https://doi.org/10.20965/jrm.2021.p0987

Review:

Transparency in Human-Machine Mutual Action

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[Received April 4, 2021; accepted June 14, 2021]

Recent advances in human-computer integration (HInt) have focused on the development of human-machine systems, where both human and machine autonomously act upon each other. However, a key challenge in designing such systems is augmenting the user's physical abilities while maintaining their sense of self-attribution. This challenge is particularly prevalent when both human and machine are capable of acting upon each other, thereby creating a human-machine mutual action (HMMA) system. To address this challenge, we present a design framework that is based on the concept of *transparency*. We define transparency in HInt as the degree to which users can self-attribute an experience when machines intervene in the users' action. Using this framework, we form a set of design guidelines and an approach for designing HMMA systems. By using transparency as our focus, we aim to provide a design approach for not only achieving human-machine fusion into a single agent, but also controlling the degrees of fusion at will. This study also highlights the effectiveness of our design approach through an analysis of existing studies that developed HMMA systems. Further development of our design approach is discussed, and future prospects for HInt and HMMA system designs are presented.

Keywords: human-computer integration, transparency, human-machine mutual action, human augmentation

1. Introduction

Over the ages, tools have been designed with consideration to the task and user. In some cases, people have learned to use tools as well as they can use their own body, thereby embodying the tools. Tools have evolved into machines equipped with intelligence. This new class of tools has opened up a new avenue for human augmentation which offers unprecedented capabilities: human-computer integration (HInt) [1].

In HInt, one of the major goals for designers is to construct systems where users and machines act as a single fused agent, which results in a human with augmented physical abilities. Here, the term "machine" refers to an artificial agent equipped with sensors to obtain information regarding the human's behavior and the environment, computers to process the information and make decisions, and actuators to act upon the human and the environment. The machine may be physical (e.g., robotic arms [2], exoskeletons [3–5], and electric muscle stimulation [6, 7]), as might first come to mind. Alternatively, it may be virtual (e.g., an avatar in a virtual reality environment [8, 9]); it may implement sensing in a virtual world and act on virtual objects to indirectly affect human behavior. The main difference between traditional tools and machines is the latter's ability to act autonomously. Thus systems seeking to achieve HInt can contain more than one independent agent, which results in a system with mutual action between human and machine. We refer to such systems as human-machine mutual action (HMMA) systems, and we believe that these systems are the future of fused human-machine systems.

The machine's independence results in a new design challenge that is not present in traditional tools, i.e., designing HInt systems to augment the user's ability while allowing the user to attribute actions to themselves [10]. Owing to the machine's agency, it is capable of acting without human involvement. This can cause it to act outside of the user's intentions, causing the user not to attribute the system output as their own action. For example, if the machine intervenes in the user's action, the user may notice the intervention and may not self-attribute the fused action (i.e., the actual outcome including the intervention). One approach to solving this particular issue is to reduce the intervention so as to be unnoticeable. However, this presents another challenge. If the intervention

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is too small, the user's abilities cannot be effectively augmented. Thus, there is a trade-off between augmentation and the attribution of agency. Therefore, the key challenge for designers is to manage this trade-off and implement HInt systems which augment the user's abilities while maintaining their sense of self-attribution during fused actions.

Herein, we present approaches and a design framework to tackle this challenge based on the concept of human-machine *transparency*. The history of transparency as an analogy to assist in design is long and diverse. In the field of human-computer interaction (HCI), transparency is used as a metaphor to qualitatively describe how the interface is experienced by the user [11]. For instance, in haptic interfaces, transparency refers to how noticeable the interface is to the user when it is not actively presenting any stimulus. This measure is widely used as an indicator to evaluate the performance of a device [12]. Namely, the less noticeable the interface is when not in use, the more transparent the interface is to the user, and the better the device. We draw from these previous works that discuss transparency in their respective domains to construct a novel framework to guide the design of HInt systems.

In this paper, we define transparency in HInt as a notion of how much users are made aware of the machine side of the human-machine system. Thus, a highly transparent system is one where the users feel that they are directly interacting with the environment, without being made aware of the presence of any machines and their intervention. By forming a design framework around this concept of transparency, we are able to identify the extent to which the machine can intervene in the user's actions without compromising how much the user self-attributes the experiences. Designing around the concept of transparency provides a direct way of assessing how well a HInt system will integrate.

To assist in applying our concept, we suggest that transparency in HInt can be subdivided into two types, which can each be linked to one of the more traditional uses of transparency as an analogy:

1. Perceptual transparency: How users feel when achieving direct sensory access to the target information, even with the mediation of sensory information by the machine.
2. Action transparency: How users feel the sense of agency for outcomes, even with intervention from a machine.

While not independent (e.g., high perceptual transparency contributes to improving action transparency), this subdivision provides a useful perspective of the aspects of system design that must be considered to achieve system transparency. Thus, along with providing the transparency design framework, we propose a transparency-based design approach for HInt systems which places an emphasis on controlling transparency in HMMA systems (**Fig. 1**).

To elucidate our design approaches, we first provide a review of the traditional transparency to which our concepts are linked (haptic transparency and sense of agency, respectively), and we describe the components of our transparency-based framework to which they correspond. Then, we describe guidelines to design transparency in a system and what some of the objectives of designing transparency may be. Finally, we introduce design approaches for HMMA systems based on the framework of transparency. We conclude with concrete examples of previous works which resemble HMMA systems and discuss future directions that can be developed using our concept, including free and continuous control of transparency to achieve degrees of fusion in HMMA systems. We envision that our design framework will pave the way for designing HMMA systems, i.e., a new class of human-machine systems in which designers can control how the user embodies the machines.

2. Perceptual Transparency

We begin by discussing system transparency in terms of human perception. The idea of perceptual transparency is, in and of itself, not a new concept. Transparency has been widely discussed in the field of interface design, particularly regards to haptics [12–14]. In the field of haptics, transparency refers to the feeling that there is no interface. When touching a remote/virtual environment through a highly transparent interface, the interface conceals its presence and allows the user to have direct sensory access to information. This concept has been widely used as a measure of performance in the domain of haptics. Thus, we first review how the concept of haptic transparency before building upon existing definitions of transparency to propose a new generalized definition for perceptual transparency, i.e., the degree of congruency between sensory predictions and perceived sensations.

2.1. Transparency in Haptic Interfaces

The transparency of an interface, particularly in the context of a force presentation, is commonly referred to as haptic transparency, and is widely used as an indicator for evaluating the performance of a device [12–14]. Perfect haptic transparency is defined as the state in which the impedance on the operating side and that on the side of the remote or virtual environment are the same [12]. For example, a haptic interface with high haptic transparency is characterized by low inertia and high back-drivability; thus, it reproduces the sensation of not touching anything in conditions where no forces should be presented [15]. Given a perfectly transparent haptic interface, the user should perceive forces only when touching a virtual or remote object, and when touching the object, experience haptic sensations identical to those that they would experience if they were actually touching the object. In contrast, a haptic interface with low haptic transparency would make the user aware of the device at all times. The

