Human-machine Symbiosis: A Multivariate Perspective for Physically Coupled Human-machine Systems

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ABSTRACT

The notion of symbiosis has been increasingly mentioned in research on physically coupled human-machine systems. Yet, a uniform specification on which aspects constitute human-machine symbiosis is missing. By combining the expertise of different disciplines, we elaborate on a multivariate perspective of symbiosis as the highest form of physically coupled human-machine systems. Four dimensions are considered: Task, interaction, performance, and experience. First, human and machine work together to accomplish a common task conceptualized on both a decision and an action level (task dimension). Second, each partner possesses an internal representation of own as well as the other partner’s intentions and influence on the environment. This alignment, which is the core of the interaction, constitutes the symbiotic understanding between both partners, being the basis of a joint, highly coordinated and effective action (interaction dimension). Third, the symbiotic interaction leads to synergetic effects regarding the intention recognition and complementary strengths of the partners, resulting in a higher overall performance (performance dimension). Fourth, symbiotic systems specifically change the user’s experiences, like flow, acceptance, sense of agency, and embodiment (experience dimension). This multivariate perspective is flexible and generic and is also applicable in diverse human-machine scenarios, helping to bridge barriers between different disciplines.
1. **INTRODUCTION**

Automatic and intelligent machines have become ever-present in today’s society whereby machines increasingly interact with humans. It was already in 1960 that Licklider (Licklider, 1960) had the visionary idea to use the biological analogy of a symbiosis when referring to human-machine interaction. With this idea of human-machine symbiosis, he intended to describe the close union and living together of humans and highly intelligent cybernetical machines in a manner that both benefit from it. He had the idea of humans and machines operating together to solve problems dynamically and interactively in real time. The vision of such a symbiosis becomes more and more present in contemporary research on human-machine interaction (e.g., (Abbink et al., 2018; Grigsby, 2018; Jarrahi, 2018; L. Wang et al., 2019)). Yet, the concept itself, its drivers, boundary conditions, and the applied scenarios of human-machine symbiosis are still very diffuse. Importantly, a highly interdisciplinary effort is needed (Rahwan et al., 2019) in order to optimize the complexity of human-machine interactions in the future. Consequently, an approach taking into account the perspectives of both counterparts of the symbiosis as well as a multivariate construct thereof is needed. Here, we propose such a multivariate perspective on human-machine symbiosis based on
FIGURE 1. Symbiosis as a multivariate concept and as the highest form of human-machine interaction (HMI) in physically coupled human-machine systems.

an interdisciplinary approach. We focus on physically coupled human-machine systems and take into account multiple dimensions. The result is a generic approach which can be applied flexibly to various scenarios of physical human-machine interaction.

1.1. Development of Human-machine Interaction

Initially, robots and automation systems were developed for industrial environments to perform repetitive tasks on their own and out of human reach. Today these machines increasingly interact with humans. In the following, we first describe different levels of the development of human-machine interaction as suggested by (Schmidtler, Knott, Hölzel, & Bengler, 2015) and (Matheson, Minto, Zampieri, Faccio, & Rosati, 2019) in order to state the preliminary stages of symbiotic systems (see Figure 1). We note that the terminologies in human-machine interaction (e.g., coexistence, cooperation, or collaboration) are neither defined precisely nor uniformly and may, thus, be used differently by several authors. The evolution of this interaction started, in the simplest form, with a human-machine coexistence in the sense that machines just share a common workplace and timeframe with the user (Schmidtler et al., 2015). Yet, humans and machines do not necessarily work conjointly since the individual tasks are different and independent of each other.

If, in addition to a shared workspace and timeframe, the machine provides some kind of assistance to the user, a system results which can be termed human-machine cooperation. Importantly, in this system, the human and the machine share a common goal. Over the last years, a considerable body of literature has steadily grown around the study and design of such assistance systems which are based on the communication of human and machine, in particular via gesture and speech (see e.g. (Green,Billinghur st, Chen, & Chase, 2007; Ende et al., 2011) (Haddadin & Croft, 2016, p. 1837 f.)). For instance, many systems enhance human perception, like a handheld drilling machine proposed by (Schoop et al., 2016) which displays the angle of the drilling hole and the actual depth.

Current technological trends enable an increasing contact between humans and machines in a
physical manner. Humans and machines act conjointly and communicate with each other, not only via gesture and speech but mainly via the haptic channel. This current stage of human-machine interaction can be termed human-machine collaboration. The terms collaboration and cooperation are sometimes used synonymously (Mörtl et al., 2012; F. Flemisch, Abbink, Itoh, Pacaux-Lemoine, & Weßel, 2016; Abbink et al., 2018), while others propose to distinguish both concepts (Bütepage & Kragic, n.d.; Jarrassé, Sanguineti, & Burdet, 2014; Matheson et al., 2019; Silverman, 1992). Here, we describe human-machine collaboration as the next developmental stage in the evolution of human-machine interaction, and this corresponds to the description of a higher form of cooperation. In addition to the haptic interaction, we adopt the differentiation that collaboration includes a dynamic distribution of roles (Jarrassé et al., 2014). This distribution of roles, as also mentioned by (F. Flemisch et al., 2016; Kucukyilmaz, Sezgin, & Basdogan, 2013; Mörtl et al., 2012; Musić & Hirche, 2017; Oguz, Kucukyilmaz, Sezgin, & Basdogan, 2010; L. Wang et al., 2019) is accomplished through negotiation based on communication (Oguz et al., 2010), intention interpretation on the basis of shared representations (Bütepage & Kragic, n.d.; F. Flemisch et al., 2016; Oguz et al., 2010) and/or interaction history (Bütepage & Kragic, n.d.; Jarrassé et al., 2014).

