# A User-Centric Framework for Assistive Robot Control via Wearable Sensing


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*To my Nanu. I wish you were here to read this.*

# Abstract

Physically assistive robots have the potential to support individuals with motor impairments in performing Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (iADLs), yet their usefulness depends critically on how users can interface with them. Traditional control frameworks are rooted in industrial and surgical robotics and do not reflect the priorities of users in assistive contexts, such as preserving a sense of agency, comfort, long-term use, etc, thereby underscoring the need for a more user-centered framing. At the same time, sensors such as inertial measurement units (IMUs) and electromyography (EMG) embedded in wearable devices have been increasingly leveraged as control interfaces for assistive robots, with their form factor and ability to capture subtle, on-body signals presenting unique opportunities for natural, user-aligned control across varying levels of motor ability. Hence, this work introduces a user-centric framework that defines three levels of control, namely active, shared, and passive control, and situates wearable sensing modalities within each level. While wearable-based active and shared control have been explored in literature, passive control using wearables remains comparatively underexamined. Building on limited prior work that demonstrated the feasibility of wearable-based passive sensing for bite timing, we conduct a thematic analysis on participant feedback on WAFFLE, a wearable-based bite-timing system for robot-assisted feeding involving fifteen able-bodied participants and two participants with motor impairments. Our analysis identifies recurring themes of feeling of control, naturalness, low workload, and social compatibility, demonstrating that implicit cues can enable interactions that feel intuitive and responsive without requiring explicit user commands. Together, these findings highlight the unique potential of wearable-based passive control systems that can align with natural human behavior to support user-aligned control interfaces.

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Finally, to my parents and my brother, thank you for everything. I am who I am because of you. I carry your faith in me in everything I do.

# Contents


**Figure 1: An overview of the pipeline to use sensors as robot control interfaces: Diverse sensing modalities such as EMGs, IMUs, and contact microphones are embedded into everyday wearable form factors such as glasses, rings, wristbands, hats and sleeves. They capture user motion and physiological cues that are then processed to infer human intent and gestures, enabling robots to execute tasks through wearable control interfaces.**

# 1 Introduction

Motor impairments can drastically limit a person's ability to carry out Activities of Daily Living (ADLs), which are defined as fundamental self-care tasks, including bathing, eating, and dressing, as well as Instrumental Activities of Daily Living (iADLs), which include more complex activities necessary for independent living, such as home management, cooking, and cleaning. In the United States alone, approximately 5 million individuals live with partial or total paralysis arising from stroke, spinal cord injury, neurodegenerative disorders, or progressive muscular diseases [1]. As a result, such individuals with reduced motor function must rely heavily on caregivers for routine tasks such as scratching an itch, bringing food to the mouth, opening a door, or moving objects across a countertop [2, 3, 4, 5]. This can significantly affect independence, sense of agency, and overall quality of life. For these individuals, the loss of motor function fundamentally reshapes how they navigate daily routines, underscoring the need for technologies that can help them regain control in daily life.

Physically assistive robots are designed to help individuals perform tasks that they would otherwise find difficult due to their motor impairments, such as feeding, grooming, dressing, or manipulating objects around the home [6, 7, 8, 9, 10]. These robots can offer the potential to support individuals in performing everyday tasks more independently and reduce caregiver burden while improving overall quality of life. However, realizing these benefits requires robots to be controlled in ways that respect each user's abilities, preferences, and desired degree of involvement.

A key challenge is that the prevailing definitions of control in robotics are rooted in autonomous manipulation and teleoperation frameworks developed for industrial, surgical, and mobile robots. These models typically optimize for efficiency, precision, or autonomy that do not map cleanly onto assistive contexts where user comfort, agency, and long-term use matter much more. As a result, many existing control paradigms implicitly assume that the robot should either execute tasks independently or respond only to direct, unambiguous commands. Such assumptions break down in caregiving scenarios. Assistive tasks are deeply personal, often preference-laden, and embedded in social and contextual cues. They require an interface perspective that is grounded in the user's experience of control. This motivates the need for a user-centric framework that articulates how different forms of control- direct, blended, or implicit- shape the interaction between users and assistive robots.

Within this landscape, wearable devices have emerged as a promising way to bridge user intent and robot behavior. They embed sensors, most commonly inertial measurement units (IMUs) and electromyography (EMG), into wearable devices and can be used to control assistive robots. Because these devices capture on-body signals directly from the user, they can sense small, residual movements that may be too subtle for camera-based interfaces or impossible to express through handheld devices. They also avoid many of the limitations of environmental sensing: unlike vision-based systems, they are robust to occlusion, lighting changes, and cluttered home environments [11, 12, 13], and unlike stationary interfaces such as joysticks or sip-and-puff devices, they do not restrict the user's posture or require access to a fixed surface. These characteristics make wearable interfaces a promising and increasingly practical way for enabling users to interact with assistive robots.

At the same time, passive control with wearable devices has emerged as a particularly underexplored mode of interaction for assistive robotics. In our framework, passive control refers to scenarios where wearable devices detect naturally occurring human cues and use these signals to modulate robot behavior without requiring explicit commands. Crucially, passive control is not the same as full autonomy: in fully autonomous systems, the robot initiates and sequences actions based on its own pre-determined timing and sequencing, independently of the user's behavior or readiness, whereas in passive control, the robot still responds directly to the user, just through implicit rather than deliberate input.

