate substitute? *Journal of Service Research, 24*(1), 9–29. https://doi.org/10.1177/1094670519878881

Zemke, D. M. V., Hertzman, J. L., Raab, C., & Singh, D. (2020). How to build a better robot: Consumer attitudes toward robot-delivered hospitality services. *Journal of Hospitality & Tourism Research, 45*(7), 1145–1165. https://doi.org/10.1177/1096348020946383

Appendix

Appendix A: Semi-Structured Interview Guide

The interview guide followed a semi-structured funnel logic, opening with broad questions about the expert's professional role and organizational context before narrowing to specific themes around service robot deployment, customer acceptance, and operational challenges. Two separate guides were developed: one targeting technology providers and distributors (Table 3), and one targeting gastronomy operators (Table 4). This differentiation allowed for perspective-specific probing while maintaining thematic comparability across both expert groups. The guides were reviewed and refined before fieldwork began to improve question clarity and logical sequencing.

Interview Guide: Provider Perspective

Table 3

Semi-Structured Interview Guide: Provider Perspective

Section	Question	Objective
A: Background & Context	**Q1:** Could you briefly describe your company and your role within it?	Establishes the respondent's perspective and relevance to the topic.
	Q2: How has your gastronomy customer base developed over the past 3 years, and which types of businesses enquire most frequently?	Identifies early adopter profiles and market dynamics (Rogers, 2003).
	Q3: What differentiates your approach from other providers in the market?	Reveals competitive positioning and differentiation logic (Porter, 1985).
B: Drivers of Adoption	**Q4:** What are the main reasons gastronomy businesses adopt robotics, and what usually triggers the initial decision?	Identifies adoption drivers, tests tactical vs. strategic view.
	Q5: Do your customers see robotics more as a short-term fix for labor shortages or as a long-term investment?	Distinguishes operational reaction vs. strategic transformation (DC View vs. MBV).
	Q6: How important is ROI, and how do you communicate its economic value?	Explores cost-benefit logic and investment justification (Resource Allocation).
C: Adoption Barriers	**Q7:** What are the most common concerns you hear during the sales process, and which barrier is hardest to overcome?	Reveals adoption barriers from the supplier side (Rogers, 2003).
	Q8: Do these barriers differ by restaurant size or type, e.g., chains vs. independent operators?	Identifies segment-specific adoption patterns.

Section	Question	Objective
	Q9: How relevant are regulatory or data-protection concerns in your customers' decisions? (privacy and surveillance)	Identifies external constraints and market conditions (MBV: External Environment).
D: Implementation	**Q10:** What requirements are needed for a successful robotics implementation, and where do projects fail?	Assesses organizational fit and common failure modes (Teece et al., 1997).
	Q11: How important is training and ongoing support after installation? Do businesses tend to underestimate this?	Explores post-adoption support and depth of use.
	Q12: How do staff typically react to robotics, and how do you handle resistance?	Examines internal acceptance and change (Davis, 1989).
E: Customer Perspective	**Q13:** How do guests typically respond to robotic service, and do reactions differ by age group, restaurant type, or region? Would you prefer a humanoid looking robot?	Captures guest acceptance and user experience variation (User Acceptance).
	Q14: Do you see robotics as a guest-attracting differentiator, or can it also alienate certain customer groups?	Tests differentiation benefit vs. brand damage risk (Barney, 2021).
F: Outlook & Industry Trends	**Q15:** How will service-robot adoption in Germany evolve in the next years?	Expert prognosis on diffusion trajectory and market maturity (DOI).
	Q16: What needs to change within the industry or at the policy level for adoption to accelerate?	Identifies enablers, policy factors, and market conditions (MBV: External Environment).
	Q17: Is there anything we have not yet discussed that you consider particularly important?	Open closing question which allows new perspectives to emerge.
	Q18: Which business types do you expect to be the first to adopt robotics at scale and why?	Identifies first-mover segments and adoption leaders.

Table 4

Semi-Structured Interview Guide: Operator Perspective

Section	Question	Objective
A: Background & Context	**Q1:** Could you briefly describe your role and your area of responsibility within the business?	Establishes the respondent's perspective and relevance to the topic.
	Q2: What type of business do you run, and who are your typical customers e.g. older or younger guests, regulars or passing trade?	Contextualizes the organizational setting and helps assess whether robotics would be feasible or relevant.

Section	Question	Objective
B: Robotics Experience & Current Status	**Q3:** Have you or your business already implemented or seriously considered service robotics? If so, how did the decision come about?	Identifies whether robotics is already being applied, tests openness to innovation (DC View).
	Q4: If not yet adopted, why not? If yes, were there any initial concerns or reservations?	Reveals perceived barriers to adoption and early hesitations.
C: Strategic Rationale & Innovation Thinking	**Q5:** What role do you think robotics could play in addressing labor shortages in your business or the industry more broadly?	Tests whether robotics is viewed as a tactical solution or strategic tool aligns with DC View and industry trends.
	Q6: For which types of tasks do you consider the use of robots in gastronomy most sensible?	Tests in which areas robotics are considered most suitable for the hospitality industry.
	Q7: Do you see robotics more as a way to differentiate from competitors or primarily as a means to reduce costs?	Explores whether robotics serves differentiation or cost leadership MBV (Porter, 1985).
	Q8: How important is it to you to be among the first businesses to adopt new technologies like robotics or do you prefer to wait until the technology is proven?	Relates to First- / Second-Mover Advantage theory identifies strategic posture (Lieberman & Montgomery, 1998).
D: Implementation Barriers	**Q9:** What do you see as the biggest internal challenges to adopting robotics in your business?	Looks at organizational readiness and innovation barriers.
	Q10: How do you think your staff would respond to the introduction of service robots with acceptance or resistance?	Explores employee acceptance and change management challenges (Davis, 1989).
	Q11: Are there external barriers such as investment costs, technical complexity, or data-protection issues that make robotics adoption difficult for you? Are there issues with privacy or surveillance concerns?	Identifies external constraints and market conditions.
E: Customer & Guest Perspective	**Q12**: Do you think your guests would accept or reject robotic service? What experiences have you had, if any? Would you prefer a more humanoid looking robot?	Explores customer expectations and connects to TAM / DOI acceptance models (Davis, 1989).
	Q13: Would robotics enhance the guest experience in your business or does it risk feeling too impersonal for your concept?	Tests the perceived impact on service quality and hospitality identity.
F: Outlook & Industry Trends	**Q14:** Do you think robotics will become a standard part of gastronomy or remain a niche solution?	Tests belief about mainstream adoption vs. continued resistance.
	Q15: Is there anything we have not yet discussed that you consider particularly important regarding this topic?	Open closing question which allows new perspectives to emerge.

Appendix B: Interview Partners

Table 5 provides an overview of all 16 expert interview participants. The sample was divided equally between gastronomy operators (OP-01 to OP-08) and technology suppliers and distributors (SP-01 to SP-08). Participants were selected through purposive criterion-based sampling, targeting individuals with direct professional experience in service robot deployment, procurement, or operational management. This composition was chosen to capture both the demand-side perspective of operators managing adoption decisions and the supply-side perspective of companies developing or distributing service robot systems in the German gastronomy market.