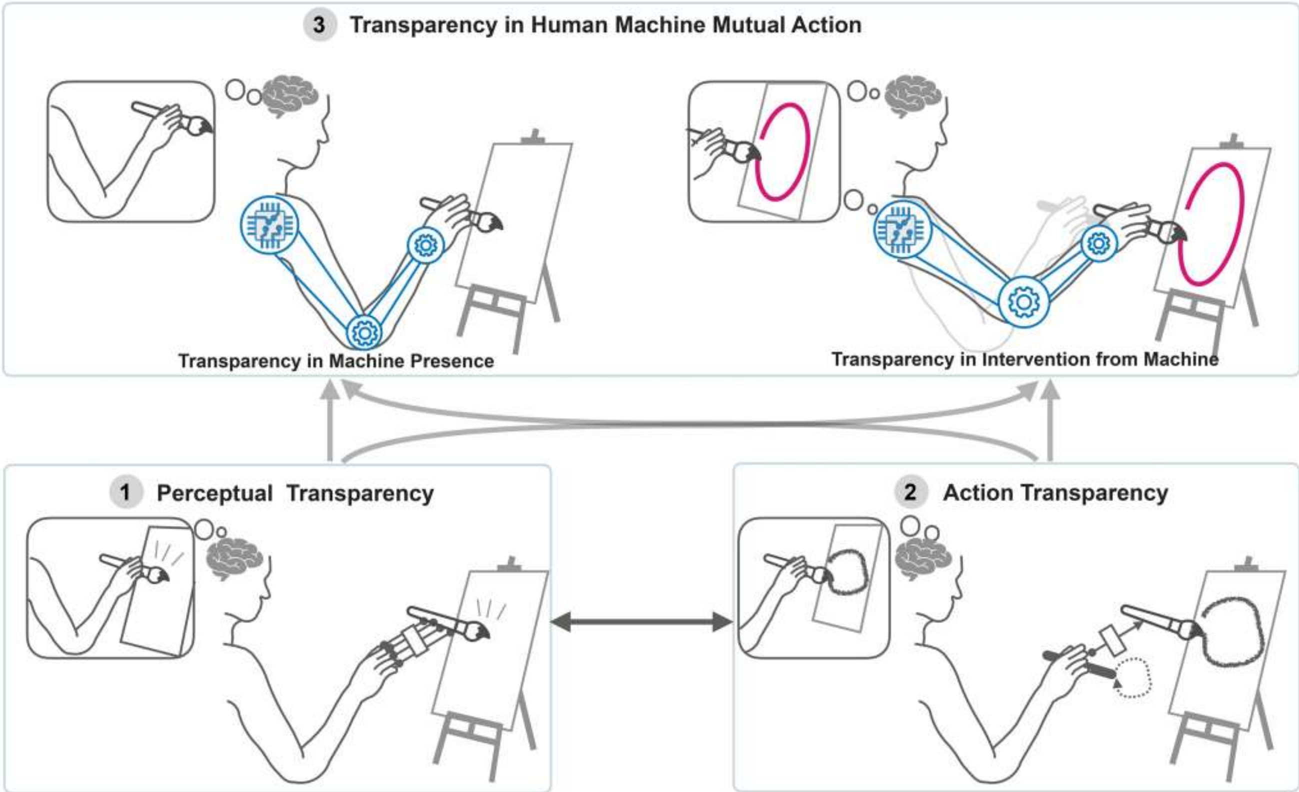

Fig. 1. Transparency-based design framework for human-computer integration (HInt), where humans and machines become an integrated agent. We define two major aspects of transparency in HInt, which directly expand on previous studies: perceptual transparency and action transparency. The former, ①, refers to how strongly users feel that they are directly accessing sensations; the latter, ②, refers to how strongly users feel a sense of agency in human-machine action outcomes. Then, based on these concepts of perceptual and action transparency, we describe approaches to achieve transparency in human-machine mutual action. These approaches, ③, seek to design two key aspects of the machine: its presence and its intervention.

user would feel resistance owing to inertia and gear friction when operating the end-effector, and they would feel forces where there should be none.

The conditions and specifications required to achieve perfect haptic transparency for humans were identified by Millet et al. [16]. Their specifications, defined based on the absolute threshold of human perception, are extremely difficult to achieve. Although a number of studies have been conducted to optimize mechanical systems and control based on fast sensing to achieve high transparency (e.g., [17]), these studies have yet to achieve perfect transparency with current technology. Another approach, encounter-type haptic presentation, has successfully achieved perfect transparency in limited contexts. Encounter-type haptic presentation is designed such that physical contact occurs between the user's body and haptic presentation device only when the user is touching a virtual object [18, 19]. Because there is no contact when no contact is supposed to be presented, this approach achieves perfect transparency until the moment of contact. However, achieving perfect transparency after contact is made remains an open issue. Thus, the pursuit of transparency in haptics research has focused on the challenge of providing a transparent window for humans to access objects in an information space with haptic sensations through machines. Therefore, the idea of haptic transparency is, and remains, an important issue and measure in the domain of haptic interfaces. However, we suggest that the metaphor of transparency can be extended beyond the domain of haptics, and that it can be generalized as a measure of perceptual system performance.

2.2. Perceptual Transparency in Human-Computer Integration

As mentioned at the beginning of this section, we propose a new measure for a system's perceptual transparency in HInt. This transparency is defined as the extent to which users can feel that they are directly accessing a target sensation with the information. This can be achieved by matching a predictive model for human senses with the actual senses as perceived.

In each situation shown in **Fig. 2**, a human perceives an object through a system (computational layer). The first three situations demonstrate how a system can appear transparent to the user. In the first situation, there is no system intervening between the human and the environment, thereby enabling the human to perceive the object directly, as shown in **Fig. 2(a)**. Clearly, in this case, there is no system to perceive between the human and the object; thus, the computational layer is transparent. In