In this paper, we consider how levels of robot autonomy can be reframed from a user-centered perspective in assistive contexts, and we examine how wearable sensing modalities intersect with these levels of control. In particular, we focus on the potential of wearables to serve as passive control interfaces. By performing a thematic analysis on a case study of a wearable-based bite-timing system for robot-assisted feeding, we examine how users experience passive control, what cues feel natural or reliable, and how wearable systems can protect users' sense of agency even in the absence of explicit commands. Our findings reveal 4 common patterns across participants, namely feelings of control, natural cues, low workload, and social compatibility. These suggest that passive wearable sensing can meaningfully shift how assistive robots integrate into users' daily lives.

The contributions of this work are as follows:

- We review prior work that uses wearable devices in caregiving and assistive-robotics settings, examining how on-body sensing has been applied across tasks and user abilities.
- We introduce a user-centric framework that defines three levels of control in assistive robotics: active, shared, and passive, and show how different wearable sensing modalities can be used as interfaces for each control level.

- We examine passive control using wearable sensing through a thematic analysis of user feedback from a wearable-based bite-timing system for robot-assisted feeding, including 15 able-bodied participants and 2 participants with motor impairments, identifying themes of control, natural cues, low workload, and social compatibility.

# 2 Wearable Devices

Wearable devices have shown a lot of promise at capturing physiological and behavioral signals in daily life. They can monitor motion, muscle activation, posture, speech-related vibrations, heart rhythms, and a range of other bodily signals continuously and unobtrusively. This has driven their widespread adoption in clinical, research, and consumer contexts for gait analysis, fall detection, neuromuscular and activity tracking, etc. [14, 15, 16, 17, 18, 19, 20]. These same sensing capabilities make wearable devices uniquely promising as control interfaces for assistive robotics, where understanding a user's intent, comfort, and current state is essential for safe and personalized interaction. Figure 1 provides an overview of how diverse sensors are embedded into everyday wearable form factors and transformed into robot control inputs.

In the context of robot control, wearable devices offer several advantages over traditional interfaces such as joysticks, sip-and-puff devices, web interfaces, or camera-based tracking. First, because they are mounted directly on the body, wearable devices can pick up residual movements that are too subtle for vision systems and too limited for handheld or desktop devices, which is an important consideration for individuals with motor impairments. Second, on-body sensing is unaffected by occlusion, poor lighting, cluttered environments, and changes in seating position, all of which commonly occur in homes. Third, wearable devices support continuous measurement of movement or muscle activity, enabling both fine-grained active control and more advanced shared or passive control strategies. Finally, they can be used without constraining the user's posture or requiring them to face a particular direction, providing flexibility during everyday tasks.

Although wearable technology encompasses a wide range of devices, such as smartglasses, body-mounted cameras, smart textiles, physiological patches etc, we focus on wearable devices with sensors whose primary function is to capture on-body physiological signals, rather than environmental signals. This distinction is important since many body-mounted devices record the world around the user (e.g., egocentric videos), but for assistive robot control, the most useful wearable devices are those that directly sense the user's intent through subtle behavioral cues.

Because of this, we narrow our attention to two types of sensors that have seen the most sustained use in assistive robotics: electromyography (EMG/HDEMG) and inertial measurement units (IMUs). We also explore how commercially available wearable devices provide different form factors that integrate these sensor types. While these examples anchor the discussion, the broader control framework we develop in later sections can support a wider range of sensing modalities.

## 2.1 Myoelectric Interfaces (EMG/HDEMG)

EMG interfaces capture the electrical activity produced by skeletal muscle activity. Surface EMG (sEMG) sensors detect these signals non-invasively from electrodes placed on the skin, while high-density EMG (HDEMG) arrays capture more detailed spatiotemporal patterns across multiple muscle fibers. The amplitude and frequency of EMG signals correlate with muscle activation strength, enabling continuous decoding of user intent. These signals can be translated into discrete gestures, proportional velocity control, or context-aware triggers based on the task.

EMG sensing has long been used in clinical and rehabilitative contexts to monitor neuromuscular health and motor recovery. For example, EMG biofeedback therapy is a common rehabilitation method for post-stroke patients and individuals with motor impairments, helping them relearn muscle coordination [21, 22]. Wearable EMG systems have been developed for monitoring muscle fatigue [15, 23, 24], prosthetic limb training [25, 26], and early detection of neuromuscular disorders [16, 18]. These applications demonstrate EMG's ability to capture intention-driven signals directly from the body. Given these properties, EMG naturally extends to the control of assistive robots. They have been used to control robotic manipulators [27, 28, 29, 30, 31] and mobile platforms [32, 33], allowing individuals with motor impairments to easily perform tasks with intuitive robot mappings.

EMG-based interfaces are particularly powerful for individuals who retain some voluntary muscle movement but have limited gross motor function: it provides a direct, body-based channel for expressing intent when movements are too small or inconsistent for vision-based or inertial sensing systems to detect. However, the same reliance on muscle activity presents challenges. For users with minimal or highly variable activation, EMG can become noisy or unreliable, leading to missed detections or false triggers. In these cases, alternative sensing modalities, such as IMUs, eye-tracking, or physiological sensors, may offer more consistent performance. Understanding where EMG excels and where it struggles is, therefore, important when selecting wearable inputs for assistive robot control.

