



# When and Why Do Users Trust AI in the Kitchen? A Hybrid Modelling Approach to the Adoption of AI-Assisted Cooking

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## ABSTRACT

This study explores how users perceive AI in various culinary scenarios. Using a hybrid model, we examined how perceived AI accuracy, general attitudes toward AI, and AI anxiety shape trust in AI cooking applications, and how this trust influences adoption intentions. Data from 380 UK participants revealed two groups: a small segment of *Engagers*, open to AI-assisted cooking, and a larger group of *Avoiders*. Trust was positively influenced by perceived accuracy and general attitudes, and negatively by AI anxiety. Trust, in turn, was key to distinguishing *Engagers* from *Avoiders*. However, adoption was highly context-dependent: AI was more accepted in practical tasks, such as using leftovers, but less so in socially meaningful settings such as dinner parties. Demographically, younger, educated individuals were more receptive. These findings highlight both opportunities and barriers for AI in the kitchen, offering insights into consumer trust and the nuanced dynamics of AI adoption in food contexts.

## KEYWORDS

Human-computer interaction; PLS-SEM; finite mixture modelling; technology acceptance; consumer behavior

## 1. Introduction

Although Generative Artificial Intelligence (GAI) systems have consolidated their status as important assistive tools across various domains of human endeavor, when it comes to their application in the food sector, people are still rather hesitant and question the credibility of GAI in culinary contexts (Xia et al., 2024). Picture a home cook contemplating whether to trust an AI-generated recipe for a family dinner – the concern is not only about the taste, but also about the safety and wellbeing of their loved ones. The lack of trust is perhaps understandable, given the potential risks: Errors in food and nutrition can directly result in health-related problems.

The challenge lies in a fascinating paradox: GAI offers significant potential in terms of addressing modern personalized cooking needs (see Ma et al., 2024, for a recent scoping review) but clashes with real-world implementation. For instance, in 2022, the YouTube channel Tasty<sup>1</sup> compared a chocolate cake recipe generated by GPT-3 with one developed by a professional food writer. Although the AI version was technically successful, it lacked the nuanced flavors of the human recipe in blind taste tests. Similarly, Goulart et al. (2025) found that GAI-generated recipes were rated lower in blind tastings compared to those by children and school cooks, likely because the AI's database produced flavor combinations unfamiliar to the target users. These

examples underline a common theme: While GAI systems are technically capable of generating recipes, their outputs often fall short of users' expectations in terms of taste, relevance, or safety.

Yet GAI's potential in terms of addressing modern cooking challenges is significant (Jung et al., 2021). Traditional cooking resources often fall short in offering flexible, personalized suggestions – something increasingly valued by users with dietary needs or limited ingredients at hand. Platforms such as DishGen can already tailor recipes based on available ingredients and user preferences (Jauhiainen & Guerra, 2023), while also attempting to manage safety concerns by flagging those combinations that might have toxic consequences. Despite such efforts, widespread trust and acceptance of these tools remains a major challenge.

GAI has already gained public attention in the food domain, as reflected in widely discussed AI-generated “imaginary” food images on Facebook and Reddit, spanning from Oreo cake to banana strawberry cake and cinnamon roll cheesecake. AI-generated food images accompanying the innovative food recipes likely increase the appeal of these new foods. The food images generated by AI can appear extraordinarily delicious and even receive higher liking scores than real food images (Califano & Spence, 2024). At the same time, however, the question arises as to how feasible it is to implement many of these recipes (Gill & Parker Bowles, 2024). The way people perceive and interact with AI-generated content

reflects what researchers term “AI naive realism” (Engel-Hermann & Skulmowski, 2024) – where the realistic appearance of AI-generated content can lead to either excessive trust or skepticism. This disconnect between appearance and reality presents a crucial challenge in building user trust, which can be particularly problematic in the case of instructional content. Therefore, though there are increasing options of AI-powered recipe generators freely available online and AI-assisted cooking instructors facilitating specific needs, users may remain uncertain about how realistic, safe, or tasty the resulting dishes are likely to be.

Several important questions emerge: Do people recognize the usefulness of AI-powered tools, especially in unusual cooking contexts where individualized suggestions are needed, such as when working with limited ingredients (e.g., when trying to use up leftovers)?<sup>2</sup> While AI’s strength in optimization is widely recognized, the limited research in applying AI to cooking contexts raises questions about the scenarios under which people are more likely to adopt AI-powered cooking assistants. Our research specifically examines how trust mechanisms influence AI adoption in cooking contexts, and identifies those scenarios where AI tools prove most beneficial. By understanding when and why users trust AI in the kitchen, we can develop more effective design principles for AI systems across various domains where trust and safety are paramount.

## 2. Study background

Previous studies have highlighted the significant role of trust in the acceptance of AI-driven technologies (Xia et al., 2024; Yang & Wibowo, 2022). Therefore, to investigate consumer acceptance and adoption behavior of AI-assisted cooking tools, it is important to profile people’s trust in such tools and even further looking into the factors influencing trust towards AI. People’s attitudes toward AI are expected to be positively correlated with how reliable they believe AI to be. Califano et al. (2024), recently reported that people’s trust in AI-generated recipes is lower relative to the traditional cookbooks when the dish is innovative, but not when the dish is traditional. When a dish appears unfamiliar or unusual, people tend to be more skeptical of AI-generated instructions. Trust in AI-powered cooking tools is also contingent on the system’s ability to understand culinary norms and practices, which are often culturally specific. For example, Goulart et al. (2025) found that children—who are typically more food-neophobic (Cappellotto & Olsen, 2021; Proserpio et al., 2020)—showed a reduced preference for recipes generated by ChatGPT as compared to those created by children or professional chefs, largely because the AI-generated recipes were perceived as too unusual. These findings point to a broader pattern of distrust in AI-generated cooking suggestions, particularly in culturally or emotionally sensitive contexts. However, further research is undoubtedly needed in order to better understand how consumers perceive the role of AI in such an essential and personal domain (i.e.,

cooking). The present study addresses this gap in the literature by examining the individual and contextual factors that influence users’ acceptance of AI-assisted cooking, and by identifying the scenarios in which people find these systems most useful.

