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The concept of hybrid human-AI regulation: Exemplifying how to support young learners' self-regulated learning

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A B S T R A C T

Hybrid systems combining artificial and human intelligence hold great promise for training human skills. In this paper, I position the concept of Hybrid Human-AI Regulation and illustrate this with an example of a first prototype of a Hybrid Human-AI Regulation (HHAIR) system. HHAIR supports self-regulated learning (SRL) in the context of adaptive learning technologies (ALTs) with the aim to develop learners' self-regulated learning skills. This prototype targets young learners (10–14 years) for whom SRL skills are critical in today's society. Many of these learners use ALTs to learn mathematics and languages every day in school. ALTs optimize learning based on learners' performance data, but even the most sophisticated ALTs fail to support SRL. In fact, most ALTs take over (offload) regulation from learners. In contrast, HHAIR positions hybrid regulation as a collaborative task of the learner and the AI which is gradually transferred from AI-regulation to self-regulation. Learners will increasingly regulate their own learning progressing through different degrees of hybrid regulation. In this way HHAIR supports optimized learning and the transfer and development of SRL skills for lifelong learning (future learning). The HHAIR concept is novel in proposing a hybrid intelligence approach training human SRL skills with AI. This paper outlines theoretical foundations from SRL theory, hybrid intelligence and learning analytics. A first prototype in the context of ALTs for young learners is described as an example of hybrid human-AI regulation and future advancement is discussed. In this way, foundational theoretical, empirical, and design work are combined in articulating the concept of Hybrid Human-AI Regulation which features forward adaptive support for SRL and transfer of control between human and AI over regulation.

1. Hybrid Human-AI regulation: supporting young learners' self-regulated learning

With technologies increasingly gaining more data and intelligence, a new era of Human-AI interaction is emerging (Kamar, 2016). There is ongoing fusion between human and artificial intelligence (AI) into so-called hybrid systems. A defining characteristic of hybrid systems is that the boundaries between AI and human decision-making fluctuate. For example, self-driving cars mostly offload driving to the AI, but in situations that are too complex for the AI to navigate, control is transferred back to the human driver. Consequently, tasks can be *offloaded* from humans to AI and *onloaded* from AI to humans (Buxbaum-Conradi et al., 2016). Hybrid systems offer potential for training complex human skills in the context of education (Harari, 2018). These systems offer opportunities to *offload* human intelligence at the start of the learning process (Dellermann et al., 2019), and *onload* tasks once learners have developed the prerequisite knowledge and skills. In this transition, AI can model and scaffold human learning. Yet the first hybrid systems to train people with AI are still to be developed.

In schools the trend to have one device (tablet or computer) per learner has furthered the integration of technology into human learning (Molenaar, 2021; OECD, 2016). Adaptive Learning Technologies (ALTs)[1] optimize learning of foundation skills in mathematics and language in many primary and secondary schools across Europe (Aleven et al., 2017; Koedinger et al., 2013; Molenaar et al., 2016). Typically, young learners practise language or maths problems on a tablet or computer, while these technologies capture rich data on learners' performance. ALTs successfully use this data to adapt instruction to learners' performance, but are still largely incapable of supporting self-regulated learning (SRL). Instead, ALTs merely take over (*offload)* regulation from learners (Molenaar et al., 2021), which is problematic as it prevents them from learning how to effectively control and monitor learning themselves (Bannert et al., 2017; Winne, 2018). There are two arguments against *offloading* regulation: i) when learners regulate their own learning, they learn more and transfer what is learned to new contexts, the *transfer learning argument*; and ii) the ability to self-regulate is a key skill for successful lifelong learning, the *future learning argument*. For these reasons, there is strong consensus that ALTs should not regulate learners, but learners should develop the SRL skills to regulate themselves (Järvelä et al., 2021).

I propose a hybrid system to develop young learners' SRL skills in ALTs. It can *offload* regulation at the start of learning (Dellermann et al.,

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[1] Adaptive Learning Technologies are learning programmes on tablet computers that learners use to practise maths, spelling and grammar.

