



Research Article

Gastronomy 4.0: Conceptualisation, scale development and validation

Taner ERDOĞAN^{1*} (orcid.org/ 0000-0001-9280-9664)

Duygu EREN² (orcid.org/ 0000-0002-9959-9521)

¹Eskişehir Osmangazi University, Faculty of Tourism, Department of Gastronomy and Culinary Arts, Eskişehir, Türkiye

²Nevşehir Hacı Bektaş Veli University, Faculty of Tourism, Department of Tourism Management, Nevşehir, Türkiye

Abstract

Purpose: This study aims to determine the impact of the practices of Gastronomy 4.0 (G4.0) on consumers' food and beverage purchasing tendencies and to develop a G4.0 scale to measure this tendency.

Design/methodology/approach: A survey technique was employed in this quantitative research. In Stage 1, the data collection tool was developed by reviewing the dimensions of G4.0 practices in the literature. To ensure its adequacy, the questionnaire was reviewed by four expert academicians. Subsequently, a linguist academician checked its comprehensibility before pilot test started with consumers. In Stage 2, the psychometric properties of the scale were examined, the dimensionality of the scale was tested, and the items of the scale were reduced accordingly. Afterwards, the reliability and validity of the scale were assessed in Stage 3. Finally, Stage 4 conducted a nomological test, where pre-existing scale questions related to the Technology Acceptance Model (TAM) and Purchase Intention (PI) were integrated into the data collection tool.

Results: The analysis results revealed that 3D Printers (3DP), Augmented Reality (AR), Cloud Computing Technologies (CCT) and Robot Technologies (RT) dimensions of G4.0 applications have a significant effect on TAM. In addition, the results of the structural model analysis confirmed that the Technology Acceptance Model (TAM) serves as a mediating variable in the relationship between Gastronomy 4.0 dimensions (specifically AR and RT) and consumers' purchase intentions. It was found that Augmented Reality and Robot Technologies had the mediating effect on the dimensions of Gastronomy 4.0 applications in the study.

Discussion: This study highlights that Gastronomy 4.0 technologies serve as strategic tools for human-technology collaboration rather than a replacement for culinary labor. By integrating robotics and augmented reality, operations gain precision and transparency, which ultimately reduces food waste and creates a safer, more inclusive dining experience for individuals with specific dietary needs. Beyond these practical and social implications, the rapid evolution of this sector necessitates that the developed scale be continuously updated and validated alongside future technological advancements.

Keywords: Gastronomy, Gastronomy 4.0, Technology Acceptance Model, Purchase Intention

Introduction

Industrial revolutions have had a significant impact in shaping the way we produce, the environment we live in and the progress towards prosperous societies (Roberts, 2015). Compared to the industrial revolutions that preceded it, Industry 4.0 is broader in scope than other revolutions. It affects many fields of science, from genetics to computer technology. What distinguishes this change from its predecessors is the simultaneous interconnection of technological developments used and experienced in the planning and development of all the affected fields (Bulut & Akçacı, 2017: 54; Ertuğrul & Deniz, 2018). While Industry 4.0 initially focused on industry and factories, today it has come to cover many sectors. It can be said that the gastronomy sector is one of the sectors that Industry 4.0 has started to rapidly affect and adapt to.

This study fills a significant gap in the literature by providing a holistic examination of innovations within Gastronomy 4.0. While previous studies have generally examined these technologies independently, this study

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* Corresponding Author: taner.erdogan@ogu.edu.tr

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offers a comprehensive perspective by developing and validating the Gastronomy 4.0 Applications Scale (G4.0). Created to measure the impact of these applications on consumer purchase intentions, this tool provides theoretical clarity and a practical instrument for future research in the transformation of the digital kitchen.

The fourth industrial revolution is reshaping the gastronomy sector through digital innovations, requiring rapid strategic adaptation. In recent years, Gastronomy 4.0 (G4.0), which has emerged as a reflection of Industry 4.0 in the food and beverage industry, has caused significant transformations in operational processes and service delivery. Although there are notable studies in the literature concerning the conceptual framework and potential impacts of components such as 3D food printers, augmented reality (AR), and robotics (e.g., Buhalis, 2020; Yıldız, 2019), a valid and reliable measurement tool that addresses the impact of these technologies on consumer behavior in a holistic, systematic, and measurable manner has not yet been developed. Recently, the applications offered by the Gastronomy 4.0 revolution in order to produce sufficient, healthy and appropriate foods with high-tech methods have been witnessed more frequently in the sector. Especially, gastronomy businesses are making various innovations to make consumers' experience extraordinary in the services they offer by using science and technology. These innovations make it easier to access the main functions, such as production and service in the gastronomy sector, with the developing technology and can be produced and presented faster. It is also very important to determine what this constantly changing concept means for consumers. Therefore, it is thought that measuring variables such as benefit and convenience effective in the behaviour of people using gastronomy technologies will contribute to the development or marketing efforts of businesses. For this purpose, the research aims to measure the impact of applications in the scope of Gastronomy 4.0 on consumers' food and beverage purchasing tendencies using TAM.

This study employs a two-stage research design that includes both scale development and empirical validation. In the first stage, following the conceptualization and development of the instrument to measure Gastronomy 4.0 (G4.0) applications, the scale's impact on purchase intention was examined, along with nomological testing. The relationship between G4.0 applications and consumer behavior was evaluated through the Technology Acceptance Model (TAM). Through this study, we clarify how G4.0 technologies directly influence the consumer decision-making process, thereby evaluating the relationship between technological adoption and purchase intention.

Literature Review

What is Gastronomy 4.0 (G4.0)?

The term Industry 4.0, which is also known as the fourth industrial revolution, was first mentioned in April 2011 at the Hannover Fair and introduced in detail (Kagermann et al., 2013; Schwab, 2016; Cotteler & Snyderman, 2017). This innovation, called the Fourth Industrial Revolution or Industry 4.0, is based on the Internet of Things, Cyber-Physical Systems (the combination of physical and virtual worlds) and the Internet of Services (Almada-Lobo, 2016: 16; Topsakal et al., 2018b). Mrugalska & Wyrwicka (2017) highlight that Industry 4.0 technologies, such as the Internet of Things, augmented/virtual reality, artificial intelligence, and robotic technologies, are utilised in the gastronomy sector (Buhalis & Leung, 2018: 47; Kim & Hall, 2019: 237; Bec et al., 2019). The application of these technologies in gastronomy is termed Gastronomy 4.0. Gastronomy 4.0 (G4.0) should not be viewed merely as a collection of digital tools, but rather as a digital transformation paradigm that encompasses "Smart Kitchens." For example, 3D food printing must be considered not only as a production method but also as a key component of personalized nutrition strategies. Similarly, AR and robotics are not just technological innovations; they are critical to achieving operational excellence. Grounded in the Technology Acceptance Model (TAM), this study aims to understand the cognitive mechanisms that translate these high-tech kitchen applications into actual consumer purchase intentions.

