

Structuring User Preferences for Task Delegation and Proactivity in Assistive Meal Preparation: Insights from a Survey Study

Han Pan

hankpan99.cs12@nycu.edu.tw

National Yang Ming Chiao Tung University
Hsinchu, Taiwan

Yu-Chun Grace Yen

yyen@cs.nycu.edu.tw

National Yang Ming Chiao Tung University
Hsinchu, Taiwan

Ti-Chung Cheng

tcheng10@illinois.edu

University of Illinois at Urbana-Champaign
Urbana, IL, USA

Yi-Ting Chen

ychen@cs.nycu.edu.tw

National Yang Ming Chiao Tung University
Hsinchu, Taiwan

Abstract

Assistive robots could alleviate the physical demands of home meal preparation, yet a central challenge lies in capturing individuals' nuanced preferences for robotic assistance across tasks and contexts. We introduce a novel framework that models how user characteristics relate to desired types of support and levels of robot proactivity. Twenty participants with diverse cooking experience completed a Quadratic Survey to indicate which physical actions they prioritize for robotic assistance and what levels of proactivity they expect. We found that user profiles and task characteristics jointly shape action prioritization, whereas expectations for proactivity are driven primarily by task and situational factors. We argue that robotic meal preparation should prioritize empowerment over replacement, and offer a design space for personalized assistive technologies.

CCS Concepts

• **Computer systems organization** → **Robotics**; • **Human-centered computing** → **User studies**; *User models*.

Keywords

Human-Robot Interaction, Proactive Assistance, Meal Preparation, User Profiling, Quadratic Surveys, Sense of Agency

1 INTRODUCTION

Preparing meal at home is not merely a survival necessity [26]; it also encourages social interaction [19], enhances overall quality of life, and fosters self-esteem and positive affect [10]. Despite these benefits, home meal preparation is discouraged by various barriers, including limited cooking skills [15], time constraints, and high perceived effort [16, 27]. Among these, the physical effort required presents a notable challenge, as people often perceive it as a burdensome 'chore' that demands significant energy.

To alleviate these physical burdens, households utilize electromechanical appliances (e.g., blenders, mixers) for specific physical tasks. However, these devices are inherently passive and limited to single-purpose execution. In contrast, emerging digital interventions primarily focus on cognitive offloading, such as cooking guidance [12, 24] and context-aware reminders [3]. While robots could bridge this gap, existing efforts largely pursue full cooking automation [22], rather than empowering the user during meal preparation. Research on Human-Food Interaction (HFI) highlights

the value of preserving user agency with technical support rather than allowing the system to take over tasks[1].

Motivated by this perspective, we examine how assistive robots might support cooks while preserving users' agency over the cooking process. Beyond *which* tasks to offload, we argue that *how* a robot engages with the user is equally important. Research on *Proactive HRI* [23] has explored robots that act on their own rather than waiting for explicit commands, with potential benefits such as improved efficiency and more natural interaction. Meal preparation presents a compelling case for such behavior, as users often juggle multiple physical tasks simultaneously. However, not all robot proactivity is equally desired [23]. Weber et al. [24] found that users with varying cooking competence and need for autonomy preferred different levels of proactive intervention in a smart cooking assistance. Prior work focuses on informational guidance and appliance orchestration[24], but it remains unclear how preferences change when robots perform the physical actions. More critically, *how might users' nuanced and potentially dynamic preferences toward proactive physical assistance be characterized?*

To answer this question, we report an interview study exploring user preferences in meal preparation across diverse user profiles. Twenty participants were invited to a 30-minute session where they reported their cooking experience and demographic information. They then completed a Quadratic Survey (QS) [6] to indicate how they decide which physical actions to delegate to a robot and which they prefer to perform themselves, as well as their expected level of proactivity. We adopted the action taxonomy proposed by Damen et al. [9], which structures the verbs of cooking activities into 13 categories. To characterize user profiles, we used three key dimensions: cooking competence, need for autonomy [24], and sense of agency [17], as physical assistance inherently concerns who executes an action and how control is shared between the user and the robot. Specifically, we ask the following research questions:

- **(RQ1)** What specific physical actions do users prioritize for robotic assistance, and to what extent do user profiles shape these priorities?
- **(RQ2)** What levels of proactivity do users expect for robotic physical assistance, and to what extent do user profiles shape these expectations?