Expert Overview

Table 5

Expert Interviews: Sample Overview (n=16)

Code	Role	Organization and Expertise
Gastronomy Operators		
OP-01	Owner / Operator	Seafood restaurant in Northern Germany with three to six employees, an early service-robot adopter that has leased a table-delivery robot for three years, originally introduced to cope with seasonal staff shortages.
OP-02	Operations Manager	Seaside beach bar and event venue in Northern Germany with a large seasonal team, a non-adopter that considers service robots impractical given its sand flooring and the personal, conversation-driven atmosphere central to its concept.
OP-03	Former Deputy Restaurant Manager	Modern franchise burger restaurant in central Germany with around fifty staff. Informant brings ten years of chain-gastronomy experience and argues service robots fit only limited clearing tasks rather than guest-facing interaction.
OP-04	Co-owner / Operations Manager	Casual-dining burger concept with three locations in a major German city and about forty-five staff. A service-robot adopter that ran a successful three-month delivery-robot pilot at its largest site, reporting strongly positive guest reactions.
OP-05	Owner / Managing Director	Owner-operated elevated comfort-food restaurant in western Germany with sixty seats and a loyal, older regular clientele; a non-adopter weighing service robots after prolonged service-staff vacancies, currently undecided between staffing relief and atmospheric concerns.
OP-06	Head of Gastronomy and Banquets	Four-star-superior hotel in southern Germany with a high international guest share, head of food-and-beverage operations and a BellaBot adopter using a service robot

		in breakfast service since late 2025, reporting measured efficiency and satisfaction gains.
OP-07	Managing Director	Group of five rural restaurants in Northern Germany serving over ten thousand guests monthly. Already operates a kitchen robot and is evaluating service robots via a planned pilot, with older-guest acceptance the main open question.
OP-08	Owner / Managing Director	Upscale fine-dining restaurant in Northern Germany with fifty-five seats and average covers of 85-110 euros, a conscious non-adopter whose sommelier-led, relationship-driven concept positions purely human service as a deliberate counterpoint to automation.
Technology Suppliers and Consultants		
SP-01	Managing Director / Owner	Robotics consultancy in Germany with around forty-five employees offering BellaBot, Keenon, and cleaning robots; takes a holistic advisory approach across restaurants, hotels, and healthcare, favoring leasing and reporting very low robot-failure rates in deployments.
SP-02	Owner / Broker	Independent robot broker with a hotel-management and tourism-consulting background, active across the German-speaking Alpine region; now sells mainly cleaning robots and offers a dissenting view that labor shortages have eased and service-robot demand has stagnated.
SP-03	Owner / Managing Director	Distributor of service, cleaning, marketing, and transport robots in Germany; led by a CEO who shifted from LED lighting and reports strong conservative resistance in German-run gastronomy, with adoption spreading through word of mouth.
SP-04	Sales and Project Manager	Provider of self-checkout and workflow systems for collective catering such as company canteens and cafeterias, active since 2008; recently added service-robot consulting and reports surprisingly strong customer interest driven by staff shortages.
SP-05	Managing Director / Owner	Software developer in Germany offering manufacturer-agnostic robot fleet-management with door and elevator integration for over fifteen hundred B2B clients; sees strongest demand for cleaning robots and attributes slow adoption to German caution and tight finances.
SP-06	Senior UX/UI Designer	Autonomous-kitchen robotics start-up in Northern Germany with a B2B subscription model; the informant designs operator and customer interfaces, notes deployments from supermarkets to a military base, and sees service robots as a growing portfolio extension.

SP-07	Managing Director / Founder	Provider-neutral consultancy in Germany specializing in automation for hospitality, care, and corporate catering; has delivered around eighty-five robot implementations since 2021, runs structured staff-acceptance workshops, and finds care facilities show the highest acceptance.
SP-08	Head of Marketing & Communications (Robotics)	Authorized Pudu robot distributor in Germany that grew out of an ice-cream café business; its marketing lead champions a 'cobotics' human-robot complementarity philosophy, notes cleaning robotics drives revenue, and cites German skepticism toward Chinese-made technology.

Appendix C: Interview Summaries

The following summaries reconstruct the substantive content of each expert interview in condensed form. All summaries were written in the past tense based on interview notes and recordings and do not constitute verbatim transcripts. Each summary focuses on themes most relevant to the research question, covering the expert's assessment of customer acceptance drivers, barriers to deployment, and strategic implications for the gastronomy sector. The summaries are organized by expert group: gastronomy operators (C.1) and technology suppliers and distributors (C.2).

C.1 Operator Interviews

Operator Interview OP-01

Robotics Experience	A delivery robot was leased and has run for about three years in a small seafood restaurant. Sourced from a nearby provider and trialed for two weeks, it carries plated dishes to numbered tables, announces its arrival, and clears used dishes.
Strategic Assessment	Adoption was driven by necessity: a winter staffing gap. The financial logic became clear afterward, with monthly leasing far below a part-time hire. Leasing was preferred over purchase to preserve capital and allow upgrades, and the robot was framed as relief, not replacement.
Implementation Barriers	Installation was simple; a technician programmed table positions and paths on site. The robot stopped for obstacles and was barred from the public sidewalk for insurance reasons. Overnight charging kept it available, and no real staff resistance arose.
Guest Perspective	Around ninety-nine percent of reactions were positive, children especially enthusiastic. Regulars asked for it by name and noticed its absence. The owner kept first contact and served elderly guests personally; rare objections eased once the rationale was explained.

Future Outlook	Continued use was certain, and the owner would choose the robot again over hiring. She was surprised how few peers had adopted after three years, and expected wider diffusion driven by labor costs and staff scarcity.

Operator Interview OP-02

Robotics Experience	No service robot was deployed and none was planned. Options were viewed briefly at a trade show but not pursued. Technology interest instead centered on AI administrative tools, specifically automated email pre-sorting and weather-linked shift scheduling, rather than guest-facing robotics on the floor.
Strategic Assessment	The venue positioned attentive, informal human service, including bartenders visibly crafting drinks, as its defining selling point. A service robot was judged incompatible with this relaxed, conversation-driven atmosphere. Staffing pressure existed, with dozens of new hires needed each year as students moved on, yet it was managed through team culture rather than automation.
Implementation Barriers	Physical conditions made deployment impractical. Much of the venue sat on sand, space was tight, and only a single fixed path existed, so a robot could at best cover part of a route before a server took over. Some staff anxiety about eventual replacement was noted.
Guest Perspective	Guests were thought to value the personal welcome and continuous attentiveness, such as a server noticing a nearly empty glass before being asked. The interviewee judged that a robot handling only transport, while staff stayed present, would likely be accepted, much as patrons already tolerate self-order terminals.
Future Outlook	Service robots were seen as better suited to new operators, high-throughput formats, and cafés where interaction matters less. Concern was voiced that order terminals erode human contact. For this concept, preserving genuine hospitality was treated as a deliberate priority over efficiency-driven automation.

Operator Interview OP-03

Robotics Experience	No service robot was used at the modern franchise burger restaurant, though the kitchen was already heavily automated, with self-cooking grills, automatic bun toasting, fryers, and digital inventory forecasting. Service robotics never reached discussion. A limited clearing robot was considered conceivable if reliable; a full-service robot was judged incompatible with the concept.
Strategic Assessment	Staff were framed as makers of special guest moments whose energetic, personal interaction defined the brand, something a robot could not reproduce. Cost reduction, not novelty, was identified as the decisive adoption motive industry-wide, since the novelty effect was expected to fade quickly.

Implementation Barriers	Reliability and maintenance of complex hardware were the central concerns, since a breakdown could not be fixed with simple tools and would undercut the labor savings sought. Limited speed and an inability to handle the full range of situations a person manages were further constraints.
Guest Perspective	The young, digitally native core clientele, mostly aged twenty-five to thirty-nine, was expected to react positively, treating a limited robot as a novelty, especially if it could deliver a programmed line. Acceptance was expected to be lower among older guests and to grow once robot service became normalized.
Future Outlook	Adoption was anticipated in rural excursion restaurants, cafés with counter ordering, and franchise chains where speed outweighs interaction. A dedicated robot-themed format was also imagined. Technological maturity was treated as the precondition for wider deployment.

Operator Interview OP-04

Robotics Experience	A delivery robot was leased and piloted for three months at the largest of three casual-dining locations, moving food and drinks from kitchen to table. The pilot followed a trade journal article on a peer deployment and was paused deliberately, with a multi-location rollout planned.
Strategic Assessment	Adoption was triggered by the simultaneous inability to fill five service positions and that article. The robot was framed as complementary, freeing staff for guest interaction rather than replacing them. A data-based business case, covering higher table turnover and fewer sick days, convinced a numbers-driven co-owner.
Implementation Barriers	On-site mapping took half a day, and two tables were repositioned for clean navigation. A two-hour staff training preceded launch. Sequential order dispatch became a necessary workflow rule, and tight passages occasionally halted the robot mid-service.
Guest Perspective	Reactions exceeded expectations, with photos, social media posts, and an estimated twenty percent rise in first-weekend reservations. Staff spontaneously named the robot, and guests addressed it directly. Younger and lunchtime guests reacted functionally, evening guests more playfully; a single older regular objected, resolved through conversation.
Future Outlook	Rollout to the remaining two locations was planned once financing and configuration were settled. Integration with the point-of-sale system, enabling automatic table routing without manual kitchen entry, was identified as the next decisive development for broader adoption.

Operator Interview OP-05

Robotics Experience	No robot was deployed; the operator was in active evaluation, rated near fifty-fifty. Consideration followed a trade-show talk, research, a consultant's outreach, and a visit to a comparable establishment using a wheeled delivery robot with an animated face, which she found approachable and unobtrusive.