Gastronomy 4.0 can be explained as "the production of sufficient, healthy and appropriate foods using high-tech methods such as 3D printing, industrial Big Data, automation and smart robots, cyber security to meet the basic needs of people and to meet expectations related to healthy nutrition, hygiene, consistency, visual, flavor, taste, smell by appealing to the senses" (Yıldız & Davutoğlu, 2020: 306). In other words, "Gastronomy 4.0 is the application of technologies within Industry 4.0 (Augmented Reality, Automation, Robot Technologies, etc.) in the production, presentation, management and marketing areas of the food and beverage sector, considering the demands and needs of people" (Yıldız and Davutoğlu, 2020: 306). Building on these conceptualisations, in the present study Gastronomy 4.0 is operationally defined and delimited as the set of Industry 4.0-derived technologies that are directly experienced or perceived by the end consumer during the

food and beverage service encounter. That is, technologies embedded in production, presentation or delivery processes with which the customer interacts, either physically or cognitively, before or during consumption.

The literature review revealed that Internet of Things, Cloud Computing Technologies, 3D Printers and Additive Manufacturing, Big Data, Augmented Reality, Automation, Robot Technologies and Virtual security technologies are widely used in the digital gastronomy or Gastronomy 4.0 applications. The adoption of Industry 4.0 technologies is expected to revolutionise the food industry, as in the automotive, aerospace and other manufacturing sectors. The application of these technologies, which will potentially replace human intelligence and labour with technologies such as 3D printing, robotics and automation in the food industry, is called Gastronomy 4.0 (Jagtap et al., 2021b). The Robot Technologies have been explored and defined by Parvez et al. (2022) and Choe et al. (2022), Augmented Reality have been explored by Bilici and Özdemir (2019), Avcılar et al. (2019), Ponzio et al. (2021), and Calderón-Fajardo et al. (2023), Cloud Computing Technologies has been explored by Mell and Grance, (2011) and Subhashini and Kavitha (2011) and Big Data has been examined by Li et al. (2020).

The Technology Acceptance Model (TAM), introduced by Davis (1986), is one of the most widely used models explaining user acceptance behaviour. This model is based on the Social Psychology Theory in general and the Theory of Reasoned Action (TRA) in particular (Fishbein and Ajzen, 1975). TAM (Venkatesh and Bala, 2008), one of the most widely applied models in the acceptance and use of information technologies, is applied to clarify customers' acceptance of an innovation in a different environment (Zaineldeen et al., 2020: 5061).

Purchase Intention (PI) is a common approach used by researchers to understand and examine actual consumer intentions and behaviour (Blackwell et al., 2006; Ghalandari and Norouzi, 2012). Intention is defined as the antecedents that motivate and direct consumers to purchase goods and services (Hawkins and Mothersbaugh, 2010).

Method

Research Design

This study aims to measure the impact of Gastronomy 4.0 applications on consumers' food and beverage purchasing tendencies, using TAM. The primary objective of this research is to develop and validate a multi-dimensional measurement scale for Gastronomy 4.0 (G4.0) applications. To establish the nomological validity of the newly developed scale, the study further examines its impact on consumers' food and beverage purchasing tendencies within a structural model integrated with the Technology Acceptance Model (TAM). Studies conducted in the literature on the cause-and-effect relationships between perceived ease of use and perceived benefit and e-commerce, online shopping, mobile payment or food ordering platforms using TAM are frequently available. However, there is no research conducted in the tourism and gastronomy sectors that evaluates these variables together and uses all technologies together. This fragmentation in the literature results in a theoretical deficiency where the multi-dimensional nature of digital transformation remains unmeasured, leaving industry stakeholders without a clear strategic roadmap for efficient technology adoption. For the literature, this gap hinders the development of a unified framework to analyze technological synergy, while for consumers, it leads to a disjointed service experience that fails to fully capitalize on the potential for joint value creation. Consequently, this study addresses these multifaceted deficiencies by providing a validated, holistic instrument that guides both academic theory and practical management toward more informed and consumer-centric Gastronomy 4.0 investments.

To achieve this objective, the study followed a four-stage sequential research design combining conceptual and empirical methods. Stage 1 consisted of a literature-based conceptualisation of G4.0 and an expert-panel and linguist review to generate and refine the initial item pool. Stage 2 involved a quantitative survey to statistically purify the item pool through exploratory factor analysis (EFA) and reliability assessment, determining the final dimensional structure of the scale. Stage 3 further examined the internal consistency, convergent and discriminant validity of the resulting scale using Cronbach's alpha, composite reliability (CR), rho_A and average variance extracted (AVE). Finally, Stage 4 tested the nomological validity of the scale by embedding it in a structural model with the Technology Acceptance Model (TAM) and Purchase Intention (PI), using Partial Least Squares Structural Equation Modelling (PLS-SEM).

The scale development and validation process followed a rigorous four-stage sequential approach. Stage 1 focused on content validity through a literature-based item pool and expert panel discussions. In Stage 2,

Exploratory Factor Analysis (EFA) was performed to reduce items and determine the factor structure. Stage 3 involved a refined reliability check to ensure internal consistency. Finally, Stage 4 tested nomological validity by evaluating convergent and discriminant validity (Fornell-Larcker criterion) and composite reliability, ensuring the scale's structural integrity before hypothesis testing.

Table 1. Overview of the Validation Stage

Stages	Objectives	Findings
Stage 1. Item creation and reduction		
Literature review	Determination of G4.0 dimensions	9 dimensions identified
Group discussion	Judging content validity	Results of discussions with experts
Linguist review	Comprehensibility check	Found valid
Stage 2. Psychometric properties of the scale		
EFA	Item reduction	27 items retained
	Testing the dimensionality of the scale	6 dimensions retained
Stage 3. Reliability and validity check		23 items retained
Stage 4. Testing nomological validity		
	Convergent validity	AVE >0.40 for all dimensions
	Discriminant validity	AVE > better than the squared correlation between all dimensions
	Composite reliability	$\alpha > 0.70$

Note(s): EFA= Exploratory Factor Analysis

Source(s): Authors' own work

Therefore, this research is expected to contribute to the literature.

Phase 1: Substance creation and reduction

In order to achieve this goal, firstly, the data collection tool was developed by examining the literature on its dimensions to measure the effect of Gastronomy 4.0 practices on consumers' purchase intention. Afterwards, the scale questions developed by different researchers about TAM and Purchase Intention in the literature were included in the data collection tool.

The population of the research consists of the customers of the businesses in Eskişehir province that use at least one of the Gastronomy 4.0 elements in their restaurants. The data were obtained from visitors who prefer food and beverage establishments with these features.