Our findings show that both user profiles and task characteristics shape which physical actions users prioritize for robotic assistance and that the expected levels of proactivity are driven primarily by

task characteristics and situational context, rather than user profiles. Moreover, proactive confirmation emerges as the preferred default. Focusing on the meal preparation scenario, this work makes three key contributions. *First*, we introduce a novel framework that enables users to articulate their preferences along the trade-off between automation and agency, informing the design of personalized assistive technologies. *Second*, we empirically characterize the relationship between user profiles and action prioritization. *Third*, we highlight proactive confirmation as a promising default interaction strategy for physical assistance, enabling the robot to learn user needs and build trust.

2 RELATED WORK

2.1 Meal Preparation Assistant

Various technologies have been developed to support home meal preparation, predominantly focusing on cognitive assistance, including step-by-step cooking guidance [4, 12, 24], smart kitchen appliances [2, 5], and specialized tools for users with cognitive impairments or older adults [3, 13, 14]. In contrast, research on the physical aspects of cooking has largely focused on autonomous robotic systems that aim to operate independently of the human cook [22]. However, the Human-Centered AI (HCAI) framework emphasizes empowering humans with technology [21]. Aligning with this, Human-Food Interaction (HFI) research further highlights that enhancing user agency is essential for preserving embodied engagement with food [1]. Yet, what physical actions home cooks wish to retain versus delegate to a robot remains underexplored.

2.2 Individual Differences in Robot Proactivity

Proactive Human–Robot Interaction explores robots that initiate actions without explicit commands, with benefits including improved team fluency and more natural interaction [23]. However, not all robot proactivity is equally desired [23]. Research on social home robots has shown that people prefer different levels of proactive behavior based on their own personality traits [25]. Closest to our work, Weber et al. [24] classified participants by cooking competence and need for autonomy. They found that distinct cooking types preferred different levels of proactive intervention in a smart cooking assistant that provides informational guidance and orchestrates smart appliances. While their system automates appliance settings, it does not take over physical execution. When a robot physically acts in the user’s workspace, the question of who executes a given action directly implicates the user’s sense of agency, which has been shown to be significantly affected by robot autonomy in household contexts [28] and is increasingly recognized as critical in HRI [11]. How individual differences shape preferences for proactive physical assistance remains an open question.

3 METHODOLOGY

To investigate which physical actions users prioritize for robotic assistance and their expected levels of proactivity across different user profiles during meal preparation (RQ1, RQ2), we conducted an interview study. We employed an iterative, user-centered approach, refining the study design based on pilot feedback. The following sections detail the study design, participant recruitment, and data collection process.

3.1 Study Design and Procedure

Our study consists of three parts. In Part 1 (User Profiling), participants complete scales measuring cooking competence, need for autonomy, and sense of agency, along with demographic questions, to classify them into distinct user profiles that serve as the basis for analyzing individual differences in both RQ1 and RQ2. In Part 2 (Physical Action Prioritization), participants indicate which common physical actions in meal preparation they most and least desire robotic assistance for (RQ1). In Part 3 (Proactivity Preferences), participants specify their expected level of robot proactivity for actions corresponding to extreme values in Part 2 and explain their reasoning (RQ2).