Data-driven and human-centered approaches differ in their level of elaboration, which further affects the accuracy of the culinary guidance provided (Goulart et al., 2025). Unlike human recipe creators who offer nuanced cooking tips (e.g., salting eggplant before air-frying to remove moisture), AI-generated recipes often omit these helpful details, thus potentially leading to suboptimal results. Sometimes, AI-powered recipe creators supplement their “food product” with apparently delicious AI-generated images, together with oversimplified cooking guidance (e.g., [https://www.facebook.com/story.php/?story\\_fbid=1015297626856145&id=100051277509953&rdr](https://www.facebook.com/story.php/?story_fbid=1015297626856145&id=100051277509953&rdr)). *Naive AI realism* refers to an unwarranted trust in the correctness of AI-generated content (Engel-Hermann & Skulmowski, 2024). In the culinary context, this can manifest in the trust that people place in AI to suggest recipes that result in tasty and safe-to-eat foods. A key issue here is the mismatch between the AI’s confidence in its generated cooking instructions and the inherent uncertainty of the actual food outcomes produced by following these recipes.

One unique aspect of food that may challenge naive AI realism is its physicality: Food is something that we incorporate into our bodies. This attribute distinguishes AI-generated recipes from other GAI content, as they provide instructions for something to be consumed. Unlike a GAI recommendation for a movie or productivity app, food directly impacts our health and well-being.<sup>3</sup> When AI suggests a recipe, consumers may not only question its accuracy in delivering an optimal or flavorful outcome but also its safety and suitability for consumption, thereby increasing the potential costs of errors in trusting such recommendations. Research has established that attitudes towards AI are negatively influenced by AI anxiety (Kaya et al., 2024), and previous failures in GAI dietary advice have likely exacerbated these concerns. For instance, inaccuracies in portion sizes and caloric information were noted by Niszczota and Rybicka (2023), and more severe issues, such as AI-generated recipes inadvertently suggesting toxic combinations, have also sometimes been reported in the press (McClure, 2023). Such risks and potentially adverse outcomes contribute to increased anxiety about adopting AI assistants in culinary contexts. Drawing these findings together, we propose that trust in AI is influenced by three key factors: attitudes towards AI, AI anxiety, and perceived AI accuracy.

The integration of AI in cooking applications presents both challenges and opportunities, with the latter motivating designers to overcome initial trust barriers. The potential for AI in culinary advisory services stems from cooking’s inherent complexity and need for adaptability as a daily task. Cooking posits a situation in which individuals simultaneously engage with multiple sources of information and cognitive tasks. People can be restrained by the cooking

materials at hand or want to be creative, which can make cooking advice searching in the traditional sense not as helpful. The context-dependent nature of cooking necessitates assistance across multiple domains, including preparation procedures, ingredient selection, quantity calculations, and recipe recommendations (Frummet et al., 2022). People can find generative conversational models (i.e., GAI-powered recipe generators in the cooking context) creating very synthesizing information from diverse sources and responding to contextual queries such as ingredient-based recipe requests like “I’d like to have a dish with lentils, chickpeas, and tomatoes.” In addition, cooking with conversational assistants have been found to enhance user engagement (Frummet et al., 2024). GAI has made it easier than ever before to provide individualized stepwise recommendation for complex task support (Nouri et al., 2020), and can potentially improve people’s life quality by enabling people to engage with tasks that they find challenging before, such as cooking unfamiliar dishes. The core of human-centric computing is not only about introducing new technologies, but also about understanding both the challenges and opportunities to inform design improvements. In the context of AI-powered cooking assistance, our research aims to examine how trust mechanisms influence adoption patterns and identify specific cooking scenarios where AI tools demonstrate optimal utility, thereby informing more targeted design approaches.

In addition to understand the cooking scenarios where GAI tools will be more helpful, it is also important to profile the target population of such technologies. Given the well-documented individual differences that exist in terms of the adoption of technology, it might be expected that those consumers with greater openness to new technologies would be more receptive to AI-powered cooking assistance. This technological openness, potentially a key predictor of engagement with AI-assisted cooking, appears to be significantly influenced by demographic factors, particularly age and education level. The research demonstrates that education level correlates positively with favourable attitudes toward AI technologies (Gnambs & Appel, 2019; cf. Kaya et al., 2024; Zhang & Dafoe, 2019). Additionally, Kaya et al. (2024) found that younger individuals who regularly use computers tend to show higher acceptance rates for AI-powered smart information technologies. Building on these established relationships between demographics and the acceptance of technology, we hypothesize that younger individuals and those with higher levels of education will demonstrate greater openness to adopting AI-assisted cooking tools.

The current research aims to provide insights into consumers’ current perception of AI in culinary contexts. More specially, as previous studies have shown the trust issues in AI-powered recipes, we further investigated the factors that underlie the trust towards GAI in food making instructions and how trust influence people’s AI choice behaviors when they need help regarding cooking. Specifically, our research will address the following research questions and hypotheses:

RQ1: How does trust in AI influence engagement in AI-assisted cooking?

H1: Trust in AI-assisted cooking is positively influenced by general attitudes towards AI (a) and perceived AI accuracy (b), and negatively influenced by AI anxiety (c).

H2: General attitudes towards AI are positively influenced by perceived AI accuracy (a) and negatively influenced by AI anxiety (b).

RQ2: In what cooking scenarios is AI assistance most accepted?

RQ3: Is there a demographic profile capturing a specific group of consumers who are more open to AI-assisted cooking?

### 3. Materials and methods

#### 3.1. Participants and procedure

Participants were recruited through Prolific Academic, a widely used online research platform that ensures responses from verified users. The target population consisted of UK residents, aged 18 years and older, who had prior experience with cooking, either regularly or occasionally. As we included colored pictures as stimuli, we only included participants who claimed to have no issue seeing colors. An additional eligibility criterion was set to require participants to have a minimum 95% approval rating on Prolific, ensuring reliable responses. The survey remained open until the pre-specified sample size was reached, and participants were compensated in line with Prolific’s fair pay policy. Data was collected via Google Forms from 380 participants in May 2024. The sample size was determined using an a priori power analysis conducted in G Power 3.1 (Faul et al., 2007), targeting a small effect size ( $f^2 \approx 0.03$ ) and a statistical power ( $1 - \beta$ ) of 0.80 with  $\alpha \approx 0.05$ . The participants had a mean age of 41.6 years ( $SD \approx 13.7$ ) and were predominantly women (67%). Most were omnivores (79%) and held either a university or postgraduate degree (57%).

