nature portfolio

Peer Review File

Shared Human-Machine Control of an Intelligent Bionic Hand Improves Grasping and Decreases Cognitive Burden for Transradial Amputees

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Parts of this Peer Review File have been redacted as indicated to remove third-party material.

This file contains all reviewer reports in order by version, followed by all author rebuttals in order by version.

Version 0:

Reviewer comments:

Reviewer #1

(Remarks to the Author)
This paper presents a novel bio-inspired control framework for bionic hands that enhances grasping precision and stability while reducing cognitive burden. The authors integrate multimodal sensors (proximity and pressure) with a commercial prosthetic hand to improve functionality for both healthy and amputee participants. The paper introduces an autonomous grasping controller that dynamically adjusts each finger's movement and pressure based on sensor feedback. This control significantly reduces excessive force while improving the success rate of fragile object tasks.
The most impressive contribution is the dynamically weighted shared control approach that blends human intent with machine control. This ensures that users maintain intuitive control while benefiting from enhanced precision and stability. Through multiple experiments involving both intact and transradial amputee participants, the authors demonstrate improved performance across various tasks including fragile object transfer, object holding, and real-world activities of daily living (ADLs).

While the study demonstrates significant performance improvements, a long-term analysis of user adaptation and skill acquisition with the new control framework would provide additional insights. Moreover, the shared-control seems to provide limited help wrt to cognitive burden.
This could be due to the authors' choice of control algorithm. While I do understand the overall idea, I am not sure this is really the way to implement it. The authors present this idea with a very limited comparison with previous works. I think this is the only/main limitation of this study. The authors should explain better the reason behind their choice and, if possible, add some comparative experiments with other solutions.
Moreover, it would be nice to split the results in the two categories of subjects to see whether there is any difference.

Reviewer #2

(Remarks to the Author)
Summary of this work:
The manuscript presents a shared control framework for a bionic hand designed to improve grasping performance and reduce the cognitive burden on transradial amputees. The approach integrates two off-the-shelf sensors—a proximity sensor (VCNL4010) and a pressure sensor (MS5637)—into a commercial prosthetic hand, enabling the system to autonomously adjust its control based on environmental feedback. Experiments involving both able-bodied subjects and amputees demonstrate improvements in grasping safety, precision, and cognitive load compared to conventional EMG-based control. However, the manuscript lacks critical technical details, raising concerns about the method's credibility, generalizability, and practical application. Additionally, while the work combines bionic and engineering concepts, its novelty and scientific contributions require clearer articulation. Therefore, I would give a decline decision.
1. Sensor system information and workflow: The paper lacks detailed information on the sensor system and workflow. The measurement range of the pressure sensor is not provided, yet available data suggest it is designed for atmospheric

pressure with a low upper force limit. This may work for lightweight, fragile objects but raises concerns when higher forces are needed, such as with spherical objects, where the sensor may saturate. Similarly, once the prosthetic fingers contact an object, the infrared proximity sensor likely reaches saturation and returns a constant value. The manuscript does not explain how effective grasping is maintained when both sensors fail to provide meaningful input. Does the prosthetic hand rely on built-in joint angle sensors to generate additional force, and is this process autonomously controlled? Additionally, how is it ensured that the applied force does not damage the object, especially since external force sensors used in experiments would not be available in everyday use?
2. Proximity Threshold for Grasping Fragile Objects: Experimental evaluations of the shared control strategy demonstrated enhanced stability, reduced cognitive load, and improved grasping accuracy. A key feature is that the prosthetic hand autonomously approaches fragile objects, allowing the user to focus solely on grasping once contact is made. However, the effectiveness of this strategy depends critically on the predefined proximity threshold at which autonomous movement is initiated. If the threshold is set too high, the hand may begin moving autonomously even without the user's intent, leading to potential inconvenience. Conversely, if set too low, rapid user movement might drive the fingers directly onto the object, negating the benefits of autonomous control. This raises the question of whether the same threshold was used for all experiments involving different fragile objects, such as paper and paper cups, or if it was adjusted based on object characteristics. Clarifying this is essential to further validate the system's applicability in real-world scenarios.
3. Grasping Force for Spherical Objects: When grasping spherical objects, the machine control adds a fixed offset to ensure stable, prolonged grasping, even when the user is fatigued. However, the manuscript does not clarify how this offset and the output force are calculated, nor whether they are predefined. With fingertip sensors saturated during grasping, it is unclear how the system regulates force to avoid damaging objects and adjusts the offset for spheres of different diameters and weights. Additionally, evidence for reduced cognitive load appears weak, as Figure 5F shows only a 0.06-second improvement in DRT response time. More substantial data is needed to support these claims.
4. Validation: The core principle is that the prosthetic hand autonomously approaches and applies grasping force, while the user adjusts the force, with the machine compensating for fatigue. However, the manuscript lacks clarity on how control strategies vary across different tasks. The paper does not provide specific numerical values for the two forces. The question is whether the control strategies differ between different task objectives, such as fragile and spherical objects. If they do, how does the system automatically switch between them? Alternatively, can a single control framework accommodate different task requirements?
5. Writing: The manuscript suffers from insufficient detail on its control strategy, making it read more like an experimental report than a cohesive study. Excessive citations in the Results and Discussion sections disrupt the flow and should be relocated to the Introduction. Key numerical values could be better presented in tabular form. Moreover, the Introduction is overly brief, preventing readers from quickly understanding the research background and existing challenges. This lack of context and clarity hampers comprehension. Improved organization and clearer explanation of methods are essential to enhance the paper's readability and better convey its contributions. Overall, the writing needs substantial improvement.
6 Figures and movie: Figure 1 is overly simplistic and should be expanded to provide an overall study overview with more relevant details. Additionally, a supplementary video demonstrating grasping tasks with various objects—different shapes and weights in daily-life scenarios—would greatly enhance the work's clarity and impact. It is also recommended to compress Supplementary Video 3, which is currently too large at 1.3 GB, to ensure better accessibility and usability.And there is little information from the supplementary materials.

Reviewer #3

(Remarks to the Author)
The paper is an interesting example of human-machine cooperative control for closing a prosthetic gripper and generating grasp force. Sensors in the fingertips support certain aspects of the task while the human retains agency over other aspects. Overall, the technical achievement is significant. However the paper is weak in several places, including poor justification of the bio-inspired claim, not enough detail in the main part of the paper to interpret data figures, and overstating generalizability of results based on very little data from persons with amputation.

1) In several places, the paper claims results can generalize to a broad range of devices, patients and tasks. However, only 4 persons with amputation were tested, and data is reported from a single task (holding a ball), with few trials. ADL testing was only described qualitatively. Additionally, only 2 of the 4 were myoelectric users, with the other 2 body-powered users who would not benefit from the new approach. 32-channel EMG was used in all subjects. It's unclear if these results can be generalized to current prosthetic arms which have far fewer EMG channels. The algorithms described in methods required calibration procedures. It is unclear how often these need to be performed, which would reduce the practical implementation of the method.

2) The claim the method is bio-inspired requires more justification. It is true normal grasping uses fingertip tactile sensors, but they are not used as described here. Normal grasping is predominantly a feedforward task based on an internal model of the object's characteristics (weight, texture, stiffness, etc.), learned from experience. Sensors are used to detect events (ie: object slip, object lift-off, contact). Unexpected events (slip) trigger reprogramming of the motor plan as needed. If the task is performed as expected, the sensors are only used to confirm everything is going as planned, and confirm task transitions (ie: object lift-off). In this application, the sensors play a much more active role in moving the fingers and reinforcing grip force. This may be the correct use in this application, but it's a stretch to claim it is bio-inspired.

3) In normal performance, information from sensors are used to modify the internal model for the next time the task is performed. It is unclear if the shared control supports this learning, or impedes it by added an additional "hidden" variable (machine contribution) during performance that the human must account for.

4) Authors show their sensors can detect no-force contact. What ADL or task requires detecting no-force contact with an object? The role of this capability only becomes more clear when reading the methods section at the end. Some hint here is needed for what this capability will be used for.

5) Fig. 2: Do you really need 2 sensors? Seems similar performance could have been achieved with just the pressure sensor and the value of the proximity sensor is not clear. The proximity sensor can be removed from the logic diagram and it seems that the algorithm would operate similarly. The importance of knowing proximity to the object should be reinforced here, versus just moving until contact is made, which can be detected with a pressure sensor.

6) Fig. 3E: It appears that the human is mostly in control during pre-grasp and grip force generation, but what is happening during the zero-force contact phase which lasts 1 sec? Unclear what triggers the transition from the zero force contact phase to the human flexion phase. Does the human have to stop EMG activation during pre-grasp and then start again to initiate the human flexion phase? This seems very unnatural. If the zero force contact phase is when all of the fingers are moving to contact the object under machine control, please make this clear. Some of this becomes more clear after reading the methods, but more information is needed here so that the reader does not have to flip back and forth between methods and the data figures.

7) The dynamically adjusted weights between human and machine control could be explained more. It's not clear how this is implemented in the control algorithm. In Fig. 3E, I can see that the machine is mostly in control during the zero force contact phase. Is this explicitly coded?

8) It is unclear what the graphic at bottom Fig. 3B represents. Does um and uh refer to the position of the digits? How can EMG be used to command position of the digit, when EMG is related directly to muscle force or grip force? Again, some of these questions are answered in methods, but more explanations are needed here to interpret the figure.

9) Page 8: The test on improving grasp security uses individual control of all 5 digits. It is unclear if and how the machine control coordinates control between different digits for a stable grasp. Also achieving individual control of digits in a person with amputation is highly unlikely.

10) Fig. 6: The caption says that the machine prevented grasp force from dropping too low and dropping the object. How did the algorithm know that this minimum force level was? Shared control results in a very erratic and variable grip force up to 5 seconds. Although the summary metrics support the advantages over human control only, it would be helpful to see a typical trial from this same patient using just human control. Also, was any training time provided for the subject? The human control might improve significantly with more exposure to the apparatus. Furthermore, responding to audio input when squeezing too hard is not a task that is useful in ADL. The methods describe an object that actually "breaks" when the force is too high. Why not use this object?

11) For the healthy control testing, were subjects naïve to the apparatus or were they well practiced with EMG control of bypass devices.

12) Fig. 7: It is disappointing that there is only a qualitative description of the results with real ADL. Is it not possible to report the number of eggs broken for each subject under machine vs. shared control?

Version 1:

Reviewer comments:

Reviewer #1

(Remarks to the Author)
Thanks for addressing my comments.

Reviewer #2

(Remarks to the Author)
After the previous revision, the logical structure and technical details of the manuscript have become clearer. However, there are still several issues that need to be addressed.

1) The core method proposed in this study involves installing pressure and proximity sensors at the fingertips of a prosthetic hand, allowing the hand to automatically approach and gently touch the object being grasped through machine control. The user then applies further control via EMG to improve the prosthetic hand's control performance. Although this method yielded good results in the experiments designed by the authors, it relies on a machine control loop based on fingertip sensors. As a result, this method cannot be applied to most prosthetic hands that do not have such hardware, limiting its scalability and universality. The authors mention in the discussion that shared control can be integrated into commercial prosthetic hands. However, this integration involves modifications to the manufacturer's processes, as well as adaptations to the structure and circuitry, which is far from straightforward. Furthermore, whether this technology can replace traditional myoelectric control still requires further validation. The authors should avoid using such exaggerated descriptions.

2) The discussion on the mismatch between the machine's intent and the user's intent is overly simplistic. Fine motor tasks and dexterous manipulation are important application scenarios for prosthetic hands, such as using the prosthetic hand to screw on a bottle cap. This task requires the user to continuously adjust the contact force and position between the prosthetic hand and the object. Under such conditions, the proposed machine control, which automatically brings the prosthetic hand closer to the object during proximity, may interfere with the user's fine motor control intentions. The authors need to clarify this point further. Additionally, some classic prosthetic hand assessment tasks, such as the Box and Block Test (BBT) and Southampton Hand Assessment Procedure (SHAP), could be considered to further demonstrate the applicability of this method to different tasks, rather than just its effectiveness for simple static grasping.

3) The authors have enhanced the introduction and discussion sections, providing the reader with a clearer understanding of the background and relevant details of the proposed method. However, these sections are overly lengthy and should be condensed while retaining the key information. Moreover, the overall system framework is presented in Figure 3, but the figure remains relatively simple. It could benefit from additional information, such as a comparison of key parameters between the proposed method and other methods, as well as a schematic diagram of the DRT experiment, to help readers quickly grasp the core content of the manuscript.

Reviewer #3

(Remarks to the Author)
The authors have done a thorough job responding to my prior concerns. The unique potential advantages of new sensor data from fingertips combined with algorithms to share control between the machine and user is much more clearly stated now. This work is a significant contribution to the field. I have no further concerns.

October 15, 2025.

Response to Reviewers

We would like to thank the reviewers for their thoughtful and insightful comments. In response, we have made substantial revisions to the manuscript. A brief summary of the changes is provided below:

- We greatly revised the methods and results to clarify the methodology and approach.
- We rewrote the introduction and discussion to provide more background knowledge on the current state of the art and to make more in-depth comparisons between our work and the state of the art.
- We added several new analyses with associated figures, including:
  - Verification of the sensor accuracy and range
  - Demonstration of the machine control conforming the digits to various objects
  - Comparison of 4-degree-of-freedom control with and without shared control
  - Normative data on the detection-response task to contextualize improvements in cognitive load
  - Comparisons of cognitive load between healthy and amputee participants
  - A preliminary analysis of the learning effects observed with the participants
  - Preliminary quantification of success rate and completion speed in an activity of daily living

We believe that the manuscript is greatly improved by these changes and hope you will too.

Thank you for your time and consideration,

Point-by-Point Responses

Reviewer #1: While the study demonstrates significant performance improvements, a long-term analysis of user adaptation and skill acquisition with the new control framework would provide additional insights.

We agree with the reviewer that a long-term study of user adaptation and skill acquisition is a critical next step in translating this work into clinical practice. Although we are unable to address this point in full in the present manuscript, we have revised the manuscript in a few ways to address this concern.

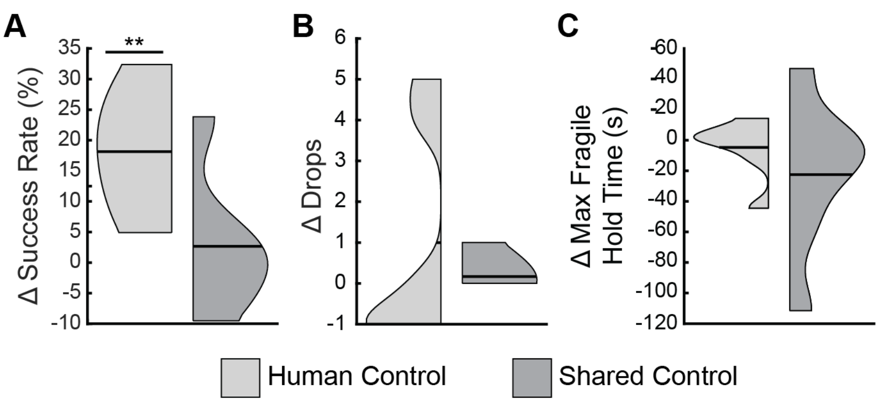
1. First, we added additional text to the manuscript introduction and abstract, clarifying the scope of the present work as a short-term, in-lab study demonstrating proof of concept.
2. Second, in line with requests from other reviewers, we have softened claims regarding generalizability to ensure the manuscript is presented as faithfully as possible.
3. Third, we added a paragraph to the discussion outlining the limitations of the current study and describing future steps towards a longer-term study.
4. Finally, and most importantly, we added a new supplemental analysis exploring the learning effects within the duration of the data we did collect. This supplemental analysis shows negligible learning taking place throughout the relatively short duration of the experiments in this study. In the discussion, we note the limitations of this short-term analysis of adaptation and skill acquisition and use this data as primary motivation for future studies exploring learning effects on a longer time horizon.