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2019), and gradually *onload* regulation once learners have developed the necessary skills. However, hybrid systems that train SRL have yet to be developed and their design involves theoretical and methodological challenges regarding the measurement and support of SRL. The overall objective of this paper is to outline the concept of Hybrid Human-AI Regulation (HHAIR) to support learners' learning. The theoretical foundations from SRL theory, hybrid intelligence and learning analytics are discussed. I will conceptualize HHAIR in the context of ALTs and for young learners and outline a prototype as a first example of Hybrid Human-AI regulation. The proposed second prototype elaborates on a more advanced Hybrid Human-AI Regulation system. In this way theoretical, empirical, and design work are combined in articulating the concept of Hybrid Human-AI Regulation which features forward adaptive support for SRL and transfer of control between human and AI over regulation. The last paragraph discusses how the HHAIR concept compares to existing SRL support tools, such as scaffolding, prompting, and pedagogical agents.

2. Theoretical foundations

The core theoretical foundation for HHAIR is SRL theory which forms the basis for measuring and supporting SRL (Winne, 2018). Self-regulated learning is conceptualized as a goal-directed process in which learners consciously make decisions that lead toward their learning goals (Azevedo, 2015). Self-regulating learners use cognitive processes (summarizing, rereading, and elaboration) to study a topic, and metacognitive processes (orientation, planning, monitoring, and evaluation) to control and monitor their learning and motivate themselves to engage in an appropriate level of learner effort (Greene & Azevedo, 2007). Effective self-regulating learners set learning goals to plan their learning and attain these goals by adjusting their strategies (Winne, 2017). They also monitor whether their actions support progress towards their learning goal (Azevedo, 2009).

Yet, research has consistently indicated that many learners experience difficulties in adequately self-regulating their learning (Greene & Azevedo, 2010; Järvelä et al., 2013). They face a utilization deficiency, that is the inability to activate self-regulated learning during learning (Winne & Baker, 2013). Although learners have the SRL skills to regulate their learning, they hardly use them. Regulation of learning is hampered (Seufert, 2018), especially when learning tasks are demanding or when students have little prior knowledge. The conditional knowledge to trigger SRL processes when needed during learning is problematic, especially when working memory capacity is under pressure. At these times, learners need help to elicit SRL processes and external support can help learners engage in successful regulation. Hence, learners' SRL is influenced by learner characteristics (ability, prior knowledge, SRL skills) and task characteristics (domain and learning goals, demands), emphasizing the need to adjust support to individual learners (Dignath et al., 2008). HHAIR, therefore, envisions adaptive forward support that elicits SRL at the right time during learning to help learners overcome the utilization deficiency.

Following the COPES model, effective self-regulating learners use learning goals to plan their learning and they attain these goals. They continuously monitor whether their actions support progress towards their learning goals in the monitoring loop (Azevedo et al., 2005) and adjust tactics, operations, and strategies, for example increasing their effort, over time in the control loop (Hadwin, 2011). Learners monitoring and control sustain the alignment between learning goals and learners' actions (Molenaar, Horvers, Dijkstra, & Baker, 2019; Molenaar et al., 2019). This monitoring and control unfolds in four loosely coupled phases in the COPES model: i) in the task definition phase, learners develop an understanding of the task, ii) during the goal-setting phase, learners set their goals and plan their learning, iii) in the enactment phase, learners execute their plans and control and monitor progress, iv) in the adaptation phase, adjustments are made when progress towards the goals is not proceeding as planned. These phases are enacted in the context of task and learner conditions that drive operations, strategies, and tactics performed by learners (Winne & Hadwin, 1998). This model emphasizes the relation between internal regulation and external factors that influence regulation. Adaptive Learning Technologies (ALTs) are such an external factor that not only affect regulation but also take over important regulation activities from the learner.

In the context of ALTs where learners mostly practise maths problems, they monitor accuracy of answers to the problems. Accuracy is understood as the number of correct answers and higher accuracy allows learners to make progress faster toward their goals. Hence, effective self-regulating learners in ALTs adjust their actions and effort to ensure learning goals are achieved and control for a productive level of accuracy. Direct feedback that indicates whether an answer is correct immediately after responding provides an important monitoring signal for learners. When accuracy drops due to factors other than lack of knowledge, learners could increase their effort to maintain accuracy (Molenaar et al., 2022). Consequently, accuracy can be viewed as a function of knowledge and effort and can be regulated by adjusting one or both of these elements. Effort remains for the learner to control, but knowledge-related regulation of accuracy is now regulated by the ALT.