Although some of these innovations have been examined and analysed individually by consumers in the literature, it has been observed that the effects of these elements on trends have not been evaluated together. It is thought that such an examination is necessary in order to provide information on how Gastronomy 4.0 applications will have an impact when examined as a whole. For this reason, a scale called Gastronomy 4.0 Practices Scale (G4.0) was developed in this study to measure the impact of Gastronomy 4.0 practices on the PI of potential consumers. The technologies used in Gastronomy 4.0 were examined in depth, and interviews were conducted with experts to develop a scale covering all innovations. The developed scale consisted of 9 dimensions, such as Cloud Computing Technologies, Robot Technologies, 3D Printers, Augmented Reality, IOT / Internet of Things, Big Data, Imaging Technologies, Automation Systems and Virtual Security, but as a result of the analyses, Imaging Technologies, Automation Systems and Virtual Security dimensions were removed from the scale. In this context, the bases of the dimensions of the scale created are explained in detail first.

When Cloud Computing Technologies are examined based on businesses where they are employed, they provide benefits in ensuring low cost, flexibility, increasing service quality and providing ease of access. Cloud Computing Technologies (CCT) centralize big data management and real-time inventory tracking, enhancing operational agility and fostering seamless data integration across various restaurant departments. In this direction, businesses are increasing their investments in this field every year (Armbrust et al., 2009: 8; Seyrek, 2011: 705). The main purpose of Industry 4.0 is to develop robots that can perceive the latest technological components around them, communicate with each other and process the collected data with the help of sensors, and to realise higher quality and lower cost production using less material for this purpose. Robot technologies (RT) are strategic assets deployed to achieve operational standardization and mitigate human error, ensuring a model of sustainable excellence and consistency in labor-intensive hospitality environments. Seo and Lee (2021) found that the perceived benefit in a restaurant served by a robot will contribute positively to the intention to revisit, and that the intention will change positively as they are perceived as useful. Five statements related to the dimension were created. A customised food design in the form of a digital 3D model, plates using 3D Printers can turn into a product and could be seen as a gastronomic element by consumers. 3D food printing represents a paradigm shift toward "mass-customization" in the digital gastronomy ecosystem, facilitating the precise assembly of nutrients and the creation of intricate geometric forms tailored to individual dietary requirements. Once the information is entered into the computer, various foods such as chocolate, cheese, cream, pasta dough and pasta can be produced using sugar or liquid (Levy et al., 2003). Five statements were created for the dimension. It is predicted that many companies operating in the tourism sector will benefit from Augmented Reality applications in the future to ensure tourist satisfaction and gain a competitive advantage over other businesses (Özkul and Kumlu, 2019: 108). Augmented Reality (AR) serves as a sophisticated visualization tool that bridges the gap between digital data and physical sensory experience, thereby managing consumer expectations and minimizing cognitive uncertainty during the pre-purchase evaluation phase. There are four statements related to this dimension. Thanks to Internet of Things technology, businesses can increase their revenues and/or control their costs by managing many processes such as product tracking, inventory management, logistics, security, energy efficiency, monitoring working conditions, and monetary transactions more effectively (Rouse, 2019, cited in Yıldız, 2019). Six statements related to the dimension were created. Instant examination and evaluation of Big Data in decision-making processes positively affect the decision-making mechanism (Ünal, 2015). Public and private institutions/organisations with Big Data use data analytics and technology to solve problems, reveal needs, plan and develop strategies for the future. There are seven statements related to the dimension.

The Technology Acceptance Model is measured in the literature under two dimensions: perceived usefulness and perceived ease of use. Among the constructs, perceived usefulness and perceived ease of use constitute the end-user's beliefs about a technology and therefore predict his/her attitude towards the technology, which in turn predicts technology acceptance (Davis, 1986; Davis, 1989; Davis et al., 1989). The Technology Acceptance Model (TAM) provides a robust theoretical framework for analyzing the psychological determinants specifically perceived usefulness and perceived ease of use that govern the transformation of technological stimuli into behavioral adoption. Perceived usefulness, in the context of online shopping, is defined as the degree to which a consumer believes that online shopping will provide access to useful information, facilitate comparison shopping, and enable faster shopping. Perceived ease of use is defined as the degree to which a consumer believes that online shopping is effortless (Vijayasarathy, 2004: 750; Davis, 1989; Moon and Kim, 2001; Hassanein and Head, 2007). In order to measure TAM, a 5-point scale (1 = Strongly Agree, 2 = Agree, 3 = Neutral, 4 = Disagree, 5 = Strongly Disagree) was used.

PI, which is defined as the probability that a consumer is willing to purchase certain products (Lee and Olafsson, 2009), also refers to the psychological decision-making process (Dhar and Varshney, 2011; Defever et al., 2011). Accordingly, consumers act according to their personal experiences and external environment (Mettas, 2011). Once the information is sufficiently collected, the consumer decides to purchase a product or service after evaluations, comparisons and judgments (Dhar and Varshney, 2011). In the decision-making process, the consumer will exhibit purchasing behaviour in line with the demands and preferences for products and services (Karatzoglou et al., 2011). In this sense, the concepts of PI, consumer behaviour and intention become very important (Ghalandari and Norouzi, 2012) Purchase intention is conceptualized as a behavioral propensity that signifies a consumer's conscious economic commitment to a product, driven by the perceived value derived from technology-mediated culinary interactions. Kendall and Sproles (1986), Lichtenstein et al. (1990), Lam (2007), and Aygün (2018) were utilised for the PI Scale. To measure PI, a 5-point scale (1 = Strongly Agree, 2 = Agree, 3 = Neutral, 4 = Disagree, 5 = Strongly Disagree) was used.

Group discussion

In order to examine the content validity of the measurement tool used to obtain the data, six expert review panels consisting of 4 academicians specialised in gastronomy and tourism were organised. The appropriateness of the dimensions and the questions was discussed with the panellists. The panel discussed whether each statement represented the construct. The experts were asked to read each statement carefully and mark problematic statements. Statements that were found inappropriate for the purpose, ambiguous, complex and meaningless were removed from the scale. Thus, a question pool consisting of 57 statements was formed.

Linguist review

In order to ensure that the statements in the question pool are written in a simple and appropriate language, that there is no confusion of meaning and that the sentence structures in the statements are consistent, a linguist academician checked their comprehensibility, and then a pilot test was conducted with consumers.

Stage 2. Psychometric properties of the scale

The pool of 57 statements obtained in this section was purified and improved by evaluating them in terms of certain statistical (reliability and validity) and psychometric criteria. To address potential perceptual discrepancies, participants were provided with standardized descriptions and visual prompts for all seven G4.0 dimensions prior to the survey, ensuring that responses were based on an informed conceptual understanding rather than being limited solely to the specific technologies present during their immediate service encounter.

In the research, a questionnaire was applied to customers eating in restaurants that use at least one of the Gastronomy 4.0 elements. During the data collection phase, 500 questionnaires were applied to the participants, but 481 forms were included in the analysis since 19 of the forms were not valid. Thus, the survey return rate was found to be 96%.

In the first part of the research analysis, it was examined whether the collected data complied with the parametric test assumptions. In this context, it was determined whether the data met the normal distribution conditions first. Then, exploratory factor analysis was conducted to examine the reliability and validity of the data. Finally, demographic findings and hypothesis tests were analysed.