Relevant changes to the manuscript are copied below for reference.

> Abstract (Lines 25-28)
> "Here, we describe the development and integration of proximity and pressure sensors into a commercial bionic arm to enable autonomous grasping of objects and show that continuously sharing control between the autonomous bionic hand and the user provides more dexterous and intuitive control with minimal training."
>
> Abstract (Lines 34-36)
> "Importantly, demonstrations include both intact and amputee participants using a modified commercial bionic arm to perform numerous tasks and activities of daily living with different grip patterns without extensive training or practice."

Introduction (Lines 114-118)
“These results serve as proof-of-concept that sharing control between the user and an autonomous bionic hand can provide immediate functional benefits while decreasing the cognitive cost of using a prosthetic hand. As such, this work constitutes an important step towards more intuitive and dexterous control of multiarticulate bionic arms and has broad implications for prosthetic and robotic arms.”

Discussion (Lines 640 – 655)
“Shared control resulted in immediate improvements in functional and cognitive performance in naïve users. An important question remains as to whether shared control can provide similar, or even greater, benefits to experienced users. As simple first-order assessment of learning, we explored the change in performance for human control and shared control between the first and last experimental blocks of the fragile-object transfer task, holding task, and fragile-holding task (Supplementary Fig. 9). No learning took place under shared control; there were no significant differences for any of the tasks. Under human control, no learning took place for the holding task or fragile-holding task, but there was a significant improvement in success rate on the fragile object transfer task. Given the timeframe of the tasks performed herein, we suspect that the limited learning that did take place would mostly be attributed to task familiarization. Future work should explore long-term motor learning associated with shared control. Shared control could potentially improve motor learning, as decreased cognitive burden is associated with an increase in motor skill acquisition[72,73]. In contrast, the machine contribution could also act as an additional hidden variable within the user’s internal model that impedes learning[74]. Regardless of long-term outcomes, the short-term benefit of enhanced dexterity and reduced cognitive load could potentially improve prosthesis adoption during the critical golden window after amputation.”



“Supplementary Fig. 9: Learning effects across the experiments for both controllers. The main experimental outcomes from the first experimental block were compared to the second experimental block. The resulting distribution was then compared to a zero-mean normal distribution to assess if any potential learning occurred between trials. A) A significant increase in performance between the first and second experimental blocks of the fragile-object transfer task was detected for the human controller ($p < 0.01$, paired t-test), indicating that participants improved their performance with the human controller across the course of the experiment. No significant difference was detected between trials for the shared controller. B) No significant learning effects were detected for the human or shared controller within the holding experiment. C) No significant learning effects were detected for the human or shared controller within the fragile-holding experiment.”

Reviewer #1: Moreover, the shared-control seems to provide limited help wrt to cognitive burden.

To better convey the improvements in the detection response task (DRT), we revised the manuscript text and added a new supplementary figure.

1. First, we note that the relative change in response time is quite large (30%) even if the absolute change is only a matter of milliseconds.
2. Second, referencing a recent manuscript validating the DRT for use in prosthetics, we now state that our observed improvement in the DRT response time correlates with a ~7% improvement in NASA TLX score.

3. Third, to provide some real-world context for what a ~120 ms improvement in DRT response time means, we now provide an example from literature showing that a 120 ms change in response time is similar to trying to operate a car radio while driving as opposed to at a standstill.
4. Fourth, we also provide real-world context for what a 30% relative improvement in DRT response time means. We cite a paper showing that a similar 30% improvement in DRT response time was observed when switching from a bionic hand to a healthy intact hand.

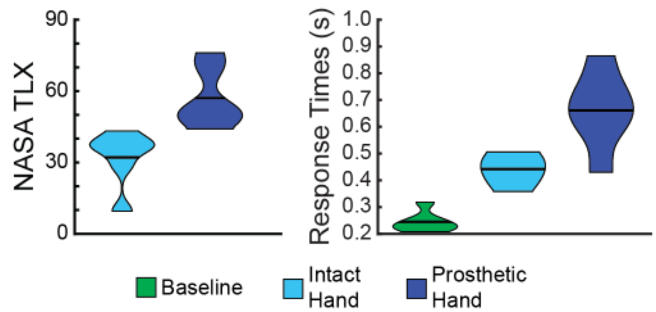
We believe these additional clarifications emphasize that, despite a small numerical change in DRT response time, there is actually a considerable relative decrease in cognitive burden taking place.

Relevant changes to the manuscript are copied below for reference.

<u>Main text (Lines 417 – 426)</u>
"While there are limited research studies using the DRT to quantify the cognitive burden of using a myoelectric hand[53], research into the effects of cognitive load on driving indicates that a change of 50 ms in the response times corresponds to a noticeably more difficult task, as human response times to the tactile DRT generally range from approximately 300 ms to 1 s[54–56]. Without an additional task, the response time to the DRT was measured to be 250 ms (Supplementary Fig. 7). Given this, the measured decrease of 60 ms corresponds to a 29% decrease in cognitive burden with respect to the range of response times when using shared control, which is similar to the 30% decrease in cognitive load observed when switching from completing a task with a 1-DOF bionic hand to an intact hand (Supplementary Fig. 7)."

<u>Main text (Lines 432 - 438)</u>
"This 120-ms change in their response times corresponds to a 24% decrease in cognitive burden by using shared control. To frame this change with respect to other real world scenarios, a 120-ms improvement was also observed when drivers operated their car radio at a standstill versus operating their radio while driving[63]. A comparison between the intact-limb and amputee participant's response times indicates that the amputee participants were slower to respond than the intact-limb participants (Supplementary Fig. 8), which could be attributed to the different task, or to their amputation or age."

<u>Methods (Lines 893 - 897)</u>
"The response rate to the DRT has been correlated with increased cognitive load and task difficulty[59–61]. In a separate experiment, the baseline response times to the tactile DRT without an additional task were measured to be approximately 250 ms (Supplementary Fig. 3). In driving tasks, average response times vary with task difficulty, ranging from baseline to approximately 800 ms, where a ceiling effect is observed[59]."



"Supplementary Fig. 7: Baseline cognitive load data for six intact-limb participants. Participants completed a baseline detection response task (DRT) alone and then again with a fragile object transfer as a secondary task. The fragile object transfer task was completed using their intact hand or a pinch grasp with a prosthetic hand using human control. The object was considered very difficult to transfer as it broke with a force of 0.7 N. A) From the NASA TLX results, a score of 32.14 ± 11.98 is considered easy as participants successfully transferred the fragile object 100% of trials using their intact hand, and 57.07 ± 12.63 corresponds to a more difficult task as the success rate was 20% when using a prosthetic hand. The prosthetic hand was controlled via a 1-DOF modified Kalman filter decoding 32 sEMG channels. B) The participants' baseline response times to the DRT without an additional task were 0.25 ± 0.04 s. Increasing the cognitive burden by introducing the secondary task increased the response time by 0.44 ± 0.06 s, and making the task more difficult by using a prosthetic hand rather than a healthy hand further increased the response time to 0.66 ± 0.15 s."

Reviewer #1: This could be due to the authors' choice of control algorithm. While I do understand the overall idea, I am not sure this is really the way to implement it. The authors present this idea with a very limited comparison with previous works. I think this is the only/main limitation of this study. The authors should explain better the reason behind their choice and, if possible, add some comparative experiments with other solutions.

To better frame this work with respect to other research into shared control, we have added additional background knowledge of two related fields: 1) shared control, and 2) semi-autonomous prostheses.

1. We now reference many prior works that used a fixed coefficient, β, to share control between the human and the machine using a simple weighted average. For example, if β was set to 0.5 (i.e., 50%), then control would be shared equally among the human (β = 50%) and machine (1 - β = 50%) and the position of the prosthesis would simply be the average of the human control and machine control. We also reference prior work which showed that even noisy machine estimates can significantly improve control under this framework when the machine has a good understanding of the human's goal. However, in our preliminary work leading up to this manuscript, we tried this approach and found it could not generalize well. The fundamental limitation we ran into is that, in the real world, machine control never really has a complete understanding of the human's goal since embedded sensors cannot readily determine the force a user intends to exert. Instead, the goal from our machine algorithm is the position at which the user would first contact the object. Providing a fixed sharing between a machine that wants to stay at the initial point of contact with near-zero force and a human who wants to exert more force to firmly grasp the object, leads to frustration and worse performance for any object that is not intended to be grasped with minimal force. Additionally, because the user's intent is shared, their dynamic range is effectively limited. In other words, if the machine is estimating a position of 0.5, and the user wants to be at a position of 0.6, but they only control half of the prosthesis, then they now have to produce an output of 0.7 to achieve that. In other words, the machine does not help the user; it simply hurts their dynamic range and requires them to produce more effort. As a more extreme example, if the machine produces an output of 0.8, it becomes theoretically impossible for the user to achieve an output of 1.0, as an equal sharing of control will only allow them to, at best, achieve 0.9 since the user cannot have an effort greater than 1.0. We have greatly expanded the results and discussion section to emphasize this point.
2. We also reference several prior works that utilized light-based or pressure-based sensors to automate the prosthetic hand to some degree. Both of these works developed and validated shared control schemes that switch between the user and the machine, so there were states when the user was not in control of the hand. Additionally, neither of these works tested their designs with amputee participants in real-world experiments.
3. Third, we now rationalize our approach in the context of the two approaches from the literature described above. Our approach combines two previous approaches that relied on embedded pressure sensors or light-based sensors and develops a shared control framework that, rather than switching between human and machine control, continuously blends the methods such that the user is always in control of the hand and benefits from the machine controller across a range of tasks.

Relevant changes to the manuscript are copied below for reference.

<u>Introduction (Lines 70 - 73)</u>
"However, among all of these works, there is a distinct lack of testing real-time control with commercially available prosthetic hands and amputee patients, and many previously developed sharing algorithms operate on distinct states that the user or machine switches between. It has been hypothesized that continuously sharing control will improve functionality and make the control algorithm more intuitive for the user [26]."

<u>Introduction (Lines 74 - 85)</u>
"One common approach is to develop a semi-autonomous prosthesis where control switches between the human user and an autonomous machine controller. For example, Zhuang et al. developed an autonomous machine controller that moved the individual fingers of a virtual prosthesis to maximize finger contact with virtual objects[31]. The human user controlled the prosthesis with surface electromyography (EMG) to initiate initial contact with the object, at which point the autonomous controller would take over and move the digits autonomously to create a multidigit grasp with a fixed force output. Although this approach was shown to improve grip stability and functional performance, it results in a single fixed force being applied to all

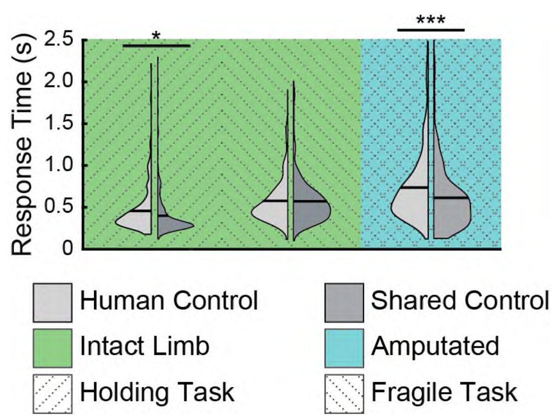
objects, making it unlikely to generalize to broader activities of daily living. Indeed, Zhuang et al. noted this limitation and hypothesized that continuously sharing control between the human and machine, instead of simply toggling between the human and machine, would improve functionality and make the control more intuitive for the user[31]."

Introduction (Lines 86 - 95)
"To this end, the other common approach to share control between a human and machine is to simply blend the human control and machine control using a simple linear coefficient, β. Under this approach, the prosthesis position is determined by human control multiplied by β plus the machine control multiplied by (1 - β). For example, Dantas et al. used this approach with a virtual prosthesis to demonstrate improved control on a virtual target touching task[33]. However, this approach requires the machine to be able to consistently provide a meaningful goal, not just under controlled conditions when triggered by the user. Indeed, Dantas et al. punted this issue by simply setting the machine goal equal to the location of the virtual target. It remains an open question as to how an autonomous machine could use real-world sensors to provide a meaningful control signal to users at all times across a range of tasks."

Discussion (Lines 716 - 719)
"Since then, other research has detected a decrease in cognitive load when using shared control via the NASA TLX survey [24]. The present work also builds on these past works by quantifying a reduction in cognitive load through a nonsubjective metric, the detection-response task."

Reviewer #1: Moreover, it would be nice to split the results in the two categories of subjects to see whether there is any difference.

We added a supplementary figure to demonstrate the differences in performance between the two populations. Because different experiments were performed with different populations, we cannot have a truly fair comparison between the two populations. Nevertheless, we did collect cognitive load data (DRT response times) across all the tasks, and we now show the DRT response times across all tasks by population. While a difference is observed between the two populations, we were unable to perform any valid statistical analysis between the groups as, not only was the population changed, but the task as well, so we could not attribute differences to the population or the task difficulty.



"Supplementary Fig. 8: Detection Response Task (DRT) results from all experiments by participant condition. Differences in the response times to the DRT were observed across the tasks and populations. The intact-limb participants had a slower response time during the fragile-object transfer task than during the holding task. The amputee participants also had slower response times during the fragile-holding task than the intact-limb population had during the non-fragile holding task. However, it is unclear if this is due to the differences in the population or the increased difficulty of the task."

Reviewer #2: The manuscript presents a shared control framework for a bionic hand designed to improve grasping performance and reduce the cognitive burden on transradial amputees. The approach integrates two off-the-shelf sensors—a proximity sensor (VCNL4010) and a pressure sensor (MS5637)—into a commercial prosthetic hand, enabling the system to autonomously adjust its control based on environmental feedback. Experiments involving both able-bodied subjects and amputees demonstrate improvements in grasping safety, precision, and cognitive load compared to conventional EMG-based control. However, the manuscript lacks critical technical details, raising concerns about the method's credibility, generalizability, and practical application. Additionally, while the work combines bionic and engineering concepts, its novelty and scientific contributions require clearer articulation.

We would like to thank the reviewer for their insights and the opportunity to revise the manuscript. We have made the following changes that we hope will provide an adequate amount of detail to demonstrate rigor, innovation, and impact:

1. First, we have restructured the introduction to include a more in-depth literature review of related works to help frame the novelty and scientific contributions.
2. Second, we have added comparisons to these prior works in the discussion section to highlight differences in our design and results.
3. Third, throughout the manuscript we have added extensive details regarding our methodology for each of the experiments to support the credibility, generalizability, and applicability of our approach.
4. Fourth, we have added a multitude of supplementary figures to provide substantially more technical details.

These changes are demonstrated alongside specific changes to the manuscript in our subsequent responses.

Reviewer #2: Sensor system information and workflow: The paper lacks detailed information on the sensor system and workflow. The measurement range of the pressure sensor is not provided, yet available data suggest it is designed for atmospheric pressure with a low upper force limit. This may work for lightweight, fragile objects but raises concerns when higher forces are needed, such as with spherical objects, where the sensor may saturate.