3.1.1 Part 1: User Profiling. To classify participants into distinct user profiles, we developed a questionnaire building on [24]. **However, our pilot test showed that self-reported cooking competency can be subjective and difficult to interpret. To increase reliability, we provided a concrete task scenario: participants imagined preparing one main course, three side dishes, and a soup from an unfamiliar cuisine, and rated their ability from “1 – Very low” (unable even with tutorials) to “5–Very high” (able to create recipes without guidance).** Participants rated their cooking competence, need for autonomy, and sense of agency with respect to that scenario on a 5-point Likert scale, adapted from the original 7-point scale in [24] based on pilot feedback. We also collected demographic information and daily cooking routines following [24].

As discussed in Section 1, we extended this framework with sense of agency, defined as the feeling of control over actions and their consequences [17] as an additional dimension.

3.1.2 Part 2: Physical Action Prioritization. We adopted the *mise en place* concept [18] to separate meal preparation into two distinct phases: (1) Preparation and (2) Cooking, as the two phases involve different situational demands that may shape assistance priorities differently. To provide participants with a concrete set of physical actions to reason about, the action list was derived from the verb taxonomy of EPIC-KITCHENS-100 [9], a large-scale egocentric video dataset of real-world home kitchen activities that captures essential actions often omitted from cookbook instructions, such as retrieving, accessing, and monitoring.

To elicit the spectrum of individual participant preferences for robotic assistance across tasks, we used Quadratic Surveys (QS) [6] rather than a conventional Likert scale. In QS, each participant receives a fixed budget of voice credits to allocate across options, with the cost of each additional vote on the same option increasing progressively. This mechanism forces meaningful trade-offs, enabling us to capture the relative ranking and the strength of preferences between them. Likert scales cannot provide the same information as individuals assess each option independently [6]. We framed the scenario as designing a personalized meal preparation assistant: participants assigned more positive votes to actions where they desired greater support from the robotic assistant, and more negative votes for those they preferred doing themselves.

3.1.3 Part 3: Proactivity Preferences. This part addressed two aspects. First, participants explained the reasoning behind the extreme values in their Quadratic Survey (QS) results from Part 2.

To facilitate reflection, we provided a set of example reasons that participants could reference but were not restricted to.

Second, for the actions corresponding to extreme values in each phase (Preparation and Cooking), participants selected their preferred level of robot proactivity and explained their choice. Extreme values were identified following [7]. We calculated the mean and standard deviation of the QS votes per person and selected actions where vote counts go beyond one standard deviation from the mean. If this criterion yielded fewer than three actions in either direction, we manually selected additional actions of interest. The proactivity levels were adapted from the ten robot autonomy levels in HRI [20]. As our focus is on physical task execution, we excluded suggestion-related levels and collapsed the notification strategies into a single autonomous level for simplicity, yielding three levels:

- (1) **Passive:** The robot waits for the user’s explicit command before acting.
- (2) **Proactive confirm:** The robot detects a need and proposes to act, but waits for approval before executing.
- (3) **Proactive assist:** The robot detects a need and immediately executes without requesting approval.

3.1.4 Procedure. We scheduled an individual session with each participant. First, participants completed the Part 1 questionnaire and briefly discussed their prior cooking experience. For Part 2, participants completed two separate QS tasks – one for each phase (Preparation and Cooking) using the QS platform [8]. A researcher was present to clarify questions and probe reasoning. Finally, for Part 3, we conducted a short interview as described in Section 3.1.3. All study materials were administered in Mandarin Chinese; physical action categories were translated from the EPIC-KITCHENS-100 verb taxonomy [9] and back-translated into English for reporting.

3.2 Recruitment and Data Collection

We recruited 20 participants through personal networks across two age cohorts: a younger cohort (N=9; 4 female, 5 male; aged 18–34) and an older cohort (N=11; 7 female, 4 male; aged 45+). Part 1 and Part 2 responses were collected via the online platform. For Part 3, we conducted short interviews in which participants first explained the reasoning behind their extreme QS values, then selected and explained their preferred proactivity level for the corresponding actions, using the criteria described in Section 3.1.3.