Normality Test and Homogeneity Test

Histogram, branch and leaf, Q-Q, Detrended and box-line graphs of the statements were analysed, and it was concluded that some of the data had negative (left) and very few had positive (right) skewness. As a result of Kolmogorov-Smirnov tests, the significance value of each variable was less than 0.05. Therefore, in light of these findings, the extreme values were removed in order to bring the data closer to the normal distribution, and thus, 25 data points were excluded from the analysis. The normal distribution of the remaining 456 data was examined again. After the outliers were removed from the study, as seen in Table 1, it was determined that the skewness and kurtosis values of 57 statements were found to be between the previously mentioned threshold values (-1 and +1).

Explanatory Factor Analysis

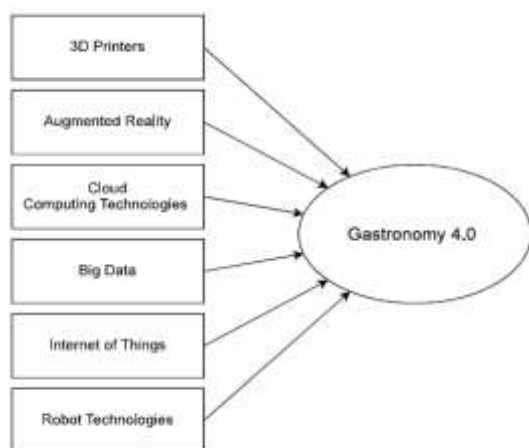
As elaborated further in Stage 3, each G4.0 dimension was conceptualised as a reflective construct, which justifies the use of exploratory factor analysis for item purification at this stage. Under the heading of exploratory factor analysis, this research used the VARIMAX rotation technique. The results of the exploratory factor analysis of the Gastronomy 4.0 scale were analysed, and the KMO sampling adequacy criterion was calculated as 0.830. Since this value is greater than 0.80, it can be considered excellent (Hair et al., 2018: 136). The fact that Bartlett's Sphericity Test value ($p < 0.05$) is significant indicates that the Gastronomy 4.0 scale complies with the assumptions of exploratory factor analysis.

When the eigen values were analysed, 7 factors greater than 1 were identified on the grounds that the factor loadings were less than 1. These factors were named as Cloud Computing Technologies (CCT), Robot Technologies (RT), 3D Printers (3DP), Augmented Reality (AR), Internet of Things (IOT), Big Data (BD), Automation Systems (AS) and Virtual Security and Online Shopping dimensions were excluded from the analysis. As a result of the Exploratory Factor Analysis, 7 statements were excluded from the analysis as they were under a different factor, 4 statements were cross-loaded, and 8 statements had factor loadings below 0.40.

As a result, after the explanatory factor analysis applied to the Gastronomy 4.0 scale, it consisted of the following dimensions: Cloud Computing Technologies (6 statements, $\alpha:0,872$), Robot Technologies (4 statements, $\alpha:0,870$), 3D Printers (4 statements, $\alpha:0,831$), Augmented Reality (4 statements, $\alpha:0,843$), Internet of Things (5 statements, $\alpha:0,730$), Big Data (4 statements, $\alpha:0,776$) and Automation Systems (3 statements, $\alpha:0,514$).

The reliability coefficient of the Automation Systems dimension was below the required level ($\alpha>0.70$) ($\alpha:0.514$). Although the current scale was examined with an exploratory intention, the level of the reliability coefficient could not be ignored. Therefore, it was decided that the dimensions and statements should be removed from the scale. The reliability analysis revealed that the Gastronomy 4.0 scale consists of 6 dimensions and 27 statements. The Cronbach's Alpha reliability value of the scale was found to be at a good level, as $\alpha:0.883$. According to the findings, it was determined that the Gastronomy 4.0 scale has structural validity and is suitable for further analysis.

Figure 1. Gastronomy 4.0 Scale



Source(s): Authors' own work

TAM items were adapted and re-validated to capture the unique sensory nuances of Gastronomy 4.0, which generic scales often overlook in culinary contexts. When the results of the exploratory factor analysis of the TAM scale are examined, it is seen that the KMO sampling adequacy criterion for the scale is 0.823, which can be considered excellent since it is greater than 0.80 (Hair et al., 2018: 136). The fact that Bartlett's Test of Sphericity value ($p<0.05$) is significant indicates that the scale complies with the assumptions of exploratory factor analysis. These results show that the sample is large enough for factor analysis and that the data are suitable for factor analysis. When the eigenvalues were analysed, a factor greater than 1 was identified, which indicates that the TAM scale has an unidimensional structure.

In the study, the cumulative variance explained by the eigenvalues for the PI scale was found to be 64% of the total variance. When the results of the explanatory factor analysis of the PI scale are examined, it is seen that the KMO sampling adequacy criterion for the scale is 0.691. It is seen that each factor loading of the statements is above 0.50. This shows that there is a good correlation between the statements and the factor to which they belong. As a result, as a result of the explanatory factor analysis applied to the PI scale, the variable has a structure covering one dimension and four statements.

Stage 3: Reliability and validity check

Regarding the validity and reliability analysis, internal consistency reliability, convergent validity and divergent validity were taken into consideration. Internal consistency reliability was evaluated by calculating three different coefficients. Accordingly, Cronbach's alpha, combined reliability (CR) and rho_A coefficients were analysed. For convergent validity, factor loadings and average variance extracted (AVE) values were considered.

Following the criteria proposed by Jarvis, Mackenzie and Podsakoff (2003) for distinguishing formative and reflective measurement models, each Gastronomy 4.0 dimension (CCT, RT, 3DP, AR, IOT, BD) was specified as a first-order reflective construct rather than as sub-facets of a single higher-order formative G4.0 index. The items measuring each dimension are conceptually interchangeable manifestations of respondents' overall

perception of that specific technology — for instance, the items assessing CCT all tap the same underlying evaluation of cloud-based services — are expected to co-vary highly, and the removal of any single item would not alter the conceptual domain of the construct, which are the defining properties of reflective indicators (Coltman et al., 2008). This specification is empirically supported by the high internal consistency (Cronbach's α), composite reliability and convergent validity (AVE) values obtained for each dimension (Table 2).

Validity and Reliability Analyses of the Scales

When the values in Table 2 are analysed, it is seen that the factor loadings are between 0.534 and 0.908. Hair et al. (2018) suggest that factor loadings should be 0.708. The authors suggest that statements with factor loadings below 0.40 should be directly removed from the model. However, they also suggest that statements with factor loadings between 0.40 and 0.70 should be removed when the AVE or CR values are below the threshold value.