After providing their informed consent, the participants were asked to read five scenarios related to meal preparation (Table 1) and imagine themselves in the depicted situations. An “expressive task” was used to measure participants’ engagement in AI-assisted cooking, which is a type of projective technique where respondents are instructed to role-play, act, draw, or depict a particular concept or scenario (Donoghue, 2000). This technique was used to gather a proxy for participants’ behaviors concerning AI-assisted cooking (see Capasso et al., 2023, for a similar approach). The scenarios were developed to explore a variety of cooking-related contexts in which AI could be used. For each scenario, the participants were asked to select their most likely choice from seven options (family, friends, cookbook, newspaper or TV show, internet search, AI systems, or other), for both dish inspiration and recipe instructions, by answering the question: “Who or what would you rely on for dish inspiration/recipe?”

In the next section, psychographic measures were collected. Trust in AI-assisted cooking was assessed using an adapted four-item scale from Gillath et al. (2021). AI anxiety was measured with three items from Cobelli et al. (2021),

**Table 1.** Five food preparation scenarios and the alternatives for sources of preparation inspirations/instructions.

Scenario descriptions	Alternatives
<p><i>Scenario 1 – “Host”</i></p> <p>Picture yourself hosting a dinner party where you aim to delight your guests with a unique and creative meal you've never prepared before.</p>	<ol style="list-style-type: none"> <li>1. Family</li> <li>2. Friends</li> <li>3. Cookbook</li> <li>4. Newspaper/TV</li> <li>5. Internet search</li> <li>6. AI systems</li> <li>7. Other</li> </ol>
<p><i>Scenario 2 – “Leftovers”</i></p> <p>Imagine you open your fridge to find it almost empty, but you spot various ingredients leftover from previous meals that you have made. You're determined to whip up something delicious using what you have.</p>	<ol style="list-style-type: none"> <li>1. Family</li> <li>2. Friends</li> <li>3. Cookbook</li> <li>4. Newspaper/TV</li> <li>5. Internet search</li> <li>6. AI systems</li> <li>7. Other</li> </ol>
<p><i>Scenario 3 – “Traditional”</i></p> <p>Visualize yourself preparing to attend a dinner at someone else's home, and you've decided to bring a traditional dish from your culinary culture to share, but you've never prepared it before.</p>	<ol style="list-style-type: none"> <li>1. Family</li> <li>2. Friends</li> <li>3. Cookbook</li> <li>4. Newspaper/TV</li> <li>5. Internet search</li> <li>6. AI systems</li> <li>7. Other</li> </ol>
<p><i>Scenario 4 – “Groceries”</i></p> <p>As you're about to head out for groceries, you realize you haven't decided what to cook yet. You're looking for something incredibly easy and quick to prepare.</p>	<ol style="list-style-type: none"> <li>1. Family</li> <li>2. Friends</li> <li>3. Cookbook</li> <li>4. Newspaper/TV</li> <li>5. Internet search</li> <li>6. AI systems</li> <li>7. Other</li> </ol>
<p><i>Scenario 5 – “New”</i></p> <p>Picture yourself at home, preparing for dinner, and you're eager to try making something entirely new and exciting.</p>	<ol style="list-style-type: none"> <li>1. Family</li> <li>2. Friends</li> <li>3. Cookbook</li> <li>4. Newspaper/TV</li> <li>5. Internet search</li> <li>6. AI systems</li> <li>7. Other</li> </ol>

while the perceived accuracy of AI was evaluated using four items from Lu et al. (2019). General attitudes towards AI were measured using the 15-item scale developed by Schepman and Rodway (2020). All of the items were rated on a Likert scale ranging from 1 (“Strongly disagree”) to 5 (“Strongly agree”) (see Table 2 for the full list of items and main statistics). Finally, sociodemographic information, such as age and sex assigned at birth, was collected.

### 3.2. Empirical analysis

A two-stage approach was followed for the empirical analysis. In Stage 1, Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to test the hypothesized relationships among the constructs. PLS-SEM was chosen over covariance-based SEM because it accommodates complex models involving latent constructs and smaller sample sizes, and it does not require multivariate normality. Importantly, PLS-SEM is particularly suited for exploratory research focused on theory development and prediction rather than strict model confirmation (Hair et al., 2017), making it well aligned with our study's objective of identifying drivers of trust and behavioral intentions. PLS-SEM, like covariance-based SEM, consists of a measurement (outer) model and a structural (inner) model. The outer model evaluates the relationships between the constructs and their indicators, while the inner model examines the relationships

among the constructs themselves (Venturini & Mehmetoglu, 2019).

The adequacy of the measurement model was confirmed using several criteria: factor loadings greater than 0.5, Cronbach's  $\alpha$  exceeding 0.7, and  $\rho_A$  values above 0.7 for indicator reliability. Convergent validity was assessed through the Average Variance Extracted (AVE), with a threshold of 0.5 or higher, while discriminant validity was verified using the Fornell-Larcker criterion (Venturini & Mehmetoglu, 2019). Evaluation of the structural model focused on the significance and strength of the path coefficients.

To determine user's adoption intention of AI-assisted cooking tools, the total number of times the AI option was selected across the five scenarios, for both inspiration and recipe purposes (given the strong correlation between the two;  $r = 0.74$ ), was calculated. Hence, this count could range from 0 to 10. As anticipated, the AI option was chosen infrequently, resulting in a count variable with excess zeros and overdispersion, meaning that the variance was larger than the mean ( $M = 0.47$ ,  $r^2 = 1.72$ ; see Figure 1). In Stage 2, to accommodate both of these features (i.e., excess zeros and overdispersion), a Zero-Inflated Poisson (ZIP) regression was applied as a two-component mixture model. Two-component mixture models have been used for modelling count variables within healthcare utilization (Deb & Trivedi, 1997) and risk behavior contexts (Lanza et al., 2011), where two or more unobserved subgroups exist in the population such that those groups posit different regression coefficients.