ALTs select the next problem based on the learners' knowledge. The technology selects instructional materials (problems and/or instruction) based on an estimate of the learners' current knowledge and/or the probability that a problem will be solved correctly by the learner (Corbett & Anderson, 1995; Klinkenberg et al., 2011; Koedinger et al., 2012). Hence, the ALT offloads part of the control loop normally performed by learners. In the control loop, the ALT selects problems aligned with the learners' learning goal that are adjusted to their current knowledge. This reduces the need for learners to plan their actions and the ALT takes over corrective selection of novel actions. If a learner does not make sufficient progress, many ALTs automatically reduce the difficulty of the problems. Without this ALT control, corrective actions are dependent on a learner's monitoring, which is often imperfect (Roebers, 2017; Van Loon et al., 2013). ALT control can therefore overcome learners' imperfect ability to adequately regulate alignment between their knowledge and problems and consequently improve accuracy.

What is being offloaded to AI is both the need for students to monitor their progress and the chance to control and make adjustments. ALTs often provide students with instant direct feedback which reduces the need for monitoring. Also, the need to select control strategies is reduced as these systems often adjust the difficulty of the problems to the students' progress. Hence, the need to signal reduced progress and the opportunity to act on this are both taken over by these systems. Nevertheless, another important element in the control and monitoring loop, namely the adjustment of effort to maintain accuracy remains the task of the learner. Even though many ALTs assume learner effort is related to a specific probability of success, it is up to the learner to apply the level of effort needed to maintain accuracy. Consequently, this educational arrangement is a form of *hybrid regulation of accuracy* where AI regulates knowledge alignment and the learner regulates effort. The reciprocal interaction between these two elements constitutes a hybrid intelligence with distributed tasks between AI and learner. Hybrid intelligence is a new field that researches and develops intelligent systems that augment rather than replace human intelligence (Akata et al., 2020, pp. 18–28). These systems are developed to leverage human strengths and compensate for human weaknesses. Humans and AI are regarded as equal team members solving tasks in cooperation (Siemon et al., 2019).

The HHAIR[2] concept embodies this by critically evaluating human regulation and augmenting human SRL with AI to overcome utilization deficiency and improve learners' SRL skills. As such HHAIR and hybrid intelligent systems in general aim to optimize the complementary strengths of human intelligence and AI, so that the two together behave

[2] For the reader who would like to see the relationship between HHAIR and scaffolding, this is explained in the last section of the paper.

more intelligently than each separately (Dellerman et al., 2019). Yet research on hybrid intelligence is still in a very early stage, and developing collaborative, adaptive, responsible, and explainable hybrid intelligent systems raises a number of important questions (Akata, 2020, pp. 18–28): i) how do we develop AI systems that work in synergy with humans, ii) how do these systems learn from and adapt to their environment, iii) how do we ensure ethical and responsible behaviour, and iv) how can humans and AI share and explain their awareness, goals, and strategies to each other? These questions are all valid issues for the development of hybrid human-AI regulation. Even though positive effects on learners' learning have been found when comparing learning with ALTs to traditional learning environments (Aleven et al., 2017; Faber et al., 2017; Molenaar et al., 2017), there are only limited insights into how learners actually regulate learning within these systems (Molenaar et al., 2021). In the next section, I will discuss how to support collaboration between learners and AI in line with views on hybrid intelligence and as a social, technological ensemble (Cukurova, 2019).

3. Dashboards as an interface in hybrid regulation

We propose to have dashboards function as an interface to facilitate interaction between the learner and AI. In fact, a distinction often made in learning analytic literature between i) *extracted analytics,* learner dashboards to explain to learners how to regulate their learning, and ii) *embedded analytics,* advanced algorithms to detect learners' progress and adjust learning material, is used here (Wise, 2014; Knoop-van Campen et al., 2021;Van Leeuwen et al., 2021). The dashboard provides information to the learner about the functioning of the AI and is key to the transition of control and role division between AI and learner. Dashboards communicate the forward adaptive support in which control over regulation is gradually transferred from AI to learners, who increasingly become more responsible for and active in their own regulation. For example, AI only models regulation in the dashboard at first and executes full control, later the students take over control supported by scaffolds from the AI. In this transition process, dashboards initially show learners how the AI monitors and controls learning, and later become a mirror that help learners understand how to monitor and control themselves.