Table 2. G4.0 Scale Exploratory Factor Analysis and Reliability Results

	Survey Statement	Factor Loading	Level of Significance	AVE	CR	Rho_A	Cronbach's Alpha
Cloud Computing Technologies	CCT 1.7	0,662	0,000	0,599	0,897	0,940	0,871
	CCT 2.8	0,534	0,000				
	CCT 3.9	0,826	0,000				
	CCT 4.10	0,885	0,000				
	CCT 5.11	0,880	0,000				
	CCT 6.12	0,795	0,000				
Robot Technologies	RT1.39	0,771	0,000	0,727	0,914	0,893	0,875
	RT2.40	0,827	0,000				
	RT3.41	0,908	0,000				
	RT4.42	0,896	0,000				
3D Printers	3DP 1.13	0,793	0,000	0,661	0,886	0,845	0,831
	3DP 2.14	0,796	0,000				
	3DP 3.15	0,876	0,000				
	3DP 4.16	0,785	0,000				
Augmented Reality	AR 1.25	0,671	0,000	0,681	0,894	0,871	0,842
	AR 2.26	0,866	0,000				
	AR 3.27	0,903	0,000				
	AR 4.28	0,842	0,000				
Internet of Things	IOT2.2	0,826	0,000	0,523	0,812	0,765	0,704
	IOT 3.3	0,807	0,000				
	IOT 4.4	0,637	0,000				
	IOT 6.6	0,595	0,000				
Big Data	BD 4.21	0,775	0,000	0,608	0,861	0,807	0,786
	BD 5.22	0,848	0,000				
	BD 6.23	0,695	0,000				
	BD 7.24	0,793	0,000				
Technology Acceptance Model	TAM1.49	0,830	0,000	0,733	0,932	0,911	0,909
	TAM2.50	0,877	0,000				
	TAM3.51	0,903	0,000				
	TAM4.52	0,845	0,000				
	TAM5.53	0,823	0,000				
Purchase Intention	PI 1.54	0,890	0,000	0,563	0,788	0,807	0,647
	PI 2.55	0,555	0,000				
	PI 3.56	0,769	0,000				

Note(s): 3DP= 3D Printers; AR= Augmented Reality; CCT= Cloud Computing Technologies; BD= Big Data; IOT= Internet of Things; RT= Robot Technologies; PI= Purchase Intention; TAM= Technology Acceptance Model

Source(s): Authors' own work

As a result of the analyses, no statement with a factor loading below 0.40 was obtained. However, a total of 2 statements (IOT5.5 and PI4.57) with factor loadings between 0.40 and 0.70 were removed from the model since the AVE value of the factor they belonged to was below 0.50. As a result of the removal of the statements from the model, the AVE values of the relevant factors met the recommended values. However, the table shows that the factor loadings of 5 statements (CCT1.7, AR1.25, IOT4.4, BD6.23 and PI2.55) are below the threshold value of 0.708. However, since the AVE and CR values of the factors including these statements were above the threshold values, it was decided to keep the statements in the model.

Table 3. HTMT Values

	3DP	AR	CCT	BD	IOT	RT	PI	TAM
3DP								
AR	0,304							
CCT	0,217	0,459						
BD	0,154	0,433	0,195					
IOT	0,223	0,370	0,313	0,484				
RT	0,307	0,549	0,348	0,473	0,453			
PI	0,340	0,569	0,371	0,326	0,360	0,657		
TAM	0,358	0,625	0,447	0,381	0,420	0,679	0,758	

Henseler et al. (2015) suggested that HTMT values should be below 0.90, if a stricter criterion desired, they should be below 0.85. When Table 3 is examined, it is determined that the HTMT coefficients are below the threshold value.

Table 4. Fornell-Larcker Criterion

	3DP	AR	CCT	BD	IOT	RT	PI	TAM
3DP	0,813							
AR	0,265	0,825						
CCT	0,171	0,448	0,774					
BD	0,125	0,360	0,193	0,780				
IOT	0,185	0,329	0,249	0,382	0,723			
RT	0,266	0,488	0,334	0,398	0,380	0,852		
PI	0,260	0,481	0,370	0,295	0,319	0,570	0,750	
TAM	0,320	0,558	0,453	0,330	0,362	0,613	0,674	0,856

The criterion proposed by Fornell and Larcker (1981) and the HTMT coefficients proposed by Henseler et al. are seen in Table 4. The values marked in bold in the table are the square root of the average variance explained, and the AVE square root value of each construct is higher than the correlation coefficients with other constructs.

Table 5. Cross Loadings on Expressions

	3DP	AR	CCT	BD	IOT	RT	PI	TAM
3DP 1.13	0,793	0,224	0,236	0,089	0,152	0,221	0,266	0,313
3DP 2.14	0,796	0,245	0,159	0,124	0,131	0,199	0,141	0,230
3DP3.15	0,876	0,212	0,137	0,090	0,165	0,215	0,205	0,235
3DP4.16	0,785	0,180	0,003	0,110	0,149	0,224	0,205	0,239
AR1.25	0,110	0,671	0,175	0,278	0,130	0,280	0,290	0,317
AR2.26	0,222	0,866	0,309	0,257	0,295	0,346	0,368	0,441
AR3.27	0,243	0,903	0,448	0,350	0,305	0,455	0,449	0,530
AR4.28	0,268	0,842	0,477	0,301	0,318	0,491	0,452	0,514
CCT1.7	0,039	0,253	0,662	0,059	0,169	0,213	0,181	0,197
CCT2.8	0,065	0,166	0,534	0,048	0,151	0,064	0,085	0,092
CCT3.9	0,121	0,288	0,826	0,101	0,146	0,211	0,212	0,272
CCT4.10	0,180	0,428	0,885	0,164	0,176	0,327	0,362	0,448
CCT5.11	0,149	0,468	0,880	0,264	0,298	0,363	0,414	0,481
CCT6.12	0,204	0,320	0,795	0,130	0,180	0,216	0,269	0,367
BD4.21	0,064	0,194	0,094	0,775	0,270	0,295	0,198	0,242
BD5.22	0,104	0,238	0,160	0,848	0,314	0,320	0,234	0,276
BD6.23	0,095	0,276	0,062	0,695	0,212	0,236	0,170	0,195

BD7.24	0,122	0,391	0,242	0,793	0,364	0,366	0,293	0,297
IOT2.2	0,210	0,355	0,304	0,363	0,826	0,403	0,303	0,364
IOT3.3	0,141	0,257	0,182	0,258	0,807	0,265	0,256	0,266
IOT4.4	0,050	0,117	0,050	0,241	0,637	0,192	0,134	0,165
IOT6.6	0,073	0,130	0,166	0,212	0,595	0,163	0,176	0,187
RT1.39	0,164	0,313	0,294	0,339	0,326	0,771	0,365	0,409
RT2.40	0,272	0,452	0,346	0,347	0,365	0,827	0,450	0,524
RT3.41	0,209	0,432	0,262	0,354	0,295	0,908	0,542	0,549
RT4.42	0,253	0,451	0,257	0,326	0,324	0,896	0,557	0,586
PI1.54	0,215	0,501	0,398	0,345	0,358	0,580	0,890	0,715
PI2.55	0,162	0,188	0,095	0,062	0,058	0,203	0,555	0,215
PI3.56	0,218	0,288	0,229	0,142	0,183	0,376	0,769	0,407
TAM1.49	0,277	0,480	0,402	0,243	0,291	0,474	0,469	0,830
TAM2.50	0,328	0,508	0,425	0,290	0,297	0,549	0,566	0,877
TAM3.51	0,340	0,495	0,389	0,295	0,354	0,571	0,572	0,903
TAM4.52	0,213	0,451	0,357	0,254	0,278	0,495	0,594	0,845
TAM5.53	0,206	0,453	0,367	0,324	0,323	0,529	0,676	0,823

Finally, the cross-loading criterion for discriminant validity was also taken into consideration. Accordingly, all reflective indicators should have the highest factor loading in the variables to which they are related. When Table 5 is analysed, it is seen that these values have the highest factor loading in the construct to which they belong. Accordingly, the discriminant validity has also been achieved.