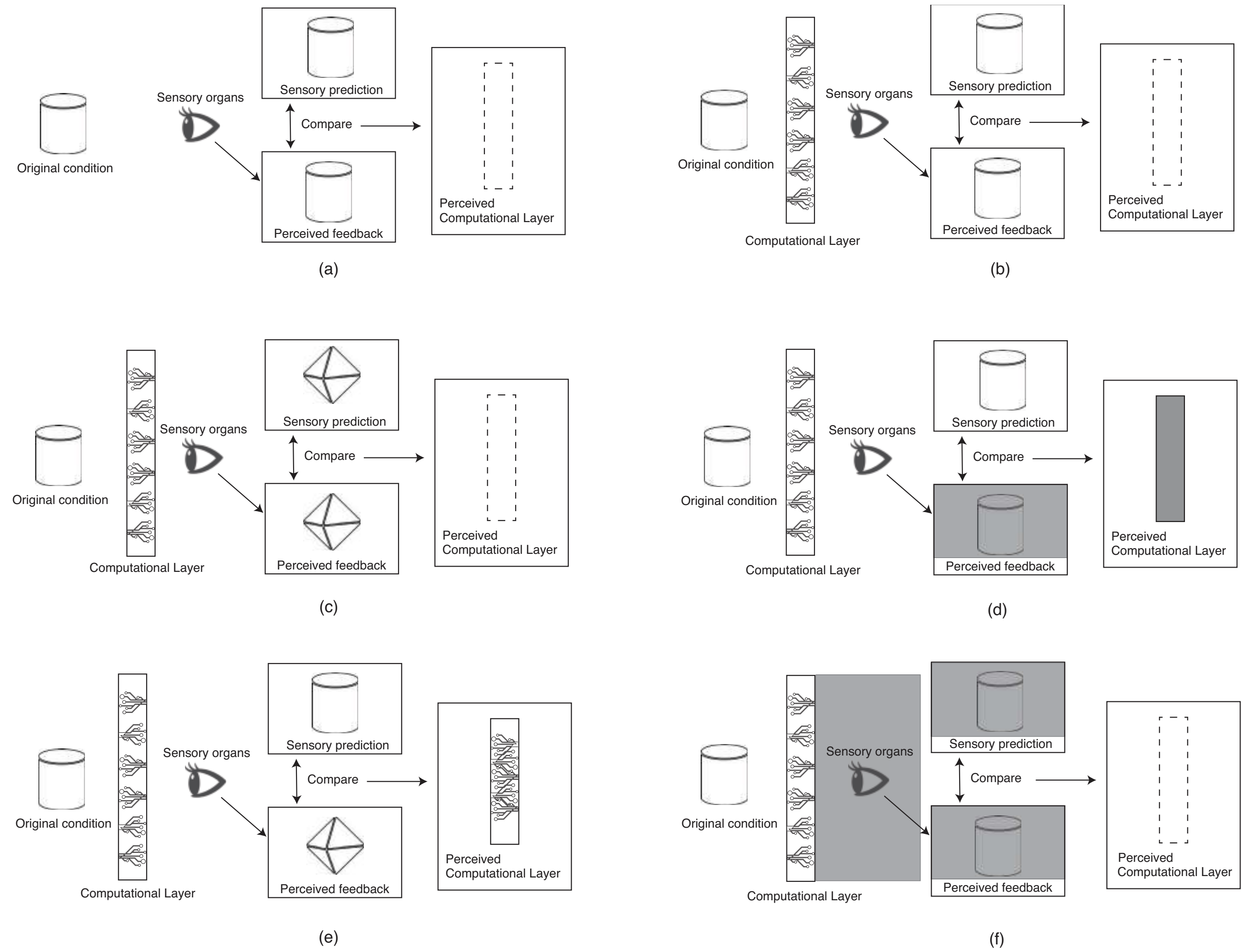

Fig. 2. Perceptual transparency in human-computer integration. Perceptual transparency can be realized through various conditions of the environment, perceived feedback, and prediction.

the second situation, a computational layer exists, but it presents a human with a sensation that is consistent with the original condition, as shown in **Fig. 2(b)**. In this case, the system becomes transparent, as there are no cues indicating its existence of the system. In the third situation, the system intervenes significantly, and it changes the original object (a cylinder) into an octahedron, as shown in **Fig. 2(c)**. However, if the octahedron is what the human expects to perceive (i.e., the perceived sensation is within the range predicted by the human), the system is perceptually transparent to the user.

The next two situations demonstrate how a system can appear non-transparent to the user. In the fourth situation, the system attempts to replicate a sensation that is consistent with the original condition; however, it does not have sufficient specifications (dynamic range, resolution, drive frequency, etc.) to do so, as shown in **Fig. 2(d)**. In this case, the human perceives the presence of the system. This situation is similar to what occurs in haptic transparency (i.e., insufficient performance to sufficiently replicate tactile sensations). In the fifth case, the system presents an octahedron when the user knows that the original object is a cylinder, as shown in **Fig. 2(e)**. In this case, the user becomes aware of the computational layer because of the mismatch between their prediction and perception. This case shows that, even if the system is capable of replicating sensations to a high degree, if the sensory presentation differs from the human's expectation, the human will notice the system's intervention and become aware of its presence. This can occur in multimodal situations, for example, when a presented tactile stimulus does not match the visual stimulus. Whereas multimodal mismatches can degrade transparency, multimodal congruency can improve the transparency of a system. For example, Shifty creates an immersive experience by matching tactile sensations to vision, and predicting the sensations that correspond to a visually presented tool [20].

Finally, the last situation demonstrates how context can temper expectations and cause the computational layer to appear transparent. In this situation, the system is unable to present a clear perception of the original object to the user (e.g., owing to low specifications). Thus, the system presents an unclear (e.g., foggy) representation of the object to the user. However, the user is in an unclear context (e.g., in a fog); therefore, they expect their perception of the object to be unclear. As a result, the computational layer appears transparent to the user, as shown in **Fig. 2(f)**.

Namely, the unclear nature of the sensations that the computational layer presents to the user is attributed to the context (e.g., environment, nature of the object) instead of the system, thereby rendering the system transparent. In concrete terms, this can refer to attributing the fuzziness of a video feed to environmental noise, such as a literal snowstorm, instead of signal transmission noise. Human perceptual characteristics, such as Weber-Fechner's law, can also affect the tempering of expectations and perceptions. Weber-Fechner's law states that when the intensity of a stimulus is strong, the noticeable difference in the stimulus increases. Thus, when the stimulus intensity is strong, the range of sensations that are judged to be the same also increases. As a result, a wider range of sensations may be deemed to be "within expectations" when the stimulus is stronger. Therefore, it is necessary to consider the possible states of both humans and the environment when designing a system and its interventions for transparency.

By formulating a generalized concept for perceptual transparency, we broadened the scope of discussion from a HInt component scale (i.e., haptic transparency) to a HInt system scale. Using our definition of perceptual transparency, it becomes possible to discuss how the presence of a machine constructed from multimodal stimuli can be made transparent to the human user. If sensations are relayed to the user according to their expectations, the user may feel that the machine is not present and/or not intervening in their perceptions or actions. Achieving transparency in the machine's presence in this way can result in a deeper level of HInt and improvements in the subjective experiences of human augmentation. For example, with sufficient transparency, users may experience fusing with the machine, where they deem the machine as part of themselves. Alternatively, sufficient transparency may make the user unaware of the machine and its interventions. In this case, users would have no choice but to attribute their augmented abilities to themselves, leading to a strong sense that their abilities have been augmented. Thus, the concept of perceptual transparency can serve as a valuable lens through which HInt system designers can view their systems.

3. Action Transparency

Perceptual transparency should be considered in HInt design, regardless of the state of the human activity. For example, perceptual transparency should be considered in both passive (e.g., static sensory experiences, passive motions) and active (e.g., voluntary actions) conditions.

However, perceptual transparency is not the only type of transparency that must be considered in HInt. In active conditions, an essential factor of transparency is the user's sense of agency in the outcomes, including intervention from the machine. Thus, we define action transparency as a subdivided component of transparency regarding the user's sense of agency, as mentioned in Section 1.

According to studies on motor learning and perception in the neurocognitive domain, a sense of agency is closely related to the motor learning process in the internal model of the brain [21–23]. In the internal model, the comparison between efferent information (motor predictions generated by an individual's internal model) and afferent information (i.e., sensory feedback resulting from the actual outcome) is used to optimize prediction [24–27]. Several studies have suggested that this sensorimotor comparison process underlies the sense of agency [22, 23, 28, 29]. Therefore, understanding the mechanisms of motor learning and perception is important when designing the user's sense of agency in HInt systems.

Thus, we first review previous studies on the mechanism of motion learning in the internal model and the latest accounts of the sense of agency. Then, we describe the definition of action transparency based on account of the sense of agency and design techniques to modify the user's action using computational interventions while maintaining action transparency.

3.1. Mechanism of Human Motor Systems

Humans are adept at controlling their bodies both quickly and accurately. Theories of motor control postulate that this is because the brain has internal models that it uses to predict sensory action feedback and generate the motor commands needed to realize the desired action *a priori*. The mechanisms of motor control and learning have been discussed over several decades. Much of this discussion is based on the concept of comparison processes, which update the internal models [24–27]. The internal models in the motor system can be considered to be a type of control system. The model receives the desired state, in the form of an explicit goal, as input and generates motor commands to achieve this based on past experience.