We have modified the manuscript to greatly expand the details regarding the sensors and the machine control. We have addressed this particular comment in the following ways:

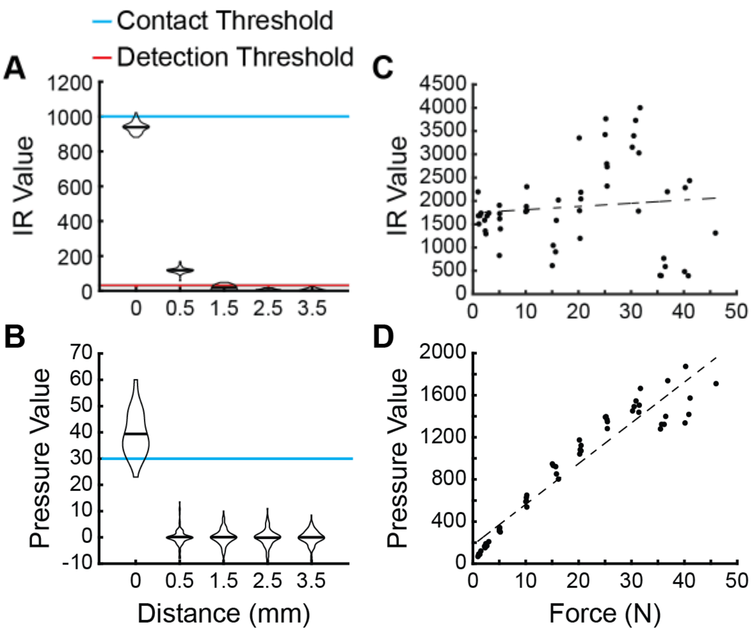
1. First, we added a supplementary figure outlining the specifications for each sensor. Relevant pieces from this supplementary figure are also captured in the manuscript main text.
2. Second, we now provide justification for the use of the particular sensors. We emphasize that use of an atmospheric pressure sensor, as opposed to a torque sensor or force sensitive resistor, allows us to uniquely capture forces from a variety of different angles.
3. Third, we have also expanded the description of the machine control to clarify how the data is used within the system workflow. We now more clearly articulate that the pressure sensors are used only to confirm contact. The absolute value of the pressure data is not important to the system and if any saturation occurred, it would not limit the system performance.
4. Fourth, we have also expanded the discussion surrounding the reliability of the sensors and the overall approach. Supplementary figure 1 shows the sensor validation. Supplementary figure 3 shows how the machine control and work across a range of different objects. Figures 4, 5, and 6 show how the shared control (machine + human together) can also be used across three different grasps to accommodate different objects. Additionally, we now emphasize in the manuscript that a key novelty of our shared control approach is that the human always remains in control. A perfect sensor or perfect machine estimate of intent is not required because the user can always correct errors. This allows the system to generalize across tasks and real-world activities, while still improving task performance and reducing user burden.

Relevant changes to the manuscript are copied below for reference.

<u>Main text (Lines 145 - 149)</u>
"Further testing demonstrated that the proximity had a range of 0 – 1.5 mm, and the pressure sensor embedded in the silicon could measure up to 35 N (Supplementary Fig. 1). Additionally, the use of pressure sensors embedded in silicone enable the sensors to detect forces applied in different directions, as opposed to load cells that only accurately measure force in specific directions [33]"

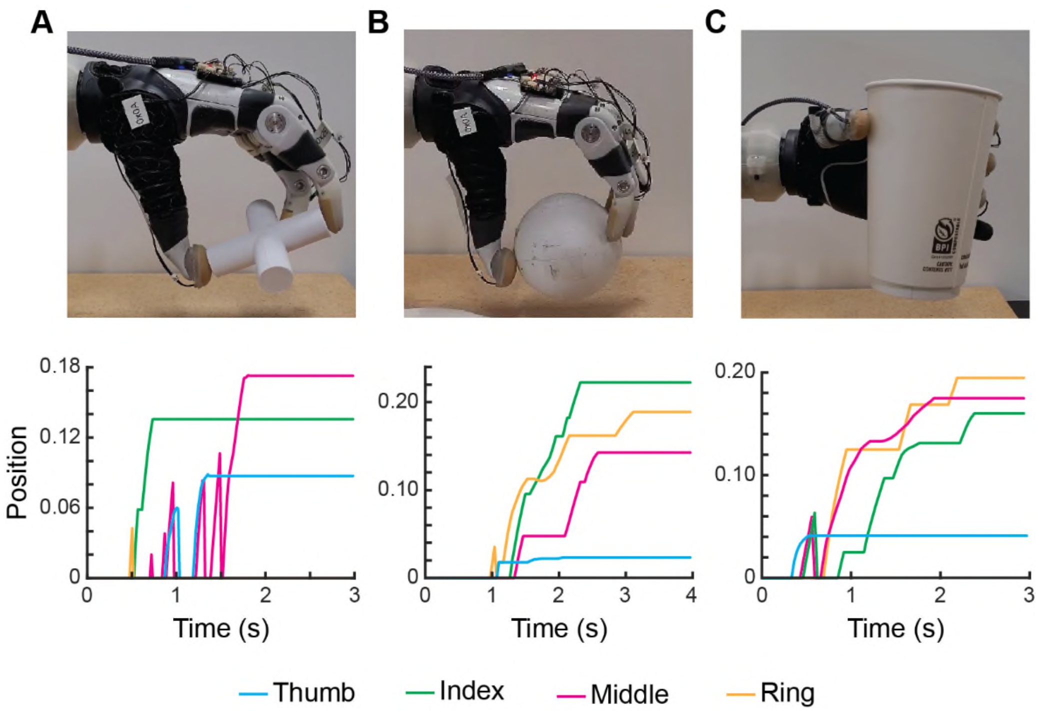
<u>Methods, Sensorized Fingertips (Lines 753 - 761)</u>
"The sensorized fingertips (Point Designs, Broomfield, CO, USA) contained a barometric pressure sensor (MS5637-02BA03, TE Connectivity) and a proximity sensor (VCNL4010, Vishay Semiconductor) [31]. The proximity sensors operate by emitting a specific wavelength of infrared light and measuring the

intensity of any reflections. The sensors are mounted in a plastic housing and embedded in silicone. The proximity sensor is capable of detecting surfaces up to 1.5 mm away. The pressure sensor embedded in the silicone is capable of reliably detecting forces less than 1 N and up to 30 N (Supplementary Fig. 1). Each of the fingertip sensors communicates with a central microcontroller (ESP32, Espressif, Shanghai, China) mounted on the back of the prosthetic hand."



Supplementary Figure 1

"Supplementary Fig. 1: Proximity (IR) and pressure readings under different conditions. A) Proximity sensor readings from a fingertip at different distances from a flat surface. A sheet of plastic was placed in front of a sensorized fingertip at various distances while sensor measurements were recorded for approximately 3 s. The proximity sensor exceeded the noise threshold when the sheet was 1.5 mm or closer. B) Under the same conditions, the pressure sensor readings were zero-mean until the plastic sheet made contact at the fingertip. C) Once the plastic sheet made contact with the fingertip, forces between 0 – 50 N were applied at known levels using a dynamometer while the maximum proximity measurements were recorded. The proximity measurements increased beyond their value at contact, but a linear model fit to the data (red line) had poor accuracy (R2 = 0.01). D) However, the maximum pressure readings recorded during the same experiment exhibit a strong linear trend up to approximately 30 N (R2 = 0.91)."



"Supplementary Fig. 3: Demonstrations of the machine controller controlling the thumb, index, middle, and ring finger with a cross-bar (A), a ball (B), and a cup (c). The kinematic traces for each digit are displayed beneath the corresponding picture. In each case, the machine controller moved each digit to a unique position such that the hand would lightly grasp each object with each DOF that "saw" the object. While the machine controller was capable of grasping each of the objects in this example, all of the objects were unweighted and relatively lightweight compared to the weighted object used in the experiments."

Reviewer 2: Similarly, once the prosthetic fingers contact an object, the infrared proximity sensor likely reaches saturation and returns a constant value.

As noted above, we have made substantial changes to the manuscript to address this point. Of relevance here:

1. We added supplementary figure 1 to validate the sensor readings and provide a detailed description of range of the IR sensor in that figure and in the methods.
2. We expanded Fig 1 to show how the IR data changes when making contact with objects. We note that the IR does not reach saturation; instead, the values continue to increase as the silicone material encasing the sensors deforms. There is also a noticeable deflection point (characterized by a sharp change in the first derivative of the sensors) that can be used to reliably detect contact with near-zero force applied.
3. We also expanded the description of the machine control to clarify how the data is used within the system workflow. Importantly, any saturation that might occur in the IR sensor during contact would have no impact on the algorithm. Supplementary figure 3 has also been added to demonstrate how the machine controller interacts with different shaped objects.
4. Finally, as detailed above, we have also expanded the discussion surrounding the reliability of the sensors and the overall approach. Additionally, we now emphasize in the manuscript that a key novelty of our shared control approach is that the human always remains in control. A perfect sensor or perfect machine estimate of intent is not required because the user can always correct.

   Fig. 1 subtext
   "As additional force is applied to the cotton, both the pressure signal (blue) and the proximity signal increase as the silicone fingertip deforms. Note that the proximity signal increases before the pressure sensors as increasing force is applied, and the pressure signal continues to increase once the proximity signal has saturated."

   Main Text (Lines 144 - 145)

"Finally, increasing proximity and pressure data when applying external force to the cotton ball validated the ability to detect external forces on the hand."

Methods (Lines 827 - 829)
"By developing the machine controller around achieving contact, rather than modulating force, there is no dependence upon the range of the proximity or pressure sensor beyond the detection of contact."

Reviewer 2: The manuscript does not explain how effective grasping is maintained when both sensors fail to provide meaningful input. Does the prosthetic hand rely on built-in joint angle sensors to generate additional force, and is this process autonomously controlled?

As noted above, we have modified the manuscript to explain the details and novelty of the algorithm more clearly.

1. First, we have greatly expanded our description to more clearly describe the prosthesis control framework. We now emphasize that we are controlling the position of each digit of the prosthesis simultaneously. Additional force on an object is simply the result of the prosthesis attempting to move to a position beyond the contact point of the object.
2. Second, we have modified the manuscript to more clearly state that the position of each digit is based on the sum of the human intent and the machine's intent (Fig. 3). The human intent is the kinematic position of each digit decoded by surface EMG using a modified Kalman filter. The machine intent is the kinematic position of each digit that would cause the digit to make initial contact with the object, decoded from infrared sensors via a multilayer perceptron.
3. Third, we highlight that under this shared control framework the user still maintains full control of the hand. The machine intent is added to the human intent to help preposition the hand. The machine intent also modifies the human intent to enhance their dynamic range around the initial contact point of objects.
4. Fourth, we note that because the user is always in control, a perfect sensor or perfect machine estimate of intent is not required. Even if the sensors fail to detect an object, the user can still move the hand and complete the task. One might suspect then that shared control provides no inherent value since the user is still in full control. However, our experimental data suggest otherwise. We repeatedly saw that the shared control improved task performance and reduced cognitive load. Thus, the added machine control does appear to be helping, even though it may not be perfect.
5. Finally, we have also greatly expanded the discussion highlighting the limitations of the overall approach. We recognize that there could theoretically be a specific corner case where the machine intent is so wrong that it leaves the user unable to complete a task. We did not observe any such events during our studies and believe these unique corner cases to be extremely unlikely without physical damage to sensor. Nevertheless, we now emphasize in the manuscript that additional long-term studies are necessary to demonstrate true generalizability and robustness in real-world use.

Abstract (Lines 25 – 31)
"Here, we describe the development and integration of proximity and pressure sensors into a commercial bionic arm to enable autonomous grasping of objects and show that continuously sharing control between the autonomous bionic hand and the user provides more dexterous and intuitive control. An artificial neural network used the embedded fingertip sensors to autonomously move each finger to contact an object while the user proportionally controlled the grasp as determined by surface electromyography. Control of the bionic hand was continuously shared between the autonomous bionic hand and the user in real-time using a bioinspired dynamically weighted sum of the autonomous controller and the user's intent."

Introduction (Lines 99 – 102)
"Importantly, to support generalizability, we then introduce a novel shared control framework that continuously blends human and machine intent, such that the machine assists the user by prepositioning each digit and enhances the human's proportional control of the grasp."

Main text (lines 258 – 260)

“The control of the hand is shared continuously such that neither the machine nor human is entirely in control of the hand and the human’s control becomes more precise as the machine moves to contact smaller objects.”

Methods (Lines 856 – 861)
“The shared control framework was designed such that the machine control would conform each digit to the surface of a detected object. If no object was detected, then the user had full control of the hand, enabling them to flex the fingers towards an object if the sensors failed to detect the surface. Once the machine controller detected the object, it would move the fingers to make contact with the surface and hold its position. The user could then flex and extend the grasp about the point of contact to make a tighter or more relaxed grasp.”

Reviewer 2: Additionally, how is it ensured that the applied force does not damage the object, especially since external force sensors used in experiments would not be available in everyday use?

We have addressed this comment in two ways:
1. First, we have modified the manuscript to more clearly state that our approach does not automate grasping force. By design, the machine alone can never exert more force on an object than minimal near-zero contact. The IR sensors cause the hand to more towards the object up until the point of contact and the pressure sensors provide a secondary fail safe to ensure that no force is applied by the machine.
2. Second, we now emphasize in the manuscript that the user is always in control of the hand and is the one regulating grasping force. Thus, whether or not the applied force damages or breaks an object is strictly up to the user.
3. Finally, we also clarified in our approach that the force measurements used in this study were strictly to quantify the precision and stability of the users control, and that the activities of daily living were used to provide a more realistic, albeit qualitative, validation in a closer approximation of real-world use.

Main Text (Lines 258 - 268)
“The control of the hand is shared continuously such that neither the machine nor human is entirely in control of the hand and the human’s control becomes more precise as the machine moves to contact smaller objects. For example, when an autonomous digit contacts a small object at 75% of its range of motion, the human’s intent is then remapped to the remaining 25% range of motion, thereby quadrupling the effective precision (Fig. 3C). Since we naturally exert only the minimum amount of force necessary to hold an object securely with our native hands [34], we further amplified human precision by mapping human intent exponentially to the remaining kinematic range of motion (Supplementary Fig. 4). Such control is consistent with our endogenous recruitment of motor neurons [48]. This shared control framework was used for all the following experiments. No parameters were tuned per experiment or object; the same framework was explored across multiple grips and tasks to quantify generalizability and translatability.”

Main Text (Lines 269 - 277)
“To establish a machine controller that can autonomously conform the grasp to objects (Supplementary Fig. 3), we trained a multilayer perceptron (MLP) to estimate the kinematic distance to an object on a digit-by-digit basis using the embedded proximity and pressure sensors (Supplementary Fig. 4). The MLP predicted kinematic distance with high accuracy throughout the entire kinematic range of the sensors. The MLP predictions were then low-pass filtered and added to the current position of each digit to serve as the machine intent such that the machine goal corresponds to the position at which the fingertip would make contact with the observed object (Fig. 3B). Both the proximity sensors and the pressure sensors are used to detect when contact is made, at which point the machine goal is frozen until contact is broken.”

Main text (Lines 323 - 326)
“Measuring the grip force enabled us to analyze the range of grip forces under shared or human control, rather than just whether the participant exceeded a predetermined force. Grip force measurements from the “fragile” object were used solely for analysis purposes and were not used by the controller in any way.”

Reviewer 2: Proximity Threshold for Grasping Fragile Objects: Experimental evaluations of the shared control strategy demonstrated enhanced stability, reduced cognitive load, and improved grasping accuracy. A key feature is that the prosthetic hand autonomously approaches fragile objects, allowing the user to focus solely on grasping once contact is made. However, the effectiveness of this strategy depends critically on the predefined proximity threshold at which autonomous movement is initiated. If the threshold is set too high, the hand may begin moving autonomously even without the user's intent, leading to potential inconvenience. Conversely, if set too low, rapid user movement might drive the fingers directly onto the object, negating the benefits of autonomous control. This raises the question of whether the same threshold was used for all experiments involving different fragile objects, such as paper and disposable cups, or if it was adjusted based on object characteristics. Clarifying this is essential to further validate the system's applicability in real-world scenarios.

We have addressed this comment in the following ways:

1. We have modified the manuscript to clarify that the exact same approach was used for the fragile transfer task (Fig. 4), the holding task (Fig. 5), the fragile-holding task (Fig. 6), and the activities of daily living (Fig. 7). We believe this is one of the fundamental strengths of our work; the same algorithm can be readily used across a variety of different use cases.
2. We have also modified the manuscript to note the potential limitations of the controller. As the reviewer points out, there are indeed unique cases where the machine intent may be out of sync with the user intent. First, in the event that the machine intent lags behind the user intent, the machine still provides substantial value in enhancing the user’s dynamic range, regulating grip force, and maintaining optimal contact with the object for a stable grasp across multiple digits. Second, we note that natural hand-arm motions are not performed sequentially. When we grasp an object, we tend to orient and start grasping our hands while our arm is still moving towards an object. Thus, it is very unlikely that the machine would activate prior to the user. In addition, even in the extreme case where an individual decides to hover over an object for approximately half a second prior to grasping it, the only downside would be potential inconvenience, possibly reflected as a greater cognitive burden. However, in practice, we saw reduced cognitive burden and enhanced task performance, suggesting that the machine intent is close enough in sync with the human intent to provide enhanced functional and cognitive performance.