**Table 2.** Items used to measure the investigated constructs, along with their main statistics.

Item	Source	Description	<i>M</i>	<i>SD</i>
TRU_1	Gillath et al. (2021)	I would be happy to follow an AI-generated recipe when cooking	3.43	0.94
TRU_2	Gillath et al. (2021)	I would trust cooking suggestions that had been generated by AI	3.36	0.93
TRU_3	Gillath et al. (2021)	Physically, I would feel safe preparing food according to AI-generated suggestions	3.61	0.93
TRU_4	Gillath et al. (2021)	Emotionally, I would feel comfortable cooking according to AI-generated recipes	3.57	0.97
ANX_1	Cobelli et al. (2021)	I feel apprehensive about using AI systems	2.99	1.06
ANX_2	Cobelli et al. (2021)	I hesitate to use AI systems for fear of making mistakes I cannot correct	2.69	1.03
ANX_3	Cobelli et al. (2021)	AI systems are somewhat intimidating to me	2.66	1.14
ACC_1	Lu et al. (2019)	AI systems are more accurate than people	2.67	0.80
ACC_2	Lu et al. (2019)	AI systems make fewer errors than people	2.84	0.91
ACC_3	Lu et al. (2019)	AI systems provide a more consistent service than people	3.10	0.97
ACC_4	Lu et al. (2019)	The information provided by AI systems is more reliable	2.73	0.80
ATT_1	Schepman and Rodway (2020)	There are many beneficial applications of AI	3.88	0.76
ATT_2	Schepman and Rodway (2020)	I am impressed by what AI can do	3.86	0.87
ATT_3	Schepman and Rodway (2020)	AI can have positive impacts on people's wellbeing	3.62	0.85
ATT_4	Schepman and Rodway (2020)	AI can provide new economic opportunities for this country	3.48	0.91
ATT_5	Schepman and Rodway (2020)	AI systems can perform better than humans	3.01	0.92
ATT_6	Schepman and Rodway (2020)	Much of society will benefit from a future full of AI	3.15	0.96
ATT_7	Schepman and Rodway (2020)	I am interested in using AI systems in my daily life	3.15	1.15
ATT_8	Schepman and Rodway (2020)	For routine transactions, I would rather interact with an AI system than with humans	2.62	1.11
ATT_9	Schepman and Rodway (2020)	AI makes me feel great about human ingenuity	2.79	0.94
ATT_10	Schepman and Rodway (2020)	An AI agent would be better than an employee in many routine jobs	2.47	1.02
ATT_11	Schepman and Rodway (2020)	I would like to use AI in my own job	2.71	1.19
ATT_12	Schepman and Rodway (2020)	AI systems can help people feel happier	2.83	0.92
ATT_13	Schepman and Rodway (2020)	Some complex decisions are best left to AI systems	2.53	1.04
ATT_14	Schepman and Rodway (2020)	I love everything about AI	2.25	0.95
ATT_15	Schepman and Rodway (2020)	I would entrust my life savings to an AI investment system	1.68	0.84

Notes: TRU  $\frac{1}{5}$  Trust in AI-assisted cooking; ANX  $\frac{1}{3}$  AI Anxiety; ACC  $\frac{1}{4}$  Perceived AI accuracy; ATT  $\frac{1}{5}$  General attitudes toward AI.

(indicating an underlying aversion of the given participant towards using GAI in a culinary context). Therefore, the ZIP model can be applied to differentiate between participants who inherently reject GAI and those who might choose it, depending on context. While this approach is analytically similar to conventional ZIP models (Lim et al., 2014), the finite mixture method used here addresses the overdispersion issue from a conceptually different perspective. Here, overdispersion is interpreted as an issue of unobserved heterogeneity, which occurs when the sample responses are drawn from multiple *latent* sub-populations (Lim et al., 2014). The ZIP regression mixture model thus allows to make probabilistic statements regarding whether a respondent belongs to the Avoider or Engager latent sub-population. Since these classes are latent, meaning they are unobserved, each individual has a probability of membership in each latent class (McLachlan & Peel, 2000).

Moreover, the predicted latent scores of trust in AI-assisted cooking from the PLS-SEM (Stage 1) were integrated into the ZIP model (Stage 2) as well: Trust scores served as predictors for both class membership (Engager versus Avoider) and AI choice rate (within the Engager class, as the Avoider class naturally has a zero rate). The combination of a behavioral and a predictive model qualifies this approach as a hybrid model (Ben-Akiva et al., 2002; Califano et al., 2024).

Finally, an analysis of AI choice rates within the Engager class was conducted across the five scenarios, along with a characterization of this niche based on sociodemographic variables, using the Bolck Croon Hageaars (BCH) three-step procedure (Bolck et al., 2004; Vermunt, 2010). A common approach when it comes to examining relationships between external variables and finite mixture components involves assigning each participant to their most likely cluster based on estimated posterior probabilities and treating these latent

**Figure 1.** Percentage of participants based on the total number of times they selected the AI option across all five cooking scenarios, considering both recipe inspiration and recipe instructions.

Here, we considered two-component mixture model as a valuable tool for profiling subgroups of consumers according to their acceptance of AI-powered cooking tools.

In the finite mixture modelling framework, a ZIP model is represented by a mixture of components that model both zero and nonzero counts, and a degenerate point mass distribution that models the zeros (StataCorp, 2023). Indeed, we do not know whether a given zero count reported here for the GAI option (82% in total; see Figure 1) comes from a Poisson distribution (meaning that GAI could have been chosen by a given participant in a non-considered scenario) or is a “hard zero” from a point mass distribution

components as manifest groupings in subsequent analyses. However, this method does not account for classification errors (Bakk et al., 2014). Bolck et al. (2004) demonstrated that the greater the classification error in the allocation process, the larger the downward bias in the parameter estimates, ultimately leading to underestimated differences between classes. To mitigate this issue, the BCH three-step approach was applied (see Vermunt, 2010, for more details). All statistical analyses were performed using Stata 18<sup>4</sup>.

#### 4. Results

Table 3 summarizes participants' stated choices for each food preparation scenario. The most frequently selected option across all five scenarios was the internet search, both for dish inspiration and recipe instructions. However, in the "Traditional" scenario, family was more commonly chosen, but only for inspiration, not for the recipe itself. AI systems were rarely selected overall, with the highest occurrence in the "Leftovers" scenario, where AI was chosen in 13% of cases for dish inspiration and 9% for the recipe itself.