Previous studies proposed that this system consists of two primary types of models: forward models and inverse models. Forward models allow the motor system to predict sensory feedback by using efference copies of the motor command. Inverse models allow the motor system to determine the motor commands that are necessary to achieve the desired state. These models are dynamically adaptable to various contexts. For example, motor systems can acquire both forward and inverse models that include the control of external objects, such as tools, such that they are considered an extension of the body [30–32].

Internal models are continuously updated and adapted (e.g., improving accuracy of controls, prediction and optimizing to the current contextual state) by different comparator mechanisms [33, 34]. In general, a comparator in a feedback control loop allows a system to improve its functionality by calculating the error between the desired state and actual state, which is estimated based on sensory feedback. This error is then used to update the con-

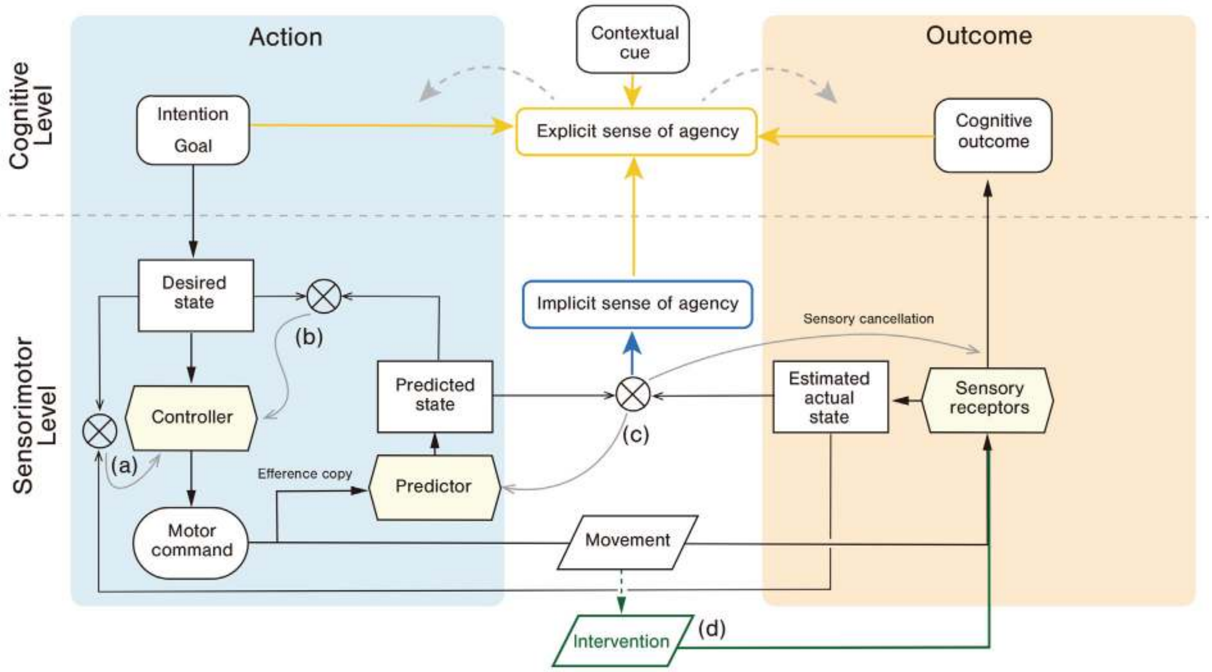

Fig. 3. Model detailing the mechanisms of the implicit and explicit sense of agency. The depicted model was developed by considering the two-step account of the sense of agency (i.e., the feeling of agency and the judgement of agency, as proposed by Synofzik et al. [35, 36]), other recent accounts of the sense of agency [37–39], and the comparator mechanism [33–35]. At the sensorimotor level, several comparators are used to update the internal models: (a) feedback error monitoring, (b) central error monitoring, and (c) optimization of prediction. Whenever there is any intervention in the human's action, (d) the sensory receptors receive both external afference signals and the reafference signals of the action. At the cognitive level, the attribution of agency is judged based on the integration and weighting of various cues. After the judgment, the cognition for the attribution of agency and context is retained as prior information, which may influence the internal information (e.g., prediction in internal models and intention) and external information (e.g., perception and cognition of actual outcome) on both the sensorimotor and cognitive levels thereafter. Namely, the human motor system (i.e., motor controls and learning) and the sense of agency interact with each other.

trol loop to minimize the discrepancy. The same mechanism is proposed to exist in the human motor system (**Fig. 3(a)**). Thus, the predicted state generated by the forward models is used in two types of comparison processes. First, it is used to make fine adjustments during motion. Comparisons between the predicted state and the initial desired state during motion enable fine adjustments to ongoing motor commands before reafferent feedback from the movement is available (**Fig. 3(b)**). Second, it is used in the comparison between the predicted state and actual sensory feedback to optimize the prediction model and cancel out or attenuate the sensory feedback of the self-generated reafference (**Fig. 3(c)**) [40–43]. However, the importance of the comparator, the internal models, and the predictions they generate are not limited to enhancing motor performance. Many previous studies argue that the congruency between the prediction generated by the internal model and actual outcome, as detected by the comparator, is an essential clue in the attribution of the sense of agency [21, 23, 29, 44].

3.2. Implicit and Explicit Sense of Agency

A sense of agency refers to the feeling that "I am the agent causing the action" [45]. Over the last several decades, two different accounts have been proposed for explaining the neurocognitive underpinnings of the sense of agency. One is the *implicit sense of agency*, which is discussed with an emphasis on the comparison process conducted using outputs of the internal model, as mentioned above. The other is the *explicit sense of agency*, which is discussed with an emphasis on the cognitive judgement obtained by a postdictive inference, which is made through the integration of various cues [46, 47]. However, when considered independently, these two paradigms are unable to produce a complete picture of the sense of agency.

Several studies have argued the distinction of these levels of the sense of agency (i.e., implicit and explicit) [35–39]. An influential account by Synofzik et al. proposed a two-step account of agency that combined the implicit and explicit sense of agency [35]. In their new account, they named the implicit sense of agency as the *feeling of agency* (FoA) and the explicit sense of agency as the *judgement of agency* (JoA) (**Fig. 3**). According to their argument, first, the FoA is represented at the sensorimotor level (**Fig. 3** lower). At this level, the actual sensory feedback of motion is merely classified as being self-caused or not self-caused, based on the comparison with the predicted sensory feedback. Therefore, there is no external attribution at this level (e.g., a feeling that "my body movement was caused by a robotic actuator"). If no sensorimotor mismatch is detected, a first-person action experience is achieved in the ongoing flow of action, and the experience of the sense of agency is obtained and withheld from further processing. However, if any sensorimotor mismatch is detected, the JoA is formed. This is an interpretative judgement of being the agent in an action on the explicit, cognitive level (**Fig. 3** upper). At this level, attribution of the agency is processed by postdictive inference, which is based on the integration and weighting of various cues. These include not only sensorimotor cues but also explicit internal cues (e.g., intention, goal, anticipation based on priming), cognition of the actual outcome as one of the external cues, and other external cues (e.g., contextual cues). If it cannot self-attribute at the cognitive level judgement, the motion is interpreted as being caused by factors outside the self.