Strategic Assessment	The trigger for considering adoption was recurring difficulty refilling service positions amid rising wage and operating costs. The central hesitation was atmosphere: a fear that loyal older regulars would read a robot as cost-cutting. Customer lifetime value of those regulars was calculated and judged likely to outweigh efficiency gains if even a few departed.
Implementation Barriers	No implementation occurred. A cautious phased path was envisaged: consult the team, run a limited trial on selected evenings, then gather direct feedback from regulars. A long-serving service member's skepticism was treated as a genuine constraint, alongside reliability and data-protection questions.
Guest Perspective	At the visited establishment, most guests, including regulars, adapted after initial skepticism, though two or three long-standing regulars reportedly stopped coming. An informal survey of about twenty of her own guests suggested most would not want a robot in this relationship-driven concept.
Future Outlook	Adoption was made conditional on three factors occurring together: an unsolvable staffing crisis, credible reference cases from comparable concepts, and a team that would accept introduction without key departures. The wider market was seen as splitting into technology-led and deliberately analogue formats.

Operator Interview OP-06

Robotics Experience	A service robot with an animated face ran in the hotel breakfast area from late 2025, delivering bread baskets and coffee refills along mapped routes while staff kept main-course service. It was chosen for its friendly appearance, stable software, and local support.
Strategic Assessment	The decision originated with the department head and required a business case, built on efficiency and staff-relief projections, to persuade a skeptical general manager. The robot was framed as freeing personnel for guest-facing work. Measured outcomes included shorter walking distances, higher breakfast-satisfaction scores, and modest upselling gains.
Implementation Barriers	A six-week preparation period covered mapping, a wireless network upgrade, and a charging station, plus two training sessions and advance guest communication via a bilingual sign. Long tablecloths and misplaced chairs caused early navigation issues, and a designated robot-attendant role emerged.
Guest Perspective	Survey responses were predominantly positive, reactions varying by nationality: Asian guests enthusiastic, German and Swiss guests reserved, a few older European travelers preferring human service and accommodated personally. An on-table information card explaining the robot reduced uncertainty and reassured guests that staff remained present.
Future Outlook	Cautious expansion to the a la carte restaurant was discussed, likely limited to internal kitchen-to-service-point transport. Priorities for future devices included property-management-system integration, multilingual voice phrases, and a slimmer body for tighter table spacing.

Operator Interview OP-07

Robotics Experience	No service robot was deployed yet, but active evaluation began about two months before the interview after seeing robots at peer establishments and a trade show. A kitchen robot had already run for a year, and the same cautious observe-then-pilot approach was planned, with a service-robot trial considered very likely.
Strategic Assessment	The primary driver was severe staffing difficulty across rural sites, including resignations caused by excessive workload. Cost reduction and staff relief were secondary, with a marketing and guest-attraction dimension acknowledged. Profitability worries eased once flexible leasing rates were understood. The operator moved quickly once a case was established.
Implementation Barriers	No service-robot implementation had occurred. Infrastructure prerequisites were identified, including ramps at two sites with level changes and difficulties in outdoor areas. Internal communication was named the main non-technical hurdle, drawing on experience introducing the kitchen robot through regular all-staff meetings that defused early resistance.
Guest Perspective	Uncertainty about guest acceptance, especially among older rural patrons, was the central concern. The operator suspected restaurateurs generally underestimated customer openness and planned a pilot at the location with the youngest demographic as a first test before any wider rollout across the five sites.
Future Outlook	Service robots were expected to grow more common in German gastronomy without becoming standard in rural or traditional formats soon, with fast food and chains likely first. The structural labor shortage was identified as the sustaining driver, and the operator voiced genuine personal enthusiasm.

Operator Interview OP-08

Robotics Experience	No service robot was deployed; adoption was rejected deliberately, not for lack of awareness. The owner informally polled about twenty regulars, of whom roughly fifteen found robots acceptable elsewhere but not here. Invisible back-office technology was embraced; guest-facing automation was not.
Strategic Assessment	The product was defined as a multi-hour human experience built on the sommelier's narrative and staff's knowledge of guests. Any technology visible to guests had to fit that identity, which a robot could not. High retention through premium wages answered staffing pressure, alongside ethical reluctance to displace jobs.
Implementation Barriers	No implementation experience existed. One theoretical scenario was described: a staffing emergency in which the alternative was closure, with a robot used strictly as a temporary bridge. Limited trust in current technology reinforced this reluctance.

Guest Perspective	Regulars were understood to treat the absence of robots as part of an unspoken contract about the restaurant's character. Guests who sustained the business through the pandemic by ordering collection menus illustrated the relationship the owner regarded as the operation's primary asset.
Future Outlook	The industry was expected to divide into technology-led efficiency formats and deliberately analogue, craft-based concepts, both viable for different needs. Purely human service was framed as a strengthening differentiator as everyday life digitized, and non-adoption was rejected as backwardness.

C.2 Supplier / Provider Interviews

Supplier Interview SP-01

Drivers of Adoption	The most frequent triggers were labor shortage in rural areas, economic efficiency in cost-sensitive urban formats such as pizzerias, and the marketing pull of a novel attraction. In cities, cost and differentiation dominated; in the countryside, staffing need came first.
Adoption Barriers	The most persistent objection was fear of negative guest reactions, which the consultancy found repeatedly unfounded. In one twelve-site chain, acceptance exceeded ninety-nine percent. Employee resistance was treated as a communication problem, strongest among larger, traditional restaurants and weakest in cafés and fast food.
Implementation	The process opened with a thirty to forty minute qualification call, then an on-site visit and a one-month pilot, which most clients retained. Roughly seventy to eighty percent chose leasing, the reported failure rate stayed under three percent, and twenty to thirty percent requested a second unit.
Customer Perspective	No regional difference in acceptance was observed across the firm's operating areas. Older guests showed greater initial caution but adjusted quickly once the robot delivered reliably. The firm explicitly advised operators to tell guests directly that staff had not been replaced.
Future Outlook	Optimism rested on word-of-mouth diffusion: once a handful of establishments in a locality deployed robots, visibility drove rapid further inquiries. Structural cost pressure and ongoing labor scarcity were expected to sustain growth, with use cases broadening steadily.

Supplier Interview SP-02

Drivers of Adoption	The original driver was pandemic-era staffing fear, which had since faded. Cleaning robots sold because their return on investment was calculable; service robots had not, since operators could rarely cut a full labor position, leaving payback weak. Long in-house distances in large hotels were the clearest justification.

Adoption Barriers	A widespread, often unjustified belief that personal service is incompatible with robots was the chief obstacle, especially in family-run hospitality defined through human contact. Spatial constraints, narrow aisles, thresholds, and sunlight, further limited viability. The broker had not sold a service robot in eighteen months.
Implementation	Mapping with LiDAR sensors took two to three hours, with predefined routes, named stations, and a circulating mode for buffets. Standard layouts had to be pre-mapped for halls that change configuration. Remapping after renovations and occasional wheel replacement were the only recurring practical issues.
Customer Perspective	Operator fear of guest rejection consistently exceeded reality. Elderly Swiss guests at upscale Alpine hotels photographed and filmed the robot, treating it almost as a familiar colleague, and children responded with delight. Reactions in genuinely upscale to-table service, however, remained untested.
Future Outlook	Stagnation was predicted unless the labor market tightened sharply again. Falling device prices were expected to lower the entry barrier, and hybrid machines combining cleaning and transport were anticipated as a possible reviver. Partial saturation of the 2022 to 2023 early-adopter wave was already observed.

Supplier Interview SP-03

Drivers of Adoption	On the operator side the leading motive was innovation image: robots signaled modernity and drew local attention. Functional value was often recognized only later. One ice-cream shop ran the robot for roughly fifteen hundred table trips a month, letting guests be served rather than queue.
Adoption Barriers	German food service was described as conservative, with openness higher among restaurateurs without German roots. The assumption that a robot means dismissing staff was the core objection. Some operators refused outright or pleaded lack of time, and the needed process changes were underestimated.
Implementation	Each site was visited to check steps, doors, route widths, and obstacles, and a model selected accordingly. A free demonstration was followed by a roughly three-week paid trial. Almost every demonstration led to purchase as reliability quickly became visible.
Customer Perspective	Guest acceptance regularly surpassed operator expectations, with selfies common and convention guests later requesting it for finger food and champagne. One restaurateur warmed from open hostility during a four-week trial to genuine enthusiasm. A guest who loudly protested job displacement was asked to leave.
Future Outlook	Strong growth was forecast, including purely functional high-capacity transport robots. Diffusion was expected to hinge on visible references and vocal advocates at industry gatherings. Deployments in award-winning five-star hotels were cited to counter the idea that robots suit only lower-end formats.