4 PRELIMINARY STUDY RESULTS

4.1 User Profiling

We adapted Weber et al.’s [24] four cooking types framework (competence x autonomy), measuring competence with a single item and autonomy with the mean of two items, both on 5-point Likert scales. We used median splits (competence Mdn = 3.0; autonomy Mdn = 3.5) to classify participants. However, high- and low-agency participants (Mdn = 3.0) appeared across all four cooking types (see Figure 1), suggesting that agency did not show a clear pattern of association with the competence–autonomy classification in our sample. Combined with the small per-cell sample sizes a three-dimensional split would produce, we instead analyzed agency as a separate additional dimension.

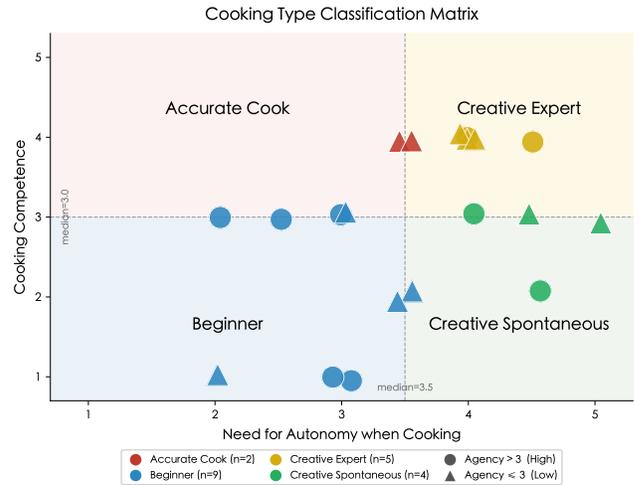


Figure 1: Cooking types matrix

The two largest groups are Beginner (n = 9) and Creative Expert (n = 5), both on the diagonal of the matrix, consistent with Weber et al.’s finding that competence and autonomy tend to correlate positively. The Accurate Cook group (n = 2) should be interpreted with caution.

4.2 Physical Action Prioritization (RQ1)

Figure 2 presents participants’ mean prioritization votes for robotic assistance across 13 physical actions during cooking, broken down by cooking type (primary classification) and agency group (additional dimension), respectively. We focus on cooking as the preparation phase yielded largely consistent patterns. We report findings in three parts: universal patterns shared across all profiles, differences by cooking type, differences by sense of agency. Given the exploratory nature of this interview study, the findings below identify preliminary patterns.

Finding 1: Shared preferences across profiles

Clean is universally the most desired action to delegate, while *Sense* is consistently among the least desired to delegate, regardless of user profile.

Clean received the highest mean votes in every subgroup (range: 5.4 to 6.8; Figures 2), while *Sense* received the lowest or near-lowest votes across all groups (range: -1.5 to -3.0), suggesting that sensory judgment: tasting, smelling, touching is widely regarded as a personal act that users wish to retain.

Finding 2: Cooking type partly shapes prioritization

Competence shapes preferences for some actions (e.g., *Split*, *Transition*), but *Manipulate* shows a pattern that neither competence nor autonomy alone can account for.

Split was notably desired by Beginners (2.9; Figure 2), with other groups showing weaker or negative preferences, suggesting

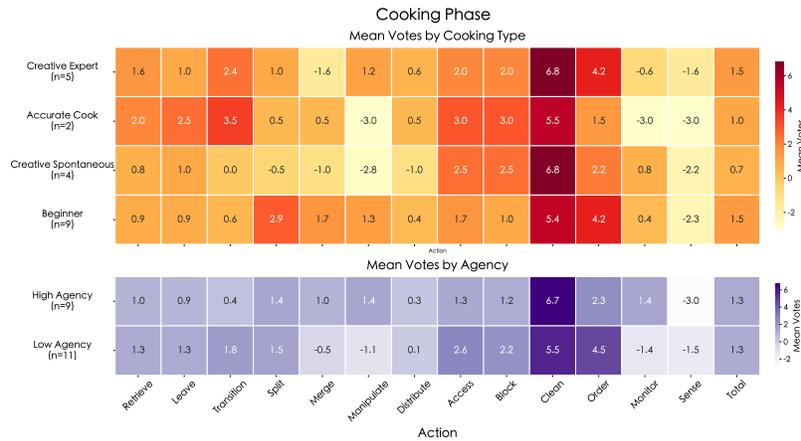


Figure 2: Mean votes classified by cooking types and sense of agency during cooking phase