   <u>Main Text (lines 266 - 268)</u>
   “This shared control framework was used for all the following experiments. No parameters were tuned per experiment or object; the same framework was explored across multiple grips and tasks to quantify generalizability and translatability.“

   <u>Discussion (lines 621 - 637)</u>
   “One could imagine a few scenarios where the shared control framework proposed in this work might impede functionality; for example, when the machine control either lags or precedes the human’s intent. In theory, the machine controller could lag behind the human’s intent or fail to detect an object if the line of sight to all of the digits is limited. In this event, the user will have decreased precision controlling the digit until contact is made, at which point the machine's goal will update, and the shared control scheme will operate as usual. In theory, it is also possible for the machine controller to precede the human’s intent. For this to happen, the user would have to reach for an object and surround the object with the prosthetic fingers but not desire to grasp it. This scenario is uncommon and unusual in activities of daily living, where grasping and reaching are performed simultaneously [72]. Nevertheless, in this event, the machine would attempt to move the fingers closer to the object to make initial near-zero contact with the object. If this was not the human’s intent, then the user could still achieve their intent, but would have to exert more physical and cognitive effort to actively extend their digits. Given the rarity and minimal impact of the machine lagging or preceding the human’s intent, we believe the shared control framework presented here provides a generalizable approach towards offloading some of the physical and cognitive burdens of dexterity while maintaining user autonomy and robust performance when working with non-ideal sensor data in the real world.”

Reviewer 2: Grasping Force for Spherical Objects: When grasping spherical objects, the machine control adds a fixed offset to ensure stable, prolonged grasping, even when the user is fatigued. However, the manuscript does not clarify how this offset and the output force are calculated, nor whether they are predefined. With fingertip sensors saturated during grasping, it is unclear how the system regulates force to avoid damaging objects and adjusts the offset for spheres of different diameters and weights.

As noted in our previous responses, we have modified the manuscript to clarify the methodology. We now more clearly articulate that the machine control uses a predefined but generalizable algorithm to touch the object with the minimal amount of force on each digit. We highlight that the fixed offset refers to a position, not a force, and that output force is strictly based on the human intent. We also note that because the machine only makes contact with objects with minimal force, it inherently cannot damage objects and dynamically can adjust to any shape and size object. Different weights are accommodated by the human user, who is in complete control of the exerted force.

Reviewer 2: Additionally, evidence for reduced cognitive load appears weak, as Figure 5F shows only a 0.06-second improvement in DRT response time. More substantial data is needed to support these claims.

Reviewer 1 also commented on this point. Our reply to reviewer 1 is copied below:

To better convey the improvements in the detection response task (DRT), we revised the manuscript text and added a new supplementary figure.

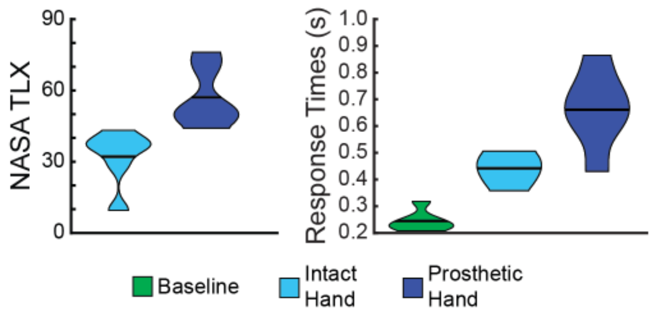
1. First, we note that the relative change in response time is quite large (30%) even if the absolute change is only a matter of milliseconds.
2. Second, referencing a recent manuscript validating the DRT for use in prosthetics, we now state that our observed improvement in the DRT response time correlates with a ~7% improvement in NASA TLX score.
3. Third, to provide some real-world context for what a ~120 ms improvement in DRT response time means, we now provide an example from literature showing that a 120 ms change in response times is similar to trying to operate a car radio while driving as opposed to at a standstill.
4. Fourth, we also provide real-world context for what a 30% relative improvement in DRT response time means. We cite a paper showing that a similar 30% improvement in DRT response time was observed when switching from a bionic hand to a healthy intact hand.

We believe these additional clarifications emphasize that, despite a small numerical change in DRT response time, there is actually a considerable relative decrease in cognitive burden taking place.

Relevant changes to the manuscript are copied below for reference.

> <u>Main text (Lines 417 – 426)</u>
> "While there are limited research studies using the DRT to quantify the cognitive burden of using a myoelectric hand [53], research into the effects of cognitive load on driving indicates that a change of 50 ms in the response times corresponds to a noticeably more difficult task, as human response times to the tactile DRT generally range from approximately 300 ms to 1 s [54–56]. Without an additional task, the response time to the DRT was measured to be 250 ms (Supplementary Fig. 7). Given this, the measured decrease of 60 ms corresponds to a 29% decrease in cognitive burden with respect to the range of response times when using shared control, which is similar to the 30% decrease in cognitive load observed when switching from completing a task with a 1-DOF bionic hand to an intact hand (Supplementary Fig. 7)."
>
> <u>Main text (Lines 432 - 438)</u>
> "This 120-ms change in their response times corresponds to a 24% decrease in cognitive burden by using shared control. To frame this change with respect to other real world scenarios, a 120-ms improvement was also observed when drivers operated their car radio at a standstill versus operating their radio while driving[63]. A comparison between the intact-limb and amputee participant's response times indicates that the amputee participants were slower to respond than the intact-limb participants (Supplementary Fig. 8), which could be attributed to the different task, or to their amputation or age."
>
> <u>Methods (Lines 893 - 897)</u>
> "The response rate to the DRT has been correlated with increased cognitive load and task difficulty[59–61]. In a separate experiment, the baseline response times to the tactile DRT without an additional task were

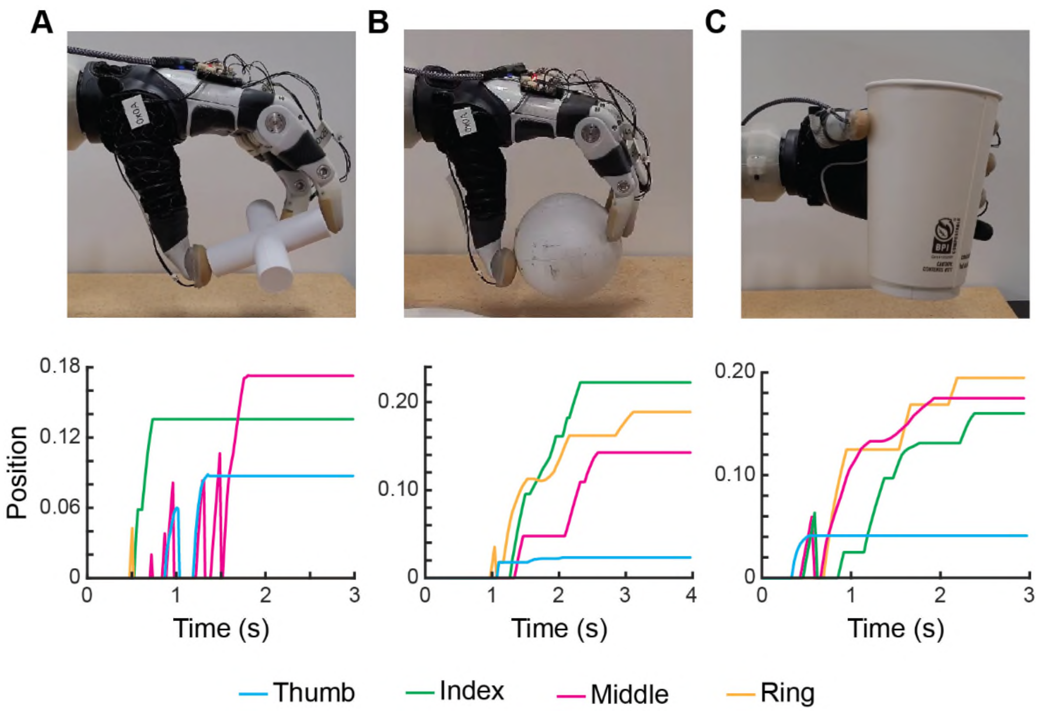
measured to be approximately 250 ms (Supplementary Fig. 3). In driving tasks, average response times vary with task difficulty, ranging from baseline to approximately 800 ms, where a ceiling effect is observed[59]."



"Supplementary Fig. 7: Baseline cognitive load data for six intact-limb participants. Participants completed a baseline detection response task (DRT) alone and then again with a fragile object transfer as a secondary task. The fragile object transfer task was completed using their intact hand or a pinch grasp with a prosthetic hand using human control. The object was considered very difficult to transfer as it broke with a force of 0.7 N. A) From the NASA TLX results, a score of 32.14 ± 11.98 is considered easy as participants successfully transferred the fragile object 100% of trials using their intact hand, and 57.07 ± 12.63 is corresponds to a more difficult task as the success rate was 20% when using a prosthetic hand. The prosthetic hand was controlled via a 1-DOF modified Kalman filter decoding 32 sEMG channels. B) The participants' baseline response times to the DRT without an additional task were 0.25 ± 0.04 s. Increasing the cognitive burden by introducing the secondary task increased the response time by 0.44 ± 0.06 s, and making the task more difficult by using a prosthetic hand rather than a healthy hand further increased the response time to 0.66 ± 0.15 s."

Reviewer 2: Validation: The core principle is that the prosthetic hand autonomously approaches and applies grasping force, while the user adjusts the force, with the machine compensating for fatigue. However, the manuscript lacks clarity on how control strategies vary across different tasks. The paper does not provide specific numerical values for the two forces. The question is whether the control strategies differ between different task objectives, such as fragile and spherical objects. If they do, how does the system automatically switch between them? Alternatively, can a single control framework accommodate different task requirements?

We have addressed this comment in the following ways:
1. First, as noted above, we have modified the manuscript to clarify that the exact same approach was used for the fragile transfer task (Fig. 4), the holding task (Fig. 5), the fragile-holding task (Fig. 6), and the activities of daily living (Fig. 7). We believe this is one of the fundamental strengths of our work; the same algorithm can be readily used across a variety of different use cases.
2. Second, we have modified the manuscript to make it clearer that the machine control does not inherently provide any force. Rather, it seeks to apply the minimum amount of force possible while making contact. We have provided Supplementary Figure 3 which now showcases the exact forces and distance the position of the machine control moves to for a variety of different objects. Please note that we are showing the machine contribution alone in Supplementary Figure 3. This machine contribution is then added to the human intent to enable more generalizable control across a variety of objects and tasks.



"Supplementary Fig. 3: Demonstrations of the machine controller controlling the thumb, index, middle, and ring finger with a cross-bar (A), a ball (B), and a cup (c). The kinematic traces for each digit are displayed beneath the corresponding picture. In each case, the machine controller moved each digit to a unique position such that the hand would lightly grasp each object with each DOF that "saw" the object. While the machine controller was capable of grasping each of the objects in this example, all of the objects were unweighted and relatively lightweight compared to the weighted object used in the experiments."

Reviewer 2: Writing: The manuscript suffers from insufficient detail on its control strategy, making it read more like an experimental report than a cohesive study.

To address this concern, we provided more detail of the control algorithms throughout the abstract, methods, the main text, and modified Fig. 3 to better clarify our methodology.

Reviewer 2: Excessive citations in the Results and Discussion sections disrupt the flow and should be relocated to the Introduction.

We have greatly expanded the introduction as requested and have reduced the number of citations in the other sections.

Reviewer 2: Key numerical values could be better presented in tabular form.

We have added supplementary tables that show all numerical values.

Reviewer 2: Moreover, the Introduction is overly brief, preventing readers from quickly understanding the research background and existing challenges.

We have greatly expanded the introduction. We now provide a comprehensive summary of the fields of shared control and semi-autonomous prosthesis which is used to more clearly explain the novelty of our approach.

Reviewer 1 also commented on this point. The relevant changes from our response above are copied below:

Introduction (Lines 70 - 73)
"However, among all of these works, there is a distinct lack of testing real-time control with commercially available prosthetic hands and amputee patients, and many previously developed sharing algorithms operate on distinct states that the user or machine switches between. It has been hypothesized that continuously sharing control will improve functionality and make the control algorithm more intuitive for the user [26]."

Introduction (Lines 74 - 85)
"One common approach is to develop a semi-autonomous prosthesis where control switches between the human user and an autonomous machine controller. For example, Zhuang et al. developed an autonomous machine controller that moved the individual fingers of a virtual prosthesis to maximize finger contact with virtual objects[31]. The human user controlled the prosthesis with surface electromyography (EMG) to initiate initial contact with the object, at which point the autonomous controller would take over and move the digits autonomously to create a multidigit grasp with a fixed force output. Although this approach was shown to improve grip stability and functional performance, it results in a single fixed force being applied to all objects, making it unlikely to generalize to broader activities of daily living. Indeed, Zhuang et al. noted this limitation and hypothesized that continuously sharing control between the human and machine, instead of simply toggling between the human and machine, would improve functionality and make the control more intuitive for the user[31]."

Introduction (Lines 86 - 95)
"To this end, the other common approach to share control between a human and machine is to simply blend the human control and machine control using a simple linear coefficient, β. Under this approach, the prosthesis position is determined by human control multiplied by β plus the machine control multiplied by $(1 - \beta)$. For example, Dantas et al. used this approach with a virtual prosthesis to demonstrate improved control on a virtual target touching task[33]. However, this approach requires the machine to be able to consistently provide a meaningful goal, not just under controlled conditions when triggered by the user. Indeed, Dantas et al. punted this issue by simply setting the machine goal equal to the location of the virtual target. It remains an open question as to how an autonomous machine could use real-world sensors to provide a meaningful control signal to users at all times across a range of tasks."

Reviewer 2: This lack of context and clarity hampers comprehension. Improved organization and clearer explanation of methods are essential to enhance the paper's readability and better convey its contributions. Overall, the writing needs substantial improvement.

We have greatly improved the context and clarity by expanding the introduction, reorganizing key figures, adding supplementary tables/figures, and reorganizing and expanding the methods. We believe the manuscript is much improved and hope you will too.

Reviewer 2: Figures and movie: Figure 1 is overly simplistic and should be expanded to provide an overall study overview with more relevant details.

We have substantially reworked each area of the manuscript to increase clarity and context. We believe these changes are comprehensive and sufficient to convey the scope and value of the study. We tell a narrative of how embedded sensors can be used to automate tasks, but how that traditional approach fundamentally limits generalizability. We then shift the narrative to describe our novel approach leveraging shared control to create a more generalizable solution. We provide Fig 3 as an overview to this generalizable approach. We believe moving this overview earlier would be confusing to the overarching narrative, but would be happy to accommodate this change if you disagree.

Reviewer 2: Additionally, a supplementary video demonstrating grasping tasks with various objects—different shapes and weights in daily-life scenarios—would greatly enhance the work's clarity and impact.

To strengthen the claim of translatability, we have added another supplementary video demonstrating how the machine control alone can conform to various shapes. Please note that this is for the machine control alone; under shared control the user can readily apply any force they want to grasp objects of different shapes and weights with as many digits as desired and with as much force as desired. The use of shared control across multiple conditions is shown across Fig. 4 (precision pinch grasp of a block), Fig. 5 (power grasp of a spherical object), and Fig. 6 (intermediate tripod pinch of a cube).

Reviewer 2: It is also recommended to compress Supplementary Video 3, which is currently too large at 1.3 GB, to ensure better accessibility and usability.