If the physical interaction is tight and ongoing, human behavior depends on the behavior of the machine and the other way round. Moreover, a mutual interference of their expectations may exist. A prominent example are exoskeletons, robotic-like devices for use in home care environments or in hospitals, where both the goals and the individual physical effort applied for their achievement are entangled and have to be jointly determined for a seamless and effective interaction. Nonetheless, similar examples arise in other domains: Collaborative workbenches are designed in Industry 4.0 settings (Unhelkar et al., 2018), where the physical coupling is established through the workpiece and the expectations with respect to the next movement and its execution interfere. Even though human-machine collaborative systems are no longer a fiction but have a realistic chance of being realized on a mechanical, sensorial, and power supply level in the future, the first realizations of these machines are often found to be barely intuitive and to have a lack of usability, leading to an overall system’s performance which is determined by the deficiencies of the human and the machine (Chen et al., 2016). From human-human physical interaction, we know from daily experience and literature reports that efficiency can be increased and individual effort can be reduced if the interaction is adequate (Curioni, Vesper, Knoblich, & Sebanz, 2019). Therefore, addressing the interaction between humans and machines is a fundamental challenge towards the breakthrough of physically coupled human-machine systems in applications, as mentioned, for example, in (Gupta, Singh, Verma, Mondal, & Gupta, 2020) for rehabilitation robotics.

The role each partner adopts with respect to the overall task is also a crucial aspect in physical human-machine interaction since it correlates with performance (Kucukyilmaz, Sezgin, & Basdogan, 2011; Mörtl et al., 2012; Reed et al., 2006). Previously, a leader-follower (e.g., teleoperation) approach was widely followed, in which the human is always in the lead and has the authority (see e.g. (Clarke, Schillhuber, Zaeh, & Ulbrich, 2007; Passenberg, Peer, & BUSS, 2010; C. Tzafestas, Velanas, & Fakiridis, 2008)). Obviously, such an approach has deficiencies, especially in cases where the machine has more information than the human has. The naive engineer’s reflex is a complete replacement of the human by the machine. However, the absence of the human does not expel the deficiencies of the machine. Consequently, the last decade has seen a considerable increase in scientific articles which assert that an optimal human-machine system should be more flexible by operating without superior control by either side (Bütepage & Kragic, n.d.; F. Flemisch et al., 2016; Gerber, Derckx, Döppner, & Schoder, 2020; Jarrassé et al., 2014; Li et al., 2015; Rothfuß, Wörner, 
Inga, & Hohmann, 2020). This implies the possibility of a context-sensitive shift of the desired level of automation, that is, the extent to which the machine acts autonomously (cf., definition of level of automation in (Endsley & Kaber, 1999) or (Sheridan & Verplank, 1978). This concept is similar to the H-Mode(s) based on the Horse Metaphor by (F. O. Flemisch, Bengler, Bubb, Winner, & Bruder, 2014) who introduce a scale of assistance ranging from 100% human control up to 100% autonomy/machine control. In between, several levels are possible which correspond to having a tight rein, loose rein, or a secured rein on a horse. The importance of flexible switching of roles and the level of automation is supported by studies indicating its impact on performance (Chiou, Hawes, & Stolkin, 2021), user-specific efficiency (Kucukyilmaz et al., 2013), but also the avoidance of human agency loss due to an inadequate selection of the level of automation (Berberian, Sarrazin, Le Blaye, & Haggard, 2012).

Despite this symmetric relationship with respect to the overall task, the human should still maintain the ability of switching the system completely off, that is, the human has a superordinate (societal) position as advocated, for example, by (Griffith, 2006). This was stated as a response to previous usage of the term symbiosis, which we review in the following.

1.2. Previous ideas related to a symbiotic human-machine interaction

In biology, the concept of symbiosis has a long history and has been used in large variety with a lot of confusion about its meaning (B. D. Martin & Schwab, 2012). The terminology in its simplest form means just living together. Referring to the coevolution of species interacting closely together, de Bary (1879) applied the term symbiosis in biology in order to describe the living together of two organisms of different species (De Bary, 1879). In this respect, it may delineate the intimate physical association between two species which lasts for a considerable span within their lifetimes (Levin et al., 2012, p. 235). Of course, human-machine symbiosis only partly mimics the biological symbiosis concept. The close physical association between human and machine is stressed – which might be restricted to short time periods during which human and machine cooperate.