Dashboards are used to show learners how their performance is related to goals (monitoring), and what needs to be adjusted to make progress (control; Jivet et al., 2017; Schwendimann et al., 2017). Over time learners receive progressively more information in the dashboards to regulate their own learning while at the same time AI regulation is reduced. Initially the AI regulates learning and the dashboards raise learners' awareness; ultimately learners regulate themselves and the AI only observes and supports them in understanding their own behaviour. The challenge lies in aligning the extracted and embedded analytics, thus the appropriate dashboard combined with AI-regulation which results in a particular degree of hybrid regulation (Kistner et al., 2010; Winne & Baker, 2013). This orchestrating function to identify learners' SRL during learning and select the appropriate degree of hybrid regulation is the core of the HHAIR concepts and requires complex interaction between AI and learner. This entails developing different dashboards and accompanying settings in the AI-algorithm to realize degrees (Molenaar et al., 2019).

The degrees of hybrid regulation can be based on knowledge about the SRL development and training literature (Dignath & Büttner, 2008; Järvelä et al., 2013). Based on theoretical models of the division and interaction between self and socially shared regulation (Jarvela et al., 2016), four degrees of hybrid regulation are proposed, which have been confirmed by previous research indicating the need for these types of support (Molenaar, Horvers, Dijkstra, & Baker, 2019). These are self-, shared-, co- and AI-regulation, which are characterized by different degrees of human and AI control over regulation (see Table 1). *AI-regulation* is characterized by AI control and simple dashboards to make the learner aware of regulation as it is executed by the AI. In this step AI regulation is automatically adjusted to the learners' performance. The simplified dashboards will be tailored to the basic SRL skills of learners. The primary aim is to make learners aware of regulation during learning.

Table 1
Degrees of Hybrid Regulation.

Degrees of hybrid regulation	AI regulation	Human regulation	Function of dashboard
AI regulation	AI monitors and adjusts extensively	Aware of AI regulation	Raising awareness of AI regulation
Co-regulation	AI monitors and adjusts in small steps	Understanding how AI monitors and controls	Showing AI monitoring and modelling AI control
Shared-regulation	AI monitors and proposes control actions to the learner	Understanding monitoring and executing control	Showing monitoring and scaffolding learners' control
Self-regulation	Observing regulation	Monitoring and self-initiation of control	Showing learners' regulation to support their understanding

The key aspect in *co-regulation* is that dashboards are an explicit reference for learners to better understand AI regulation. Dashboards explicitly model how the AI regulates their learning. This allows the learner to move on from simple awareness to a passive understanding of the regulation. For example, clear indicators are included in the dashboard that show learners when the AI reduced and the difficulty levels of problems increased. In *shared-regulation* learners are asked to execute control actions that were previously governed by the AI during AI and co-regulation. Dashboards continue to function as an explicit reference for learners to understand shared-regulation. Learners receive additional scaffolding in the dashboards on control actions recommended by the AI. In this way, learners can increase or decrease the difficulty of problems themselves but are still supported by the AI. Passive understanding of regulation is replaced by active control over regulation but this active control is still supported by the AI with scaffolds to support the learners' regulation. Finally, in *self-regulated learning* the AI transfers all control over regulation back to the learner. Dashboards function as an explicit reference for learners to understand their regulation, but learners are themselves responsible for their control and monitoring actions. The scaffolding is faded and learners are expected to have acquired the SRL skills to interpret the personalized visualization and translate this into control actions that support their regulation. It is important to note that self-regulated learning initiated by the learner is present in all degrees of hybrid regulation but the external control and support is reduced and learners increasingly become more dependent on internal triggers and control actions. Below I illustrate the role of dashboards in hybrid regulation with a first prototype that shows how co-regulation functions in practice.

4. Prototype 1.0

The first prototype was developed based on the COPES model in which the distinction between internal (upper level of the model) and external regulation (lower level of the model) is made explicit (see Fig. 1, Molenaar et al., 2020).

In HHAIR 1.0 three learner-facing dashboards function as a visual layer between the internal regulation of the learner and the external regulation support provided by the ALT. Their primary function is to support learners to explicitly engage in the four phases that are critical for successful self-regulation. As such, the different visualizations function as a reference for learners to become more aware of their own regulation process. As described above, dashboards function as a mirror for learners to understand how they can monitor their progress, supporting them to recognize the need for control actions and thus driving their internal regulation process following the SRL phases in the COPES