## 2.2 Inertial Measurement Units (IMUs)

IMUs are sensors that measure acceleration, velocity, and magnetic orientation by fusing a gyroscope, accelerometer, and magnetometer together. By integrating these signals, IMUs estimate motion, orientation, and posture without requiring external cameras or tracking systems. When embedded in wearable form factors such as headsets or garments, IMUs provide continuous, high-frequency information about movement of the user. Their robustness to lighting, occlusion, and environmental clutter has made them a widely adopted tool for capturing human motion unobtrusively.

IMU wearables have been extensively used in healthcare and rehabilitation by clinicians to capture quantitative measures of gait [14, 34, 19], posture [35, 36, 37], and limb activity [38, 39]. They have also shown their effectiveness in tracking joint kinematics for stroke patients. [17, 40, 41] IMUs have also been used to monitor and quantify everyday motor activites in people with impairments and older adults [42, 43, 20]. These applications highlight IMUs' ability to capture fine-grained, continuous behavioral data in both clinical and real-world environments. Given these sensing capabilities, IMUs have become a natural choice for wearable robot-control interfaces. They have been used to teleoperate mobile manipulators and robotic arms by mapping head-, hand-, or whole-body motion to robot base or end-effector movement [44, 45, 46, 47, 48, 49, 50, 51, 52, 53]. These interfaces support proportional, real-time input and can operate reliably even when vision-based tracking is infeasible.

IMU-based interfaces are most appropriate for users with reliable, repeatable motion in the head, torso, or upper body. They are especially advantageous when vision-based systems are impractical due to lighting conditions. IMUs offer continuous, proportional control that mirrors natural body motion, supporting both active and shared autonomy paradigms. However, IMUs require stable mounting, occasional recalibration to mitigate drift, and careful mapping to avoid fatigue during long-term use. For users with inconsistent movement or minimal motor ability, other modalities, such as EMG, eye-tracking, or physiological sensing, may provide greater reliability.

### 2.3 Commercially Available Wearables

Commercial wearables, such as smartwatches, smartglasses, and sensor-enabled rings, have made these sensing capabilities mainstream. These devices typically integrate IMUs, heart-rate sensors, PPG, ECG, microphones, etc., enabling continuous monitoring of motion, cardiovascular activity, sleep, and safety-related events. Because these sensing modalities mirror many of the signals used in assistive-robotics research, commercially available wearables provide a practical, widely distributed foundation for future robot interfaces.

Commercial smartwatches have been used to detect atrial fibrillation and irregular heart rhythms [54, 55, 56], for reliable fall detection in older adults [57, 58, 59], and have been used to monitor post-cardiac event recovery [60]. They have also been widely used for physical activity and sleep monitoring [61, 62, 63], and large-scale deployments show their potential to provide population-level insights into health [64, 65, 66]. Smartglasses represent another commercially available platform for on-body sensing. Prior work has shown that the IMUs embedded in smartglasses can reliably track human motion and activity [67, 68, 69, 70].

The growing diversity of commercially available wearable devices highlights an important design principle: the form factor determines which bodily signals can be captured. Wrist-worn devices are well-suited for gross arm movement, heart rhythms, and activity patterns; head-worn devices capture gaze-related head motion and speech vibrations, and ring-based wearables detect subtle finger motion. These categories align naturally with the control framework described earlier: although EMG and IMU sensors dominate current assistive-robotics research, the form factors determine the type of signal that we are able to obtain from the body, which in turn determines its use as a control interface.

## 3 User-Centric Levels of Control

Recent advances in wearable sensing provide powerful ways to capture users' residual movement and behavior, but sensing alone does not determine how these signals are translated into robot behavior. In assistive robotics, the relationship between user signals and robot action fundamentally shapes what the interaction feels like, how much effort the user expends, and what roles robot and human autonomy play. To situate wearable interfaces within this broader landscape, we organize assisted-robot interaction into three user-centric levels of control: active, shared, and passive. These levels reflect how directly the user drives the robot, how much robot autonomy contributes to execution, and how robot behavior aligns with naturally occurring human cues. Figure 2 visualizes these levels of control along interacting dimensions of direct user actuation, intent inference, and robot autonomy. In the following subsections, we examine each level, describing how it works, why it matters, and how wearable sensors uniquely support that mode of interaction.