The results from the PLS-SEM measurement model demonstrated good indicator reliability (Table 4), with all factor loadings greater than 0.5, Cronbach's  $\alpha$  exceeding 0.7, and  $\rho_A$  values above 0.7. Convergent validity was also established, with AVE values surpassing 0.5. Discriminant validity was confirmed using the Fornell-Larcker criterion: The AVE

for each construct exceeded the squared correlations between the construct itself and the other constructs, considered one by one (Table 5).

The results of the structural model (Figure 2, Stage 1) reveal the relationships analysed among the constructs. Trust in AI-assisted cooking was positively predicted by attitudes (H1a) and perceived accuracy (H1b), while negatively predicted by AI anxiety (H1c). General attitudes toward AI were strongly and positively influenced by perceived AI accuracy (H2a), and negatively, albeit moderately, influenced by AI anxiety (H2b). Trust in AI-assisted cooking was positively predicted by perceived accuracy and attitudes, while negatively predicted by AI anxiety. Overall, the model accounted for a significant portion of the variance in both attitudes ( $R^2 = 0.52$ ) and trust ( $R^2 = 0.39$ ).

Trust in AI-assisted cooking, as predicted by the other constructs, was incorporated into the ZIP regression mixture model in Stage 2 to explain participants' classification as either Avoiders or Engagers, as well as to explain the AI choice rate within the latter class. The results (Figure 2, Stage 2) indicate that participants with higher levels of trust (1 SD) were 5.44 times more likely to be Engagers rather than Avoiders. Figure 3 shows that, at 1 SD above the sample mean for predicted trust, the probability of engagement was estimated at around 50%, rising to 80% at 2 SD. Interestingly, within the Engager class, trust level did not influence the AI choice rate itself, which had a mean value estimated at 2.2, 95% CI [1.47, 2.94]. Overall,

Table 3. Participants' stated choices for each scenario.

Scenario descriptions	Alternatives	Dish inspiration		Dish recipe	
		<i>n</i>	Percent	<i>n</i>	Percent
<b>Scenario 1 – "Host"</b> Picture yourself hosting a dinner party where you aim to delight your guests with a unique and creative meal you've never prepared before.	1. Family	37	9.74	17	4.47
	2. Friends	24	6.32	4	1.05
	3. Cookbook	74	19.47	99	26.05
	4. Newspaper/TV	10	2.63	1	0.26
	5. Internet search	226	59.47	250	65.79
	6. AI systems	7	1.84	7	1.84
	7. Other	2	0.53	2	0.53
<b>Scenario 2 – "Leftovers"</b> Imagine you open your fridge to find it almost empty, but you spot various ingredients leftover from previous meals that you have made. You're determined to whip up something delicious using what you have.	1. Family	31	8.16	27	7.11
	2. Friends	9	2.37	9	2.37
	3. Cookbook	30	7.89	27	7.11
	4. Newspaper/TV	3	0.79	2	0.53
	5. Internet search	228	60.00	250	65.79
	6. AI systems	48	12.63	33	8.68
	7. Other	31	8.16	32	8.42
<b>Scenario 3 – "Traditional"</b> Visualize yourself preparing to attend a dinner at someone else's home, and you've decided to bring a traditional dish from your culinary culture to share, but you've never prepared it before.	1. Family	151	39.74	131	34.47
	2. Friends	22	5.79	13	3.42
	3. Cookbook	65	17.11	70	18.42
	4. Newspaper/TV	0	0.00	0	0.00
	5. Internet search	135	35.53	160	42.11
	6. AI systems	6	1.58	5	1.32
	7. Other	1	0.26	1	0.26
<b>Scenario 4 – "Groceries"</b> As you're about to head out for groceries, you realize you haven't decided what to cook yet. You're looking for something incredibly easy and quick to prepare.	1. Family	25	6.58	21	5.53
	2. Friends	15	3.95	13	3.42
	3. Cookbook	41	10.79	43	11.32
	4. Newspaper/TV	5	1.32	1	0.26
	5. Internet search	242	63.68	256	67.37
	6. AI systems	19	5.00	19	5.00
	7. Other	33	8.68	27	7.11
<b>Scenario 5 – "New"</b> Picture yourself at home, preparing for dinner, and you're eager to try making something entirely new and exciting.	1. Family	9	2.37	7	1.84
	2. Friends	12	3.16	6	1.58
	3. Cookbook	93	24.47	96	25.26
	4. Newspaper/TV	12	3.16	7	1.84
	5. Internet search	230	60.53	246	64.74
	6. AI systems	20	5.26	15	3.95
	7. Other	4	1.05	3	0.79

the Avoider class represented 82% of the total sample, with the Engager niche comprising the remaining 18%. Recall that 82% of the data consists of zero counts as well. Thus, our model

**Table 4.** PLS-SEM measurement model, with factor loadings, Cronbach's A and  $\rho_{\text{A}}$ .

	Trust	Anxiety	Accuracy	Attitudes
TRU_1	0.869			
TRU_2	0.884			
TRU_3	0.881			
TRU_4	0.894			
ANX_1		0.911		
ANX_2		0.883		
ANX_3		0.828		
ACC_1			0.869	
ACC_2			0.857	
ACC_3			0.836	
ACC_4			0.862	
ATT_1				0.726
ATT_2				0.708
ATT_3				0.770
ATT_4				0.689
ATT_5				0.643
ATT_6				0.789
ATT_7				0.791
ATT_8				0.639
ATT_9				0.694
ATT_10				0.681
ATT_11				0.769
ATT_12				0.730
ATT_13				0.598
ATT_14				0.706
Cronbach's a	0.905	0.849	0.879	0.924
$\rho_{\text{A}}$	0.909	0.887	0.879	0.927

Notes: TRU  $i_{ij}$  Trust in AI-assisted cooking; ANX  $i_{ij}$  AI Anxiety; ACC  $i_{ij}$  Perceived AI accuracy; ATT  $i_{ij}$  General attitudes toward AI; ATT\_15 was removed due to low factor loading ( $< 0.5$ ).

**Table 5.** Squared inter-factor correlations versus AVE.

	Trust	Anxiety	Accuracy	Attitudes
Trust	—			
Anxiety	0.218	—		
Accuracy	0.224	0.120	—	
Attitudes	0.349	0.290	0.405	—
AVE	0.778	0.765	0.733	0.506

suggests that these zeros for GAI selections are entirely due to the point mass component, indicating that these participants' aversion would likely remain unaffected, even if additional cooking scenarios were to be considered. Together, our findings provide an overview of how trust in AI influence engagement in AI-assisted cooking and the predicting factors of trust in AI (**RQ1**).