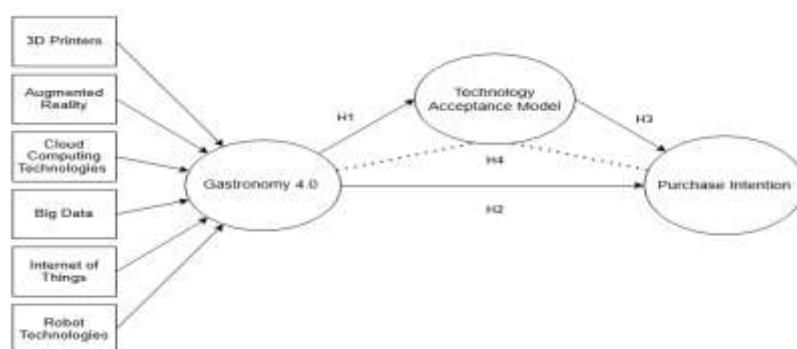
Stage 4: Testing nomological validity

Nomological validity is achieved by verifying the relationships of the main variable with other variables with which a scale is theoretically related using empirical data. This type of validity is based on the systematic examination of constructs and data in line with hypotheses derived from the theory of Peter (1981) and Kılıç and Gürlek (2024).

Research Model and Hypothesis Development

In the model on which the research is based, Gastronomy 4.0 practices are the independent variable and the mediating role of TAM in the effect of Gastronomy 4.0 practices on purchase intention is examined. Based on the S-O-R framework, this study uses TAM as a mediator to explain how G4.0 stimuli translate into purchase intention. This approach justifies the causal link between technological interaction and behavioral response, framing G4.0 as a functional driver of consumer decisions.

Figure 2. Research Model



Source(s): Authors' on work

The literature suggests that robot technologies in gastronomy and hospitality contexts have been investigated by Parvez et al. (2022) and Choe et al. (2022). Augmented reality (AR) applications have been widely explored by Bilici and Özdemir (2019), Avcılar et al. (2019), Ponzio et al. (2021), and Calderón-Fajardo et al. (2023). Based on the idea that the applications that constitute Gastronomy 4.0 will directly and positively affect the technology acceptance model, H1 was developed. Borovska and Yılmaz (2021) concluded that smart restaurant applications have a direct positive effect on perceived usefulness and usefulness.

H1: Gastronomy 4.0 practices have a significant impact on TAM.

Given that G4.0 applications comprise six distinct dimensions, H1 was further specified into six sub-hypotheses:

H1a: 3D Printers (3DP) have a significant impact on TAM.

H1b: Augmented Reality (AR) has a significant impact on TAM.

H1c: Cloud Computing Technologies (CCT) have a significant impact on TAM.

H1d: Big Data (BD) has a significant impact on TAM.

H1e: Internet of Things (IOT) has a significant impact on TAM.

H1f: Robot Technologies (RT) have a significant impact on TAM.

Seo and Lee (2021) state that the perceived benefit in a restaurant served by a robot will contribute positively to the intention to revisit, and the intention will change positively as the benefits are perceived. Ignacia, Wiastuti, and Lemy (2018) state that the use of mobile applications in the restaurant has a positive effect on purchase intention. Nassar and Fouad (2022) state that consumers have a positive attitude towards 3D printed foods and also reveal their purchase intention. Considering all these studies, it is thought that the advantages and opportunities offered by the applications within the scope of Gastronomy 4.0 to businesses and, therefore, to their guests will positively affect the purchase intentions of consumers, and H2 was developed.

H2: Gastronomy 4.0 applications have a significant impact on purchase intention.

Similarly, H2 was specified into six sub-hypotheses:

H2a: 3DP has a significant impact on PI.

H2b: AR has a significant impact on PI.

H2c: CCT has a significant impact on PI.

H2d: BD has a significant impact on PI.

H2e: IOT has a significant impact on PI.

H2f: RT has a significant impact on PI.

Studies examining the effect of the Technology Acceptance Model on purchase intention have been conducted in various contexts, including mobile services (Park, Lee, and Yi, 2011; Purnomo and Lee, 2013; Mutahar, Daud, Ramayah, Putit, and Isaac, 2017), online shopping (Koufaris, 2002; Gefen, Karahanna, and Straub, 2003b; McCloskey, 2004) and online reservation (Küçükusta, Law, Besbes, and Legohérel, 2015).

H3: TAM has a significant effect on purchase intention.

H4 hypothesis was formed based on the studies of Koufaris (2002), Gefen et al. (2003), McCloskey (2004), Küçükusta et al. (2015), and Ponzio et al. (2021), showing the Mediating Effect of the Technology Acceptance Model on Purchase Intention.

H4: TAM has a Mediating Effect on Purchase Intention.

Accordingly, H4 was also specified into six sub-hypotheses, testing the mediating role of TAM in the relationship between each G4.0 dimension and PI:

H4a: TAM mediates the effect of 3DP on PI.

H4b: TAM mediates the effect of AR on PI.

H4c: TAM mediates the effect of CCT on PI.

H4d: TAM mediates the effect of BD on PI.

H4e: TAM mediates the effect of IOT on PI.

H4f: TAM mediates the effect of RT on PI.

Findings

When the demographic characteristics of the participants in the study were analysed, it was seen that the majority of them were male and their ages were between 21 and 30. The concentration of participants in the

21–30 age group reflects the 'early adopter' profile of Gastronomy 4.0, as younger demographics demonstrate a higher propensity for interacting with physical-digital hybrid innovations. This demographic focus was maintained to ensure the scale was validated by tech-engaged respondents, thereby providing more reliable data for the initial conceptualization of the G4.0 framework. It was also found that the majority of the participants have an associate's degree. It was observed that they had an income between 4001 and 6000 TL and worked in the private sector.

Prior to the hypothesis testing, the dataset was checked for multicollinearity. The results showed no issues, as all VIF, Tolerance, and Condition Index values remained within acceptable thresholds, confirming the distinctness of the independent variables.