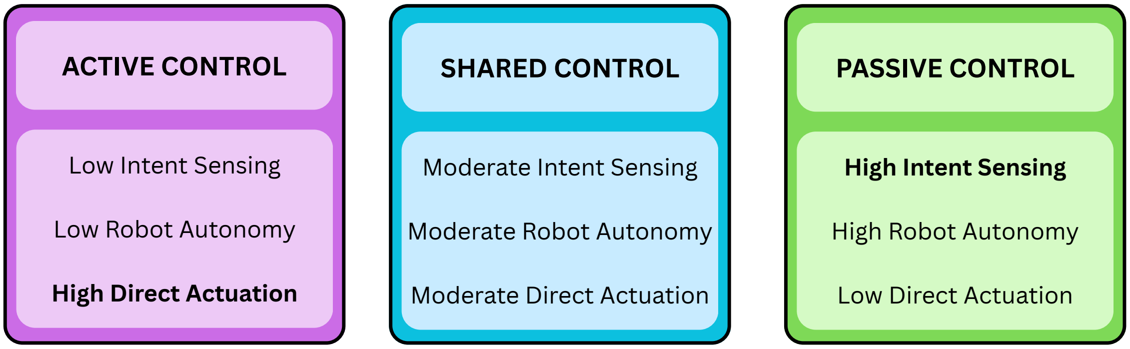


**Figure 2: User-centric control levels positioned along three dimensions: intent sensing, robot autonomy, and direct actuation from the user. Active control requires little to no intent sensing and robot autonomy, with the user performing all of the direct actuation. Shared control blends moderate intent sensing with mid-level robot autonomy based on the intent sensing with the user still providing some direct actuation. Passive control relies on high-level intent inference and high robot autonomy, with minimal to no direct actuation from the user.**

## 3.1 Active Control

**Active control refers to where the user's intentional actions or movements directly trigger robotic movements.**

In assistive robotics, active control has traditionally relied on web-based interfaces [71, 72, 73, 74], hand- or mouth-operated joysticks [75, 76], speech interfaces [77, 78, 79, 80, 81, 82] etc. Although web-based interfaces can be accessed with a standard mouse, many users rely on alternative tools, including head- and eye-tracking [83, 84, 85, 86, 87]. Active control keeps the human unambiguously in the loop for initiation, timing, and direction, properties that are especially important for preference-laden ADLs such as feeding and dressing.

Recent work has increasingly explored wearable interfaces as an alternative interface for active control in assistive tasks. These systems leverage body-worn sensors, most commonly IMUs, EMG armbands, or head-mounted devices, to provide continuous, user-driven control signals for tasks such as feeding, dressing, reaching, and object manipulation. In practice, active control using wearable devices follows a common pipeline. On-body sensors (head IMU, multi-IMU shirt, EMG/HDEMG sleeve) stream continuous signals at tens to hundreds of hertz. These signals are mapped to robot commands either proportionally (e.g., head orientation angles to end-effector velocity) or via classification that triggers the end-effector (e.g., EMG gestures for "drive," "wrist," or "grasp"). Finally, a single, reliable input (eg,. clicker or switch) handles mode selection. IMU-based interfaces have been used to map head, wrist, or torso motion to robot end-effector movement, enabling users with limited mobility to teleoperate manipulators with high precision and reduced workspace constraints [50, 51, 52, 53, 46]. EMG-based methods likewise translate muscle activation patterns into control commands, offering hands-free ways for initiating robot motion, selecting modes, or executing multi-DOF trajectories [88, 29]. Across these systems, wearable active control provides users a direct, personalized means of commanding assistive robots.

Active control offers several advantages to a user. First, it preserves their sense of agency: the user sets the pace, approach, and timing, and can abort instantly, which is critical for tasks that require the robot to operate near the face or body. Second, it supports natural preferences. For example, when feeding, bite size and utensil angle differ from person to person, and sometimes even within individual sessions: active control allows users to make these choices without requiring the system to infer them. However, this level of control comes with costs. Directly operating the robot can place substantial cognitive demands on users, especially when tasks are repetitive, require precise positioning, or involve frequent mode-switching across joints. In these situations, the interaction can become mentally and physically tiring. Many of the sub-steps that users must explicitly manage in active control could be safely abstracted away while still allowing them to guide the essential parts of the task, preserving a sense of control without the full operational burden. These limitations motivate the need for alternatives, such as shared control, that can offload certain demands while still keeping the user directly involved.

## 3.2 Shared Control

**Shared control combines user input from direct teleoperation interfaces with the robot's autonomy, leveraging the robot's understanding of human intentions and the surrounding environment and resulting in a reduction in cognitive load for the user.**

Shared control occupies the middle ground between active and passive control: the user remains intentionally engaged, but the robot contributes autonomous assistance, such as stabilizing motion, enforcing safety, or refining trajectories. In practice, the robot's autonomy consists of capabilities such as estimating object and human pose, filtering tremor or noise, shaping motion primitives, avoiding collisions, and inferring likely goals. Arbitration, deciding how strongly to weight user inputs versus autonomous proposals, is central to shared control. High arbitration weight on the user gives them more direct influence; higher autonomy weight lets the robot handle low-level execution. Effective systems adjusts this balance so that the robot helps without overriding or confusing the user.

In practice, shared control for assistive robotics has been explored across a wide range of tasks and input modalities [44, 89, 90, 91, 92, 93, 94, 95, 96]. Across these systems, the physical form of the input varies, but the high-level pattern is similar: the user guides overall direction, while the shared-control policy autonomously handles the fine-grained decisions that would otherwise be difficult or tedious to perform. Methodologically, much of the shared-control literature focuses on how to implement assistance and arbitration, rather than on the qualitative differences between input modalities. Some of the core questions include how to blend user and robot policies, how to infer the user's goal, and how to adapt the level of assistance over time [97, 98, 99]. There are a few exceptions that begin to look at interface modality more directly to examine how different input devices might inform assistive autonomy design [100, 101, 102, 103]. However, compared to the substantial body of work on arbitration rules, goal-prediction algorithms, and policy-blending schemes, the form of input is often treated as interchangeable. This gap motivates our focus on wearable interfaces: rather than viewing them as just another input method to plug into an existing shared-control framework, we argue that their specific properties, such as being body-worn and being able to continuously monitor any residual movement, shape how people experience shared control.