Furthermore, according to this framework, the sensorimotor and conceptual levels are continuously integrated, and they interact with each other. The FoA (i.e., the implicit sense of agency) generally serves as the reliable and robust cue for explicit inference at the cognitive level. Inversely, JoA (i.e., the explicit sense of agency) as well as contextual cues can change priors on the sensorimotor level. Furthermore, several recent studies have reported that obtaining an explicit sense of agency helps to improve motor control. Kasahara et al. investigated the effect of the sense of agency on learning by examining how preemptive muscle contraction by electrical muscle stimulation (EMS) affected the reaction time (RT) of participants in the task of pressing a button in response to visual stimuli [48]. They showed that RT improved after the participants performed muscle-driven learning in advance while maintaining a sense of agency. However, the improvement in RT was not significant when the EMS was too early and a sense of agency was not maintained. Matsumiya also investigated the correlation between an explicit sense of agency and control of eye movement while visually tracking hand movements [49]. Their results showed that improvements in the time taken to initiate eye movements are correlated with an explicit sense of agency in the motion of the hand. These findings suggest that the acquisition of the sense of agency affects the learning process of the internal model.

3.3. Action Transparency in Human-Computer Integration

Our above review of the mechanism of the human motor system and subsequent discussion of the sense of agency have shown that it is important to achieve a sense of agency when performing motor actions. When designing HMMA syatems to achieve HInt, it is important to maintain a sense of agency when the computer intervenes in human action. Maintaining a sense of agency contributes to driving learning and adaptation and improving the accuracy of the human-computer co-action. Conversely, compromising the user's sense of agency may degrade the overall capability of the HInt system, as the user may not be able to make use of their innate abilities (e.g., predictive motor control). Furthermore, compromising the user's sense of agency in individual and collective work can also lead to a lack of motivation for actions because it is difficult to feel a sense of accomplishment [50]. However, it is challenging to maintain the sense of agency in systems where the computer assists and augments the user's behavior (i.e., when the user experiences action outcomes that are different from the original physical action). For example, Coyle et al. reported that, when a user manipulates a mouse cursor, assistance techniques such as changing the cursor's speed can have a significant impact on the user's sense of agency [51]. Therefore, it is necessary to identify the extent to which the machine can intervene in the user's actions without compromising the user's sense of agency.

Here, we propose that action transparency should be a key component in designing situations in which the user can achieve a sense of agency in HMMA. As mentioned in Section 1, action transparency refers to the degree to which users feel a sense of agency in their action outcomes, even with the intervention from the machine. Thus, based on the discussion presented above, to design an effective and unnoticeable intervention, it is crucial to consider both factors that influence the implicit sense of agency (e.g., sensorimotor discrepancies by action intervention) and the explicit sense of agency (e.g., contextual cues). Namely, designers must ensure either that the sensorimotor discrepancies are small or that there are sufficient contextual cues that will ensure that the user experiences a sense of agency. However, this implies that if there are enough reliable contextual cues for the user to achieve a sense of agency, it is possible to perform larger interventions, which would typically result in large sensorimotor discrepancies, without the user noticing.

Many previous studies in the areas of human augmentation and cognitive psychology have studied methods that intervene in the users' movements without compromising their sense of agency. The techniques to achieve perceptual transparency that were discussed in the previous section form a large body of this work. They contribute to the achievement of action transparency because the perception of sensory feedback is used for sensorimotor integration and comparison in the human motor system. Additionally, the transparency of the machine's presence may provide contextual cues for explicit judgement. For example, when a machine is sufficiently hidden, users are more likely to self-attribute actions because there is no one else to attribute the cause of motion to.

More generally, many studies have discussed that spatio-temporal congruency between the user's prediction and the actual outcome is important for the attribution of the sense of agency [42, 52–54]. However, many studies have also reported that the spatio-temporal discrepancy can be tolerated within a particular range [8, 28, 53, 55–57]. Moreover, it is known that the action-outcome models dynamically change through learning and adaptation [8, 58–60]. These results suggest that we can change the tolerance range of temporal offset and spatial mismatch by adapting to the condition. Additionally, consistency with the user's intentions has a significant impact on the user's sense of agency. For example, it was observed that users are less likely to notice interventions that are consistent with their intention (e.g., assistance) than those that are inconsistent (e.g., interference) [61].

In this section, we considered the latest concepts on the sense of agency, and we discussed action transparency for the case where the machine intervenes in the user's action. It is notable that the process of the sense of agency can be divided into two levels, and the levels interact with each other. The key aspect is that a variety of contextual cues, as well as the congruency between the action and the actual outcome, are involved in the judgement at the cognitive level. Furthermore, achieving the user's sense of agency may contribute to driving their motor learning. These points emphasize that designers of HInt systems need to consider the context as well as the human-machine interaction.

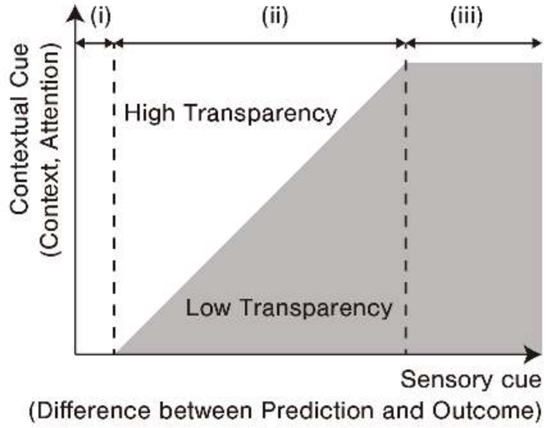

Fig. 4. Generalized framework of transparency. We defined three domains based on sensory cues: (i) unquestionably transparent, (ii) ambiguously transparent, and (iii) non-transparent.

4. Generalized Framework of Transparency

In Section 2, we introduced the idea of transparency as the congruency between expectations and reality by discussing the transparency of perception. We then discussed action transparency in Section 3 to describe how the transparency of a system can vary depending on two factors: (1) the difference between the user's predictions generated by their internal model and the actual outcomes they experience (sensory cues), and (2) contextual cues which imply that the result they experience is what they should expect (e.g., prior information about the environment that causes the user to pay less attention to the machine and its intervention). Furthermore, we discussed how a sense of agency could be obtained in two ways, based on the two-step account of agency. First, an implicit sense of agency can be obtained by sufficiently high congruency between predictions and sensorimotor feedback. Then, if insufficient congruency is achieved, people can be made to judge that they should have an explicit sense of agency through contextual cues. However, it should be noted that if congruency is too low, no amount of contextual cues would be able to induce a sense of agency.

Herein, we discuss transparency in a general context to present a framework upon which transparency-based design approaches can be built. We present this framework in the form of a map showing the types of transparency that can exist in a HInt system, as shown in **Fig. 4**. The map was constructed with the assumption that the mechanism behind transparency works similarly to the two-step account of agency. Namely, transparency is primarily achieved by a high degree of congruency between predictions and feedback and secondarily by contextual cues. By drawing this map, we observe that there are three domains of transparency, as follows:

(i) Unquestionably transparent domain: the domain in which the system is always transparent to the user (i.e., congruency is sufficiently high).

(ii) Ambiguously transparent domain: the domain in which the system's transparency depends on the contextual cues (i.e., congruency is insufficient to induce transparency by itself).

(iii) Non-transparent domain: the domain in which the system is always non-transparent (i.e., congruency is significantly low).

The location of the HInt system on this map depends on all parts of the system (i.e., the machine, the human, and the environment within which they exist).

Previous works typically do not distinguish between domains (i) and (ii), or between (ii) and (iii). In most cases, systems are distinguished as transparent or non-transparent based on cognitive judgements. This is owing to the mixed attribution of the non-transparent nature of the systems to the cognitive and sensory aspects of transparency, as was the case with the traditional account of the sense of agency. However, with the advent of deeper and more advanced HInt systems for human augmentation, there is a need to design in domain (ii) instead of domain (i) or (iii).