Thank you for noting this. Supplementary Video 3 has been compressed.

Reviewer 2: And there is little information from the supplementary materials.

Additional figures, videos, and tables have been included to increase the level of detail in the manuscript.

Reviewer 3: In several places, the paper claims results can generalize to a broad range of devices, patients and tasks. However, only 4 persons with amputation were tested, and data is reported from a single task (holding a ball), with few trials.

We agree with the reviewer that additional work is necessary to truly demonstrate generalizability across a broad range of devices, patients, and tasks. We have addressed this concern in the following ways:

1. First and foremost, we have softened all the claims of generalizability throughout the manuscript. We now clearly state the limitations of study throughout the manuscript.
2. Second, in the discussion we added a dedicated paragraph describing the limitations of the study and describe the future work needed to demonstrate true generalizability.
3. Third, we also reference other works with transradial amputees to provide a frame of reference for the sample size used in this study. Although the absolute number of transradial amputees involved in this study is small (N = 4), we note that this number is fairly large relatively to most prior works using cohorts of 1-2 patients for virtual experiments. We believe that 4 transradial amputees and 6 intact participants provides a strong initial demonstration towards generalizability.

Relevant changes to the manuscript are copied below for reference.

> <u>Introduction (Lines 111 – 114)</u>
> "Importantly, as a further demonstration of generalizability and translational potential, we demonstrate greater grip precision, improved grip security, and reduced cognitive burden through a series of experiments with multiple intact-limb participants and four transradial amputees using a physical prosthesis."
>
> <u>Discussion (Lines 572 – 576)</u>
> "We show generalizability through a variety of different grasps and tasks and facilitate translation through integration with a widely-used commercial prostheses and by validating the system with four transradial amputees which, to our knowledge, is the largest patient population to date to test shared control in a real world setting."
>
> <u>Discussion (Lines 638 – 643)</u>
> "We demonstrated that shared control can generalize to a variety of objects and grip patterns common in activities of daily living. However, this does not necessarily mean that shared control will generalize well to everyday real-world use. A long-term at-home clinical trial with multiple participants is necessary to validate real-world generalizability and to demonstrate improvements in independence and quality of life. Such a study could also answer questions regarding the impact of shared control on prosthesis adoption and learnability."

Reviewer 3: ADL testing was only described qualitatively.

We have addressed this point in the following ways:

1. We collected additional pilot data of an amputee participant completing a simulated drinking task to assess how shared control might improve ADLs. The results of this experiment have been added to the main text and Fig. 7.
2. We believe the next step for this research is a take-home trial where users test the shared control framework outside of the laboratory in their day-to-day life and quality of life and usability metrics are reported. Although this is outside of the scope for this initial manuscript, we have noted this limitation of the present study and have expanded the discussion to outline this critical future work.

Main text (Lines 538 - 554)

"Occupational therapists often rate amputee patients' performance on activities of daily living using subjective graded scales. For example, the Activities Measure for Upper-Limb Amputees (AM-ULA) scores amputees on 5 categories: extent of completion, speed of completion, movement quality, skillfulness, and independence. Although the activities completed with AM-ULA are not well-suited for next-generation prostheses capable of a delicate touch41,66,67, the rate and speed of completion score criteria are quantitative and can easily be applied to other activities of daily living. To this end, we quantified the speed and success rate of one participant as they completed six trials of the drinking task with disposable cups, during which they attempted to pick up the cup from the table, bring it to their mouth and mime a sip, and then return it to the table. This real-world activity of daily living is considerably difficult. These common disposable cups break with approximately 7 N; in contrast, the fragile holding task required the amputees to maintain forces below 15 N. Under human control, the participant crushed the disposable cup five out of the six trials and dropped it twice (Fig. 7D). However, with shared control, the participant successfully completed the task four out of the six times. No significant difference in the task speed was observed; the participant took 9.67 ± 3.27 s to make a grasp and lift the cup to their mouth with human control, and only 7.60 ± 2.59 s with shared control ($p = 0.26$; unpaired t-test; Fig. 7E)."

(Redacted)

Fig. 7. Shared control supports activities of daily living. Participants completed various ADLs with and without shared control. Shared control was particularly helpful for tasks that involved a precise grasp and grip force, including, lifting a disposable cup to their mouth without crushing it using a power grasp **(A)**, moving an egg without breaking it using a tripod grasp **(B)**, and picking up a sheet of paper without crinkling it using a pinch grasp **(C)**. An amputee participant attempted to drink out of a disposable cup six times with either control algorithm **(D)**. The participant successfully lifted the cup to their mouth and set it back on a table four times, but was unable to do so a single time with the human controller. **E)** The time it took for the participant to make a grasp that they felt confident in, and lift the cup up to their mouth was also recorded, though no differences were observed.

Discussion (Lines 638 – 643)
"We demonstrated that shared control can generalize to a variety of objects and grip patterns common in activities of daily living. However, this does not necessarily mean that shared control will generalize well to everyday real-world use. A long-term at-home clinical trial with multiple participants is necessary to validate real-world generalizability and to demonstrate improvements in independence and quality of life. Such a study could also answer questions regarding the impact of shared control on prosthesis adoption and learnability."

Reviewer 3: Additionally, only 2 of the 4 were myoelectric users, with the other 2 body-powered users who would not benefit from the new approach.

As a counterpoint, we would argue that body-powered users are more likely to benefit from the new approach than prior myoelectric users. The most advanced commercial myoelectric prostheses use pattern recognition to select among different grasps with fixed force output. These commercial myoelectric prostheses are limited by an inability to regulate grip force and the need to explicitly select different grasping patterns for different objects. In contrast, the shared control approach introduced here enables fine force regulation and greater grip stability across a variety of grasps. We believe that these improvements may ultimately lead to greater adoption of myoelectric prostheses for patients who might have otherwise selected a body-powered hook. We have modified the discussion to emphasize this point, along with the caveat that future work is necessary to truly assess the ability of this shared control approach to improve prosthesis adoption.

Relevant changes to the manuscript are copied below for reference.

Discussion (lines 660 - 675)
"Among the amputee patients, shared control provided similar benefits to those that used a myoelectric prosthesis and those that used a body-powered prosthesis. Future work should explore the impact of shared control among myoelectric and body-powered users with a greater number of patients. Shared control is most straightforwardly applicable to myoelectric users since shared control could be readily implemented into commercial multiarticulate bionic arms like the TASKA hand used in this study. However, the ability of shared control to reduce the cognitive load of controlling a multiarticulate bionic arm may also make myoelectric control more appealing to patients who would have otherwise opted for a body-powered prosthesis. Although there are many differences among body-powered and myoelectric prostheses (e.g., weight), body powered prosthesis are often considered to require less attention, and this is a major contributing factor in prosthesis selection[77]. Indeed, body-powered prostheses require less training time[78] and provide residual sensory feedback that has been hypothesized to reduce cognitive and visual demand[79]. Given that shared control can reduce the cognitive demand of a myoelectric prosthesis, future work should explore the ability of shared control to reduce prosthesis abandonment among myoelectric users, as myoelectric prostheses have yet to improve prosthesis adoption over body-powered alternatives[5]."

Reviewer 3: 32-channel EMG was used in all subjects. It's unclear if these results can be generalized to current prosthetic arms which have far fewer EMG channels. The algorithms described in methods required calibration procedures. It is unclear how often these need to be performed, which would reduce the practical implementation of the method.

We have addressed this comment in the following ways:

1. First, we have greatly expanded the methodology regarding our EMG controller as requested in comments from other reviewers. This includes a detailed description of the number of channels used for this work, and in prior works with this same EMG control algorithm. We also specifically note that the EMG control algorithm was calibrated once per day/donning for each participant, consistent with prior work using this algorithm and consistent with most commercially available pattern recognition controllers.
2. Second, we have added a paragraph to the discussion highlighting the feasibility of leveraging this shared control framework with other commercially available EMG control algorithms. We specifically describe the

differences in the number of channels as well. In brief, we believe the shared control framework can be readily applied to other EMG controllers and those with less channels and potentially worse performance would likely benefit most from this work, although future work is needed to validate this.

Introduction (Lines 53 - 57)
"Ideally, prosthesis users could similarly control the individual position of each prosthetic digit to generate any arbitrary grasp and exert any desired force. However, simultaneous and proportional control of multiple degrees of freedom is difficult to achieve; as the number of degrees of freedom increases, errors compound, cognitive burden grows, and task performance decreases [13,14]."

Discussion (Lines 683 – 708)
"Commercial myoelectric prostheses are also typically controlled using either pattern recognition[91] or dual-site control[92,93], both of which require the user to sequentially select among grip patterns with a fixed force output[92]. In contrast, here we demonstrate simultaneous and proportional control of each digit in real-time. By eliminating the need to sequentially switch between grip patterns, simultaneous and proportional control has been shown to improve performance relative to pattern recognition for a 3-DOF prosthesis[94]. Simultaneous and proportional control of more than 3 DOFs has been achieved previously using a modified Kalman filter[42]. Indeed, a modified Kalman filter has been used to control up to 10 DOFs[95], deployed on computationally limited hardware[96–98], and used to complete various activities of daily living[41,42,99]. Although promising, it is recognized that the performance and intuitiveness of simultaneous and proportional control algorithms decrease as the number of controllable DOFs increases, and this is also true for the modified Kalman filter[96]. In the present work, we demonstrate the ability of shared control to enable simultaneous and proportional control of a greater number of DOFs while decreasing the overall cognitive burden.
An important question remains as to whether the shared control framework employed herein can be readily extended to other, more traditional, control strategies like pattern recognition or dual-site control. Explicit validation is required, but in theory, both pattern recognition and dual-site control could benefit from the shared control framework outlined here. Parallel dual-site control of multiple DOFs[94] is akin to the modified Kalman filter, and we would likely see similar improvements in grip security, grip precision, and cognitive load. In the case of pattern recognition, the shared control framework could increase grip security and/or precision by helping maintain digit contact and distributing forces more equally among the active DOFs, but would likely have minimal impact on cognitive load. Future shared control frameworks with pattern recognition in mind could leverage the embedded sensors to inform grip selections, which, if done well, could improve the speed and reduce the cognitive demand of coordinated multi-gesture tasks."

Reviewer 3: The claim the method is bio-inspired requires more justification. It is true normal grasping uses fingertip tactile sensors, but they are not used as described here. Normal grasping is predominantly a feedforward task based on an internal model of the object's characteristics (weight, texture, stiffness, etc.), learned from experience. Sensors are used to detect events (ie: object slip, object lift-off, contact). Unexpected events (slip) trigger reprogramming of the motor plan as needed. If the task is performed as expected, the sensors are only used to confirm everything is going as planned, and confirm task transitions (ie: object lift-off). In this application, the sensors play a much more active role in moving the fingers and reinforcing grip force. This may be the correct use in this application, but it's a stretch to claim it is bio-inspired.

We agree with the reviewer and have softened claims regarding the bioinspired nature of the control algorithm. We did not mean to imply that the use of the sensors was bioinspired. Rather, our intent was to note that the exponentially weighted control approach was more in line with that of human motor control, where greater precision is achieved at lower forces. We now describe this as the justification for the term bioinspired in the manuscript. Recognizing this may also be somewhat of a stretch, we have generally opted to simply remove most uses of the term bioinspired.

Introduction, (Lines 244 – 247)
"To this end, we developed a novel shared control framework that continuously merges human and machine intent. Our framework is inspired by the intact biological hand's ability to seamlessly conform to an object, as opposed to prosthesis users who rely on their vision to properly grasp objects [45]."

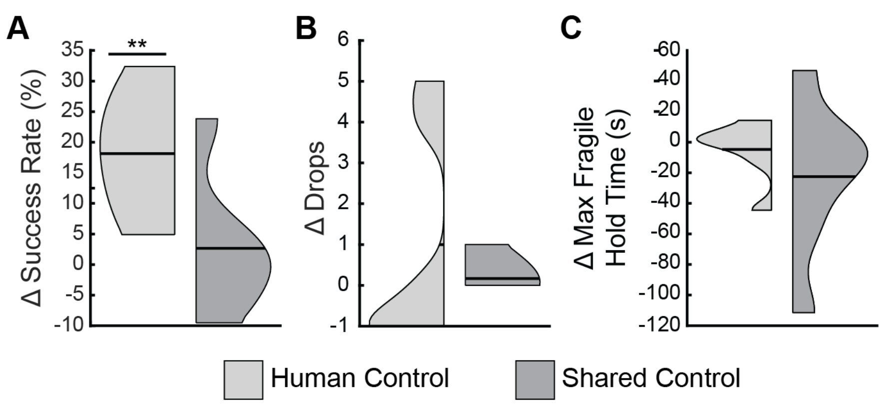
Main Text, Control is Shared between User and Autonomous Bionic Hand (Lines 603 – 607)
"Here, we introduce a new shared control framework that uses a dynamically weighted sum to allow simultaneous and independent contributions from the user and the autonomous bionic arm. This approach was inspired by biological grasping that maximizes contact area while limiting grasping forces[71]."

Reviewer 3: In normal performance, information from sensors are used to modify the internal model for the next time the task is performed. It is unclear if the shared control supports this learning, or impedes it by added an additional "hidden" variable (machine contribution) during performance that the human must account for.

This is an excellent point that warrants further investigation. Unfortunately, we were unable to explore the full effect of learning in the present study, and so we address this point in a few ways:

1. First, we have modified the discussion to outline the need for future work exploring the learnability of this shared control approach. We speculate that the hidden variable here would not impede learning given it's ability to reduce cognitive load, but understandably require a long-term study to test this hypothesis.
2. Second, we added a supplemental figure 9 to showcase any possible learning within the span of the data we collected. We show that no learning was detected across any of the conditions in any of the experiments, except potentially the human control during the fragile object transfer task. No learning was detected within any of the shared control experiments.

Discussion (Lines 644 - 659)
"Shared control resulted in immediate improvements in functional and cognitive performance in naïve users. An important question remains as to whether shared control can provide similar, or even greater, benefits to experienced users. As a simple first-order assessment of learning, we explored the change in performance for human control and shared control between the first and last experimental blocks of the fragile-object transfer task, holding task, and fragile-holding task (Supplementary Fig. 9). No learning took place under shared control; there were no significant differences for any of the tasks. Under human control, no learning took place for the holding task or fragile-holding task, but there was a significant improvement in success rate on the fragile object transfer task. Given the timeframe of the tasks performed herein, we suspect that the limited learning that did take place would mostly be attributed to task familiarization. Future work should explore long-term motor learning associated with shared control. Shared control could potentially improve motor learning, as decreased cognitive burden is associated with an increase in motor skill acquisition[73,74]. In contrast, the machine contribution could also act as an additional hidden variable within the user's internal model that impedes learning[75]. Regardless of long-term outcomes, the short-term benefit of enhanced dexterity and reduced cognitive load could potentially improve prosthesis adoption during the critical golden window after amputation[76]."



"Supplementary Fig. 9: Learning effects across the experiments for both controllers. The main experimental outcomes from the first experimental block were compared to the second experimental block. The resulting distribution was then compared to a zero-mean normal distribution to assess if any potential learning occurred between trials. A) A significant increase in performance between the first and second experimental blocks of the fragile-object transfer task was detected for the human controller ($p < 0.01$, paired t-test), indicating that participants improved their performance with the human controller across the course of the experiment. No significant difference was detected between trials for the shared controller. B) No significant learning effects were detected for the human or shared controller within the holding experiment. C) No significant learning effects were detected for the human or shared controller within the fragile-holding experiment."

Reviewer 3: Authors show their sensors can detect no-force contact. What ADL or task requires detecting no-force contact with an object? The role of this capability only becomes more clear when reading the methods section at the end. Some hint here is needed for what this capability will be used for.

To improve the readability of the manuscript, we have included additional background information in the introduction and adjusted the main text to include more details and justification of the shared and machine control algorithms. In the discussion, we also highlight other examples of where near-zero contact with objects might be relevant.