Supplier Interview SP-04

Drivers of Adoption	For its core self-checkout systems, early motivation mixed technology curiosity with modernization, a modern canteen serving as a talent-attraction asset; operational benefit followed in use. For the added service-robot consulting, the skilled-worker shortage in collective catering was the dominant driver, with operators seeking peak-service relief rather than headcount cuts.
Adoption Barriers	The largest obstacle for self-checkout was the scale of the systemic changeover, since cash-register and merchandise-management systems often had to change first, producing long project runtimes. Fear of digitalization among older staff created hesitation. Service concepts with extensive component choice or many loose goods resisted clean automation.
Implementation	An on-premise server was preferred over cloud to limit errors, with wired connections at every hardware point and careful RFID antenna placement avoiding metal. For built-in installations, work began early with kitchen planners. Each project was effectively bespoke; most end users adapted within two to three weeks.
Customer Perspective	As the guest-facing layer, the system was often blamed for errors originating in back-end networks or peripherals. Acceptance nonetheless rose over time, and a major industrial client repeatedly equipped new sites. Growing trust in workplace technology eased each rollout.
Future Outlook	Little dramatic new hardware was expected; existing solutions would spread further, alongside pre-order apps, smart fryers, and digital signage. Service robotics had become markedly more present over two years, supported by improved navigation and leasing around four to seven hundred euros monthly, and was seen as a complementary extension.

Supplier Interview SP-05

Drivers of Adoption	The dominant driver was staffing scarcity, compounded by minimum-wage rises of roughly fifty percent that pushed labor costs up sharply. Working-hour rules created evening coverage gaps a robot could fill without legal limits. The standard purchase rationale was cost recovery through shorter walking distances and equal output with fewer people.
Adoption Barriers	Resistance to advice and to change was the most common barrier, with operators dismissing the economics while invoking customer-preference concerns the interviewee considered largely unfounded. Current devices were also seen as not yet advanced enough for some tasks. Physical obstacles included uneven floors, thresholds, and older buildings lacking barrier-free access.
Implementation	Setup involved teaching table positions and pushing the robot through the space to build a floor map, then marking zones it must avoid, such as mirrors and low tables. Barrier-free conditions were essential; old wooden flooring with deep gaps was a failure case. German chain franchisees were a blocked segment, as head offices resisted even where the same brands used robots abroad.

Customer Perspective	Operators became enthusiastic once they saw a robot working, and guests turned positive after watching it perform, though an initial skeptical share was normal. In senior-care settings the robot was accepted when framed as help available when no staff member otherwise would be.
Future Outlook	Adoption was expected to advance incrementally in barrier-free, economically favorable settings rather than broadly. German chains lagged foreign counterparts markedly, and national caution demanded fully proven reliability. Improving investment conditions depended on tax stabilization and wider economic recovery.

Supplier Interview SP-06

Drivers of Adoption	Adoption of the autonomous kitchen system was driven less by upfront cost saving than by a visible technology statement and by filling kitchen-staff gaps, turning eight cooks into two robot operators. Fresh, customizable food on demand was an added draw, with cost benefits expected later.
Adoption Barriers	The main demand was patience, since a physical system of mechanics, hardware, and software needed on-site technicians when it failed. The subscription model clashed with client expectations of bespoke machines the firm could not build per request. Smaller start-ups struggled to fund subscriptions.
Implementation	Service ran door to door: the team deployed, assembled, and tested each robot, then stayed on site for days or weeks. The skilled-labor picture was read as nuanced, since language requirements and urban-rural differences shaped where shortages bit.
Customer Perspective	Guests were frequently excited, filming the robot and asking how it worked or whether it would replace jobs. Enthusiasm ran from middle-aged customers through Gen-Z, while older patrons were curious but largely unmoved. The robot functioned as an eye-catching attraction.
Future Outlook	Service and delivery robots had been added as an end-to-end automation extension, with traction described as strong and the German-speaking market catching up under labor pressure. Improved navigation and clearer economics were expected to make service robots a standard option within a few years.

Supplier Interview SP-07

Drivers of Adoption	Staff relief, freeing service personnel from physically demanding, repetitive transport, was identified as the core value proposition. A simple cost-reduction framing was rejected in favor of augmentation, robots extending rather than replacing people. The consultancy reported its fastest-growing demand here, with care facilities, not restaurants, showing the highest acceptance of all sectors served.
Adoption Barriers	Three objections recurred: perceived impersonality in upscale settings, cost, and staff rejection. Cost was met with a fourteen to eighteen month payback estimate, impersonality with the argument that

	personality comes from staff. The gravest, staff rejection, had ended three projects where management introduced a robot without preparing the team.
Implementation	A structured sequence ran from on-site stocktaking of rooms, processes, and network, through a three-hour staff acceptance workshop, to a four-week accompanied launch. Weak wireless infrastructure was the single most common technical obstacle, and floor maps needed updating after renovations or seasonal rearrangement of seating.
Customer Perspective	Across twenty-two surveyed projects, guest reactions were sixty-eight percent positive, twenty-four percent neutral, and eight percent negative, with negatives concentrated among guests over sixty-five, in upscale concepts, and in the opening weeks. Families with children reacted most positively. An animated robot face measurably improved acceptance.
Future Outlook	Within five years an operation without a service robot was expected to be the exception in hospitality and chain restaurants, as leasing costs fell and devices gained voice and system integration. Germany lagged comparable European markets, held back by tech skepticism and an intense job-loss debate, yet all three constraints were expected to weaken.

Supplier Interview SP-08

Drivers of Adoption	For service robots the relief dimension outweighed labor replacement, though both appeared depending on how the operator introduced the technology. A consistent cobotics framing, machines supporting rather than replacing staff, was central. In hotels, innovation signaling mattered; load-carrying models also moved heavy dish loads across floors.
Adoption Barriers	German caution was strong, including an unjustified barrier around the robots' Chinese origin despite smooth collaboration. Staff could quietly boycott a robot when the operator failed to involve them, so internal communication was decisive. Each venue differed in flooring, ceilings, aisle width, and layout, so a transparent process met individual requirements every time.
Implementation	A salesperson first assessed the site, followed by a technician, with the model chosen by navigation technology and environment, whether carpet, hard floor, or cold storage. Color-coded one-way systems and workflow protocols were defined with the operator. Staff had to be brought along deliberately, since unprepared teams could obstruct the robot rather than adopt it.
Customer Perspective	Guests split into two types: a minority irritated enough to block the robot, and many who filmed it and could not look away. Marketing analytics showed clear regional variation, with strongest interest in Bavaria, Baden-Wuerttemberg, North Rhine-Westphalia, and Hesse, and the weakest in the eastern states, attributed largely to economic conditions.
Future Outlook	The service-robot market was seen as near saturation among the more innovative operators and hotels, while cleaning robotics and warehouse logistics held the larger growth potential. Humanoid robots were arriving but stayed too expensive for gastronomy.

Appendix D: Coding Scheme

The qualitative coding process followed a hybrid design combining deductive and inductive strategies. Deductive codes were derived from the theoretical frameworks reviewed in Chapter 2: TAM, UTAUT, UTAUT2, and Diffusion of Innovations. Inductive codes emerged from the interview data using the Gioia et al. (2013) methodology, which proceeds from first-order descriptive codes through second-order theoretical themes to aggregate dimensions. Figure 12 illustrates the overall coding design and the relationship between deductive and inductive elements. Figure 13 shows the inductive coding structure, tracing the path from raw interview passages to the aggregate dimensions identified across the material. The hybrid process yielded 30 codes across 6 aggregate dimensions: 20 deductive and 10 inductive. Table 6 presents the full coding framework with code definitions and theoretical anchoring. Table 7 reports the frequency of evidence mentions per code across both expert groups, enabling comparison between operators and technology suppliers.