Working in domain (ii) is especially relevant for the design of HMMA systems for human augmentation. In the context of human augmentation, domain (iii) can refer to systems that strongly intervene in the user's actions to achieve significantly better results. This is because strong interventions typically result in a large gap between what the user expects, based on their internal model, and the actual outcomes they perceive. In such cases, users cannot attribute the actions made by the human-machine system to themselves. This typically leads to a sense of irrelevance instead of a sense of self-attribution. Conversely, domain (i) refers to systems that intervene minimally in the user's actions. While such systems allow the user not to notice the machine and have a high sense of self-attribution, it would also minimally augment the user's capabilities. Thus, the design of systems in domain (ii), where significant augmentation can be achieved while the user still retains a sense of self-attribution, is necessary to develop advanced HInt systems (e.g., HMMA systems).

5. Transparency-Based Design Approaches for Human-Machine Mutual Action

Herein, we present transparency-based design approaches for designing HMMA systems. Our approaches are directed towards developing systems for operating in domain (ii) of transparency, in which significant human augmentation can be achieved while still allowing the user to maintain a sense of self-attribution regarding the machine-augmented actions. In particular, our approach follows from our suggestion that system transparency can consist of (passive) perceptual transparency and (active) action transparency. Through our design approach, we suggest that transparency in HMMA systems can be achieved by designing two aspects of the machine: (1) machine presence and (2) machine intervention.

Machine presence refers to how strongly the user feels that the machine is actively involved in the system and how much it seems to influence any actions made by the user. This sense of machine presence is formed based on sensory information related to the physical existence and movements of the machine. If the machine presence increases, the user can recognize the machine as a candidate for the attribution of action outcomes, and the user's sense of active involvement may be lost. By managing the machine's presence and making it transparent, designers can minimize alternative options for attribution, thereby enabling the user to attribute action outcomes to themselves and experience augmentation with user self-attribution.

In contrast to machine presence, which can be experienced even in passive states, machine intervention is only experienced when the human and machine perform an action. During machine intervention, the actions of the machine interact with the actions performed by the user to affect the outcome. This intervention can enhance the user's motor ability and improve their performance. However, because intervention modifies the user's actions, it can cause the actual outcome of the actions and the user's predictions to differ, which degrades the user's sense of self-attribution. By making machine intervention transparent (e.g., unnoticeable), designers can achieve augmentation while maintaining user self-attribution.

In this section, we detail the approaches to controlling machine presence and intervention to achieve transparency in HMMA systems. Even though the two notions can be designed independently to some extent, they also influence each other. To clarify how they interact, we first present an interaction model and subsequently describe the approaches to designing for machine presence and intervention.

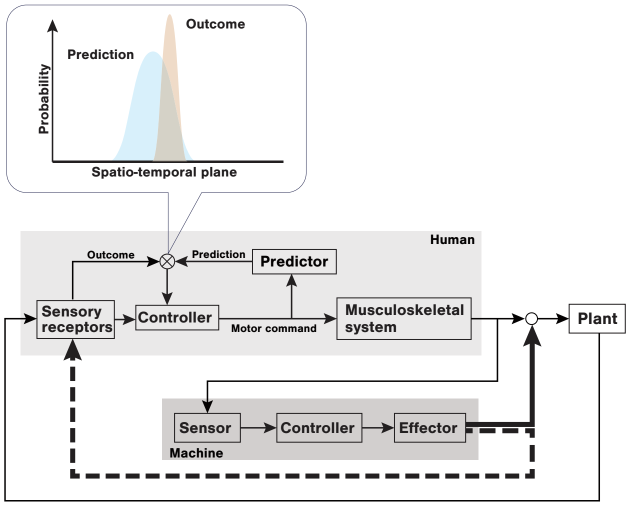

Fig. 5. Interaction model describing a HMMA system. The human's internal control process is also shown. The highlighted arrows that represent outputs from the machine are the human-machine interactions primarily related to the machine presence (dashed arrow from the effector) and intervention (solid arrow from the effector).

5.1. Interaction Model

To clarify the composition of an HMMA system, the interactions between the components, and the design factors that must be considered, we first introduce an interaction model that describes the flow of information between the human and machine (**Fig. 5**). The proposed model consists of a human sub-system, machine sub-system, and plant (the environment that the HMMA system interacts with). The human sub-system includes sensory feedback, self body control, and prediction models to perform motor actions. The machine sub-system can sense the output of the human sub-system, and it affects the human's motor actions. The plant is a generalized control target of the entire system. The human performs motor actions by planning motions based on sensory information and transmitting motor commands to the musculoskeletal system. The machine consists of a sensor that recognizes the human's action, a controller to adjust its own action, and an effector that can affect the human sub-system.

Both the machine presence and intervention stem from the physical manifestation of the machine; thus, they are clearly intertwined. However, they differ in the principles by which they affect a sense of self-attribution. The machine presence is related to the existence of alternative targets for attribution, whereas machine intervention is related to the congruency between action predictions and outcomes. In the following subsections, we describe approaches to design each of these concepts to achieve augmentation with self-attribution.

5.2. Designing Machine Presence

A sense of machine presence is primarily generated by the information received by human sensory receptors directly from the machine's effector output (dashed arrow

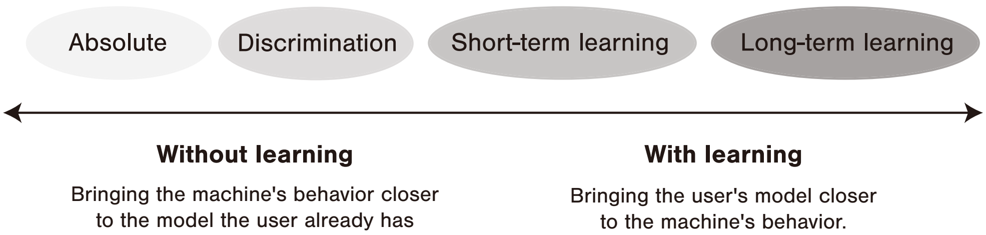

Fig. 6. Approaches to designing machine presence. The approaches can be broadly categorized into approaches with and without learning, and each category can be further separated into two approaches. The approaches without learning can be separated into absolute and discrimination approaches, whereas approaches with learning can be separated into approaches that use short-term or long-term learning.

from the effector in **Fig. 5**). A large machine presence causes the user to overestimate the contribution of the machine, and it increases the likelihood that the outcome of the action will be attributed to the machine. That is, in situations where a system designer wishes to attribute action outcomes to the user, a large machine presence increases the risk of any action outcome being misattributed to the machine. By reducing this sense of presence, we aim to achieve a state in which the outcome of motor actions can be easily attributed to the user.

The machine's presence can be reduced by increasing the degree of congruency between the user's predictive model of the machine behavior (at all times, both during and outside of interventions) and the sensory cues obtained from the machine. **Fig. 6** shows four approaches to the design of machine presence. There are two main classes of approaches to reducing machine presence: approaches without learning and those with learning. The former approaches bring the machine's behavior closer to the predictions generated by the internal model that the user already has. The latter approaches train the user's internal model to expect the machine's behavior.

Approaches without learning focus on designing stimuli that the human receives from the machine to be below the perceivable intensity of the user. There are two main sub-categories to approaches without learning: the absolute and discrimination approaches. The absolute approach sets stimuli below the absolute threshold of detection, and the discrimination approach sets stimuli below the discrimination threshold.