> Introduction (Lines 64 - 95)
> "To this end, one biomimetic approach to make bionic arms more dexterous and intuitive would be to leverage multimodal sensors to aid with some aspects of manual dexterity, thereby offloading some of the cognitive demand to the bionic arm itself. Indeed, researchers have used optical sensors to preposition robotic hands[27–30], force sensors to guide force output[31,32], and even acoustic sensors to detect and prevent slip[32]. These prior works demonstrate that even a single sensing modality can improve functional outcomes on specific tasks in controlled environments. However, among all of these works, there is a distinct lack of testing with users performing real-world tasks with physical prostheses. Additionally, the algorithms used to leverage multimodal sensor data to offload aspects of dexterity are often task specific and unable to generalize to the diversity of objects and grasps seen in the real world.
>
> One common approach is to develop a semi-autonomous prosthesis where control switches between the human user and an autonomous machine controller. For example, Zhuang et al. developed an autonomous machine controller that moved the individual fingers of a virtual prosthesis to maximize finger contact with virtual objects[31]. The human user controlled the prosthesis with surface electromyography (EMG) to initiate initial contact with the object, at which point the autonomous controller would take over and move the digits autonomously to create a multidigit grasp with a fixed force output. Although this approach was shown to improve grip stability and functional performance, it results in a single fixed force being applied to all objects, making it unlikely to generalize to broader activities of daily living. Indeed, Zhuang et al. noted this limitation and hypothesized that continuously sharing control between the human and machine, instead of simply toggling between the human and machine, would improve functionality and make the control more intuitive for the user[31].
>
> To this end, the other common approach to share control between a human and machine is to simply blend the human control and machine control using a simple linear coefficient, β. Under this approach, the prosthesis position is determined by human control multiplied by β plus the machine control multiplied by (1 - β). For example, Dantas et al. used this approach with a virtual prosthesis to demonstrate improved control on a virtual target touching task[33]. However, this approach requires the machine to be able to consistently provide a meaningful goal, not just under controlled conditions when triggered by the user. Indeed, Dantas et al. punted this issue by simply setting the machine goal equal to the location of the virtual target. It remains an open question as to how an autonomous machine could use real-world sensors to provide a meaningful control signal to users at all times across a range of tasks."
>
> Main Text, Multi-Modal Sensors Allow for Zero-Force Contact Detection (Lines 141 - 144)
> "Being able to detect near-zero force contact is crucial if one wishes to emulate the precision and dexterity of the intact human hand, as our hand control is based heavily on feedback from highly tuned mechanoreceptors that encode subtle and fast deformations in the skin[36]."

Reviewer 3: Fig. 2: Do you really need 2 sensors? Seems similar performance could have been achieved with just the pressure sensor and the value of the proximity sensor is not clear. The proximity sensor can be removed from the logic diagram and it seems that the algorithm would operate similarly. The importance of knowing proximity to the object should be reinforced here, versus just moving until contact is made, which can be detected with a pressure sensor.

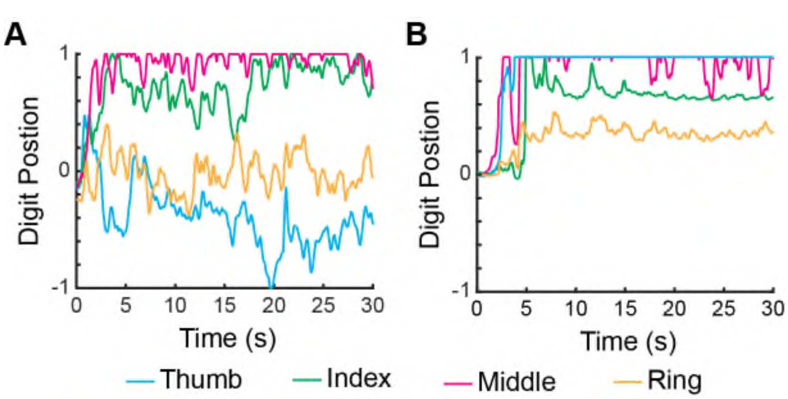
This is a great question. Interestingly, from our work we found that the infrared sensor is actually the more important sensor for this approach.

1. First, several commercial prostheses limit the force applied to objects through feedback from torque sensors, motor encoders, or motor overcurrents. The feedback nature of this approach makes it less useful for quick tasks like fragile object transfers. In practice, we also found that the user's EMG control was often too fast for the sensors to have any meaningful benefit (i.e., the pressure sensors often go from zero to a very large value within a single sample because the prosthesis moves quickly). In contrast, the feedforward nature of the infrared sensors allows for a more seamless blending of the human and machine intent.
2. Second, and more importantly, there is also the added benefit of the machine helping initiate movements that may have not otherwise happened. For example, when grasping dynamically shaped objects, the infrared sensors will encourage each digit to move towards the object to make contact, coordinating a more stable multi-finger grasp. We show this in Fig 5 and Supplementary Fig. 6, where more fingers made contact with the object on average. Although activities of daily living are difficult to quantify, we also observed the additional fingers making contact with the object to be particularly helpful for holding circular objects, like eggs, stable as a pinch grasp allows the objects to spin.

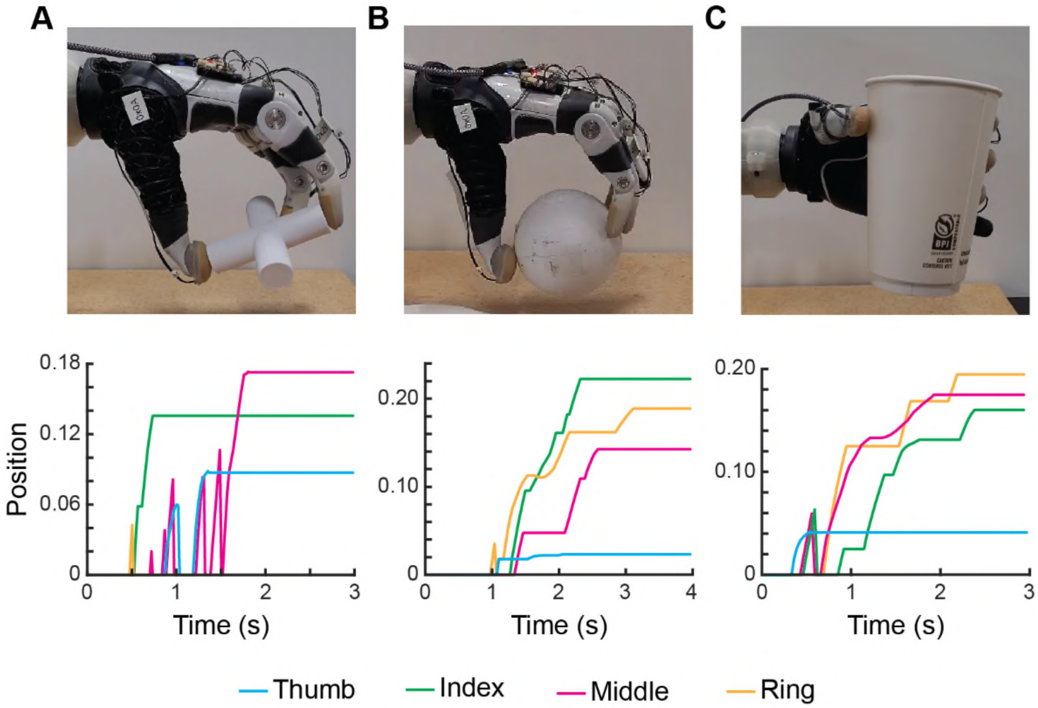
We have greatly expanded the results and discussion sections to address both of these points.

Figure 3 subtext (Linex 287 – 291)
"A) Simultaneous and proportional position control of multiple digits is difficult to achieve with surface EMG alone. Prosthesis users have a difficult time making and maintaining precise grasps, as small changes in the digit's position (dashed line) can cause rapid changes in the grip force (blue line) once the digit contacts an object."

Discussion (Lines 589 – 598)
"In principle, the shared control algorithm presented here could operate with only a single modality. However, in practice, the multimodal configuration provided more robust control given that sensor data is often non-ideal in the real world. Using pressure sensors alone requires the machine control to operate entirely in a reactive manner. The pressure sensors would need to be sampled at a much faster rate than the actuation speed of the prosthesis to ensure the machine stops quickly enough to provide near-zero contact force. In practice, this was not feasible due to the users' desire to operate the prosthesis quickly, the momentum of the prosthesis once in motion, the delays associated with power-efficient sensor readings, and wireless communication. In contrast, the feedforward nature of the infrared sensors allows for a more seamless blending of the human and machine intent. Additionally, the infrared sensors have the added benefit of initiating movement on their own to maximize the number of digits making contact with the object. Combined, the multimodal infrared and pressure sensors provide both a feedforward and a feedback approach to ensure robust operation under uncertainty."



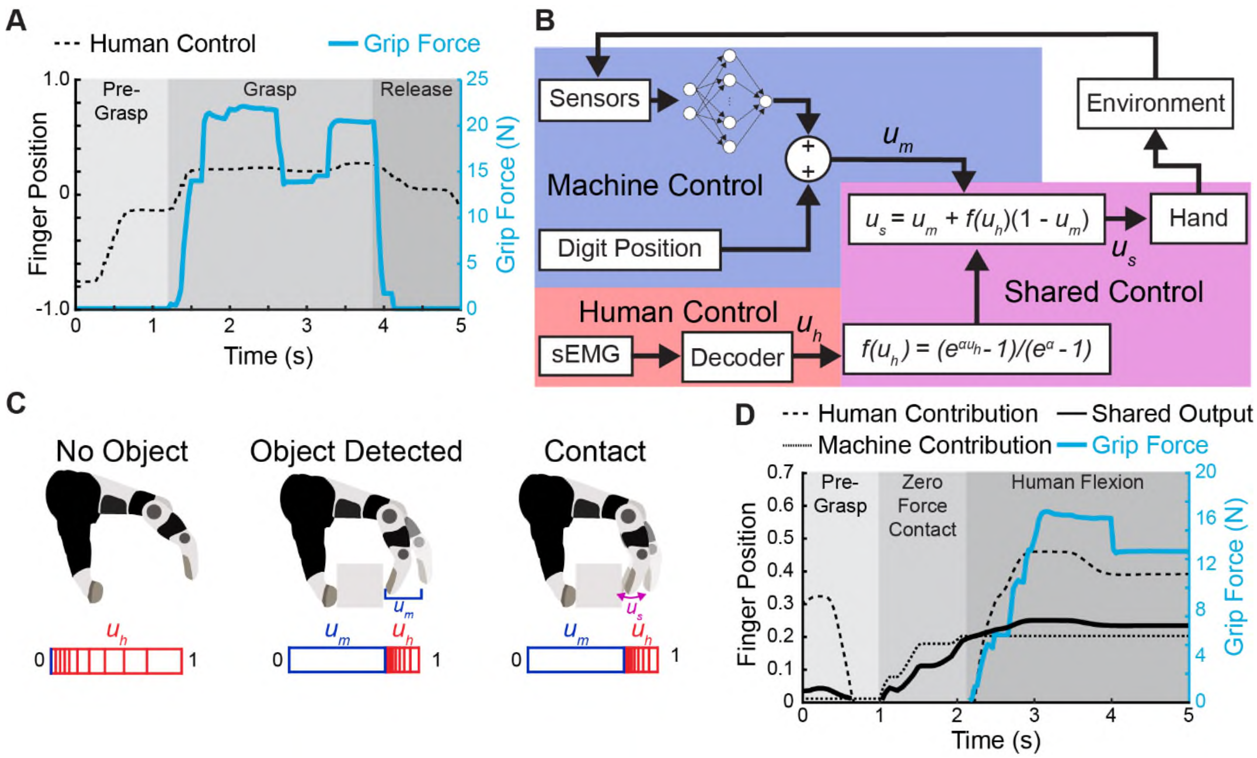
"Supplementary Fig. 6: Simultaneous control of four independent digits during the holding task. A) The first 30 s of the most successful trial with human control demonstrates the degree of noise present in the kinematics as decoded from the 32 sEMG channels via a Kalman filter. When using human control, participants had a difficult time controlling all four digits and maintained the grasp by focusing on maintaining the flexed position of any digit that made contact with the object. Note that while the thumb was not flexed, participants were able to hold onto the ball by squeezing it against the palm. B) In contrast, the first 30s of the most successful trial with shared control demonstrate greater stability across all of the digits. The noise observed in the human controller's output is diminished due to the exponential scaling in the shared control framework."



"Supplementary Fig. 3: Demonstrations of the machine controller controlling the thumb, index, middle, and ring finger with a cross-bar (A), a ball (B), and a cup (c). The kinematic traces for each digit are displayed beneath the corresponding picture. In each case, the machine controller moved each digit to a unique position such that the hand would lightly grasp each object with each DOF that "saw" the object. While the machine controller was capable of grasping each of the objects in this example, all of the objects were unweighted and relatively lightweight compared to the weighted object used in the experiments."

Reviewer 3: Fig. 3E: It appears that the human is mostly in control during pre-grasp and grip force generation, but what is happening during the zero-force contact phase, which lasts 1 sec? Unclear what triggers the transition from the zero force contact phase to the human flexion phase. Does the human have to stop EMG activation during pre-grasp and then start again to initiate the human flexion phase? This seems very unnatural. If the zero force contact phase is when all of the fingers are moving to contact the object under machine control, please make this clear. Some of this becomes more clear after reading the methods, but more information is needed here so that the reader does not have to flip back and forth between methods and the data figures.

We have revised this figure to make this clearer. The grasp is made up of multiple fingers interacting with the object and the user pausing to test their grasp. We have added additional information to the main text, Fig. 3E, and the subtext of Fig. 3 to help clarify this point.



Main text (Lines 244 – 254)

"To this end, we developed a novel shared control framework that continuously merges human and machine intent. Our framework is inspired by the intact biological hand's ability to seamlessly conform to an object, as opposed to prosthesis users who rely on their vision to properly grasp objects [45]. The shared control framework leverages a machine controller to conform each independent finger to make minimal-force contact with an object (Supplementary Fig. 3) while allowing the human user to modify the grasp about the point of contact by controlling the position of each digit decoded from surface EMG. By continuously sharing control, the human maintains the ability to regulate their grasp while offloading the conformation of the prosthetic hand around a given object to the machine. Importantly, the human user controls each independent digit simultaneously and proportionally, a task which would otherwise be error-prone and cognitively burdensome without machine assistance (Fig. 3A) [42,46]."

Fig. 3 subtext (Lines 306 – 317)

"D) This shared control scheme leveraged the accuracy of the machine controller to move each finger independently to make contact with an object, but not exert pressure. In this example, the user extends their grasp as they reach towards the object (0 to 1 s). The machine contribution then moves the digit to the object, and the user attempts to lift the object while making zero-force contact, but could not (~1 to 2 s). The user then flexes to increase the human controller's contribution to the shared control framework, which tightens the grasp around the object, but with much greater precision than they could do so without the machine controller's assistance (~2 to 5 s). While this example trace serves as a representation of the algorithm in a step-by-step fashion, it is important to note that the shared control algorithm is continuously blending the user's intent with the autonomous bionic hand, positioning the finger in real time. Note how small changes in the digit's position can result in large changes in the grip force around an object."

Reviewer 3: The dynamically adjusted weights between human and machine control could be explained more. It's not clear how this is implemented in the control algorithm. In Fig. 3E, I can see that the machine is mostly in control during the zero force contact phase. Is this explicitly coded?

We have added additional text and supplementary figures to clarify that with shared control, the human's contribution is modified by an exponential function to increase their precision about the point of contact as dictated by the machine controller. This is explicitly coded, but is dynamic based on the machine intent.