Table 6 shows that, among Engagers, AI was most frequently chosen in the "Leftover" scenario for both dish inspiration (75%) and dish recipe (52%). This was followed by the "New" scenario, where AI was selected for dish inspiration (31%), the "Groceries" scenario for both

**Figure 3.** Probability of engagement as a function of trust in AI-assisted cooking. Notes: The shaded area represents the 95% CI of the estimated probability (line).

**Figure 2.** Results of the hybrid model: Stage 1 refers to the structural model of the PLS-SEM, while stage 2 refers to the ZIP regression mixture model.

Notes: Estimates in Stage 1 are expressed as standardized beta coefficients, whereas those in Stage 2 are presented as odds ratios (OR) or incidence rate ratios (IRR).  $p < 0.01$ ;  $p < 0.001$ ;  $n.s.$   $i_{ij}$   $p > 0.05$ .



inspiration and recipe (30%), and the “New” scenario for the recipe (23%). In the “Host” scenario, AI was chosen for both inspiration and recipe in 11% of cases. Finally, in the “Traditional” scenario, AI was chosen in 9% of cases for dish inspiration and in 8% of cases for the dish recipe. Overall, the participants were more likely to choose AI systems for inspiration than for the recipe itself,  $\chi^2(1) = 4.71$ ,  $p = 0.03$ . Here, we profiled the user’s adoption intention of AI assistance across culinary scenarios and provided an answer to **RQ2** “In what cooking scenarios is AI assistance most accepted?”

The BCH three-step approach was applied to explore the demographic and psychographic characteristics of Avoiders and Engagers. The results in Table 6 indicate that younger participants and those with higher levels of education were more likely to engage in AI-assisted cooking (RQ3). Additionally, Engagers scored significantly higher on psychographic measures of trust in AI-assisted cooking, perceived AI accuracy, and attitude toward AI, while exhibiting significantly lower AI anxiety compared to Avoiders (Table 7, Figure 4).

## 5. Discussion

The findings of the present study reveal intriguing dynamics in consumer attitudes and behavioral intentions towards AI

usage across various cooking scenarios. The results indicate a general reluctance currently amongst participants to seek help from AI on culinary tasks, despite its widespread adoption in other recommendation contexts (Davenport et al., 2020). Across all scenarios, participants were far more likely to choose internet searches or traditional sources such as cookbooks for dish inspiration and recipe guidance, with AI systems accounting for only a small fraction of selections. User’s preference for turning to internet search for advice is embedded in the long-established behavioral pattern that social media is where information gathers and where people share their personal experiences (Hollow & Martorana, 2025). The limited selection of AI for culinary advice highlights the challenges of integrating AI into areas where cultural identity, emotional attachment, personal preference, and safety play significant roles, such as cooking (McCabe & de Waal Malefyt, 2015; Spence, 2017; Spence & Piqueras-Fiszman, 2014). Moreover, the reluctance toward AI-powered cooking advisors likely reflects a broader hesitation towards accepting technology in areas that are directly linked to consumption (Cox & Evans, 2008; Verneau et al., 2014). However, it is important to note that the situation regarding may change rapidly in the years ahead, depending how the technology, as well as consumer attitudes toward such technologies, develop.

### 5.1. How does trust in AI influence engagement in AI-assisted cooking?

Regarding the antecedents of trust in AI-assisted cooking, our study confirmed the positive impact of general attitudes toward AI and perceived AI accuracy, as well as the negative influence of AI anxiety. Specifically, when users perceive AI as accurate and reliable, they are more inclined to trust it in sensitive contexts like cooking, where the outcomes directly affect health, well-being, and satisfaction. Siau and Wang (2018) underscore this connection by highlighting the

**Table 6.** Estimated percentage of AI choices for each scenario within the Engager class.

Scenario	Dish inspiration		Dish recipe	
	Percent	SE	Percent	SE
1 – “Host”	10.94 <sup>a</sup>	3.93	10.94 <sup>ab</sup>	3.93
2 – “Leftovers”	75.00 <sup>c</sup>	5.46	51.56 <sup>d</sup>	6.30
3 – “Traditional”	9.38 <sup>a</sup>	3.67	7.81 <sup>a</sup>	3.38
4 – “Groceries”	29.69 <sup>b</sup>	5.76	29.69 <sup>c</sup>	5.76
5 – “New”	31.25 <sup>b</sup>	5.84	23.44 <sup>bc</sup>	5.34

Notes: Different superscript letters within the same column indicate significant differences at the 5% level (Bonferroni-corrected).

**Table 7.** Demographic and psychographic characteristics of Avoiders and Engagers.

		Sample (SD)	Avoiders (SE)	Engagers (SE)	$\chi^2$	p-value
Age (years)		41.63 (13.69)	42.48 (0.79)	37.84 (1.60)	6.54	0.011
Cooking expertise		2.10 (0.65)	2.11 (0.04)	2.06 (0.07)	0.26	0.608
Sex at birth	Female	67%	56%	11%	21.08	<0.001
	Male	33%	26%	7%		
Education	Secondary school	10%	10%	0%		
	Higher (e.g., A-levels)	21%	17%	4%		
	Undergraduate degree	47%	38%	9%	0.05	0.818
	Postgraduate degree	22%	16%	5%		
Dietary restrictions	Yes	79%	65%	14%		
	No	21%	17%	4%		
Trust in AI-assisted cooking		3.49 (0.83)	3.34 (0.06)	4.34 (0.07)	207.93	<0.001
AI anxiety		2.78 (0.94)	2.96 (0.07)	1.77 (0.08)	130.07	<0.001
Perceived AI accuracy		2.83 (0.74)	2.70 (0.05)	3.60 (0.10)	99.52	<0.001
Attitude towards AI		2.94 (0.67)	2.79 (0.05)	3.75 (0.07)	255.87	<0.001

Notes: Cooking expertise ranged from 0 (“None”) to 4 (“Expert”). Pearson chi-squared tests between latent profiles were computed using the BCH method (see Bolck et al., 2004).