In the absolute approach, the stimulus generated from a machine is controlled to be below the threshold intensity for human sensory detection. Example of this method include making a machine optically transparent or placing it in a position where its motion cannot be seen by the user. In the discrimination approach, the intensity of stimuli is appropriately controlled so that changes in the intensity are imperceptible. An example of this is to make the machine move so slowly that the user has difficulty detecting the motion. Note that these two thresholds can also change dynamically depending on the situation, the user's adaptation, and the relationship between stimuli from different modals.

A system that keeps all stimuli below these two thresholds can eliminate the machine presence from the user's perception. However, in practice, it is difficult to control all stimuli and achieve an imperceptible state. In this case, approaches with learning can be an effective tool. This approach takes advantage of the fact that stimulus information that is consistent with the user's prediction model can be cognitively eliminated. By learning an appropriate model, users can learn to ignore the machine's presence. For example, when we wear clothes, our skin is in constant contact with the cloth, and we perceive the surface texture and the mass of the cloth itself. However, most of the time, we are unaware of these sensations unless we pay attention to them.

Based on the results of previous studies [62, 63], we assume that predictive models are formed in a two-step process: (1) approximation by combining existing internal models that the users have acquired through previous experience (short-term learning), and (2) optimization of new internal models through repeated learning (long-term learning). To reduce the presence of the machine in short-term use, the former process is utilized by providing interfaces and machine behaviors that are consistent with the user's past experiences. An example of this is to provide an interface through which the user can perform motor actions in the same way that the biological body performs daily movements (e.g., mapping human hand movements to a machine's manipulator movements). Approaches that use long-term learning utilize an internal model that is acquired by the user based on the statistics of the sensory feedback. This model takes time to develop; however, it has the potential to reduce the presence of the machine in many situations. To facilitate model acquisition, the system must be designed to withstand and be suitable for long-term use (i.e., it must not impose significant physiological or cognitive burdens).

We have described the approaches to designing machine presence. These approaches can be used alone or in combination to design the desired machine presence. Next, we describe the machine intervention, which is the other aspect of HMMA that should be designed.

5.3. Designing Machine Intervention

Machine intervention refers to machine actions that affect the user's motor actions and their outcomes (solid arrow from the effector in **Fig. 5**). When executed prop-

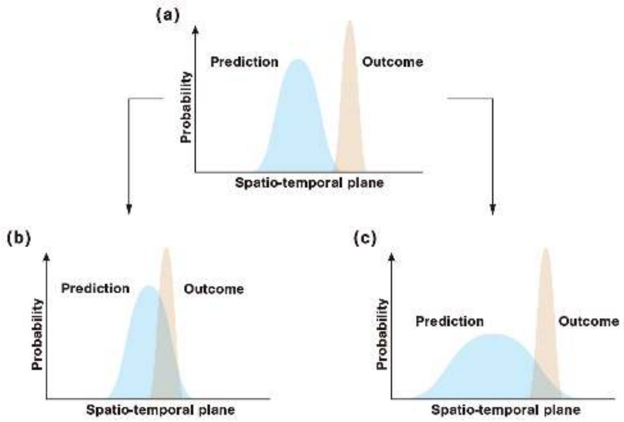

Fig. 7. Examples of relationships between the user's predictions and the actual outcomes. Compared with state (a), the user's sense of agency is more likely to be maintained in states (b) and (c).

erly, this intervention can augment the user's abilities. However, even when positive augmentation is successful, badly designed interventions can leave users without a sense that their abilities were augmented. Instead, it can feel as if the machine is acting independently to achieve the outcome. By designing machine interventions, we aim to achieve an enhancement of the user's action performance while maintaining a sense of self-attribution.

As described in Section 3, previous studies have suggested that humans have internal models to predict the outcome of their own motor actions. This prediction is formed internally by a human; it is probabilistic and considers various types of uncertainty, including model uncertainty, uncertainty regarding the environment, and uncertainty of motor command execution. In this study, we propose an approach to design interventions by sensing the user's state in real time and dynamically controlling the amount of intervention based on the amount of uncertainty the user expects (estimated from the user's state). The plot in the upper part of **Fig. 5** shows the comparison made between the user's internal prediction and action outcome with spatio-temporal uncertainty. Appropriate control of the relationship between the prediction and outcome can guide the design of interventions in HMMA.

To illustrate how predictions and outcomes can be controlled to maintain self-attribution, we present several possible relationships between predictions and outcomes, as shown in **Fig. 7**. In state (a), the system outcome, which is a result of the machine's interventions can be identified as being distinct from the user's prediction, which can compromise the sense of agency. In state (b), the system outcome more closely matches the user's prediction through control of the intervention. Because the outcome is reasonably congruent with the prediction, there is a smaller probability that this type of intervention will compromise the user's sense of agency. In state (c), the user's prediction is more uncertain; however, the outcome remains similar to that achieved in state (a). Owing to the higher uncertainty in the user's prediction, the user may accept the outcome as being within their prediction, and they will maintain a sense of agency.

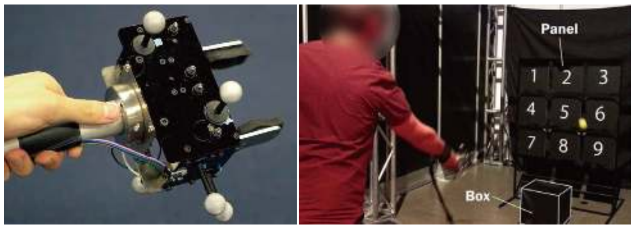

Fig. 8. PickHits is an HMMA prototype for augmenting human throwing abilities.

The changes from state (a) to (b) and from state (a) to (c) represent two approaches to controlling interventions. In the former, interventions are tailored to match the user's prediction. While this intervention has minimal risk of compromising transparency for the user, it has the disadvantage of a limited range of augmentation, and it requires high machine performance, such as accuracy and precision. In the latter, the user's uncertainty is actively modulated to make the outcome acceptable for the user. This approach has the advantage of enabling larger or less precise interventions. However, designing the system to generate excessive uncertainty in the prediction can lead the human to deem the machine unpredictable, which leads to a loss of transparency. Thus, a balance between modulating uncertainty and designing interventions that have an expected result is required to achieve transparency in HMMA systems.

6. Examples of Transparency Design in HMMA

Herein, we present concrete examples of HMMA systems that have been developed to achieve HInt, and we examine them through the lens of transparency to elucidate the insights that our approaches and framework provide.

6.1. PickHits

Our first example, PickHits (**Fig. 8**), consists of a handheld device that acts as a release controller for the user's throwing action [64, 65]. The device is handheld, and it has a button that allows the user to manually control the release. The device's movements are measured in real time using optical motion capture cameras and an inertial measurement unit sensor on the device to recognize the user's throwing motion. The device aims to control the release timing of the user's throwing action at the optimal timing based on targets.

To reduce machine presence, PickHits was designed to minimize any disturbance of the user's movement by employing a handheld device and a simple interface, in which a button opens and closes the device's gripper during manual operation. In this system, the release timing of the throw is controlled by the machine via intervention.

Fig. 9. The Tight Game is an HMMA prototype designed to augment human strength.

The uncertainty of the user's prediction was designed based on a delay between the user's button push and the release upon the opening of the gripper. The longer the time interval between the button push and the release, the higher the uncertainty according to Weber's law. To achieve release timing control with intervention from machine, the interval was set at approximately 75 ms, which maintains a high sense of agency and maximally reduces uncertainty. With this configuration, we achieved the control of the release timing without the user being aware of it. This suggests that the throwing ability can be adjusted implicitly by the machine. This shows that the user can attribute the throwing experience with PickHits system to themselves, and a high transparency is achieved.