There exist ideas to describe interactions between humans and machines as symbiotic (e.g., (Griffith, 2006; Lesh, Marks, Rich, & Sidner, 2004; Parker & Pin, 1988; S. G. Tzafestas, 2006)). In these works, the characteristics of symbiosis are said to include a capitalization on the individual strengths of humans and machines in order to assist the human in satisfying individual goals, that is, automation should be human-centered. In other studies, the term symbiosis describes scenarios characterized by a potentially permanent and close physical interaction between a human and a (passive or active) machine. Examples are power-extending exoskeletons or a robotic kinematic chain supporting human movement for rehabilitation purposes such as muscle strengthening (Pervez & Ryu, 2008), haptic feedback-based co-adaptation of human and machine during physical interaction, with the possibility of arbitrary role-switching (K.-J. Wang, Sun, Xia, & Mao, 2016), or industrial human-robot collaborative assembly contexts in the sense of a continuous mutual engagement via a multimodal communication (for instance, via voice commands and gesture instructions; (L. Wang et al., 2019)). Some effort has been made to transfer the idea of symbiosis to concrete interaction scenarios, for example, in decision making problems (Jarrahi, 2018; Grigsby, 2018), or in manufacturing (Ferreira, Doltinis, & Lohse, 2014). In addition, the idea of machines establishing a direct communication with the human brain to achieve symbiosis has also been mentioned (Schalk, 2008; van Erp, Veltman, & Grootjen, 2010). However, to the best of the authors’ knowledge, a clear presentation and discussion of the main aspects of a symbiotic
interaction in physically coupled human-machine systems does not exist to date.

Other literature proposes frameworks for the description of human-machine cooperation or collaboration models (Abbink et al., 2018; F. Flemisch et al., 2016; Pacaux-Lemoine & Itoh, 2015; Rothfuß et al., 2020). However, these works attempt to describe human-machine interaction by a one-dimensional model, therefore missing a clear description of the various dimensions influencing the interaction. In addition, the term symbiosis is used in (Abbink et al., 2018) to describe relationships between humans and machines with shared information, demonstration, and action, and in (F. Flemisch, Abbink, Itoh, Pacaux-Lemoine, & Weßel, 2019) as a similar term to “cooperation”. To summarize, the literature does not exhibit a clear consensus on the meaning of symbiosis, its main drivers, characteristics, and its effects.

1.3. Human and machine shared control - a joint framework in terms of feedback control systems

Due to the significance of haptic interaction in physically coupled human-machine systems, an adequate framework is needed to describe the control system which emerges from the human-machine interaction. Human-machine systems including continuous physical interaction and haptic feedback are called shared control systems (Abbink, Mulder, & Boer, 2012; F. Flemisch et al., 2016). They are characterized by humans and machines “interacting congruently in a perception-action cycle to perform a dynamic task that either the human or the robot could execute individually under ideal circumstances” (Abbink et al., 2018, p. 511). Figure 2 shows a schematic representation of a general human-machine shared control system.

The human and the machine can be seen as controllers within a feedback control system, simultaneously influencing the environment based on continuously obtained sensory information (Flad, Otten, Schwab, & Hohmann, 2014). This information may include direct haptic feedback from the
partner’s control output. Both feedforward and feedback elements can be utilized by each of the two partners in order to select actions to achieve a desired goal, for example, in the form of a position set-point, which in the literature is usually assumed to be given and be even identical for both partners (e.g., (Honing, Gibo, Kuiper, & Abbink, 2014; Mörtl et al., 2012; Inga, Eitel, Flad, & Hohmann, 2018)). Different and in particular non-compatible goals lead to disagreements in the control output and generate conflicts. Hence, the use of human behavior models becomes essential (Boink, van Paassen, Mulder, & Abbink, 2014; Mars & Chevrel, 2017; Inga et al., 2018). Shared control systems have been mostly considered as a framework for joint action at a haptic level in various applications including driving assistance systems (Flad, Frohlich, & Hohmann, 2017; Mars & Chevrel, 2017), or teleoperation in robotics (Mörtl et al., 2012; Smisek, Sunil, van Paassen, Abbink, & Mulder, 2017). Shared control is deemed an important basis for human-machine cooperation and collaboration (F. Flemisch et al., 2016). However, it only provides a basic framework for the perception-action cycle in human-machine haptic interaction which is not sufficient for a full description of all aspects in human-machine interaction, e.g. the influence of the interferences of actions and decision (Pacaux-Lemoine & Itoh, 2015). For example, besides the coupling depicted in Figure 2, the overall system behavior is affected by an upper level of interaction, usually not included in shared control approaches. This upper level defines the goals of the shared control system on the lower haptic level, which are set-points in the feedback control system of Figure 2. In addition, the relationship between shared control and upper interaction levels is discussed in some works (e.g., (Abbink et al., 2018; F. Flemisch et al., 2016)), but the connection between the levels is mostly reduced to the reception of feedback from the environment and the transmission of goals from upper levels to lower levels. Given the entanglement of the human and machine decisions and the strong dynamic interaction between controllers with potentially incomplete information, it is conceivable that a highly performant human-machine feedback control system demands a kind of alignment between internal models or expectations.

1.4. From shared control to human-machine symbiosis

Shared control and its control-theoretical representation lay the foundation for an analysis of the interplay between humans and machines during a cooperation or collaboration. However, shared control systems are focused on the perception-action cycle at a haptic interaction level and thus are only one possible aspect of human-machine interaction, including symbiosis. Moreover, as reviewed in Section 1.2., previous usage of the term symbiosis is mostly not tailored for physically coupled human-machine systems. We propose human-machine symbiosis as a term implying not only the close, potentially continuous physical interaction in human-machine systems, but also a higher form of collaboration. This includes

• a symmetric relationship with respect to the overall task,
• the possibility of smoothly switching roles and the level of automation across various task abstraction levels,
• synergetic effects of each partner’s strengths which include the seamless fusion of information and mutual understanding towards a highly coordinated action resulting in a higher overall performance which is more than the sum of its parts,
• and an interaction form with the highest acceptance and the best human-sided experience.
These properties, their mechanisms, and their drivers are strongly correlated with each other. Due to the involvement of both human and machine partners, the evaluation and design of physically coupled human-machine systems has to include engineering, information technology and psychological disciplines. In light of the need of an interdisciplinary analysis, we aim for a multivariate perspective on symbiosis as the highest form of interaction in physically coupled human-machine systems, as depicted in Figure 1.