**Figure 4.** Comparison of Avoiders and Engagers on psychographic measures.

Notes: Likert scales ranged from 1 to 5. Error bars indicate the standard errors of the estimated means. All of the differences between Avoiders and Engagers were statistically significant at  $p < 0.001$ .

perceived competence of AI systems as a fundamental driver of people's trust. Positive general attitudes toward AI contribute to context-specific trust, aligning with the notion that the trustor's beliefs about the trustee shape the trust relationship (Hancock et al., 2023). Conversely, AI anxiety introduces hesitation, as apprehensions about AI's unpredictability or perceived lack of control can deter users from fully engaging with AI systems in personal, potentially high-stakes environments such as the kitchen (Saßmannshausen et al., 2021; Sheridan, 2019; Vassilikopoulou et al., 2018).

Our findings further indicate that the perceived accuracy of AI shapes general attitudes toward it. Those users who perceive AI to be accurate and reliable are more likely to hold favourable attitudes towards its use. This aligns with Gursoy et al. (2019), who found that perceived accuracy plays a key role in developing positive attitudes and enhancing trust in AI-based systems, particularly in service contexts. As users come to regard AI as more effective and precise, their willingness to engage with and adopt these technologies increases. However, it is important to note that this perception may also reinforce naive AI realism—the belief that AI-generated information or recommendations inherently mirror real-world accuracy and reliability. Engel-Hermann and Skulmowski (2024) caution that naive AI realism can lead users to overestimate AI's capabilities, potentially neglecting the limitations or contextual nuances. In culinary applications, for instance, the persuasive realism of AI-generated recipes and images may contribute to a misplaced confidence in AI's ability to produce safe, appetizing, or culturally appropriate outcomes. While perceived accuracy encourages trust, it may also mask underlying risks, such as errors in ingredient combinations or cooking instructions that could lead to disappointing or unsafe results.

AI anxiety exerts a moderately negative influence on general attitudes toward AI. This finding supports previous research highlighting anxiety as a considerable barrier to the adoption of AI. Anxiety related to AI often stems from concerns about job security, privacy, and a general lack of understanding regarding how AI operates. Kaya et al. (2024) found that heightened levels of AI anxiety are associated with more negative attitudes towards AI. This supports the notion that anxiety may diminish the perception of AI's advantages while amplifying fears and concerns, ultimately leading to reduced acceptance and trust in the technology.

## ***5.2. Food preparation scenarios in which AI is more accepted and the demographic profile of consumers who are more open to AI-assisted cooking***

The ZIP regression mixture model identified a small segment of participants who were comparatively more open to AI-assisted cooking. This niche group, representing 18% of the total sample, chose the AI option an average of 2.2 times out of 10 scenarios. This subgroup likely represents the targeted users of such AI-powered cooking tools. Our analysis indicates that trust plays a pivotal role in influencing engagement with AI-assisted cooking. The results demonstrate that higher levels of trust significantly increased with the probability of the users being classified as an Engager rather than an Avoider. Previous studies have also highlighted the significant role of trust in the acceptance of novel technologies (Wu et al., 2011) and AI in particular (Yang & Wibowo, 2022). However, once a participant had been identified as an Engager, their level of trust did not further influence the rate of AI selection across different cooking scenarios. This result suggests that once individuals cross the threshold from

avoidant into engagement, situational factors, rather than general trust levels, drive usage patterns.

Indeed, acceptance of AI varied depending on the context. The “Leftovers” scenario yielded the highest rate of AI selection, suggesting that consumers may be more receptive to AI assistance when facing practical constraints such as limited ingredients. In this context, AI is perceived as a practical tool offering analytical utility, aligning well with the structured problem-solving tasks consumers expect it to excel in Huang and Rust (2018). This finding aligns with research suggesting that when AI is viewed as an optimizer, particularly in constrained scenarios, it is more likely to be trusted and adopted (Kim et al., 2021). Conversely, the consistently low preference for AI in socially meaningful scenarios, such as “Host” and “Traditional,” indicates boundaries where AI’s role remains limited. These boundaries appear to be drawn where social expectations significantly influence people’s judgement. In this regard, in a previous online experiment in which participants were asked to imagine preparing a dinner at home with friends—a socially meaningful scenario—Califano et al. (2024) found that participants trusted creative recipes less when these were suggested by an AI system as compared to those from a cookbook. The utilitarian value of AI therefore also depends on the costs of making errors in various contexts (Saßmannshausen et al., 2021; Sheridan, 2019), where higher perceived severity can make trust in GAI more challenging to establish (Vassilikopoulou et al., 2018; Yang & Wibowo, 2022).

The demographic analysis of the Engager class also sheds light on the profile of those individuals who appear to be more inclined to adopt AI for culinary purposes. Perhaps unsurprisingly, younger participants and those with higher levels of education were more likely to be Engagers, suggesting both a generational divide in openness to AI adoption and a potential link between education and technological curiosity or literacy. This result aligns with broader trends in the acceptance of technology and automated decision-making, where younger and more educated individuals are generally more willing to experiment with such technologies (Araujo et al., 2020; Thurman et al., 2019).

Taken together, the current research provided insights into consumers’ current perception of AI in culinary contexts. More specially, we profiled how trust in AI influence engagement in AI-assisted cooking (RQ1); the cooking scenarios where AI assistance is more accepted (RQ2); and a demographic profile capturing the niche group of consumers who are more open to AI-assisted cooking (RQ3). Nonetheless, there are several limitations to this study that should be acknowledged. First, the sample was drawn exclusively from the UK and predominantly consisted of individuals with university or postgraduate degrees. This demographic skew may limit the generalizability of the findings to broader populations (Henrich et al., 2010; though see Woods et al., 2015), particularly those with different cultural backgrounds or varying levels of education. Future studies could aim to include a more diverse sample to gain

insights across a wider spectrum of cultural and educational contexts.

Second, the study relied on self-reported data, which is inherently subject to biases such as social desirability and recall bias. Participants’ actual behavior might differ from their reported choices, especially in real-world cooking scenarios. Future research could incorporate observational or experimental methods to validate and expand upon these findings. Third, the scenarios presented in this study, while designed to capture a range of cooking situations, may not fully encompass all of the contexts in which individuals might consider using AI for culinary tasks. Therefore, further exploration of additional scenarios and nuanced contexts—such as professional cooking or cooking for special dietary needs—could provide a more comprehensive understanding of AI adoption in the culinary field.