Shared control using wearables would follow a pipeline analogous to that of active-control and wearables but with an autonomy layer inserted between sensing and actuation. Continuous wearable signals are decoded into intent cues such as movement direction, goal likelihood, while perception modules estimate object location, human pose, and environmental constraints. The shared-control system then combines these sources through an arbitration policy, which may blend velocity commands or adjust robot behavior based on confidence. A simple discrete input (e.g., switch, button, vocal cue) can provide confirmation or override, ensuring that autonomy supports the user's intent rather than replacing it.

Shared control offers several advantages to a user. First, it reduces cognitive workload by allowing the robot to handle stabilization, fine alignment, and repetitive sub-steps while the user specifies goals or general motion trends. Second, it improves precision: during tasks such as feeding or dressing, users can issue coarse movements while the robot autonomously filters tremor, shapes trajectories, or adjusts approach angles to be safe and comfortable. Third, shared control lowers the barrier to entry for users with limited motor bandwidth: even small, noisy, or intermittent inputs can be amplified into functional, high-quality assistance. At the same time, shared control carries trade-offs. If the robot's autonomous behaviors are not transparent or predictable, users may feel overridden or confused when trajectories deviate from their input. Systems must therefore carefully balance assistance and user authority, ensuring that autonomy supports rather than conflicts with human intent. While shared control alleviates many of the burdens of full teleoperation, it still relies on users providing deliberate input. This makes it less suitable for tasks where timing is subtle, continuous, or difficult to explicitly signal, motivating the need for passive control.

## 3.3 Passive Control

**Passive control enables robots to detect implicit signals which are small, unintentional signals users give through everyday behavior, such as chewing pauses or shifts in posture, and adjust their behavior accordingly, thereby reducing the need for frequent user input during repetitive tasks and lowering the user's overall workload.**

In practice, passive control does not require a user to issue deliberate or continuous commands to the robot, instead, the robot responds to cues that naturally arise from the user's behavior. Importantly, passive control is not equivalent to full autonomy: in fully autonomous systems the robot independently decides when and how actions should proceed, whereas in passive control the robot remains tightly coupled to the user's timing. The robot advances only when the user's natural behavior indicates readiness or task progression, making passive control particularly well-suited for activities that depend on subtle timing, or caregiver-like responsiveness.

Passive control offers several advantages. Because the user no longer has to provide inputs, it can substantially reduce both cognitive and physical workload. This makes passive control especially well-suited for long, repetitive, or timing-dependent tasks in which users may not, want, or be able, to repeatedly teleoperate. Instead of actively driving the robot, the user's natural behaviors, such as chewing rhythms, brief pauses, posture adjustments, or other unconscious signals, indicate when the robot should proceed. For people with impairments, this ability to remain engaged without supplying explicit input can dramatically improve comfort during extended use.

However, passive control also presents significant challenges. Implicit cues are often subtle, noisy, or context-dependent, making them harder to interpret than intentional inputs. Systems must avoid both over-sensitivity, which can trigger premature or unwanted actions, and under-sensitivity, which can cause delays or unresponsiveness. Effective passive control therefore, requires reliable sensing, robust filtering, and careful modeling of user state and task context. These considerations highlight why passive control remains far less explored than active or shared control, despite its strong potential for enabling seamless, caregiver-like interactions.

In assistive robotics, passive control has relied on sensing modalities that infer user intent or user state without explicit commands. For example, gaze fixations [104, 105, 106, 107] have been used to infer desired object targets, body pose or posture shifts [108, 109, 110, 111] can indicate readiness for the next step in dressing and measurements such as muscle activation trends, or fatigue signatures can modulate robot assistance levels [112]. Traditionally, these signals have been sensed using external perception systems, such as RGB or depth cameras, motion-capture setups, or fixed eye-tracking hardware, that require stable viewpoints and controlled lighting. These setups can be sensitive to occlusion, difficult to deploy in real homes, and often place constraints on where users can be positioned relative to the robot.

This motivates a deeper examination of passive control with wearables since they offer an alternative way to capture similar implicit cues directly from the body while remaining unaffected by some of the problems that vision-based systems face. Most wearable-based systems in assistive robotics have been designed for teleoperation or goal-driven shared control. As a result, the field lacks a clear understanding of how continuous, naturally occurring signals captured unobtrusively from the body might support tasks that users perform every day but do not want to explicitly command. Tasks such as feeding, bathing, or dressing require subtle timing and responsiveness to the user's state which are qualities that are difficult for fully autonomous systems to infer and adapt to, and burdensome for users to continuously teleoperate.

Given the sparse amount of existing literature that uses passive control with wearables, we examine an early advancement from our group that uses continuous signals from wearables to infer bite timing during robot-assisted feeding. By evaluating a real wearable-based passive control system in detail, we validate our intuition that combining wearables with implicit sensing can open new opportunities for assistive robots, particularly in tasks that change daily or rely on natural timing.