Hybrid Qualitative Coding Process

Figure 12

Coding Design: Combining Inductive and Deductive Coding

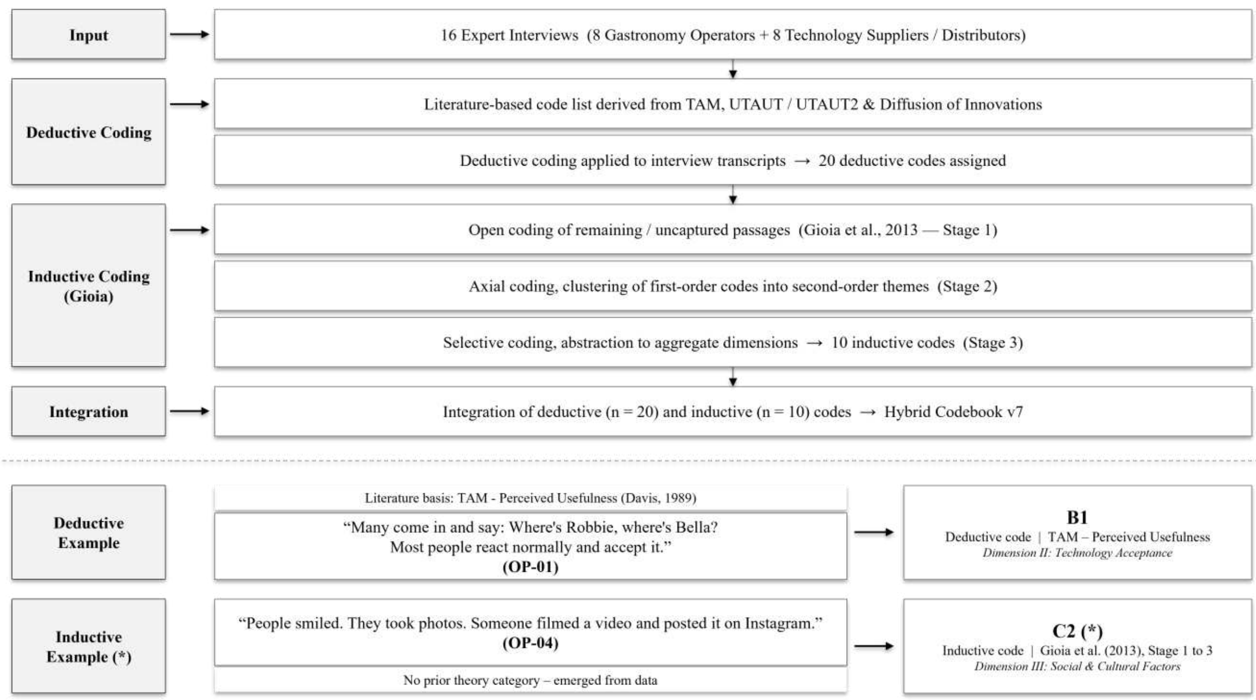
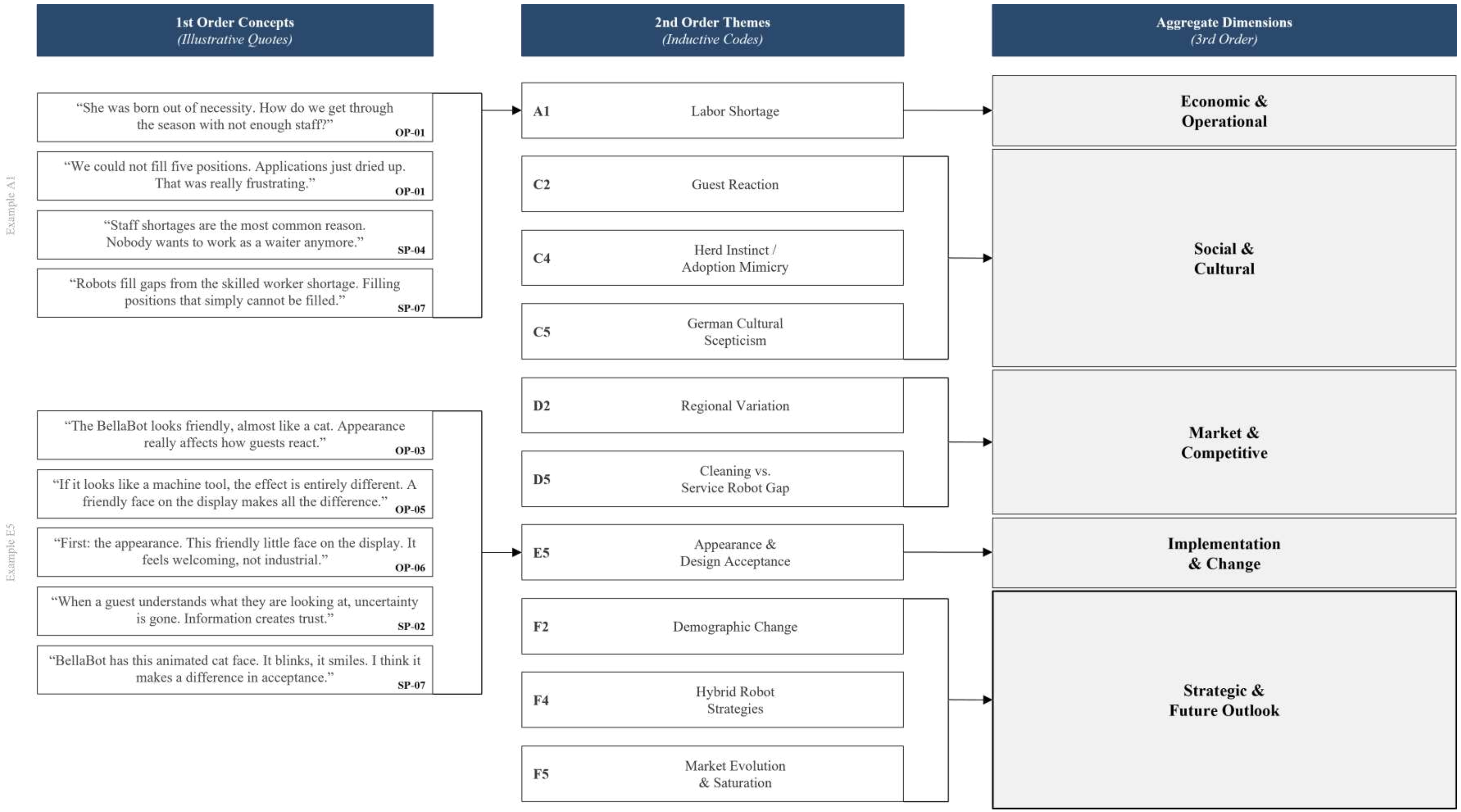


Figure 13

Inductive Coding Structure (Gioia et al., 2013)



Expert Interview Coding Framework

30 codes across 6 aggregate dimensions | Deductive: TAM / UTAUT / UTAUT2 / Diffusion of Innovations | Inductive (*): Gioia et al. (2013), 10 codes emerged from data | 16 interviews: 8 Gastronomy Operators (OP) + 8 Technology Suppliers / Distributors (SP)

Table 6

Hybrid Qualitative Coding Framework

Category	Code ID	Sub-Category	Origin	Definition	Theoretical Anchor
A: Economic & Operational Drivers	**A1**	Labor Shortage ★	Inductive	Chronic understaffing as primary push factor; robots fill roles that cannot be recruited.	UTAUT: PE; DoI: RA [context-specific, emerged inductively]
	A2	Cost Pressure & Price Sensitivity	Deductive	Financial viability of robot investment; price as adoption barrier or enabler by operational scale.	TAM: PU; DoI: Cost of Innovation
	A3	Return-on-Investment Calculation	Deductive	Explicit payback-period logic as decisive adoption criterion; quantifiable return required.	UTAUT: PE; Economic rationality
	A4	Staff Relief & Workload Reduction	Deductive	Reducing physical strain; freeing service staff for high-value guest interaction.	UTAUT: PE; Effort Expectancy
	A5	Process Optimization	Deductive	Broader operational re-engineering enabled by robot deployment beyond delivery substitution.	UTAUT: FC; DoI: Compatibility
B: Technology Acceptance	**B1**	Perceived Usefulness	Deductive	Operator belief that robot genuinely improves efficiency or guest experience.	TAM: PU; UTAUT: PE
	B2	Perceived Ease of Use	Deductive	Operator perception of how straightforward robot deployment and daily operation are.	TAM: PEOU; UTAUT: EE
	B3	Trust in Technology	Deductive	Confidence that hardware and navigation perform reliably and safely in live conditions.	TAM: Trust construct; Technology readiness
	B4	Technology Anxiety	Deductive	Personal fear or apprehension toward robotic technology inhibiting adoption intention.	TAM: Tech anxiety; UTAUT2: HM (negative)
	B5	Operational Compatibility	Deductive	Degree to which robot navigation and physical form fit restaurant layout and workflow.	DoI: Compatibility; TAM: PEOU
C: Social & Cultural Factors	**C1**	Social Influence	Deductive	Peer and reference-site effects; competitor adoption legitimizes and triggers own decision.	UTAUT: SI; DoI: Observability
	C2	Guest Reaction ★	Inductive	Actual or anticipated emotional response of guests to robot presence; shapes adoption intent.	UTAUT2: HM; Social acceptance [emerged inductively from operator accounts]
	C3	Staff Resistance	Deductive	Employee pushback driven by job-loss fears or perceived loss of workplace identity.	UTAUT: SI; Change management
	C4	Herd Instinct / Adoption Mimicry ★	Inductive	Competitor adoption in a visible peer group triggers mimicry rather than rational evaluation.	DoI: Observability; Social contagion [not in TAM/UTAUT]
	C5	German Cultural Scepticism ★	Inductive	Distinctive risk-aversion and documentation-demand pattern among German buyers.	DoI: Compatibility; Cultural context [not in TAM/UTAUT]