that low-competence participants prefer to delegate technically challenging actions. *Transition* was highly valued by the two high-competence groups, Accurate Cooks (3.5; though $n=2$ warrants cautious interpretation) and Creative Experts (2.4), but not by low-competence groups, indicating that skilled cooks prefer to outsource logistics to focus on core cooking. *Manipulate* showed the sharpest split: Beginners (1.3) and Creative Experts (1.2) were open to delegation, while Creative Spontaneous (-2.8) and Accurate Cooks (-3.0; $n=2$) strongly resisted it. This divide does not follow competence or autonomy alone, as the two accepting groups sit on opposite ends of both dimensions, as do the two resisting groups.

Finding 3: Sense of agency captures patterns beyond cooking type

High-agency participants prefer to delegate cooking actions (e.g., *Manipulate*, *Monitor*) but retain sensory ones (i.e. *Sense*), while low-agency participants prefer to delegate non-cooking actions (e.g., *Order*, *Transition*).

The two agency groups showed divergent patterns depending on the type of action (Figure 2). For sensory actions, high-agency participants were more reluctant to delegate *Sense* (-3.0 vs. -1.5), consistent with a stronger desire to personally verify outcomes. For cooking actions, the pattern reversed: high-agency participants were more open to delegating *Manipulate* (1.4 vs. -1.1) and *Monitor* (1.4 vs. -1.4), while low-agency participants preferred to delegate non-cooking actions such as *Order* (4.5 vs. 2.3) and *Transition* (1.8 vs. 0.4). This suggests that sense of agency may operate differently across action types, warranting further investigation.

4.3 Expected Proactivity Levels (RQ2)

Finding 4: Proactivity depends on task and situation, not user profile

Proactivity preferences are driven by task and situational factors, not by user profile. Most participants preferred proactive confirmation as the default.

This preference showed no clear differentiation by cooking type or sense of agency. While a few participants consistently preferred proactive assistance for all actions, most treated proactive confirmation as the default, citing the low cost of a verbal check and concerns about unexpected behavior. They shifted toward accepting proactive assistance when the task followed a predictable routine and would not interfere with their workspace. Some participants framed this default as provisional, noting that extended collaboration and established trust could shift them toward accepting proactive assistance, a point we return to in the Future Work section.

5 FUTURE WORK AND CONCLUSION

The workshop theme of *Evolving Assistance for Everyday Life* foregrounds how robots can progressively adapt their support over time. We seek to expand this perspective by emphasizing that evolving assistance requires not only adapting strategies over time, but also understanding *whether* assistance is desired and *what* to assist with in the first place. We therefore highlight proactive confirmation as a promising default interaction strategy for physical assistance. By proposing actions and awaiting approval, the robot learns about the user’s needs while building trust for eventually transitioning to proactive assistance. The preference elicitation approach in this study can serve as an initial policy, progressively refined through such confirmatory interactions.

Our next step is to conduct in-depth interviews to further uncover how task characteristics and situational context shape these expectations, informing adaptive policies for future longitudinal studies. We also plan to explore alternative study methods. In our survey, participants assign weights to text-based action descriptions. However, users with different levels of technological literacy may interpret the format and quality of robotic assistance differently. An alternative approach would be to present simulated robot executions, but this may introduce bias toward a particular robot’s appearance, speed, or execution style. In conclusion, this work serves as a first step toward assistive robots that empower home cooks through progressively adaptive support.

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