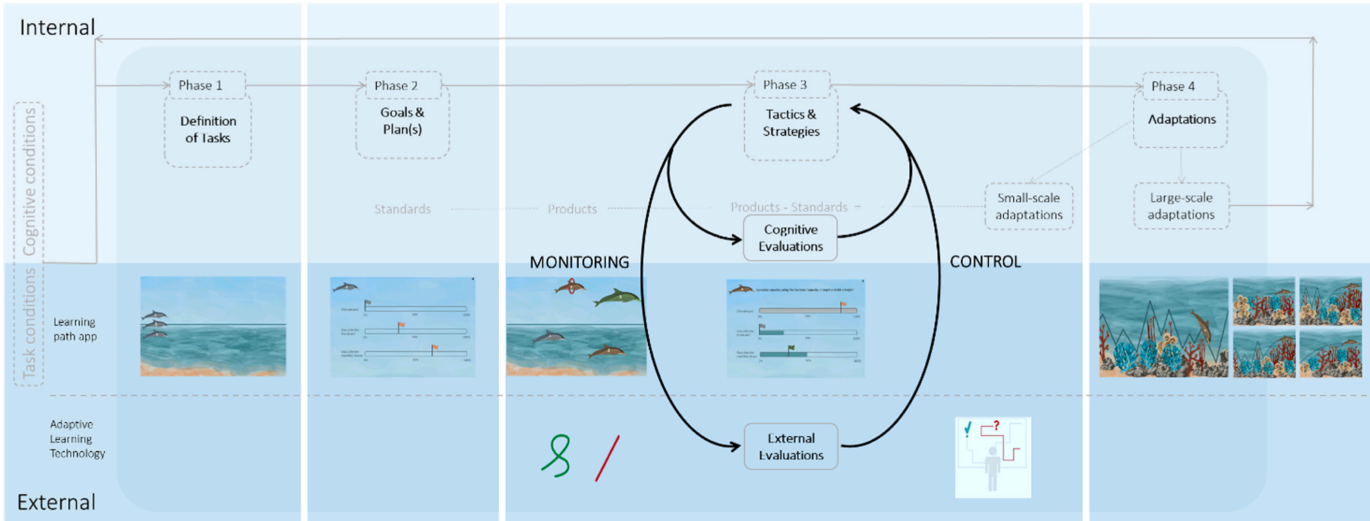

Fig. 1. HHAIR 1.0 prototype.

model.

This prototype is integrated in the context of learning maths with an ALT for learners aged between 10 and 12 (Molenaar et al., 2020). The HHAIR 1.0 prototype is the learning path app participating schools use in addition to their regular ALT. The AI@EDU infrastructure is the data infrastructure from the ALT to the learning path app. The AI@EDU infrastructure allows us to test novel artificial intelligence solutions in existing ALTs that are used in schools. In this way, we develop and refine AI solutions within schools without disrupting the curriculum or day-to-day school activities. This constitutes a unique approach to realizing *ethics-by-design* and quick prototyping with educational professionals, teacher, and learners. The ALT's data was used in HHAIR 1.0 to develop different elements of the dashboards used. Below I describe the different dashboards and their relation with internal regulation in more detail (see also Appendix).

First, in the *task definition phase,* learners need to develop an understanding of the task to be able to formulate appropriate learning goals. In this phase, learners are supported by the "*overview screen*" which summarizes their tasks as visualized by the three dolphins that all represent one skill to be learned over the three lessons that learners are working with the app.

Second, in the *goal-setting phase,* learners need to translate their task perception into goals. The "*goal-setting screen*" functions as an external prompt to support learners to articulate when learning goals are reached. Learners indicate their learning goal for each subskill and lesson. After each lesson, they can see their progress on this subskill both on the goal-setting screen and on the overview screen by the position of the dolphin. The goal setting is based on the idea of feed-up, which comes from feedback literature (Hattie & Timberley, 2007). *Feed-up* represents an external trigger to support learners to articulate *when* learning goals are reached. Feed-up prompts are used to support learners to explicitly set goals and standards for regulation. These standards help them to formulate criteria that indicate *how* they know when a learning goal has been reached, which drives cognitive evaluations in the enactment phase. Consequently, the goal-setting screen has been developed to ground learners' cognitive evaluations in the enactment phase of the COPES model.