Category	Code ID	Sub-Category	Origin	Definition	Theoretical Anchor
D: Market & Competitive Context	**D1**	Market Maturity	Deductive	Current early-adopter stage of service-robot market in German gastronomy.	DoI: Diffusion S-curve; Market lifecycle
	D2	Regional Variation ★	Inductive	Geographic disparities in adoption: urban and southern Germany leads; rural / eastern lags.	DoI: Adoption rate [Germany-specific, emerged inductively]
	D3	Innovation Image	Deductive	Robot adoption as marketing signal of modernity, sustainability, or premium positioning.	DoI: Image construct; UTAUT2: HM
	D4	Competitive Pressure	Deductive	Awareness that competitor adoption forces re-evaluation of own market position.	DoI: Competitive pressure; UTAUT: SI
	D5	Cleaning vs. Service Robot Gap ★	Inductive	Cleaning robots achieve faster ROI, creating a two-speed adoption dynamic in the market.	DoI: Relative Advantage differentiation [not in TAM/UTAUT]
E: Implementation & Change Management	**E1**	Communication as Key Success Factor	Deductive	Pre-launch communication with staff and guests is decisive for adoption smoothness.	UTAUT: FC; Change management
	E2	Structured Change Management	Deductive	Formal project approach to robot integration: training, timeline, and stakeholder management.	Kotter change model; UTAUT: FC
	E3	Customization & Site Adaptation	Deductive	Physical and software adaptation required per venue; no universal installation template exists.	DoI: Compatibility; TAM: PEOU
	E4	Staff Training & Ongoing Support	Deductive	Structured onboarding and continuous training critical given high hospitality staff turnover.	UTAUT: EE; Facilitating Conditions
	E5	Appearance & Design Acceptance ★	Inductive	Non-threatening, non-humanoid robot aesthetics affect staff and guest acceptance.	Uncanny valley; TAM: PEOU [not explicit in UTAUT]
F: Strategic & Future Outlook	**F1**	Future Vision & Strategic Horizon	Deductive	Forward-looking operator/supplier assessment of robot adoption as long-term necessity.	DoI: Diffusion curve; Strategic foresight
	F2	Demographic Change ★	Inductive	Aging workforce and generational shift creating structural labor scarcity in hospitality.	Macro-environment; DoI: RA [emerged inductively]
	F3	Barriers to Scale	Deductive	Regulatory, financial, and organizational obstacles preventing scale-up from pilot.	DoI: Complexity; UTAUT: FC
	F4	Hybrid Robot Strategies ★	Inductive	Combining cleaning and service robots as transitional pathway reducing per-unit risk.	DoI: RA; Portfolio theory [emerged inductively]
	F5	Market Evolution & Saturation ★	Inductive	Innovator segment near saturation; market must expand to early majority for sustained growth.	DoI: S-curve; Innovator saturation [not in TAM/UTAUT]

Note. ★ Inductive code, emerged via Gioia et al. (2013) three-stage analysis; not pre-defined from theory | Deductive codes derived from: TAM (Davis, 1989), UTAUT/UTAUT2 (Venkatesh 2003, 2012), Diffusion of Innovations (Rogers, 2003) | Abbreviations: PU = Perceived Usefulness, PEOU = Perceived Ease of Use, PE = Performance Expectancy, EE = Effort Expectancy, SI = Social Influence, FC = Facilitating Conditions, HM = Hedonic Motivation, RA = Relative Advantage

Code Frequency Overview

Table 7

Code Frequency Overview by Expert Group

Category	Code	Code Name	Gastronomy Operators (n=8) ●	Technology Suppliers (n=8) ●	Total (n=16) ●
A: Economic & Operational Drivers	**A1**	Labor Shortage (*)	**6**	**7**	**13**
	A2	Cost Pressure & Price Sensitivity	4	**6**	**10**
	A3	Return-on-Investment Calculation	**6**	**7**	**13**
	A4	Staff Relief & Workload Reduction	**6**	**7**	**13**
	A5	Process Optimization	4	**7**	**11**
B: Technology Acceptance	**B1**	Perceived Usefulness	**5**	**8**	**13**
	B2	Perceived Ease of Use	4	**6**	**10**
	B3	Trust in Technology	**7**	**8**	**15**
	B4	Technology Anxiety	4	3	**7**
	B5	Operational Compatibility	**8**	**7**	**15**
C: Social & Cultural Factors	**C1**	Social Influence	4	**7**	**11**
	C2	Guest Reaction (*)	4	**8**	**12**
	C3	Staff Resistance	**7**	**5**	**12**
	C4	Herd Instinct / Adoption Mimicry (*)	2	4	**6**
	C5	German Cultural Scepticism (*)	3	3	**6**
D: Market & Competitive Context	**D1**	Market Maturity	1	**8**	**9**
	D2	Regional Variation (*)	0	**7**	**7**
	D3	Innovation Image	4	**6**	**10**
	D4	Competitive Pressure	4	**7**	**11**
	D5	Cleaning vs. Service Robot Gap (*)	0	4	**4**

Category	Code	Code Name	Gastronomy Operators (n=8) ●	Technology Suppliers (n=8) ●	Total (n=16) ●
E: Implementation & Change Management	**E1**	Communication as Key Success Factor	**6**	**7**	**13**
	E2	Structured Change Management	**6**	**7**	**13**
	E3	Customization & Site Adaptation	4	**7**	**11**
	E4	Staff Training & Ongoing Support	**5**	**7**	**12**
	E5	Appearance & Design Acceptance (*)	3	**5**	**8**
F: Strategic & Future Outlook	**F1**	Future Vision & Strategic Horizon	4	**8**	**12**
	F2	Demographic Change (*)	4	**7**	**11**
	F3	Barriers to Scale	**5**	**8**	**13**
	F4	Hybrid Robot Strategies (*)	2	**6**	**8**
	F5	Market Evolution & Saturation (*)	0	**7**	**7**

Note. ● = primary evidence (explicitly & prominently articulated) | (*) = inductive code (emerged from data via Gioia) | Bold = majority of group (≥ 5 of 8)

Appendix E: Quantitative Survey Design

Table 8 reproduces the full survey instrument used in the quantitative data collection phase. The survey was administered online via Qualtrics and structured in sequential blocks: demographic and background questions, prior experience with service robots, construct measurement items, and a final open-response item. Robot type images presented in question Q12 are referenced in the note below the table.