Measurement Model

To test the research model, Partial Least Squares Path Analysis was assessed using Smart-PLS (Henseler et al., 2015). For the research model, the PLS algorithm was run to calculate linearity, path coefficients, R2 and effect size (f^2). Blindfolding analysis was run to calculate predictive power (Q^2). In order to evaluate the significance of PLS path coefficients, t values were calculated by taking 5000 subsamples from the sample with resampling (bootstrapping). Regarding the research results, VIF values are shown in the table, while R2, f^2 and Q^2 values are presented in Table 6.

Table 6. Variance Inflation Factor (VIF)

	VIF Value
3DP -> PI	1,112
3DP -> TAM	1,112
AR -> PI	1,591
AR -> TAM	1,591
CCT -> PI	1,290
CCT -> TAM	1,290
BD -> PI	1,321
BD -> TAM	1,321
NI -> PI	1,300
NI -> TAM	1,300
RT -> PI	1,530
RT -> TAM	1,530

Before testing the research model, it was examined whether there was a multicollinearity problem among the variables. Variance Inflation Factor (VIF) was examined to determine whether there is a collinearity problem. When the table is analysed, it is understood that there is no collinearity problem between the variables since the VIF values are between the threshold values.

When the R2 values given in Table 7 obtained for the model are examined, it is determined that the Purchase Intention dimension is explained at a moderate level, with an R2 value of 0.503, and the TAM dimension is 0.510.

Table 7. Partial Estimator (Q^2) and R2 Values

	R ²	f^2	
		TAM	PI
3DP		0,023	0,001
AR		0,070	0,009
CCT		0,053	0,003
BD		0,001	0,000
IOT		0,007	0,001
RT		0,186	0,052
PI	0,503		
TAM	0,510		0,205

When the table is analysed, it is seen that the effect size of 3DP, AR, CCT exogenous variables on the TAM endogenous variable is small, while the effect size of RT exogenous variable is medium. The results reveal that there is no effect size in BD and IOT variables. In addition, the effect size of the exogenous variables on

the PI variable could not be determined except for the RT exogenous variable (0.052 - small). The effect size of the TAM variable is 0.205 (medium).

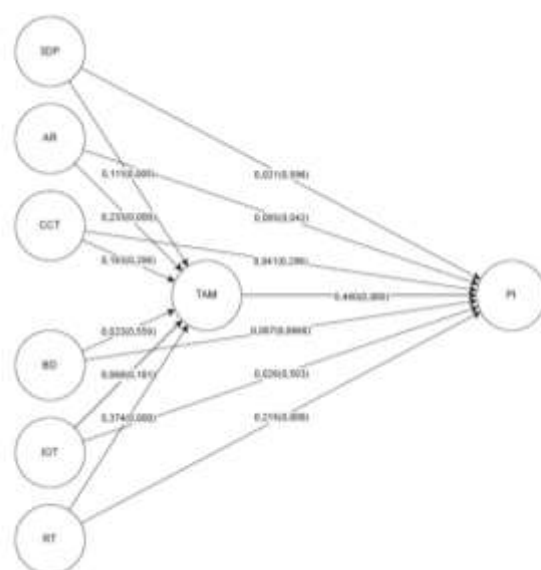
The results for direct effects in the research model (path coefficient, t statistic, p value and acceptance/rejection status of hypotheses) are given in Table 8. Accordingly, it was determined that the Gastronomy 4.0 Applications variable has a positive and significant effect on the TAM of 3D Printers ($\beta=0.111$; $p<0.005$), Augmented Reality ($\beta=0.233$; $p<0.000$), Cloud Computing Technologies ($\beta=0.183$; $p<0.000$) and Robot Technologies ($\beta=0.374$; $p<0.000$) dimensions.

Table 8. Path Analysis Results

	Road coefficient	T statistics	P values	Hypothesis result
3D Printers -> Technology Acceptance Model	0,111	2,785	0,005	Accepted
Augmented Reality -> Technology Acceptance Model	0,233	5,413	0,000	Accepted
Cloud Computing Technologies -> Technology Acceptance Model	0,183	4,838	0,000	Accepted
Big Data -> Technology Acceptance Model	0,023	0,585	0,559	Rejected
Internet of Things-> Technology Acceptance Model	0,068	1,640	0,101	Rejected
Robot Technologies -> Technology Acceptance Model	0,374	7,198	0,000	Accepted
3D Printers -> Purchase Intention	0,021	0,530	0,596	Rejected
Augmented Reality -> Purchase Intention	0,085	2,029	0,042	Accepted
Cloud Computing Technologies -> Purchase Intention	0,041	1,045	0,296	Rejected
Big Data -> Purchase Intention	0,007	0,176	0,860	Rejected
Internet of Things-> Purchase Intention	0,026	0,578	0,563	Rejected
Robot Technologies -> Purchase Intention	0,215	4,660	0,000	Accepted
Technology Acceptance Model -> Purchase Intention	0,460	10,258	0,000	Accepted

However, BD ($\beta=0.023$; $p<0.559$) and IOT ($\beta=0.068$; $p<0.101$) dimensions had no significant effect on TAM. In addition, AR ($\beta=0.085$; $p<0.042$) and RT ($\beta=0.215$; $p<0.000$) dimensions were found to positively and significantly affect Purchase Intention (PI). However, 3DP ($\beta=0.021$; $p<0.596$), CCT ($\beta=0.041$; $p<0.296$), BD ($\beta=0.007$; $p<0.860$) and IOT ($\beta=0.026$; $p<0.563$) dimensions had no significant effect on PI. However, TAM ($\beta=0.460$; $p<0.000$) had a positive and significant effect on PI.

Figure 3. Coefficients for the Research Model



In light of these results, H1a, H1b, H1c, H1f, H2b, H2f and H3 were accepted. H1d, H1e, H2a, H2c, H2d and H2e were rejected.

Mediation Effect Analysis Results

Table 9. Indirect Impact Analysis Results

	Road coefficient	T statistics	P values	Hypothesis result
CCT -> TAM -> PI	0,084	4,241	0,000	Rejected
IOT -> TAM -> PI	0,031	1,610	0,107	Rejected
3DP -> TAM -> PI	0,051	2,698	0,007	Rejected
BD -> TAM -> PI	0,010	0,587	0,557	Rejected
AR -> TAM -> PI	0,107	4,705	0,000	Accepted
RT -> TAM -> PI	0,172	6,213	0,000	Accepted

The coefficients and significance levels before and after including the mediating variable in the model were evaluated. As a result of the bootstrap mediation analysis, a significant partial mediation effect of the Technology Acceptance Model (TAM) was confirmed for the Augmented Reality (AR) and Robot Technologies (RT) dimensions of G4.0 applications. Therefore, H4b (AR) and H4f (RT) were supported (accepted). On the other hand, TAM was not found to exert a significant mediating role in the relationships between 3D Printers, Cloud Computing Technologies, Big Data, Internet of Things, and Purchase Intention. Consequently, H4a (3DP), H4c (CCT), H4d (BD), and H4e (IOT) were rejected (Table 9).