### 5.3. Design implications in AI-assisted cooking advisory services

Building on the findings presented above, which identified trust as a central determinant of AI adoption and revealed stark differences between Engagers and Avoiders across scenarios, we now turn to the implications these insights hold for the design of AI-assisted cooking systems. In particular, the evidence that adoption is highly context-dependent—and more likely when users face practical constraints—suggests that design efforts should prioritize trust-building features, contextual sensitivity, and transparent communication. Below, we outline several recommendations to guide the development of more acceptable and effective AI tools in culinary contexts.

While AI holds significant potential as a kitchen assistant, our findings reveal persistent barriers to its adoption, particularly regarding trust, perceived accuracy, and contextual appropriateness. To mitigate these challenges, AI-assisted cooking systems should integrate both technical improvements and user-centred interaction strategies. One fundamental step toward increasing trust is enhancing transparency through explainable AI (Bedue & Fritzsche, 2022), where systems provide clear justifications for ingredient choices, step-by-step logic behind modifications, and warnings regarding potential safety concerns. Incorporating confidence scores (Ma et al., 2023; Zhang et al., 2020)—similar to reliability indicators in other AI-driven domains—could help users assess the likelihood of a successful cooking outcome. This implementation could also counteract AI naïve realism, in which users overestimate the reliability of AI-generated content. Since cooking relies on sensory experience and cultural familiarity, misplaced confidence in AI recommendations could lead to suboptimal results.

The hesitation to adopt AI-generated cooking advice originates from the reliability issues associated with the potential for GAI to generate incorrect or unfaithful information. Retrieval-augmented generation (RAG) has been explored as a potential solution to enhance the reliability of generated content by AI (Zakka et al., 2024). By matching generated content with established database information

(e.g., chef's recipes database), the RAG system could generate more reliable information and annotate traceable sources from external knowledge bases, thus increasing the transparency of AI-generated content, promoting the transparency of AI-generated content. Therefore, the trust issues towards AI-powered cooking advisors can be tackled by incorporating RAG system and tagging the sources of information with which users can track and interpret the reliability of the generated content if they want to. Another critical aspect in designing an AI-powered cooking assistant that people will be more willing to accept is to improve AI's sensitivity to context. Our results indicate that AI is more readily accepted in functional cooking scenarios—such as optimizing meals with leftover ingredients—than in socially significant contexts like hosting a dinner party. AI systems could be designed to recognize these situational cues, adjusting their recommendations accordingly. For example, while users may welcome AI's analytical approach in efficiency-driven tasks, they may prefer human-curated or chef-endorsed recipes when preparing meals for social occasions.

Beyond technical refinements, interactional design plays a crucial role in fostering adoption. AI-powered cooking assistants could benefit from more intuitive interfaces, such as voice-based interactions that allow for hands-free, real-time guidance in the kitchen. Additionally, AI could facilitate more social and collaborative cooking experiences, such as allowing multiple users to co-design recipes. These features would arguably reinforce AI's role as an assistive tool rather than a substitute for human decision-making.

## 6. Conclusions

The findings of this study offer valuable insights into consumer perceptions of AI in culinary contexts, highlighting both opportunities and challenges. While a small group of consumers exhibits openness to AI-assisted cooking, the broader hesitance underlines significant barriers related to trust and the perceived appropriateness of AI for certain cooking tasks. The high openness that was observed in the "Leftovers" scenario suggests that AI may be particularly useful in functional cooking situations—especially when resources are limited or creativity is needed. AI-generated assistance appears less desirable in socially and culturally meaningful cooking contexts, where concerns about AI's cultural understanding or authenticity may limit its perceived appropriateness. Based on the scenarios-based preference for AI-assisted cooking advice adoption, future AI cooking tools should prioritize providing reliable, adaptable suggestions tailored to the user's available ingredients and immediate needs.

Future research could further explore the nuances of people's trust in AI by examining the specific attributes of AI systems that help to foster or else undermine trust in contexts such as cooking. Ultimately, understanding the interplay between cultural values, emotional attachment, and technological acceptance is crucial for promoting the responsible and effective integration of AI into personal domains. To enhance trust, AI developers should consider

incorporating trust-building features into user interfaces, such as confidence scores, transparency about how recommendations are generated, and an accessible list of data sources used to inform the cooking advice. These design elements will be helpful in strengthening user trust while reducing the risk of AI naive realism.

From a policy perspective, ensuring the ethical deployment of AI in the context of food technology requires guidelines that promote transparency, safety, and user autonomy. Policymakers could establish AI certification standards for food-related applications, ensuring AI-generated recipes align with nutritional and safety regulations. Furthermore, public awareness campaigns could help bridge the trust gap by educating consumers about AI's benefits and limitations, fostering informed adoption.

These insights contribute to the broader discourse on human-AI collaboration, emphasizing that AI's role in cooking should be assistive rather than authoritative. By fostering trust through transparency, personalized experiences, and ethical oversight, developers and policymakers can enhance AI's practical impact, ensuring its acceptance in everyday culinary decision-making.

## Notes

1. <https://www.youtube.com/watch?v=gpm1QvQaYxA>.
2. As Hollow and Martorana (2025, p. 18) note, everyone has been there, facing: "the eternal question – what to cook for dinner tonight? To help answer questions, people turn to social media, looking for inspiration and there they find content that appeals to them."
3. In fact, it has been suggested that eating is one of the most dangerous things we do (see Woods, 1991).
4. PLS-SEM, as well as the BCH three-step procedure, were performed using community-contributed software for Stata: PLSSEM (Venturini & Mehmetoglu, 2019) and STEP3 (Califano, 2023), respectively.

## Authors' contributions

Giovanbattista Califano – conceptualization, data curation, formal analysis, investigation, methodology, project administration, visualization, writing – original draft. Tianyi Zhang – conceptualization, investigation, methodology, project administration, writing – original draft. Charles Spence – conceptualization, supervision, writing – review & editing.

## Disclosure statement

The authors confirm that they have no COI in relation to the publication of this manuscript.

## Ethics statement

The study was approved by the Central University Research Ethics Committee of University of Oxford [R85145/RE001].

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## Data availability statement

Raw data of this study is available from the first author upon request.

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