2. IDEA OF A MULTIVARIATE PERSPECTIVE

Describing human-machine symbiosis demands an approach that, on the one hand, allows for an adequate framework in which automation design can be conducted, and on the other hand, complies with an optimal involvement of the users’ capacities and internal models of the interaction. However, as discussed in Section 1, previous models of human-machine interaction do not sufficiently describe the various mechanisms and properties of physically coupled human-machine systems. Thus, we propose a novel multivariate approach for the investigation of the features of human-machine symbiosis including the following dimensions: Task, interaction, performance, and experience. We note that the first three dimensions refer to the human-machine system while the dimension of experience is restricted to the human part of the symbiotic system.

2.1. Task Dimension

The task dimension in symbiotic human-machine systems defines the scope of the interaction within the different degrees of abstraction of an overall complex task. An overall complex task can represent, for example, “assembly of product X”, “drive from A to B”. In stand-alone scenarios, that is, either the human or machine without the counterpart, modeling the behavior (human) or stating a framework (machine) for the completion of such an overall complex task involves a subdivision into several hierarchical levels. For example, three-level architectures in (Saridis, 1983; Volpe et al., 2001) have been proposed for machine or automation design. Similarly, such a subdivision is also present in several human behavior models (Donges, 1999; Michon, 1985), which were mainly proposed towards the development of human-behavior models to be included in driving assistance systems. The levels are defined in an application-specific way, that is, navigation level (route selection), guidance level (maneuver selection, e.g., overtaking), and stabilization level (vehicle control) to achieve a desired position or trajectory (Donges, 1999).

Recent literature proposes human-machine interaction models (Abbink et al., 2018; F. Flemisch et al., 2016; Rothfuß et al., 2020) based on similar hierarchical levels. (F. Flemisch et al., 2016) define three levels, that is, strategic, tactical, and operational levels, and explain the analogy to the aforementioned navigation, guidance, and stabilization levels proposed for driving models. (Abbink et al., 2018) propose the same layers as (F. Flemisch et al., 2016), yet, adding a fourth execution level below the operational level. They suggest that the operational level defines a goal in terms of a desired system control action (e.g., necessary acceleration to reach a desired velocity in a car) and that the execution level defines lower-level control actions (e.g., muscle activation or neural signals). (F. Flemisch et al., 2019) add an upper fourth level of cooperation and metacommunication, which is a level transversal to the previous three. This fourth level defines the needed abilities of both partners to cooperate with each other on all levels. (F. Flemisch et al., 2019) emphasize that this “communication about cooperation” is comparable to the extensions of shared control
proposed in (Pacaux-Lemoine & Itoh, 2015) in the sense that it defines the modus of the cooperation. (Rothfuß et al., 2020) propose a model with four levels including decomposition, decision, trajectory, and action level. The first two levels can be associated with the strategic and guidance levels, respectively. The trajectory level gives the desired environmental state values - for example, sequence of set-points in Figure 2 - to the action level. Finally, the action level selects the necessary control values to influence the environment to achieve the desired state values and the chosen “maneuver”. This action level is therefore comparable to the operational level in the three-level model of (F. Flemisch et al., 2016). In this paper, building upon the mentioned literature, we define the task dimension of human-machine symbiosis in physically coupled systems using a layer model consisting of the decomposition level, decision level, and action level, depicted in Figure 3.

The model defines an interplay between each of the levels, similar to the previously proposed human-machine interaction models in the literature (Abbink et al., 2018; F. Flemisch et al., 2016; Rothfuß et al., 2020). We consider the corresponding input of the action level to result from the decision level, for example, a subtask in the form of a desired position of a jointly controlled object. The input of the decision level, that is, the set of possible maneuvers/subtasks to complete the complex task, is passed from a third level, for example, the so-called decomposition level (Rothfuß
et al., 2020). While currently far from reality, it is theoretically possible to determine a higher-level goal based on the individual plans of both the human and the machine in a symbiotic way, see, for example, the original vision of symbiosis of (Licklider, 1960) or the concept of “joint cognitive system” of (Silverman, 1992). However, this would imply a long-term communication, negotiation, and conflict arbitration process (F. Flemisch et al., 2016). In this paper, we focus on symbiosis for physically interacting human-machine systems, and thus consider the output of the strategic level to be fixed. Despite our focus on the lower task levels, an extension of human-machine symbiosis towards higher, more cognitive levels - in the spirit of the first work of (Licklider, 1960) - is conceivable. We also disregard the trajectory level included in the model by (Rothfuß et al., 2020) in favor of a higher compliance with current theories of human motion behavior, which support the idea that decision-making and sensorimotor control are entangled. This also explains the necessary direct feedback from the action level to the decision level. The literature conjectures that sensorimotor control is based on optimality principles (Todorov, 2004) and the movements are goal-directed, complying with the theory of planned behavior of (Ajzen, 1985). The theories based on optimality principles are currently replacing previous approaches of open-loop trajectory planning (e.g., (Flash & Hogan, 1985; Uno, Kawato, & Suzuki, 1989)) which is realized by a lower-level control mechanism afterwards. We follow the approach by (F. Flemisch et al., 2016; Rothfuß et al., 2020) and consider a single action level which also encompasses the interaction with the machine, yet, still allowing for the integration of current theories of human sensorimotor control. Indeed, the neuroscientific community seeks a cohesive framework (Scott, 2004). Thus, recent literature suggests that the aforementioned optimality principles, and in particular optimal feedback control theory, are strong candidates to describe various aspects of motor behavior including goal-directed actions and task-related fast reactions with time constants in the order of magnitude of seconds and milliseconds, respectively (Gallivan, Chapman, Wolpert, & Flanagan, 2018; Nashed, Crevecoeur, & Scott, 2012; Pruszynski & Scott, 2012). In this respect, sensory feedback from the environment, feedback from the action level to the decision level, and the definition and specification of the interaction mechanisms within each level are crucial for a description of symbiotic human-machine systems. The next section specifies the interplay between the human and the machine within and across the decision and action levels.