### 3.3.1 WAFFLE: A Wearable Approach to Bite Timing Estimation in Robot-Assisted Feeding

Bite timing refers to determining the appropriate moment for an assistive feeding robot to deliver food to the user: a decision that, in human caregiving, is based on subtle behavioral cues such as pausing between chews, turning toward the utensil, or briefly stopping conversation. WAFFLE [113] introduces a wearable, learning-based approach for estimating this timing by detecting these naturally occurring signals without requiring explicit user commands.

WAFFLE uses two unobtrusive wearable sensors: a single IMU mounted on the left side of a glasses frame and a throat contact microphone worn at the neck. The IMU captures head movements and chewing-related vibrations, while the throat microphone detects vocal-cord vibrations from chewing and speaking without recording ambient audio, preserving privacy. Vision-based approaches are vulnerable to occlusions, variable robot pose, user movement, and changes in seating or social-dining configurations, making them unreliable in real-world contexts. These limitations motivate the use of wearables, which maintain a consistent frame of reference and remain robust across diverse dining environments.

WAFFLE was evaluated in two main studies. In the first study, fifteen participants without motor impairments (referred to in subsequent sections as P1-15) completed individual and social dining sessions using three bite-timing methods: Fixed Interval, Mouth Open, and WAFFLE, while being fed by the Obi [114] robot positioned to the side. Participants completed three consecutive trials per method, with method order being single-blind. After each method, participants rated timing appropriateness and responded to 7-point Likert items assessing distraction by the robot, feeling of control, robot understanding, appropriateness of robot movement, seamlessness, mental workload, physical workload, and natural conversation. In the second study, two participants with motor impairments (referred to in subsequent sections as I1-2) used WAFFLE in their homes with the FEAST robot, selecting their preferred assertiveness threshold before completing individual and social dining sessions

Across these evaluations, WAFFLE either matched or outperformed baseline methods. In individual dining, 100% of participants found WAFFLE's timing appropriate, and it received the most "Right Time" ratings. It also produced lower cognitive and physical workload and matched ratings for robot understanding and seamlessness with non-wearable methods despite relying on implicit cues. In social dining, WAFFLE matched or exceeded baselines, particularly on distraction and natural conversation, where explicit triggers like mouth opening were disruptive. In the study with individuals with motor impairments, both participants rated WAFFLE's timing as appropriate and described the interaction as natural, intuitive, and comparable to, or even better than, their human caregivers. Collectively, the results show that WAFFLE generalizes across robots, participants, foods, and dining contexts, providing robust bite-timing.

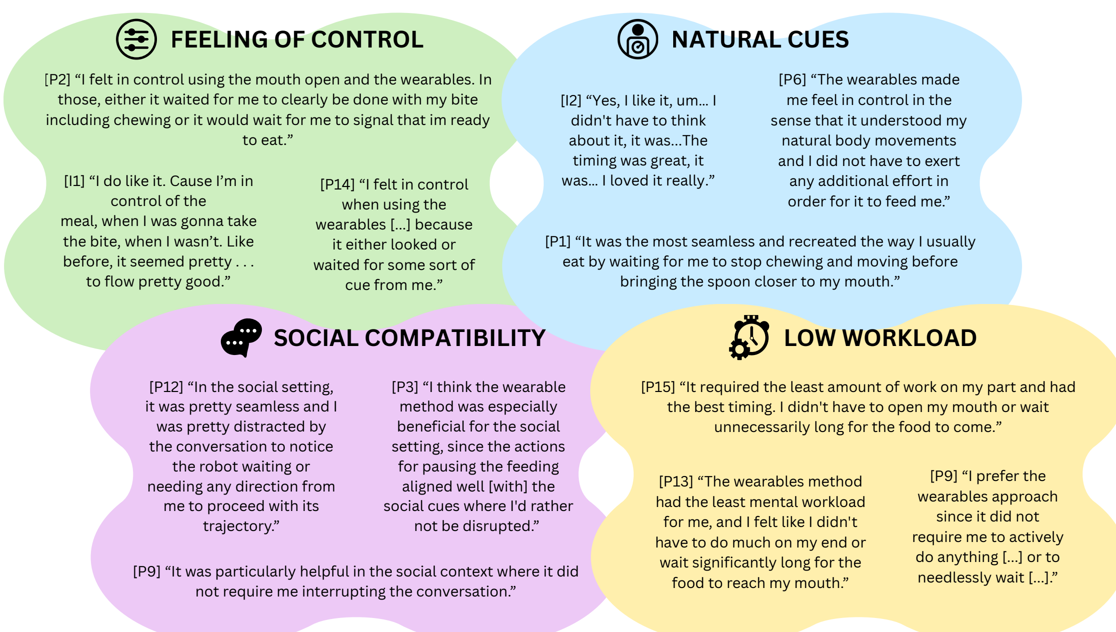


**Figure 3: A subset of quotes from our study involving 15 participants without motor impairments and 2 participants with motor impairments is presented and organized according to the categories outlined in our thematic analysis.**

### 3.3.2 Thematic Analysis

In addition to Likert items, we asked participants some open-ended questions during our study. Consequently, we conducted a thematic analysis of these participant responses, focusing on the wearable sensing method for assistive feeding. The analysis identified four core themes: namely (1) feeling of control, (2) natural cues, (3) social compatibility, and (4) low workload that capture how users perceived the experience of being fed through wearable-based passive sensing methods.