Third, in the *enactment phase,* learners work towards their learning goals while monitoring their progress and controlling their actions and strategies as needed. The need for adaptation is determined by cognitive evaluation in which learners compare their current product to their standard to determine progress. Previous research has shown that young learners' monitoring of accuracy is often poor (Aghababyan et al., 2017; Foster et al., 2017; Van Loon et al., 2013). Young learners tend to overestimate their performance, which leads to unjustified regulation actions. For example, if a learner believes he is making strong progress, he may reduce his effort. Overestimation leads to unjustified reduction of effort which could impede further progress. Although learners tend to overestimate their performance in the context of ALTs, there are also learners that consistently underestimates their performance in this context (Molenaar et al., 2020). For this reason, the HHAIR prototype includes performance feedback to provide learners with accurate representations of their actual performance directly in the overview screen, in the goal-setting screen and in the learning path screen.

On the "*overview screen*" progress is symbolized by the position of the dolphin and the dolphins' attributes (hoop and ball) which indicate whether learning goals have been reached. One layer deeper, on the "*goal-setting screen*", detailed information on performance is provided which indicates the exact relation between goals (standards) and current performance (products). This screen can be viewed as an external cue to trigger cognitive evaluation, i.e. to compare the goals set with learning products to evaluate progress. This helps learners realize when their progress is not as expected and they need to adapt (small scale adaptation in Fig. 1), for instance by re-evaluating their degree of effort. This idea is in line with the notion of feed-forward from the feedback literature. Feed-forward is an external cue to re-evaluate plans and adjust strategies. For example, when a learner verbalizes how to adapt learning strategies and actions to ensure future learning. This screen, therefore, provides a cue for learners to explicitly evaluate their progress and determine the need for control actions (Hattie & Timberley, 2007).

Fourth, in *the adaptation phase,* learners enact adaptations. As described above, small-scale adaptations are often embedded in the enactment phase when learners adjust effort or strategies based on cognitive evaluations. Large-scale adaptations entail reflection and drive improved regulation in the next learning cycle. The "*learning path screen*" shows personal progress over time. Here the moment-by-moment-learning curves (MbMLC curves) are used to indicate when learners learned during their practice session (Baker et al., 2011, 2013). The learning paths show learners how they learned over time and this helps them to derive actionable feedback to improve regulation the next time (Molenaar, Horvers, Dijkstra, & Baker, 2019). The names of the learning paths are designed for young learners and are: "high swimmer (immediate drop), quick swimmer (immediate peak), climber in two steps (double spikes), slow climber (close multiple spikes) and climber and descender (separated multiple spikes),"[3]. The MbMLC curves helped learners to explicitly understand their progress over a lesson in order to formulate improvement for the next lesson.

To summarize, the HHAIR 1.0 prototype contains three dashboards (overview, goal setting, and learning path) that are designed to support learners' internal regulation. The visualizations were explicitly developed as external feedback to help learners with a valid reference for their regulation process. Based on this reference, learners can optimize their internal regulation process. Trace data from the ALT are used in HHAIR to provide learners with continuous feedback about their performance, progress, and how progress towards their learning goal is related to their actions. In this way we extend the role of learner-facing dashboards from discussing *what* learners have learned to also incorporate *how* learners have learned.

The first study showed that learners in the HHAIR condition improved regulation during learning, as shown by increased accuracy and less complex MbMLCs, more than learners in the control group (Molenaar et al., 2020). Although learners in the HHAIR condition scored higher on the post-test, they only showed marginally more progress. Learners in the HHAIR condition did show enhanced transfer of their knowledge to a structurally different situation. Finally, there was a difference in relative monitoring accuracy, indicating that learners in the HHAIR condition were more likely to underestimate their knowledge than learners in the control group. Overall, these findings indicate that HHAIR 1.0 affected learners' accuracy during practising, MbMLCs and relative monitoring accuracy.

5. Hybrid Human-AI regulation 2.0

Following this first prototype study, the aim is to continue to articulate the functioning of the AI in more detail and develop the other degrees of hybrid human regulation. Central to hybrid human-AI regulation is the forward adaptive support to gradually transfer control from the AI back to the learner. This conceptual model of Hybrid Human-AI Regulation was developed based on the theoretical foundations, previous empirical work and prototype design outlined above. The model again depicts the four phases of the COPES model, indicating the learners' internal regulation processes and external regulation processes executed by the AI-regulation. These two components form the basis for the transfer of control over regulation. AI regulation is used to support learners' regulation when they lack the skills to successfully self-regulate. This component offloads regulation from the learner to the AI based on the SRL skills and learning behaviour of the learner. The learner-faced dashboards function as the interface between these two components of HHAIR. They help learners to better understand how the AI regulates during learning. In this way learners are expected to become increasingly more aware of how to perform control and monitoring during learning. The transition from AI to human regulation takes place by the upward iteration between AI and human regulatory actions. The relative importance of AI regulation is reduced with the transfer of control from AI to human regulation.