Table 8

Survey Instrument: Full Questionnaire

No.	Survey Question	Response Options	Question Type	Construct
Block 1: Socio-Demographic Characteristics				
Q1	How old are you?	18-24 / 25-34 / 35-44 / 45-54 / 55-64 / 65 or older	Single choice	Age
Q2	What gender do you identify as?	Male / Female / Non-binary	Single choice	Gender
Q3	What is your highest level of education?	Secondary School / Vocational Training / Bachelor's / Master's / Ph.D. / Other	Single choice	Education Level
Q4	In which country do you currently live?	Germany / Portugal / Another EU country / Other non-EU country	Single choice	Country of Residence
Block 2: Technology Familiarity & Restaurant Behavior				
Q5	I am familiar with modern digital technologies (e.g., artificial intelligence, smart devices).	Not at all familiar / Unfamiliar / Not very familiar / Neither nor / Somewhat familiar / Familiar / Very familiar	Single choice (7-point ordinal)	Tech Familiarity
Q6	How often do you visit restaurants, cafés, and other dining establishments?	Less than once a month / 1-2 times/month / 3-4 times/month / More than once a week	Single choice	Restaurant Visit Frequency
Q7	What type of restaurant do you visit most often?	Casual Dining / Fine Dining / Fast Food / Hotel Restaurant / Cafés / Snack bar	Multiple choice	Restaurant Type Preference

No.	Survey Question	Response Options	Question Type	Construct
Q8	Have you ever seen or interacted with a service robot in a restaurant?	Yes / No / Not sure	Single choice	Prior Robot Experience
Q9	How would you rate your overall experience with the service robot?	Very negative / Negative / Rather negative / Neither nor / Rather positive / Positive / Very positive	Single choice (7-point ordinal)	Experience Quality
Q10	For which tasks would a service robot be particularly well-suited?	Order taking / Food delivery / Clearing plates / Payment processing / None of the above / Other	Multiple choice	Perceived Robot Role
Q12	Which of the following service robots would you most like to have as a server?*	Robot Type 1 / Type 2 / Type 3 / No preference	Single choice	Robot Type Preference
Block 3: Perceived Usefulness / Performance Expectancy (TAM / UTAUT)				
Q11_1	Service robots in restaurants allow me to get my order faster.	1 = Strongly disagree, 7 = Strongly agree	7-point Likert scale	Perceived Usefulness
Q11_2	A service robot ensures greater accuracy in the delivery of my order than traditional service.	1 = Strongly disagree, 7 = Strongly agree	7-point Likert scale	Perceived Usefulness
Q11_3	Robot-assisted service makes the entire dining experience more efficient.	1 = Strongly disagree, 7 = Strongly agree	7-point Likert scale	Perceived Usefulness
Block 4: Perceived Ease of Use / Effort Expectancy (TAM / UTAUT)				
Q13_1	Interacting with a service robot requires very little effort on my part.	1 = Strongly disagree, 7 = Strongly agree	7-point Likert scale	Perceived Ease of Use
Q13_2	I find it intuitive to use a service robot.	1 = Strongly disagree, 7 = Strongly agree	7-point Likert scale	Perceived Ease of Use
Q13_3	When I see other guests interacting with service robots without any trouble, I feel more comfortable doing so myself.	1 = Strongly disagree, 7 = Strongly agree	7-point Likert scale	Social Facilitation
Block 5: Hedonic Motivation & Compatibility (UTAUT2 / DOI)				
Q13_4	I find the idea of being served by a robot in a restaurant entertaining.	1 = Strongly disagree, 7 = Strongly agree	7-point Likert scale	Hedonic Motivation
Q13_5	The novelty of service robots makes a restaurant more appealing to me.	1 = Strongly disagree, 7 = Strongly agree	7-point Likert scale	Hedonic Motivation

No.	Survey Question	Response Options	Question Type	Construct
Q14_1	Service robots meet my expectations for a modern, forward-thinking restaurant.	1 = Strongly disagree, 7 = Strongly agree	7-point Likert scale	Compatibility
Q14_2	Using a service robot fits in well with my general habits and lifestyle.	1 = Strongly disagree, 7 = Strongly agree	7-point Likert scale	Compatibility
Block 6: Social Influence (TAM2 / UTAUT)				
Q14_3	In my social circle, I'm usually one of the first to try out new technologies.	1 = Strongly disagree, 7 = Strongly agree	7-point Likert scale	Innovativeness
Q14_4	My friends and family would support my use of service robots in restaurants.	1 = Strongly disagree, 7 = Strongly agree	7-point Likert scale	Social Influence
Block 7: Human Service Preference (Control Variables)				
Q14_5	When I go to a restaurant, I prefer to be served by a person rather than a robot.	1 = Strongly disagree, 7 = Strongly agree	7-point Likert scale	Human Service Preference (R)
Q14_6	For me, human interaction and attentive service are key elements of a successful dining experience.	1 = Strongly disagree, 7 = Strongly agree	7-point Likert scale	Human Interaction Value (R)
Attention Check				
Q15	If you are reading this, please select answer option "50".	0 / 25 / 50 / 75 / 100	Single choice	Attention Check
Block 8: Trust (TAM3)				
Q16_1	I trust that service robots will fulfill my orders accurately and reliably.	1 = Strongly disagree, 7 = Strongly agree	7-point Likert scale	Trust
Q16_2	I feel comfortable relying on a service robot for part of my restaurant visit.	1 = Strongly disagree, 7 = Strongly agree	7-point Likert scale	Trust
Q16_3	I have reservations about the use of service robots in the restaurant industry.	1 = Strongly disagree, 7 = Strongly agree	7-point Likert scale	Trust (reverse-coded)
Block 9: Concerns & Perceived Fit by Restaurant Type				
Q17	What specific concerns do you have regarding service robots?	Technical errors / Data security / Loss of human connection / Hygiene /	Multiple choice	Perceived Risk / Barriers

No.	Survey Question	Response Options	Question Type	Construct
		Difficult to use / No concerns / Other		
Q18_1	How well do service robots fit into Fine Dining?	1 = Does not fit at all, 7 = Fits very well	7-point rating scale	Perceived Fit
Q18_2	How well do service robots fit into Casual Dining?	1 = Does not fit at all, 7 = Fits very well	7-point rating scale	Perceived Fit
Q18_3	How well do service robots fit into Hotel Restaurants?	1 = Does not fit at all, 7 = Fits very well	7-point rating scale	Perceived Fit
Q18_4	How well do service robots fit into Fast Food / Franchise restaurants?	1 = Does not fit at all, 7 = Fits very well	7-point rating scale	Perceived Fit
Q18_5	How well do service robots fit into Cafés / Coffee Shops?	1 = Does not fit at all, 7 = Fits very well	7-point rating scale	Perceived Fit
Q18_6	How well do service robots fit into Snack Bars?	1 = Does not fit at all, 7 = Fits very well	7-point rating scale	Perceived Fit
Block 10: Behavioral Intention to Accept Service Robots (Dependent Variable)				
Q19_1	I plan to use service robots in a restaurant, provided they are available.	1 = Strongly disagree, 7 = Strongly agree	7-point Likert scale	Behavioral Intention
Q19_2	I would be fine with being served by a service robot the next time I go to a restaurant.	1 = Strongly disagree, 7 = Strongly agree	7-point Likert scale	Acceptance Intention (Primary DV)
Q19_3	I plan to visit restaurants that use service robots in the future.	1 = Strongly disagree, 7 = Strongly agree	7-point Likert scale	Behavioral Intention
Q19_4	I am more willing to accept service robots if they complement human service rather than replace it.	1 = Strongly disagree, 7 = Strongly agree	7-point Likert scale	Complementarity Condition

Note. * Robot types presented as answer options for Q12. Left to right: Type 1 (autonomous delivery robot), Type 2 (BellaBot), Type 3 (humanoid robot).

Type 1	Type 2	Type 3
		

Appendix F: Data Cleaning & Constructs

The raw Qualtrics export was subjected to a three-stage screening procedure prior to analysis. Table 9 documents each exclusion step and the resulting sample size.

Table 9

Sample Derivation: Data Screening Sequence

Step	Action	Remaining n
Initial export	Raw Qualtrics responses collected via online platform	280
Incomplete submissions excluded	Responses with survey progress below 100% removed	257
Attention check failures excluded	Respondents selecting an incorrect response to the embedded attention check removed	245
Non-German residents excluded	Respondents not residing in Germany at time of survey excluded	210
Final analytical sample	Responses used for hypothesis testing	210

Note. Screening was applied sequentially in the order listed. No speeder filter was applied. The final analytical sample (n = 210) underpins all descriptive analyses; the OLS regression model (Section 4.2.3) operates on n = 187 complete cases after listwise deletion on control variables.

Table 10 documents the operationalization of all constructs included in the survey. For each construct, the table lists the survey item wording, the item code, the theoretical source from which the item was adapted, and whether reverse-coding was applied. Constructs were operationalized as unweighted arithmetic means of their constituent items. Behavioral Intention item BI4 was excluded from the BI composite because it measures a conditional acceptance scenario rather than unconditional intention, which would have introduced construct contamination.