Main text (Lines 255 – 258)

"In contrast to prior works that toggle between human and machine control[31], or use a fixed proportion of human and machine control[33,47], our shared control framework uses a dynamically weighted sum of human and machine control that is dependent on the relative position of each digit (Fig. 3B). The control of the hand is shared continuously such that neither the machine nor human is entirely in control of the hand and the human's control becomes more precise as the machine moves to contact smaller objects. For example, when an autonomous digit contacts a small object at 75% of its range of motion, the human's intent is then remapped to the remaining 25% range of motion, thereby quadrupling the effective precision (Fig. 3C). Since we naturally exert only the minimum amount of force necessary to hold an object securely with our native hands [34], we further amplified human precision by mapping human intent exponentially to the remaining kinematic range of motion (Supplementary Fig. 4). Such control is consistent with our endogenous recruitment of motor neurons [48]. This shared control framework was used for all the following experiments. No parameters were tuned per experiment or object; the same framework was explored across multiple grips and tasks to quantify generalizability and translatability."

Fig. 3

We modified Fig. 3 to better outline the shared control framework. See the figure above and in the manuscript.

Fig. 3 subtext

We updated the subtext of Fig. 3 to provide more detail regarding the shared control framework. See caption on the image above as well as in the manuscript.

Reviewer 3: It is unclear what the graphic at bottom Fig. 3B represents. Does um and uh refer to the position of the digits? How can EMG be used to command position of the digit, when EMG is related directly to muscle force or grip force? Again, some of these questions are answered in methods, but more explanations are needed here to interpret the figure.

We have addressed the comment in the following ways:

1. To better clarify the shared control framework we have modified Fig. 3B and its subtext to provide a more complete example.
2. We have also altered Fig. 3 and provided Supplementary Fig. 4C to better demonstrate the flow of the shared control framework.
3. Additionally, we have moved relevant text from the methods to the results and figure captions to provide readers with a self-contained description of the approach.
4. Finally, we have greatly expanded our description of our human intent algorithm, the modified Kalman filter, which is used to regress the kinematic position of each digit based on EMG.

Reviewer 3: Page 8: The test on improving grasp security uses individual control of all 5 digits. It is unclear if and how the machine control coordinates control between different digits for a stable grasp. Also achieving individual control of digits in a person with amputation is highly unlikely.

We thank the reviewer for their comment. We believe the ability to achieve stable individual control of each digit in amputees is a key novelty of this work. We have addressed this comment in the following ways:

1. First, we have greatly expanded the methods section to describe the algorithm we use to provide simultaneous and proportional control of each digit. We emphasize that this algorithm, the modified Kalman filter, has been used in several prior papers demonstrating its ability to regress multiple degrees of freedom in real-time.
2. Second, we also note the limitations of even state-of-the-art approaches like the modified Kalman filter. As the reviewer correctly points out, coordinating control among multiple degrees of freedom in real-time to achieve a stable grasp is difficult. We now reference multiple papers highlighting this challenge for the modified Kalman filter as well as other simultaneous proportional control algorithms.
3. Third, we now more clearly articulate how the shared control enables more coordinated control across multiple degrees of freedom. Most notably, each digit has its own embedded sensors that allow them to

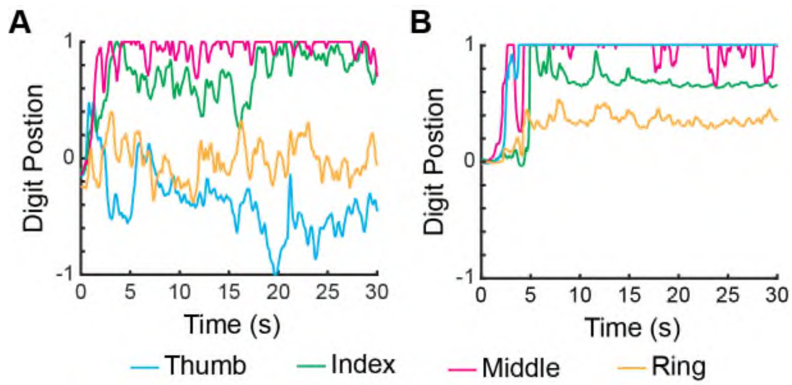
operate independently. In other words, machine control is blended with human control on a digit-by-digit basis. For example, when performing a pinch, the machine control can hold the thumb stationary once it has made contact while also driving the index finger forward towards the point of initial contact. As another example, when performing a power grasp on an irregularly shaped object, the machine can independent set the target point for each digit such that they make contact with the object at different positions. Because each digit is already making contact with the object, the user can simply focus on the level of force they want to apply with each digit, as minor errors in the position of each digit are damped by the more stable machine control. We now provide supplementary figure 6 to show this in greater detail.

<u>Methods (Lines 834 - 847)</u>
"The human position goal, u_h, was computed using a modified Kalman filter (MKF)[42]. The MKF was trained to correlate sEMG features measured from the forearm to kinematic positions. Training data was collected as the participants actively attempted to move their (intact or amputated) hand alongside preprogrammed movements of the prosthesis. Preprogrammed movements consisted of both flexion and extension for the thumb, index, middle, ring, and pinky fingers. Participants completed four trials of flexion and four trials of extension for each digit. The resultant MKF provided the user with proportional position control of all five digits on the TASKA hand. sEMG features used for estimating motor intent consisted of the 300-ms smoothed mean absolute value (MAV) of 528 sEMG channels (32 single-ended channels and 496 calculated differential pairs) calculated at 30 Hz. To reduce computation complexity, the 528 sEMG features were down-selected to 48 sEMG features via Gram-Schmidt orthogonalization[47,108]. The human position goal, u_h, was limited to a range of -1 to +1, where -1 represents maximum digit extension, and +1 represents maximum digit flexion. A nonlinear, latching filter was applied to the human position goal to limit jitter and smooth the human intent for the ADL assessment [46]."

<u>Introduction (Lines 53 – 57)</u>
"Ideally, prosthesis users could similarly control the individual position of each prosthetic digit to generate any arbitrary grasp and exert any desired force. However, simultaneous and proportional control of multiple degrees of freedom is difficult to achieve; as the number of degrees of freedom increases, errors compound, cognitive burden grows, and task performance decreases [13,14]."

<u>Main Text (Lines 278 – 285)</u>
"Human intent was the output of a modified Kalman filter [42] used to regress the kinematic position of each digit using surface EMG[43]. The Kalman filter has been used extensively to proportionally control prosthetic hands with multiple independent DOFs [42,49], but control becomes jittery, error-prone, and cognitively burdensome when controlling multiple DOFs simultaneously [14,46]. The resultant shared control allows for quick and precise position control of each digit individually such that the user can produce a wide range of forces on a given object (Fig. 3D). Allowing the user to control the position of the hand, in contrast to directly controlling force output, is consistent with the brain's natural position-based encoding scheme for the hand[50]."

<u>Discussion (Lines 595 – 598)</u>
"Additionally, the infrared sensors have the added benefit of initiating movement on their own to maximize the number of digits making contact with the object. Combined, the multimodal infrared and pressure sensors provide both a feedforward and a feedback approach to ensure robust operation under uncertainty."



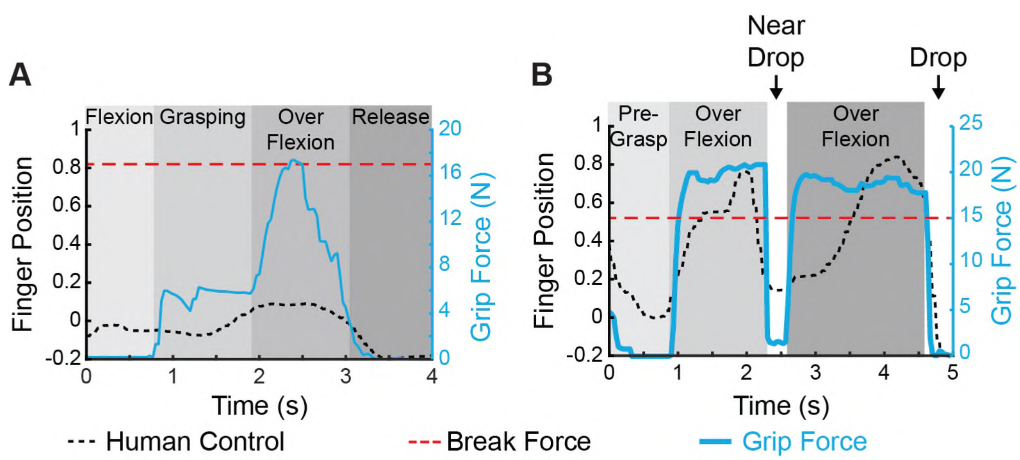
“Supplementary Fig. 6: Simultaneous control of four independent digits during the holding task. A) The first 30 s of the most successful trial with human control demonstrates the degree of noise present in the kinematics as decoded from the 32 sEMG channels via a Kalman filter. When using human control, participants had a difficult time controlling all four digits and maintained the grasp by focusing on maintaining the flexed position of any digit that made contact with the object. Note that while the thumb was not flexed, participants were able to hold onto the ball by squeezing it against the palm. B) In contrast, the first 30s of the most successful trial with shared control demonstrate greater stability across all of the digits. The noise observed in the human controller’s output is diminished due to the exponential scaling in the shared control framework.”

Reviewer 3: Fig. 6: The caption says that the machine prevented grasp force from dropping too low and dropping the object. How did the algorithm know that this minimum force level was?

Thank you for pointing out this inaccurate description. More precisely, it is the machine controller’s contribution to the shared control framework that prevents the participant from dropping the object. As such, we have updated the subtext of Fig. 6 and improved specificity throughout the manuscript.

Reviewer 3: Shared control results in a very erratic and variable grip force up to 5 seconds. Although the summary metrics support the advantages over human control only, it would be helpful to see a typical trial from this same patient using just human control.

Thank you for this recommendation. We have added supplementary figures that demonstrate the human’s control effect on grip force.



“Supplementary Fig. 5: Examples of the human controller interacting with instrumented fragile object. A) An intact-limb participant controlled a pinch grasp to transfer a fragile-object over a barrier without exceeding a break force of 17 N. A Kalman filter decoded 32 sEMG channels to a single DOF. Note how relatively small changes in the decoder’s output result in large changes in grip force once the fingers have made contact with the object. B) Using the same method, an amputee participant controlled a one-DOF tripod grasp to hold the instrumented object while maintaining a grip force below 15 N and not dropping the object. Similar to the intact-limb participant, small changes in the decoded grip position resulted in large, fast changes in the grip force, resulting in exceeding the break threshold and dropping the object.”

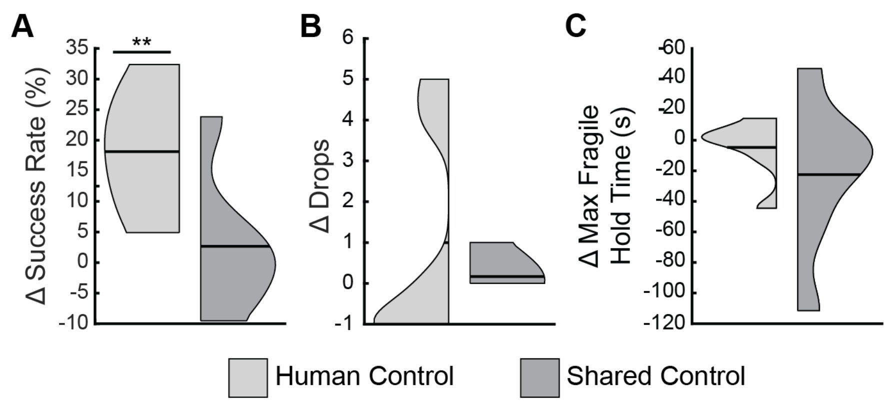
Reviewer 3: Also, was any training time provided for the subject? The human control might improve significantly with more exposure to the apparatus.

Additional details regarding training time are now provided in the methods section. We have also included Supplementary Figure 7, which demonstrates that no learning was detected between any of the shared control experimental blocks. Additionally, future work outlining experiments to quantify the learning rates associated with human and shared control is proposed in the discussion section, as previously discussed.

Methods, Fragile Holding Task (Lines 920 – 921)
“Participants were given up to 1 minute to practice before each experimental block.”

Methods, Holding Task (Lines 936 – 937)
“Participants were given up to 1 minute to practice before each experimental block.

Methods, Fragile Holding Task (Lines 956 – 960)
“Participants were given up to 15 minutes to practice before each experimental block. The additional practice time enabled participants to learn how to use the shared and human control, as both control schemes were from the direct-drive control that many of them were familiar with. If participants felt comfortable with the given control scheme, then they could forgo the remainder of their practice time.”



“Supplementary Fig. 9: Learning effects across the experiments for both controllers. The main experimental outcomes from the first experimental block were compared to the second experimental block. The resulting distribution was then compared to a zero-mean normal distribution to assess if any potential learning occurred between trials. A) A significant increase in performance between the first and second experimental blocks of the fragile-object transfer task was detected for the human controller ($p <$ 0.01, paired t-test), indicating that participants improved their performance with the human controller across the course of the experiment. No significant difference was detected between trials for the shared controller. B) No significant learning effects were detected for the human or shared controller within the holding experiment. C) No significant learning effects were detected for the human or shared controller within the fragile-holding experiment. “

Reviewer 3: Furthermore, responding to audio input when squeezing too hard is not a task that is useful in ADL. The methods describe an object that actually “breaks” when the force is too high. Why not use this object?

We have modified the manuscript in the following ways to address this point:

1. First, we modified the manuscript text to more clearly state that we used two different “fragile” objects for this manuscript. The first is a mechanical object with an embedded magnet that actually “breaks” when the force is too high. The second is an instrumented 3D-printed object with an embedded strain gauge that

measures the exact force applied to the object; instead of mechanically “breaking” the 3D-printed object emits a sound and changes color to indicate the user has “broken” it.

2. Second, we now clearly describe the benefit of switching to the instrumented 3D-printed object. We note that the instrumented version allows for continuous measurement of grip force which was used to quantify grip precision.
3. Third, we have also modified the manuscript to provide some clinical relevance to the task. We now emphasize different activities of daily living where maintaining a precise grip force is vital (e.g., pouring from a cup without crushing it, transferring an egg without breaking it). We also connect the fragile object tasks in Figs 4, 5, and 6, to the selected activities of daily living in Fig 7.

Main text (Lines 321 - 324)
“This time, however, we embedded a strain gauge into the “fragile” object[51,52] to track the cumulative force exerted on the object by the hand (Fig. 4A). Measuring the grip force enabled us to analyze the range of grip forces under shared or human control, rather than just whether the participant exceeded a predetermined force.”

Main Text (Lines 539 - 533)
“Three tasks stood out: bringing a disposable cup to their mouth, transferring an egg between two plates, and picking up a piece of paper (Fig. 7). Each of these tasks corresponded to one of the grasps used in the prior experiments. Drinking from the disposable cup used a power grasp (Fig. 5A), moving the egg used a tripod grasp (Fig. 6A), and moving the piece of paper was completed with a pinch grasp (Fig. 4A).”

Main Text (544 – 549)
“To this end, we quantified the speed and success rate of one participant as they completed six trials of the drinking task with disposable cups, during which they attempted to pick up the cup from the table, bring it to their mouth and mime a sip, and then return it to the table. This real-world activity of daily living is considerably difficult. These common disposable cups break with approximately 7 N; in contrast, the fragile holding task required the amputees to maintain forces below 15 N.”

Fig. 7 subtext
“Fig. 7. Shared control supports activities of daily living**.** Participants completed various ADLs with and without shared control. Shared control was particularly helpful for tasks that involved a precise grasp and grip force, including, lifting a disposable cup to their mouth without crushing it using a power grasp (A), moving an egg without breaking it using a tripod grasp (B), and picking up a sheet of paper without crinkling it using a pinch grasp (C). One participant also attempted to drink out of a disposable cup six times with both control algorithms (D). Under shared control, the participant successfully lifted the cup to their mouth and set it back on a table four times, but was unable to do so a single time with human control alone. E) No significant differences were observed in the time it took for the participant to make a grasp that they felt confident in and lift the cup up to their mouth.”