2.2. Interaction Dimension

While the task dimension defines the level of interaction in terms of an overall task, the mechanisms of interaction at each of these levels need to be defined such that a symbiotic human-machine system arises. The interaction dimension defines the main characteristics of the interplay between the partners across the levels of the task dimension. We conjecture the following features of a symbiotic interaction

1. a highly skilled and coordinated joint action: Symbiotic action is characterized by a low cognitive effort for task completion. Therefore, in the well-known subdivision by human behavior in knowledge-, rule-, and skill-based (KRS) behavior of (Rasmussen, 1983), symbiosis implies skill-based behavior on both the action and decision levels, while permitting rule-based behavior on the decision level.

2. the possibility of a coordinated shift of the desired level of automation. In particular, a hybrid approach optimally combining context-sensitive, machine-induced shifts based on task-
related triggers and human-induced shifts is characteristic to symbiotic systems.

3. congruent individual representations of the interaction, including each partner’s own intention and the expectation about the intentions of the other partner, as well as the effect of the execution of the decisions and actions, including

4. feedback from each partner and from the environment within a perception and shared-action cycle.

In the following, we propose an interaction framework for symbiotic human-machine systems which captures the proposed features. The representation of the interaction can be interpreted in terms of own intention and expectation about the intentions of the other partner.

2.2.1 Interaction on the Decision Level

Figure 4 shows the interaction on the decision level. Both the human and the machine (gray rounded rectangles) obtain sensory feedback from the environment that is processed in the perception block. This feedback includes information from the environment in the form of states, for example, positions, velocities, orientations of the jointly manipulated object or systems. However, it also includes performance metrics (cf., Section 2.3.). This feedback is processed by the human and the machine (percept block) and is interpreted in the form of signs or cues, as well as continuous and task-relevant signals. These are swiftly processed to activate single or sequences of skill-based behaviors of the human-machine system. The heart of the interaction dimension is the symbiotic understanding between the human and the machine. The blue blocks depict the individual representation each of them has considering the other partner, including their own expectations on the interaction as well as a model which describes the interference of the expectations and potential actions. Symbiotic understanding implies that these representations and thus the human and machine conceptions of each other and of the unity they form, while not necessarily being identical, are congruent to each other and compatible with the common higher-level goal, allowing the capitalization on individual strengths and the goal-oriented fusion of information available to each partner. These individual conceptions must include the recursive connections and coupled control loops with potentially both feedforward and feedback components (cf., Section 1.3.). In addition, symbiotic understanding on the decision level permits the shift of the desired level of automation (cf., Section 1.1.), that is, the extent to which the machine acts autonomously. Symbiotic understanding also enables a flexible initiation and realization of various levels of automation, thus allowing for an adequate individual prediction of the overall human-machine system behavior (green H/M blocks), after which the negotiation of the chosen decision takes place (yellow H/M blocks, see e.g. (Rothfuß, Wörner, Inga, Kiesel, & Hohmann, 2021) for first realizations of human-machine negotiation on the decision level). These decisions are passed down to the lower action level as individual, yet mutually congruent goals.

2.2.2 Interaction on the Action Level

Figure 5 depicts the interaction dimension on the action level. On this level, we similarly have individual perception and representations or models of each partner as on the decision level. However, the action level includes the common coupling due to the simultaneous action execution at
FIGURE 4. Interaction dimension on the decision level for human-machine symbiosis: Symbiotic understanding allows the prediction of the overall system behavior and thus a symbiotic decision emerges which consists of each partner’s own decision. Symbiotic understanding is based on the complex task and its decomposition, as well as on the perception of environmental feedback as continuous signals and signs in the form of skilled behavior activation cues (cf. (Rasmussen, 1983)). Additionally, feedback from the environment and of the symbiotic action permits the consideration of the behavior at the lower action level in the chosen decisions. Human (H) and machine (M) blocks denote individual representations with respect to the corresponding elements.

this lower haptic level. The output of the yellow H-block is the internal representation of the optimal human action, which is combined with perceived feedback from the environment and the information from the decision level for a symbiotic understanding at this level. An analogous procedure takes place on the machine side. Symbiotic understanding at this action level also includes an efficient intention recognition based on the haptic feedback, which also allows for the perception and emergence of a desired level of automation. We note that the level of automation at the action level has to be described with a continuous-valued approach accordingly to the continuous interaction (Braun, Flad, & Hohmann, 2019), contrary to its counterpart at the decision level where discrete-valued shifts (as defined by (Endsley & Kaber, 1999) or (Sheridan & Verplank, 1978)) are also conceivable (see, e.g., (Chiou et al., 2021)). We hypothesize that symbiotic understanding, prediction, and execution can be merged into a consistent symbiotic interaction model which allows the continuous description of the overall symbiotic human-machine system behavior at a particular task level. The symbiotic interaction, which yields highly skilled behavior, results in a better performance compared to individual actions by both partners when solving a task. This
FIGURE 5. Interaction dimension at the action level for human-machine symbiosis: Symbiotic understanding is the foundation of an overall system behavior prediction and thus of a highly skilled symbiotic action execution (joint action). Symbiotic understanding is based on the perception of environmental feedback as continuous signals, the individual decisions and the symbiotic decision from the upper decision level. Human (H) and machine (M) blocks denote individual representations with respect to the corresponding elements.