#### 3.3.2.1 Feeling of Control

Across the study, 9 of 15 participants without impairments and both participants with motor impairments described the wearable method as giving them a strong sense of control over the feeding process. Rather than issuing explicit commands or relying on a fixed timing cycle, they felt that the robot advanced when they were ready, framing control not as performing a deliberate gesture, but as the robot understanding their intentions. As I1 explained, “I do like it. Cause I’m in control of the meal, when I was gonna take the bite, when I wasn’t. Like before, it seemed pretty · · ·it seemed to flow pretty good.” The ability to pause simply by continuing to chew or by stopping briefly made the interaction feel natural and unforced. I1 also noted that the robot stopped reliably: “Yes. It stopped when I wanted to.” Participants without impairments expressed similar sentiments. P2 said the wearables matched their own timing: “it waited for me to clearly be done… so I didn’t feel rushed or frustrated with slowness”, and P14 appreciated that the robot “waited for some sort of cue from me.” For many, the fact that the system responded to ongoing behavior allowed them to engage in conversation or look around the room while still feeling in control.

However, 5 participants felt more in control with the mouth-open (baseline) method because its explicit cue provided a clear, intentional signal. As P3 described, “it relied on an explicit cue [· · ·] the wearables came second in this regard.” P5 expressed a similar concern, noting that if they wanted to delay a bite using the wearable method, they had to improvise, saying, “I needed to come up with something that will pause the arm from coming in like talking or chewing.” Others mentioned technical or behavioral mismatches. P12 noted that the wearable devices did not always detect ongoing chewing, and P11 felt constrained by needing to remain “unnaturally still.”

Overall, these responses show that wearable-based passive control can support a strong sense of agency for many users, particularly those who value timing that adapts to their natural eating pace. But they also highlight that some users prefer explicit, intentional cues to guarantee control. The diversity of reactions underscores that the concept of feeling of control is shaped not just by whether users can stop or start the robot, but by whether the signaling mechanism aligns with their preferred way of communicating readiness.

#### 3.3.2.2 Natural Cues

9 of the 15 participants without impairments and 1 of 2 participants with impairments described the wearable method as the most natural way for the robot to determine bite timing. Participants noted that the system responded to signals they were already producing, such as chewing, pausing, or briefly stopping conversation, rather than requiring them to perform an explicit gesture. For the participant with impairments who strongly preferred the wearable devices, the appeal lay in not needing to interrupt their flow of activity: “I didn’t have to think

about it · · · I didn't have to stop what I was doing and do a specific action." They later added that the timing felt effortless: "It was almost seamless · · · I loved it really."

Several participants without impairments echoed this sentiment, highlighting that the wearable devices aligned with how they would naturally pace their own eating. P1 described the method as "the most seamless" because it simply waited for chewing or talking to stop before bringing in the next bite. Others emphasized how the system adjusted: P3 noted that its awareness of chewing created "natural brakes," and P2 appreciated that the timing adapted when they wanted to take longer between signals. Participants also said that the wearable devices made the robot feel more responsive to their body rather than forcing them into a fixed pattern. P6 summarized this as the robot understanding "my natural body movements," and P5 remarked that the system "adjust[ed] to the environment · · · like a person would."

Not every participant experienced the interaction this way. Three participants preferred the predictability or explicitness of the other methods. P8 valued the fixed schedule for planning conversation, and P11 found the wearable devices "annoying" because staying still felt unnatural. A few participants expressed concerns about occasional misdetections. P12 pointed out that the system "sometimes didn't pick up on the fact that I was still chewing." These reactions show that while the wearables generally supported a natural-feeling interaction, the experience depended on how well the sensing aligned with each person's eating style and comfort.

Overall, participants who favored the wearable approach described it not as performing a special signal but as the robot picking up on cues they were already giving. This sense of the robot adapting to their ordinary behavior, without demanding a separate action, was central to why many found the method intuitive and unobtrusive.

#### 3.3.2.3 Social Compatibility

In the social dining setting, 4 of 15 participants without impairments and 1 of 2 participants with impairments described the wearable method as the least disruptive to conversation. Many appreciated that the robot paused naturally when they were speaking and resumed only when their behavior indicated readiness. The participant with impairments emphasized this directly, noting that the wearable devices let them "have a conversation and eat at the same time." For several others, the appeal came from not needing to stop mid-sentence or perform a visible cue. P9 explained that the method "did not require me interrupting the conversation," and P3 felt it aligned with social norms, saying the wearable cues matched the moments when they "would rather not be disrupted."

Participants also highlighted that the system's responses blended into the flow of interactions. One participant noted that during social dining, the method was "pretty seamless," adding that they were often so absorbed in conversation they barely noticed the robot waiting in the background. P15 described a similar experience, appreciating that the robot stayed still during conversation and only moved forward once they stopped talking: "I could continue having a conversation… it wouldn't make the conversation awkward." They contrasted this with mouth-open and fixed-interval timing, both of which forced them to break conversational rhythm. Only one participant (P7) found it "slightly distracting" during conversation, though still preferable to the other methods.

Overall, we see that participants favored the wearable method because it respected conversational timing rather than interrupting it, allowing users to engage socially without having to manage the robot's behavior moment-to-moment.