Table 10

Construct Operationalization: Survey Items and Theoretical Sources

Construct	Abbr.	Item	Survey Item Text	Theory
Perceived Usefulness	**PU**	**PU1**	Service robots in restaurants allow me to get my order faster.	TAM / UTAUT
		PU2	A service robot ensures greater accuracy in the delivery of my order than traditional service.	
		PU3	Robot-assisted service makes the entire dining experience more efficient.	

Construct	Abbr.	Item	Survey Item Text	Theory
Perceived Ease of Use	**PEOU**	**PEOU1**	Interacting with a service robot requires very little effort on my part.	TAM / UTAUT
		PEOU2	I find it intuitive to use a service robot.	
Social Influence	**SI**	**SI1**	When I see other guests interacting with service robots without any trouble, I feel more comfortable doing so myself.	TAM2 / UTAUT
		SI2	My friends and family would support my use of service robots in restaurants.	
Hedonic Motivation	**HM**	**HM1**	I find the idea of being served by a robot in a restaurant entertaining.	UTAUT2
		HM2	The novelty of service robots makes a restaurant more appealing to me.	
Compatibility	**CO**	**CO1**	Service robots meet my expectations for a modern, forward-thinking restaurant.	DOI / UTAUT2
		CO2	Using a service robot fits in well with my general habits and lifestyle.	
Human Touch Preference	**HTP**	**HTP1**	When I go to a restaurant, I prefer to be served by a person rather than a robot.	Lin et al. (2020)
		HTP2	For me, human interaction and attentive service are key elements of a successful dining experience.	
Trust	**TR**	**TR1**	I trust that service robots will fulfill my orders accurately and reliably.	TAM3
		TR2	I feel comfortable relying on a service robot for part of my restaurant visit.	
Behavioral Intention (DV)	**BI**	**BI1**	I plan to use service robots in a restaurant, provided they are available.	TAM / UTAUT
		BI2	I would be fine with being served by a service robot the next time I go to a restaurant.	
		BI3	I plan to visit restaurants that use service robots in the future.	

Note. (R) = reverse-coded item. All constructs are operationalized as unweighted arithmetic means of their constituent Likert-scale items (1–7 scale). BI4 excluded from Behavioral Intention due to conditional item framing. All items measured on a 7-point Likert scale (1 = Strongly disagree, 7 = Strongly agree).

Table 11 reports descriptive statistics for all constructs included in the analysis. Mean scores reflect respondents' average agreement on the 7-point Likert scale, with higher values indicating stronger endorsement of the construct. Human Touch Preference recorded the highest mean (M = 5.44), followed by Trust (M = 5.26) and Behavioral Intention (M = 4.93), indicating that acceptance levels exceeded the scale midpoint while a pronounced preference for human service delivery remained active.

Table 11

Descriptive Statistics for all Constructs

Construct	**N**	**M**	**SD**
Perceived Usefulness (PU)	210	4.45	1.39
Perceived Ease of Use (PEOU)	210	4.81	1.42
Social Influence (SI)	210	4.75	1.33
Hedonic Motivation (HM)	210	4.13	1.67
Compatibility (CO)	210	4.10	1.61
Human Touch Preference (HTP)	210	5.44	1.26
Trust (TR)	210	5.26	1.27
Personal Innovativeness (PI)	210	4.14	1.80
Behavioral Intention (BI)	210	4.93	1.26

Note. M = mean; SD = standard deviation. All construct scores are unweighted item averages on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). PI was measured by a single item.

Table 12 reports Pearson inter-item correlations for the two-item constructs in the survey. Two-item scales cannot produce Cronbach's alpha values above .70 by mathematical constraint when item count is limited to two (Eisinga et al., 2012). Inter-item Pearson correlations therefore serve as the primary reliability indicator for these constructs. All reported correlations are statistically significant at $p < .001$, confirming adequate item coherence for each two-item construct.

Table 12

Pearson Inter-Item Correlation for Two-Item Constructs

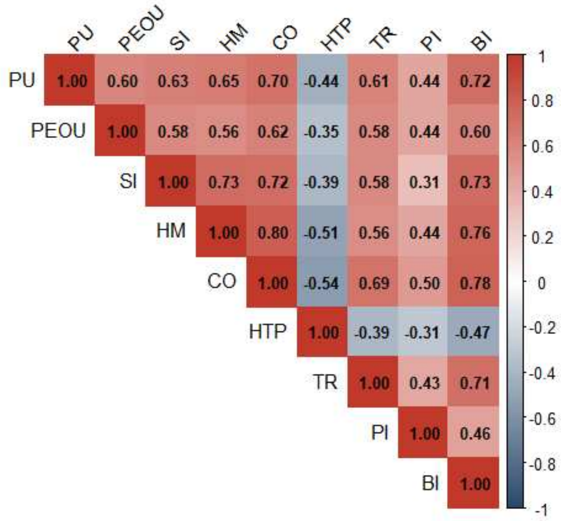
Construct	Items	r	p	Aggregated
Social Influence (SI)	SI1, SI2	0.475	< .001	Yes
Perceived Ease of Use (PEOU)	PEOU1, PEOU2	0.616	< .001	Yes
Hedonic Motivation (HM)	HM1, HM2	0.692	< .001	Yes
Compatibility (CO)	CO1, CO2	0.604	< .001	Yes
Human Touch Pref. (HTP)	HTP1, HTP2	0.539	< .001	Yes
Trust (TR)	TR1, TR2	0.648	< .001	Yes

Note. All inter-item correlations significant at $p < .001$. Constructs measured with three items (PU, BI) are assessed via Cronbach's alpha only and are not included here.

Figure 14 displays the bivariate correlation matrix for all construct mean scores ($n = 210$). Pearson r values are shown for each construct pair. Compatibility ($r = .78$), Hedonic Motivation ($r = .76$), Social Influence ($r = .73$), Trust ($r = .71$), and Perceived Usefulness ($r = .72$) all showed strong positive correlations with Behavioral Intention. Human Touch Preference ($r = -.47$) was the only construct negatively correlated with Behavioral Intention, consistent with its role as an acceptance barrier in the regression model. The matrix also reveals moderate to high intercorrelations among the acceptance-oriented constructs, which informed the decision to include Variance Inflation Factor diagnostics in the regression model (Appendix G, Table 13).

Figure 14

Bivariate Correlation Matrix of Construct Mean Scores (n=210)



Note. Values are Pearson r. All correlations significant at p < .01 or higher. HTP shows negative correlations with acceptance-oriented constructs, consistent with its barrier role in the regression model.

Appendix G: Regression & Robustness

Appendix G documents the diagnostic checks conducted to verify that the OLS regression assumptions were satisfied before interpreting the main model results. Two tests were performed. Table 13 reports Variance Inflation Factors (VIF) for all predictors included in the regression model. VIF values below 5.0 indicate acceptable levels of multicollinearity; all predictors fell below this threshold, with Compatibility recording the maximum (VIF = 4.28). Table 14 presents the results of the Breusch-Pagan test for heteroscedasticity. The null hypothesis of homoscedastic errors was not rejected (BP = 17.981, df = 13, p = .158), confirming that the OLS assumption of constant error variance was satisfied. Both tests together support the reliability and interpretability of the regression coefficients reported in Section 4.2.5.

Table 13

Variance Inflation Factors for OLS Regression Predictors

Variable	VIF	Assessment
Perceived Usefulness (PU)	2.67	Acceptable
Perceived Ease of Use (PEOU)	2.03	Acceptable
Social Influence (SI)	2.62	Acceptable
Hedonic Motivation (HM)	3.29	Acceptable
Compatibility (CO)	4.28	Acceptable
Human Touch Preference (HTP)	1.46	Low
Trust (TR)	2.40	Acceptable
Age	1.36	Low
Gender	1.27	Low
Education	1.19	Low
Dining Frequency	1.13	Low
Robot Experience	1.21	Low
Personal Innovativeness (PI)	1.81	Low

Note. VIF < 2 = Low; VIF < 5 = Acceptable; VIF ≥ 5 = Problematic. All values fall below the acceptable threshold. No multicollinearity detected.

Table 14

Breusch-Pagan Heteroscedasticity Test

Test	BP Statistic	df	p	Result
Breusch-Pagan Test	17.981	13	.158	No heteroscedasticity ✓

Note. H_0: Homoscedasticity. p > .05 indicates the OLS assumption of homoscedastic errors is satisfied. The null hypothesis is not rejected (BP = 17.981, df = 13, p = .158).