6.2. The Tight Game

Our second example, the Tight Game (**Fig. 9**), is a prototype that is used to investigate how human power can be extended using tug of war as a test bed [66]. This system consists of force sensors that are embedded in the rope and machines, including high torque motors hidden behind the users. Using the force sensors, the system observes how each user applies force in real time, and it recognizes actions of users independently. Based on the recognized action, the machines control the output power to assist the user.

System configurations were designed to reduce the machine presence. The machine's mechanism was designed to have high backdrivability so that it does not interfere with the user's movement. To visually hide the machine, it was placed behind the user. Additionally, a constant force was applied from behind each user even when the intervention was not performed. The magnitude of this constant force was approximately 100 N. Because the forces were in different directions, and they cancelled each other out; thus, no assistance was performed in this state. This force created a situation that made it more difficult for the user to perceive the assistive force compared with the case of applying the assistive force from a zero force state; thus, this reduces the machine presence. For this intervention, it was assumed that the uncertainty would decrease depending on the amount of force exerted by the user [67]. A method was proposed to measure the amount of force applied by the users in real time and control the rate of change of the assistance according to the estimated uncertainty. In addition, when the opponent user is assisted, the assist is performed in synchronization with the opponent user's motion. Therefore, the perceived sensory feedback does not deviate from the prediction, and it makes the machine presence transparent.

7. Future Prospects and Limitations

Herein, we discuss the future avenues of research as clarified by our proposed concept of transparency, as well as the limitations of our framework in its current form.

7.1. Free Transparency Control

The main focus of the two prototypes introduced in Section 6 was how a high level of transparency may be achieved in an HMMA system. However, the goal of transparency design is not limited to achieving a high level of transparency. For example, there are times when states of low transparency are more beneficial than high transparency states. Thus, the ultimate goal of transparency-based design is not only to achieve high transparency, but also to make it possible to freely control the transparency. Here, we detail the idea of free transparency control and its possible benefits through several applications achievable through proper control of transparency.

7.1.1. Driving Motor Learning

Our focus is to achieve high transparency, but not only while users are using HMMA systems. When designing training assistance systems, it is necessary to achieve a high transparency state when the machine is removed. When the user continues training with the machine's assistance for a long time, the user's motor model may adapt to the intervened state. If the amount of intervention is too large in the late stages of training, the model after learning may not match the unintervened physical body motions. Conversely, if the amount of intervention is not sufficient at the beginning of the training, the system may not be able to effectively assist the user's motor learning. Hence, to enable successful motor learning, the system needs to adjust the intervention dynamically to assist the user's training while ensuring that the user's motor model after training matches the unintervened motion.

A simple technique that may first come to mind is a gradual reduction in the amount of assistance. For example, Lammfromm et al. [68] developed a virtual reality system for users' learning juggling. They proposed an initial ball speed slower than the realistic temporal constraints of juggling; this speed gradually increased based on users' performance in the virtual reality emvironment. Such a design contributes to preventing sensorimotor conflicts in unintervened motions after training, while enabling the machine to effectively provide assistance at the beginning of the training. However, note that it is essential to maintain a particular degree of the sense of agency for movement during any training stage. This technique can also be applied to rehabilitation and sports training.

7.1.2. Notifications

Notifications provide an example of a system that transitions from high to low transparency. One specific example is smartwatch notifications. When a user is accustomed to wearing a watch, it typically enters a high transparency state (i.e., the user does not notice that they are wearing a watch). The act of notifying the user, either through vibrations or sounds, can be considered as the transition from high to low transparency via a disruption in sensorimotor congruency. Given that the user is instantly aware of the watch after the notification, this is a jarring transition from a high to low transparency state, and can cause discomfort. However, the careful design of notifications can induce subtle and less-intrusive transitions across the boundary. For example, in the "Mindless Attractor" [56], a speaker's voice is modulated to attract the user's attention without causing discomfort. In future research, we will determine the relationship between notification and transparency, and propose HMMA systems using these notification techniques.

7.1.3. Presence of Others

When designers aim to intentionally create the presence of others, a low transparency state may be more desirable than a high transparency state.

For example, in our first prototype, we developed the Tight Game [66] as a system in which the machine extends the user's power implicitly. However, for a future application, we may be able to design an intervention method that makes the user feel the presence of another user who is not there (e.g., virtual teammates and opponents, the telexistence of remote players) by using appropriately low transparency.

Moreover, it is a novel experience for users to execute a mutual action with a machine while feeling the presence of the machine as an autonomous agent. PickHits [64] is also helpful in providing users with such experiences. The handheld device is equipped with a button to release the ball; however, the machine can release the ball autonomously without the user pressing the button. Thus, the user and machine are autonomously acting on each other by playing their respective roles in the throwing sequence (i.e., the user swings their arm, and the machine releases the ball). This explicit mutual action with the machine provides the user with a unique experience, in which they are not sure of the dominant agent.

This perspective can shed light on new HMMA possibilities by investigating whether machines can actually produce the presence of others.

7.2. Limitations

Despite the current and potential future utilization of our framework, there are some limitations that need to be addressed. First, the proposed framework for transparency is still in the conceptual stage, and a specific experimental evaluation has not yet been conducted. Additionally, we have not implemented concrete examples of HMMA systems wherein both the human and machine exist as independent agents that are capable of autonomous motor actions that simultaneously affect each other. To address these limitations and provide more support for our concept, our future work will include the implementation of examples, particularly of systems with dynamically varying transparency, and evaluating them in terms of the users' subjective experiences. In addition, the descriptions of the models in HMMA and the design framework may not be complete. Thus, through further research, we intend to update these descriptions. For instance, other human brain principles (e.g., the free energy principle [69, 70]) and new results from psychophysical experiments may be relevant to our framework.

8. Conclusion

In this paper, we first discussed our design framework for HInt, in which humans and machines become fused agents. This design framework placed the analogy of system transparency at its core. We focused our discussion on two specific transparencies (i.e., perceptual and action transparency), and we reviewed previous studies that discuss the concepts on which our framework was built (i.e., haptic transparency and the sense of agency). We then proposed a set of guidelines to design transparency in HInt. In these guidelines, we stated that achieving high transparency was not the only possible goal when designing with a focus on transparency. That is, transparency is a parameter for controlling the relationship between humans and machines according to the designer's purpose. We then presented approaches to design HInt systems with HMMA based on our guidelines. In this approach, we proposed that there are two aspects of machine transparency (i.e., machine presence and machine intervention) in human-computer systems, and we made suggestions on how they should be designed based on known mechanisms behind perceptual and action transparency. To demonstrate the types of system designs that our approach may be used for, we presented concrete examples of some HMMA systems. We analyzed them using our framework and assessed them using our design approach. Finally, we described further applications and extensions to our transparency-based design framework and approach as well as future prospects for HInt and HMMA systems.

Despite it being a preliminary framework, we believe that our concept of transparency and its use in HMMA design can provide designers of human-computer systems with new insights into HInt design. Namely, we believe that it provides a useful analogy and a clear description of the factors that influence HInt and sheds light on the possibility of using the degree of fusion as a controllable parameter in a system to achieve desired effects. Ultimately, we believe that this new framework will contribute to promoting human augmentation by enabling human-machine fusion through mutual action.

Acknowledgements

This work is supported by JST ERATO Grant Number JPMJER1701, Japan.

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