2.3. Performance Dimension

Symbiosis in human-machine systems constitutes the most effective interaction form which allows for the emergence of synergies. Therefore, we conjecture that the performance of the overall system goes beyond the possible performance each partner could deliver on his own. It also allows for various kinds of interaction, including shared control, where the human or the robot could execute the task individually (Abbink et al., 2018). The evaluation variables of the performance of a system depend on the specific use case and can therefore vary considerably (e.g., (Gray, John, & Atwood, 1993; Khademian & Hashtrudi-Zaad, 2011; Uhl, Lindenmann, & Matthiesen, 2021)). Generally speaking, however, there are three different aspects for evaluating performance: Efficiency as the ratio between work and time, the number of application errors, as well as the quality of the work result (Nielsen & Levy, 1994). In order to enable an increase in performance, the technical system must be adapted to the application (e.g., (Hoelz, Kleinhans, & Matthiesen, 2021)) and es-
especially to the user (Matthiesen & Germann, 2018; Vedder & Carey, 2005). Performance is also an aspect of usability (Germann, Jahnke, & Matthiesen, 2019), which according to (DIN EN ISO 9241-11:2018-11: Ergonomics of human-system interaction - Part 11: Usability: Definitions and concepts (ISO 9241-11:2018); German version EN ISO 9241-11:2018, 2018) is the extent to which a technical system can be used effectively, efficiently, and satisfactorily by a defined user in its relevant application. Therefore, a high usability is a necessary condition for symbiotic human-machine interaction to emerge and systematic approaches for its analysis are needed, e.g. the Usability Study Evaluation Process of (Germann, Helmstetter, Fotler, & Matthiesen, 2021).

As described in the interaction dimension (cf., Section 2.2.), the symbiotic interaction between human and machine is characterized by mutual understanding which involves intention recognition as well as a highly coordinated joint execution of the task. The impact of this interaction on the performance (see Figure 6) is described in the following: The two-sided understanding within a symbiotic human-machine interaction enables not only the human to recognize the intention of the machine for intuitive operation, but also the machine to recognize the intention of the human so that both partners can optimally and swiftly adapt to each other. This reduces the number of application errors that occur and simultaneously increases the efficiency of both partners. In a human-machine interaction, a particularly high increase in performance is achieved when the weakness of one partner can be compensated by the strength of the other (Abbink et al., 2018). An example of this is a situation where either partner perceives task-relevant information which is unavailable to the other. Therefore, in a human-machine symbiosis, at each task level described in Section 2.1., the “stronger” partner takes the lead. This corresponds to the hybrid approach to switching the level of automation mentioned for the interaction dimension in Section 2.2.. We note that the symbiotic interaction also permits different levels of automation between task levels. For example, if it is favorable for the task, then the human can take the lead at the decision level, while the machine takes the lead at the action level. As soon as the subtask is completed, the machine may take the initiative to continue with another subtask, thus obtaining the lead at the decision level. Besides increasing efficiency, the individual strengths of the partners lead to an improved quality of the work result.

In addition to the high performance, long-term effects also are characteristic of symbiotic human-machine systems. Thus, the short-term increase in efficiency leads to energy savings in the medium term and due to the optimal interaction to a minimum risk of physical harm for the human being and less wear on the machine in the long term. Other aspects of usability are also necessary for symbiotic systems, such as ergonomics and vibration comfort. Indeed, for instance, bad ergonomics is reported in currently developed exoskeletons (Fox, Aranko, Heilala, & Vahala, 2020). Therefore, it becomes apparent that the user’s perception and experience play a decisive role in the consideration of usability in addition to performance (Germann et al., 2019). The human-sided experience dimension will be described in more detail in the next section.

### 2.4. Experience Dimension

Optimization in the sense of a better overall performance has been a common focus in the development of human-machine systems (cf., Section 2.3.). In the multivariate perspective for symbiotic systems, the first three dimensions, that is task, interaction, and performance dimension, refer to the whole human-machine system. The fourth dimension is somewhat special, as the experience dimension is restricted to the human partner of the interaction system. Here, we refer to four con-
FIGURE 6. Influence model of the symbiotic interaction of human (H) and machine (M) on the quality of the performance, which is an aspect of usability. Symbiotic interaction leads to a high quality of the work result, high efficiency, and a low number of application errors.

Structs of human experience that may be of special interest: Flow experience, acceptance, sense of agency, and embodiment (see Figure 7).