Methods, (Lines 904 - 910)
“Six intact-limb participants completed a fragile-object transfer task with the Electronic Grip Gauge (EGG)[63]. The EGG consists of a weighted 3D-printed block containing a load cell and accelerometer to measure grip force and lift force, respectively. Similar to the mechanical fragile object, the EGG would emit a sound when the grip force exceeded a threshold. As opposed to the pass-fail nature of the mechanical fragile object used to evaluate the autonomous controller, the EGG provides time series data, allowing for a deeper analysis of how different control schemes might affect grip force, such as analyzing the average or peak grip forces.”

Reviewer 3: For the healthy control testing, were subjects naïve to the apparatus or were they well practiced with EMG control of bypass devices.

Thank you for pointing out this ambiguity. We have modified the manuscript to state that all intact-limb participants were naïve prosthesis users.

Reviewer 3: Fig. 7: It is disappointing that there is only a qualitative description of the results with real ADL. Is it not possible to report the number of eggs broken for each subject under machine vs. shared control?

As noted above, we have modified the manuscript in the following way to address this comment:

1. We collected additional pilot data of an amputee participant completing a simulated drinking task to assess how shared control might improve ADLs. The results of this experiment have been added to the main text and Fig. 7.
2. We believe the next step for this research is a take-home trial where users test the shared control framework outside of the laboratory in their day-to-day life and quality of life and usability metrics are reported. Although this is outside of the scope for this initial manuscript, we have noted this limitation of the present study and have expanded the discussion to outline this critical future work.

Main text (Lines 538 - 554)

"Occupational therapists often rate amputee patients' performance on activities of daily living using subjective graded scales. For example, the Activities Measure for Upper-Limb Amputees (AM-ULA) scores amputees on 5 categories: extent of completion, speed of completion, movement quality, skillfulness, and independence. Although the activities completed with AM-ULA are not well-suited for next-generation prostheses capable of a delicate touch[41,66,67], the rate and speed of completion score criteria are quantitative and can easily be applied to other activities of daily living. To this end, we quantified the speed and success rate of one participant as they completed six trials of the drinking task with disposable cups, during which they attempted to pick up the cup from the table, bring it to their mouth and mime a sip, and then return it to the table. This real-world activity of daily living is considerably difficult. These common cups break with approximately 7 N; in contrast, the fragile holding task required the amputees to maintain forces below 15 N. Under human control, the participant crushed the cups five out of the six trials and dropped it twice (Fig. 7D). However, with shared control, the participant successfully completed the task four out of the six times. No significant difference in the task speed was observed; the participant took 9.67 ± 3.27 s to make a grasp and lift the cup to their mouth with human control, and only 7.60 ± 2.59 s with shared control ($p = 0.26$; unpaired t-test; Fig. 7E)."

(Redacted)

Fig. 7. Shared control supports activities of daily living. Participants completed various ADLs with and without shared control. Shared control was particularly helpful for tasks that involved a precise grasp and grip force, including, lifting a disposable cup to their mouth without crushing it using a power grasp (A), moving an egg without breaking it using a tripod grasp (B), and picking up a sheet of paper without crinkling it using a pinch grasp (C). One participant also attempted to drink out of a disposable cup six times with both control algorithms (D). Under shared control, the participant successfully lifted the cup to their mouth and set it back on a table four times, but was unable to do so a single time with human control alone. E) No significant differences were observed in the time it took for the participant to make a grasp that they felt confident in and lift the cup up to their mouth.

Discussion (Lines 638 – 644)

“We demonstrated that shared control can generalize to a variety of objects and grip patterns common in activities of daily living. However, this does not necessarily mean that shared control will generalize well to everyday real-world use. A long-term at-home clinical trial with multiple participants is necessary to validate real-world generalizability and to demonstrate improvements in independence and quality of life. Such a study could also answer questions regarding the impact of shared control on prosthesis adoption and learnability.”

September 17, 2025.

Response to Reviewers

We would like to thank the reviewer for their additional insightful comments. In response, we have further revised the manuscript. A brief summary of the changes is provided below:

- We have condensed the introduction and discussion where possible without removing content previously requested.
- We moderated generalizability claims.
- We discuss how the collected experimental results transfer to common clinical assessments.

We believe that the manuscript has been further improved with these changes.

Point-by-Point Responses

Reviewer #2: The core method proposed in this study involves installing pressure and proximity sensors at the fingertips of a prosthetic hand, allowing the hand to automatically approach and gently touch the object being grasped through machine control. The user then applies further control via EMG to improve the prosthetic hand's control performance. Although this method yielded good results in the experiments designed by the authors, it relies on a machine control loop based on fingertip sensors. As a result, this method cannot be applied to most prosthetic hands that do not have such hardware, limiting its scalability and universality. The authors mention in the discussion that shared control can be integrated into commercial prosthetic hands. However, this integration involves modifications to the manufacturer's processes, as well as adaptations to the structure and circuitry, which is far from straightforward. Furthermore, whether this technology can replace traditional myoelectric control still requires further validation. The authors should avoid using such exaggerated descriptions.

We would like to thank the reviewer for their additional insights to improve the manuscript. We have tempered the language around translation and updated the manuscript to propose a path to implement this shared control approach in commercial prostheses.

1. We have softened the language regarding translation throughout the manuscript.
2. The sensors used in this trial were designed to be retrofitted on multiple existing, nonsensorized hands, such as the beBionic. We have added text regarding the availability of the sensorized fingertips in the methods and discussion.
3. Although commercial prostheses lack proximity sensors, many do contain torque or force sensors. As such, we have proposed a means to retool the shared control algorithm to operate with existing prostheses. We have also added qualifications that some commercial prostheses lack the proper sensors for any shared control approach.
4. We have moderated the language around translation and included discussion of future work to validate the shared control strategy in take-home trials to assess its impact on patient quality of life.

   Discussion (Linex 567 – 570)
   "In principle, the shared control algorithm presented here could operate with only a single modality that detects contact. The algorithm presented in this work could, in theory, operate using the fingertip pressure sensors already available in commercial hand prostheses[1,68,69]."

   Discussion (Lines 580 – 582)
   "With this in mind, the fingertip sensor modules used in this work have been designed to be retrofitted onto different commercial prosthetic hands, providing a straightforward means to translate the shared control algorithm as is[37]."

   Discussion (Lines 667 – 674)
   "Commercial myoelectric prostheses are usually controlled in an open loop with no explicit feedback. The few commercial prostheses with feedback typically use motor current to indirectly estimate and limit exerted force. However, there is a recognizable trend of more commercial bionic hands becoming more sensorized with multiple pressure sensors across the hand[1,68,69]. Embedded pressure sensors allow for faster reactions and gentler forces and maintain functionality during passive interactions in which the motors are not active. As sensor arrays become more common in commercial bionic hands, shared control work will become more relevant and impactful."

   Methods, Sensorized Fingertips (Lines 754 – 755)

“The housing of the fingertip sensors was designed in multiple form factors to fit different commercial bionic hands, but only the TASKA form factor was used in this work.”

Reviewer #2: The discussion on the mismatch between the machine's intent and the user's intent is overly simplistic. Fine motor tasks and dexterous manipulation are important application scenarios for prosthetic hands, such as using the prosthetic hand to screw on a bottle cap. This task requires the user to continuously adjust the contact force and position between the prosthetic hand and the object. Under such conditions, the proposed machine control, which automatically brings the prosthetic hand closer to the object during proximity, may interfere with the user's fine motor control intentions. The authors need to clarify this point further.

To ensure that we have not exaggerated our results, we have softened the language around translation to fine motor ADLs.

Discussion (Lines 611 – 618)
“These examples provide a rough baseline for how the system might behave under relatively simple conditions. However, the impact of more complex sensorimotor tasks, like opening a bottle cap or tying shoelaces remains an important question worthy of future research.”

Reviewer #2: Additionally, some classic prosthetic hand assessment tasks, such as the Box and Block Test (BBT) and Southampton Hand Assessment Procedure (SHAP), could be considered to further demonstrate the applicability of this method to different tasks, rather than just its effectiveness for simple static grasping.

While comparing performance across validated clinical functionality assessments would improve the impact of the work, we believe that this work is beyond the scope of the current manuscript, and neither the Box and Blocks test nor the SHAP test would enhance the scientific rigor.

1. We argue that completing the Box and Blocks task would be redundant, as we already validated the system using a precision pinch grasp in a fragile-block transfer task, which is ecologically similar and correlated with the Box and Blocks transfer task.
2. The SHAP test could be a beneficial assessment for evaluating real-world usefulness, but it is unfortunately no longer available for purchase (https://www.shap.ecs.soton.ac.uk/) and therefore has limited value as a standardized clinical assessment. We would need to recreate the objects used in the SHAP test, which, in essence, we have already done. The manuscript, as it stands now, demonstrates reliability across different objects/shapes (blocks, spheres, cylinders) and across different activities of daily living, very much in line with the spirit of the SHAP test.
3. Recognizing the spirit of the reviewer’s comment, we have modified the manuscript discussion to mention the importance of validating the shared control system on primary endpoints for reimbursement decisions, such as patient reported outcomes or standardized functional assessments like the AMULA.

Discussion (Lines 624 – 634)
“We demonstrated that shared control can generalize to a variety of objects and grip patterns common in activities of daily living. Indeed, the tasks performed mimicked standard clinical tasks to assess patient functionality. For example, the fragile-object transfer task is effectively a more difficult version of the box and blocks tasks, and the holding tasks with different-shaped objects is similar to portions of the Southhampton Hand Assessment Procedure[74]. However, this does not necessarily mean that shared control will generalize well to everyday real-world use. A long-term at-home clinical trial, along with modern clinical

assessments, like the Activities Measure for Upper Limb Amputees (AMULA)[75], is necessary to validate real-world generalizability and to demonstrate improvements in independence and quality of life. Such a study could also answer questions regarding the impact of shared control on prosthesis adoption and learnability."

Reviewer #2: The authors have enhanced the introduction and discussion sections, providing the reader with a clearer understanding of the background and relevant details of the proposed method. However, these sections are overly lengthy and should be condensed while retaining the key information.

We have modified the manuscript to make it more concise. We try to strike a balance between being more concise and including the information that was requested by other reviewers. As such, we have made edits throughout the introduction and discussion to improve readability.

Reviewer #2: Moreover, the overall system framework is presented in Figure 3, but the figure remains relatively simple. It could benefit from additional information, such as a comparison of key parameters between the proposed method and other methods, as well as a schematic diagram of the DRT experiment, to help readers quickly grasp the core content of the manuscript.

We have added additional content to Fig. 3 to improve the clarity of the manuscript. Specifically, we have added a subfigure that outlines the primary tasks and the secondary DRT.

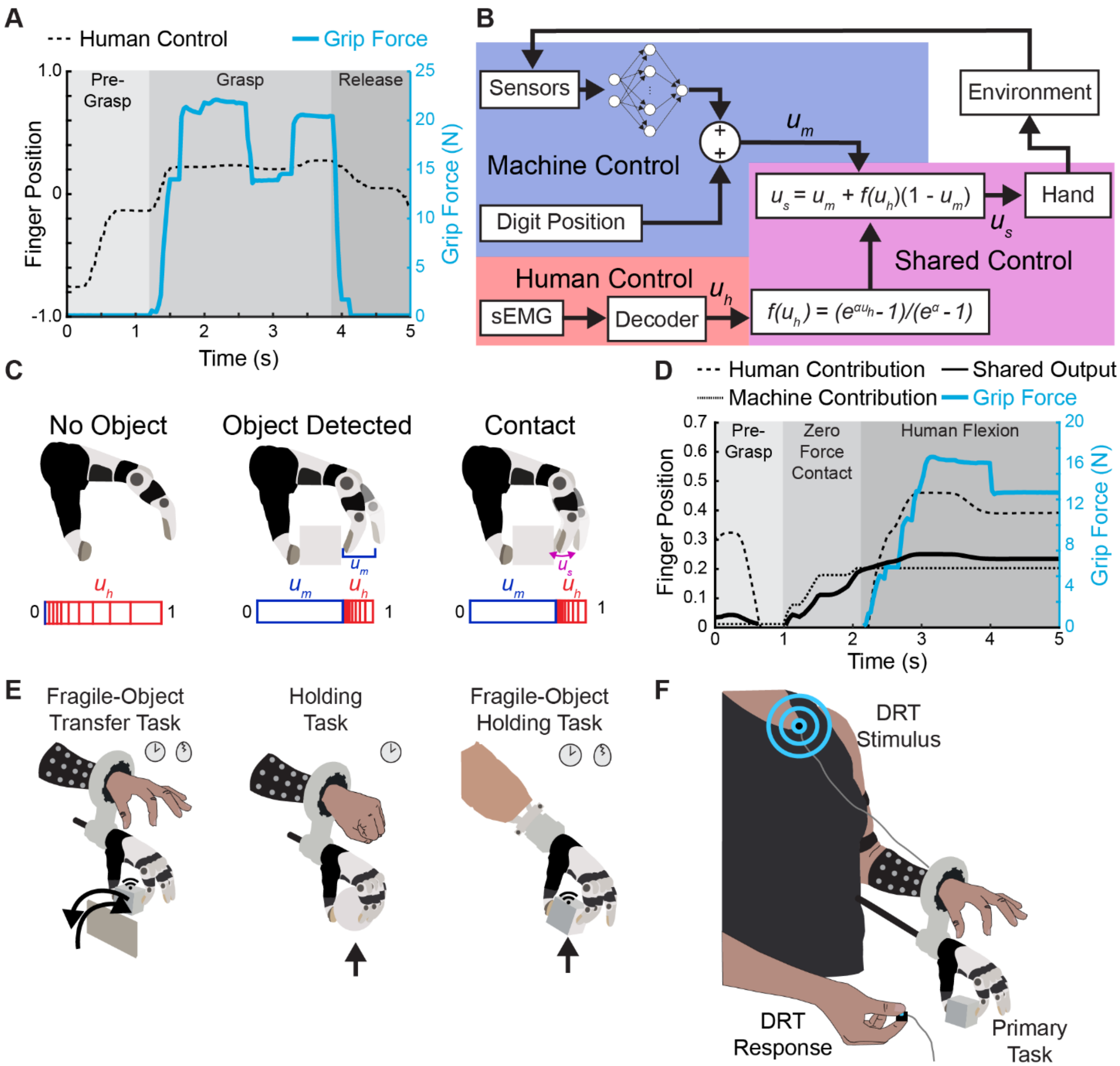


Fig. 3. Machine assistance using shared control. A) Proportional position control of multiple digits is difficult to achieve with surface EMG alone, as small changes in the digit's position (dashed line) can cause rapid changes in the grip force (blue line). B) The shared control algorithm continuously combines human (uh) and machine controllers (um) to compute the position (us) for each digit using a dynamically weighted sum. Neither controller is ever completely in control of the hand, as the controllers are continuously shared. Machine control was an MLP that estimated the distance to make contact with an object from proximity data. Human control was the movement about the contact point as decoded from surface EMG. Human control was modified by an exponential function to enhance precision about the contact point. C) If no object is detected, the shared control output is based solely on the human control. The box and hashmarks show the range and precision of the human contribution (red) being remapped exponentially to enhance shared control precision. When an object is within proximity, the machine's contribution (blue) moves the digit to make contact. The human contribution is then remapped to the remaining range of motion, enabling users to make fine

adjustments to their grasp. D) With shared control, the user extends their grasp as they reach towards the object (0 to 1 s). The machine then moves the digit to the object, and the user attempts to lift the object while making zero-force contact, but is unable (~1 to 2 s). The user then tightens the grasp around the object (~2 to 5 s). It is important to note that the shared control algorithm continuously blends the user's intent with the autonomous hand, rather than in a sequential manner. E) To validate the shared control algorithm, intact limb participants completed fragile-object transfer and holding tasks, and tranradial amputee participants completed a fragile-object holding task. F) All participants also completed a detection response task (DRT) alongside each primary task, which consisted of pressing a button in response to a randomly timed vibrotactile stimulus.