#### 3.3.2.4 Low Workload

6 of the 15 participants without impairments emphasized that they did not need to think about signaling for the next bite or interrupt their eating to perform an explicit cue. As P2 explained, the wearable devices demanded "the least amount of thinking," both because it waited for them to finish chewing and because they no longer had to decide when to signal. Several participants echoed that the method reduced the small decisions present in the other interfaces. Participants also noted that the wearable system did not introduce additional actions into the eating process. Instead, it responded to behaviors they were already producing. P9 preferred the wearable devices because it "did not require me to actively do anything," distinguishing it from mouth-open cues that required repeated, deliberate gestures. Similarly, P13 emphasized that they "didn't have to perform the action of opening my mouth for every bite" and described the method as having the "least mental workload."

Overall, participants who favored the wearable method described it as needing low workload because it eliminated having to provide explicit actions, allowing them to focus on eating or conversation without managing the robot's timing.

### 3.3.3 Reflection

Overall, these themes offer insight into what passive control with wearable devices could potentially afford users which that are not captured by timing metrics or Likert scores alone. The qualitative responses show that participants valued the system not simply because it succeeded at predicting bite timing, but because it did so in a way that aligned with how they naturally behaved. Themes of feeling of control, natural cues, low workload, and social compatibility emerged repeatedly, suggesting that passive sensing is most successful when it fades into the background and responds to ongoing behavior rather than demanding additional effort or attention. These findings help articulate why wearable devices are a promising platform for passive control: their ability to capture subtle, continuous signals off a human body allows assistive robots to adapt to users without requiring explicit commands or constraining where they sit, look, or move. The thematic analysis therefore broadens our understanding of passive control. This user-centered perspective helps clarify where passive wearable sensing is most likely to succeed, where it may fall short, and why it offers a distinct design space from both explicit teleoperation and fully autonomous decision-making.

# 4 Future Work and Opportunities

While this thesis examined one system using wearable-based passive control in robot-assisted feeding, the broader intersection of wearable sensing and passive control presents several compelling avenues for future exploration. Passive control remains an emerging mode of interaction, and many of its strengths such as low workload, natural timing, and user-driven responsiveness have yet to be fully leveraged across the wide landscape of assistive tasks.

A natural next step is to extend passive wearable sensing beyond feeding to additional Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (iADLs). Many everyday tasks contain subtle behavioral cues: pauses, shifts in posture, changes in muscle activity that could similarly serve as implicit signals of readiness or intent. Promising applications include:

- Dressing assistance, where micro-movements of the arms, shoulders, or torso could indicate readiness for garment transitions or the next step in the dressing sequence.
- Functional tasks around the home, where posture adjustments might indicate when users are ready for objects to be brought closer, or repositioned.
- Grooming and hygiene, where stillness, brief pauses, or subtle head orientation changes could signal readiness for brushing, shaving, or facial care.

Longitudinal adaptation represents another key opportunity. Wearable-based passive control may be particularly effective when systems learn from continued daily use: adapting to changes in motor ability, personalizing inference thresholds, or refining models of movement patterns unique to each user. Developing passive-control systems that evolve with the user over weeks or months could dramatically increase reliability and comfort while reducing the need for recalibration. Additionally, real-world deployment remains a crucial challenge. Future work should explore how passive wearable control performs in diverse home environments, social dining settings, or public spaces where lighting, clutter, and movement vary unpredictably. Testing systems over extended durations will also help uncover practical considerations such as sensor drift, comfort, durability, etc. that are essential for adoption.

Future work may also explore additional wearable modalities that extend beyond IMUs and EMG. Physiological sensors such as PPG or skin conductance may reveal stress and discomfort bone and emerging smart textiles could capture distributed body movements that traditional sensors miss. Combining these signals through multimodal sensor fusion could increase robustness, especially in unpredictable home environments.

Another promising direction involves expanding the proposed framework itself. Although this thesis characterizes control along three levels from the perspective of the user, future research could position these levels within a richer multidimensional design space. Axes such as robot autonomy versus user actuation may allow researchers to reason more precisely about when certain wearable modalities are appropriate or how systems should adjust autonomy over time. Extending the framework in this manner could help researchers tailor interactions to individual users, specific tasks, or different abilities.

# 5 Conclusion

This thesis presents a user-centric framework for understanding control in assistive robotics from the user's perspective and examines how wearable sensing can support three distinct levels of control: active, shared, and passive. Through a review of prior work, we show that wearable devices, particularly EMG and IMU sensors, are uniquely positioned to provide reliable, personalized input in contexts where traditional interfaces may fall short. While active and shared wearable-based control have been explored extensively, passive control remains comparatively underutilized.

Our thematic analysis of a wearable-based bite-timing system illustrates that passive control using wearable sensing can provide meaningful benefits, including strong feelings of control, natural pacing, reduced cognitive effort, and improved social interaction. These findings highlight passive wearable sensing as a promising direction for enabling assistive robots to behave in ways that feel intuitive, non-disruptive, and aligned with users' everyday behavior.

Ultimately, this work suggests that wearable devices will likely play an important role in the future of user-centered assistive robotics. By coupling on-body sensing with models of human behavior, assistive robots can become more adaptive, responsive, and more seamlessly integrated into the daily lives of people with motor impairments. Continued exploration of passive sensing modalities, richer autonomy frameworks, and long-term personalization will help unlock the full potential of wearables as interfaces for supporting independence and quality of life.

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