2.4.1 Flow Experience
Highest quality of the human’s experience is expected in the case of a high balance between perceived challenge and perceived skill. This highest overall quality of subjective experience is referred to as a flow state in which the person feels cognitively efficient, motivated, happy, and is acting with full involvement (e.g., (Csikszentmihalyi & LeFevre, 1989; Moneta & Csikszentmihalyi, 1996), for a meta-analysis, see (Fong, Zaleski, & Leach, 2015)). Flow states have been observed to have a greater influence on the quality of our experiences irrespective of whether we are working or leisuring (Csikszentmihalyi & LeFevre, 1989), to predict performance (Engeser & Rheinberg, 2008), and they may optimize energy expenditure (Peifer, Kluge, Rummel, & Kolossa, 2020). Consequently, when thinking about optimizing the interaction of human and machine, the experience of flow while conjointly performing a challenging task is the final goal, from the humans’ point of view.

In computer-mediated environments, a model has been proposed separating person (trait and state aspects) from artifact (e.g., computer, tool, toy, or software aspects) and from task components (PAT), as well as interactions of these components (e.g., person-task interaction in terms of the challenge-skill balance, an immediate feedback, perceived control, or clear goals) as antecedents of flow (Finneran & Zhang, 2003). Interestingly, these different PAT components have
FIGURE 7. Experience dimension for the symbiotic interaction of human (H) and machine (M): A symbiotic system may change the user’s experience resulting (1) in some flow experience due to the fact that the task challenges fit optimally to the user’s capacities, (2) in a high acceptance for the machine use in terms of the symbiotic interaction, (3) in an embodiment of (parts of) the machine, and (4) in a change of the sense of agency as the user may perceive control not just for own, but also for effects elicited by the machine.

some main similarities to our multivariate perspective on human-machine interaction. For example, the! main importance of the challenge-skill balance of the person-task interaction directly links to our described task dimension (cf., Section 2.1.) in terms of an optimal balance between task affordances and the capacities and skills perceived by the user. Thus, if the task challenges fit optimally to the perceived capacities of the user, we would expect the user to experience some flow. Moreover, the capacities of the user may be perceived higher in the case of an optimal coupling with the machine.

Flow can be operationalized using unidimensional or multidimensional methods (Hoffman & Novak, 2009). Unidimensional methods ask participants to report flow experience using only up to three items, referring to a brief narrative description of flow experience which had been presented to the participants beforehand (Hoffman & Novak, 2009). Multidimensional measures employ validated and commonly used scales relating to several constituent constructs related to flow (e.g., Flow Kurzskala FKS, (Rheinberg & Vollmeyer, 2003); Dispositional Flow Scale 2 DFS-2, Flow State Scale 2 FSS-2, and their short versions, (Jackson, Martin, & Eklund, 2008); short and core flow scale, (A. J. Martin & Jackson, 2008); WOrk-reLated Flow inventory WOLF, (Bakker, 2008)). Moreover, an experience sampling methodology can be employed, asking participants repeatedly
to indicate their current flow state while being engaged in a certain activity (Fullagar & Kelloway, 2009).

Apart from the human’s experience itself (i.e., in terms of flow experience), the optimization of the interaction of the human and the machine is of main interest (Berberian, 2019). A highly adaptive partnership would be characterized by mutual understanding and trust, leading to an effortless interaction where a new joint agent identity, a kind of “we” might emerge (Jenkins et al., 2021). In terms of the human’s experience, this relates to the acceptance of human-machine systems (for a meta-analysis, see (King & He, 2006)), to sense of agency (e.g., (Ruess, Thomaschke, & Kiesel, 2017, 2018), as well as embodiment (for a review, see (Schettler, Raja, & Anderson, 2019)).

2.4.2 Acceptance

An important basis for a successful human-machine interaction is the acceptance of the technology. In the Technology Acceptance Model (TAM; for a meta-analysis, see (King & He, 2006); and the latest version TAM3, (Venkatesh & Bala, 2008)), it is proposed that behavioral intention influences behavior. The behavioral intention itself is predicted by the perceived ease of use, the perceived usefulness, attitudes, subjective norms and perceived behavioral control (e.g., (King & He, 2006)). Thus, acceptance may relate to the user’s experience of the symbiotic interaction with the machine, as mentioned in the interaction dimension (cf., Section 2.2.): High acceptance of the machine should result in interacting with the machine in a symbiotic manner. The other way round, if the interaction with the machine is symbiotic, high acceptance ratings would be expected. Acceptance has been operationalized employing scales that refer to existing technologies (e.g., (Chintalapati & Daruri, 2017; van der Laan, Heino, & de Waard, 1997; Vantrepotte, Berberian, Pagliari, & Chambon, 2021)) or to future technologies described in scenario texts (Reinares-Lara, Olarte-Pascual, & Pelegrin-Borondo, 2018; Toft, Schuitema, & Thøgersen, 2014). Additionally, Cognitive-Affective Mapping, a recently developed method that bridges the gap between quantitative and qualitative research traditions (Reuter, Mansell, Rhea, & Kiesel, 2021; Thagard, 2010), may be employed in terms of anticipatory acceptance prediction of emerging technologies.

2.4.3 Sense of Agency

The feeling of controlling and causing changes in the environment is called sense of agency (e.g., (Haggard & Chambon, 2012)) and suggested to be an important cue in optimizing human-machine interaction (Berberian, 2019). It implies that the human senses agency for environmental changes caused by the symbiotic human-machine system. Thus, this sense of agency relates to the environment and to the performance dimension (cf., Section 2.3.). If the interaction is symbiotic, a high sense of agency, also for positive performance effects caused by the machine, would be expected. Sense of agency is said to influence cooperativeness, team performance, and fluency (Dagioglou & Karkaletsis, 2021). Consequently, a high sense of agency should also increase the performance itself.