Conclusion and Recommendations

Structural Equation Modelling (SEM) was established to analyse the research hypotheses, and their validity was tested. As a result of the analysis, it was determined that the first hypotheses of the study, focusing on 3DP, AR, RT and CCT, have a significant effect on TAM. Therefore, H1a, H1b, H1c and H1f hypotheses were supported. On the other hand, BD and IOT were found not to have a significant effect on TAM. Therefore, H1d and H1e were rejected. The literature suggests that RT affects TAM, as suggested by Parvez et al. (2022) and Choe et al. (2022), and these findings support the results of this study. In situations that require us to avoid close contact with people, such as pandemics, machine-human interaction has started to be perceived as more reliable, and consumers may prefer to use RT due to hygiene, privacy, social trend (Zemke et al., 2020) or subjective norms (Choe et al., 2022). Another accepted hypothesis of the study suggested that augmented reality affects TAM, which is similar to the results of Bilici and Özdemir (2019); Avcılar et al., (2019); Ponzoa et al., (2021) and Calderón et al., (2023). The reason why the AR dimension provides this effect may be that customers think that they will enjoy the time they will spend in the restaurant more when these technologies are used, and that they can avoid placing the wrong order when the food is supported with visuals on the menu. The finding that Robot Technologies (RT) exert a medium effect on TAM, while 3DP and AR remain at a

small effect size, suggests a shift in consumer utility perception. Unlike visual novelties like AR, RT offers a tangible functional advantage in service speed and standardization—key priorities for the modern diner. This indicates that while Gastronomy 4.0 is multifaceted, consumers prioritize process-oriented automation over sensory-oriented digital augmentations. This nuance distinguishes our findings from previous studies that often treat G4.0 technologies as a monolithic group, highlighting that the 'utility' in TAM is context-dependent on the physical service encounter. On the other hand, Li et al., (2020) state that BD is significant on TAM. These results do not coincide with the research findings. However, although BD and IOT, which are G4.0 applications, accelerate and improve the quality of the service that consumers perceive, they are not face-to-face with consumers like RT and AR technologies. BD may have created the perception that it is not useful for consumers because it enables the use of information such as the distribution, preferences, frequency of use or marital status of consumers, as well as reporting their physical conditions through companies, and identifying their favourite food group from the traces they leave on forums.

In line with the second hypothesis of the study, AR and RT were found to have a significant effect on PI. Therefore, H2b and H2f were supported. On the other hand, it is determined that 3DP, CCT, BD and IOT do not have a significant effect on PI. Therefore, H2a, H2c, H2d and H2e were rejected. Kayabaşı et al. (2022) state that RT affects intention to use. Bilici and Özdemir (2019); Avcılar et al. (2019); Ponzoa et al. (2021), and Calderón et al. (2023) state that AR is effective on PI. These results are in line with the findings of this study. On the other hand, Hasanah et al. (2021) and Ignacia et al. (2018) found that CCT affects PI. This result does not coincide with the research results. However, the fact that consumers are not directly involved in these issues, which are operationally very important, can be considered effective in the rejection of the hypothesis. Cloud Computing, which has a very important role in Industry 4.0, can provide companies with the opportunity to act simultaneously, such as giving raises or promotions, or storing data in the cloud. The reason why the IoT dimension is not effective on both TAM and PI can be considered as a result of the fact that these devices, which communicate with each other and work smoothly, contribute to companies, but this contribution to customers is reflected indirectly rather than directly.

The fourth main hypothesis of the study proposed that TAM has a mediating effect on the relationship between G4.0 dimensions and Purchase Intention. The empirical results supported the mediating role of TAM specifically for Augmented Reality and Robot Technologies; thus, H4b and H4f were supported. Conversely, TAM did not show a mediating effect for 3DP, CCT, BD, and IOT, leading to the rejection of H4a, H4c, H4d, and H4e. Ponzoa et al. (2021) state that TAM has a mediating role in the effect of 3DP on PI. These results are not supported by the research findings. It is thought that the fact that this technology, cannot be frequently encountered due to the difficulty of access to equipment and materials used in restaurants and other businesses. Thus, it has not yet become so widespread that its absence cannot be felt, and this could be the reason for these results.

Recommendations for businesses:

RT is used with robotic applications, especially in the service and kitchen departments of restaurants. Although the use of robots in restaurants, which is one of the dimensions of Gastronomy 4.0, has not yet been experienced by most customers, it is understood that it will be adopted if it provides benefits and convenience from the mediating variability effect that emerged as a result of the research. Since the reduction of labour costs and the complete and flawless application of standard recipes will be reflected on consumers, the use of RT should be given importance. Customer satisfaction can be achieved and improved by maintaining or improving product, process and service standards through the use of RT. The absence of defects/errors in the food and beverages or services offered can positively affect PI in the long term.

In restaurants, accidents such as burns, cuts and similar accidents or occupational diseases such as urticaria, gastritis, etc. may result in work and labour losses, and delays and cancellations in catering or service can adversely affect PI. Therefore, the use of this RT is recommended, especially in high-risk areas.

AR is used especially in the service section of restaurants with augmented reality glasses, 3D projectors and applications. By using augmented reality technologies, misunderstandings can be prevented by providing images of the size and presentation of the food from the menu before it is ordered. In this way, fast and trouble-free product preparation and presentation can be achieved. Using AR can ensure that customers have a pleasant time by showing the processes, products or animations related to them during the waiting period. The use of augmented reality glasses by kitchen staff could help find food recipes quickly without searching through books or standard recipe files, thus reducing operational errors. Preparation and presentation processes can be

shortened by using augmented reality applications in businesses for the location, arrangement and access of products.

Recommendations For Researchers

The Gastronomy 4.0 scale can be improved. The scale used is designed according to the use of technologies that can be supported by the literature and can be improved as technology develops. Research can be conducted in different destinations and food & beverage establishments. Research can be conducted on different consumer profiles. The data set can be expanded. Qualitative methods can be used as well to create a data set from a broader perspective.

Limitations and Future Research Directions

There are several limitations in this research that provide opportunities for future studies. The first relates to the current stage of technological integration in the industry; since G4.0 technologies are not yet standardized across all restaurants, participants evaluated their intentions based on hypothetical scenarios rather than direct, long-term experience. Secondly, as noted by Ajzen and Fishbein (1974), behavioral intention is subject to change during the interval between measurement and the actual observation of behavior. Furthermore, the cross-sectional nature of the data collection limits the long-term estimation of these intentions.

Additionally, the sample selection was concentrated in specific urban hubs and a younger demographic (early adopters), which may affect the generalizability of the findings. Future research should expand the keywords and technological scope to include emerging Gastronomy 4.0 innovations and employ longitudinal designs to observe how intentions evolve as these technologies become industry standards. It is assumed that respondents provided honest answers and that the statistical methods employed are appropriate for the research objectives. “This article is derived from the doctoral dissertation entitled ‘The Effects Of Gastronomy 4.0 Applications On Consumer’s Food And Beverage Purchase Intentions: Examining The Technology Acceptance Model.’”

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