Sense of agency can be operationalized both explicitly as well as implicitly. Explicit measures use one single item asking on a Likert-scale for the amount of control (e.g., (Wen, Kuroki, & Asama, 2019)) or employ some validated and standardized scales (e.g., Sense of Agency Scale SoAS, (Tapal, Oren, Dar, & Eitam, 2017); Sense of Agency Scale for Heavy Machine Operation SoAS-HMO, (Raima, Ito, Saiki, Yamazaki, & Kurita, 2020); or Sense of Agency Rating Scale SOARS, (Polito, Barnier, & Woody, 2013)). Implicit measures assess sense of agency in terms of intentional binding,
a biased time perception in action contexts (Haggard & Chambon, 2012; Humphreys & Buehner, 2009; Ruess, Thomaschke, & Kiesel, 2020), or sensory attenuation, a biased intensity perception in action contexts (e.g., Hughes, Desantis, & Waszak, 2013). Implicit and explicit measures may relate to different processes of sense of agency (e.g., Dewey & Knoblich, 2014; Imaizumi & Tanno, 2019). Thus, for optimizing human-machine interaction on both action and decision levels of a task and also towards an intuitive manner, implicit and explicit sense of agency should be assessed.

2.4.4 Embodiment

Finally, symbiotic systems may result in a changed experience of the own body. This refers to the embodiment, that is, the feeling that an object is integrated into the body scheme (for a review, see Schettler et al., 2019). For example, tool-use changed the estimated forearm length of the participants (Sposito, Bolognini, Vallar, & Maravita, 2012), some embodiment has been observed for robotic hands (Alimardani, Nishio, & Ishiguro, 2013), or, in a more anecdotal way, car drivers often report to even sense pain in case they witness a car crash (Sheller, 2004). Symbiosis in physically coupled human-machine systems is expected to change the embodiment by incorporating at least parts of the machine into the own body scheme.

Embodiment can be operationalized either explicitly, employing questionnaires (e.g., Hoffmann, Bock, & Rosenthal, 2018), or implicitly, in terms of the rubber hand illusion (Botvinick & Cohen, 1998). In this illusion, participants see stimulations exerted to a rubber hand and perceive this stimulation as if it was exerted to their own hand (Botvinick & Cohen, 1998).

Currently, the relation of all four variables of the experience dimension to each other (i.e., flow experience, acceptance, sense of agency, and embodiment) is unclear. Elaborating on the interplay of these variables will increase our understanding and thus the accuracy to predict human experience in human-machine interactions and to develop future interaction scenarios in terms of symbiotic systems.

2.5 Limitations and Future Perspectives

We see the multivariate perspective to provide a holistic, far-end, and long-term optimization of physically coupled human-machine systems as it takes into account various disciplines integrated in the four dimensions. Positive effects may be achieved both in multiple dimensions and in the long-run by asking for the optimal trade-off between different dimensions instead of singularly focused optimization in one dimension. For example, our multivariate perspective asks for a trade-off between closely coupled physical interaction and interacting at all levels of a common task, or for a trade-off between performative optimization and improving experience variables at the same time. Thereby, some negative side-effects of the development of human-machine interaction may be prevented, presumably being especially important in the long term. Other examples may be energy efficiency, wearout of the machine, or dependency and loss of capacity of the human, but also ethical or sustainability aspects. So far, negative side-effects or long-term negative effects of human-machine interaction were mainly evaluated and addressed separately from the development of human-machine interaction. Our multivariate perspective also allows to consider negative (side-)effects and to find an optimal balance of different challenges in the development of human-machine interaction.
We note that the multivariate perspective is a framework which, in the future, can be specified in more detail: For example, the task dimension may be amplified separating not just the action and decision level, but an operational or the decomposition level. Similarly, the interaction dimension in terms of the feedback control loops and a recursive intention recognition with real-time updating of human and machine representations may become more sophisticated. For the performance dimension, so far, we refer to two main advantages of symbiotic systems (i.e., intention recognition and complementary strengths) which need to be specified and complemented. For the experience dimension, additionally to the suggested variables (i.e., flow experience, acceptance, sense of agency, and embodiment), variables like trust or ethical aspects, may be addressed in the future.

3. CONCLUSION

In the field of physically coupled human-machine systems, the idea of a “true collaboration” or “symbiosis” has been recently mentioned in the literature. Here, we propose a multivariate perspective as necessary aspects to consider in the future development of physically coupled human-machine systems, which consists of four dimensions: Task, interaction, performance, and experience dimension. First, human and machine form a unity as they (physically) work together and complement each other to accomplish a common task. The interaction between both partners as well as the utilization of their individual strengths may occur on different levels of a common task, on which each of the partners may take the lead depending on the individual strengths (task dimension). Both partners recognize the intention of the other in the sense that they are able to predict each other’s actions; they continuously adapt to each other and complement their individual strengths. However, the human and machine partners are considered equals with respect to the task and each of them may take the initiative (interaction dimension). The resulting symbiotic state is characterized by a higher overall performance (performance dimension). In addition, the users experience some kind of flow, higher acceptance of the technology, some sense of agency for effects elicited by the machine, as well as embodiment for parts of the machine devices (experience dimension). This multivariate perspective is generic, flexible and applicable as a shared, interdisciplinary terminology towards an optimal interaction between humans and machines in various application scenarios.
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