The HHAIR model is depicted in Fig. 2. Similar to the prototype version, the upper section reflects internal regulation and the lower part external regulation. Again, HHAIR 2.0 will follow the four phases of the COPES model to give learners external cues that support internal regulation. In this model there are 4 degrees of hybrid regulation as discussed above. The AI-regulation and self-regulation degree have not yet been developed. The first design of co-regulation was described above with a strong focus on modelling the monitoring loop. The shared-regulation degree is depicted in detail in Fig. 2 and here learners will execute the control loop together with the AI. This collaborative control over the selection of learning materials is expected to support students' control enactment and allow them to execute more control compared to the co-regulation degree.

[3] In the original language it has a more positive sound to it; the terms do not translate well.

6. Relevance

The relevance of the HHAIR concept is two-fold. First, SRL skills are deemed essential for humans in the upcoming AI era. Human intelligence will increasingly be augmented by artificial intelligence. Human agency and oversight are needed to take a leading role in these transitions and regulation skills are critical in these contexts. The OECD (2018) estimates that 45% of today's procedural jobs will be replaced by robots in the near future. There is global consensus that uniquely human skills and competencies, that AI cannot easily replicate, will be necessary to succeed in a rapidly changing world (World Economic Forum, 2018). The ability to self-regulate, i.e. to take initiative, set goals, and monitor self and others, is at the heart of these human skills and competences. Furthermore, SRL skills are needed for effective lifelong learning (at school and in the workplace), to equip learners with agency (the feeling that one controls one's own life) and to provide a means to adapt and regulate behaviour in challenging situations throughout life (e.g., family, hobbies, and work).

Second, Hybrid Human-AI Regulation drives refinements in the measurement and support of SRL skills. Measurement of SRL has been difficult and researchers have been struggling with this issue for over two decades (Azevedo, 2015; Bannert et al., 2017; Veenman et al., 2006). Novel measurements of SRL are used to drive innovation in SRL support, such as HHAIR. Accurate measurement of SRL *during* learning has been a challenge for decades (Azevedo, 2009; Azevedo et al., 2018; Schellings & Van Hout-Wolters, 2011). It has gradually been discovered that triangulation of different multimodal data streams provides valuable new ways to measure learners' application of SRL during learning (Azevedo & Gašević, 2019). In the emerging Self-Regulated Learning Analytics field, different multimodal data streams, such as log, eye gaze and physiological data, are being used to develop new ways to measure SRL unobtrusively during learning (Azevedo et al., 2018; Molenaar, 2021). AI techniques are being applied to better recognize learners' regulatory activities and their development over time (Molenaar et al., 2021; Winne & Baker, 2013). SRL is a dynamic iterative process that evolves over time, and these new techniques help us to explore time and order in SRL (Bannert & Järvelä, 2021; Molenaar & Wise, 2022). In this work interactions between sequential and temporal characteristics of SRL and learning are being further investigated (Srivastava et al., 2022; Molenaar & Järvelä, 2014; Van der Graaf et al., 2021). With technologies increasingly gaining more data and intelligence to resolve these challenges, understanding of how SRL skills develop over time is expected to grow (Azevedo & Gašević, 2019; Winne & Baker, 2013) and work on HHAIR will help to develop this understanding.

7. HHAIR compared with existing forms of SRL support

The proposed HHAIR concept is different from other support techniques that have been used to assist learners' regulation such as prompts (Bannert et al., 2009), scaffolding (Greene et al., 2010; Molenaar, Chiu, et al., 2011) and pedagogical agents providing feedback (Azevedo et al., 2016). These techniques have been effective for improving learning but less successful in developing SRL skills that sustain effective regulation in the absence of support. A drawback to these techniques is that they do not help learners to make explicit inferences about how their actions are related to progress towards learning goals. In HHAIR, dashboards make this relation explicit for learners as well as the transition between external and internal support.

Traditional SRL support facilitated local corrections, but it did not provide sufficient information to train monitoring accuracy or teach learners to determine the need for small and large-scale adaptations themselves. This support may not trigger learners' own cognitive evaluation, which is essential for them to develop their SRL skills and central

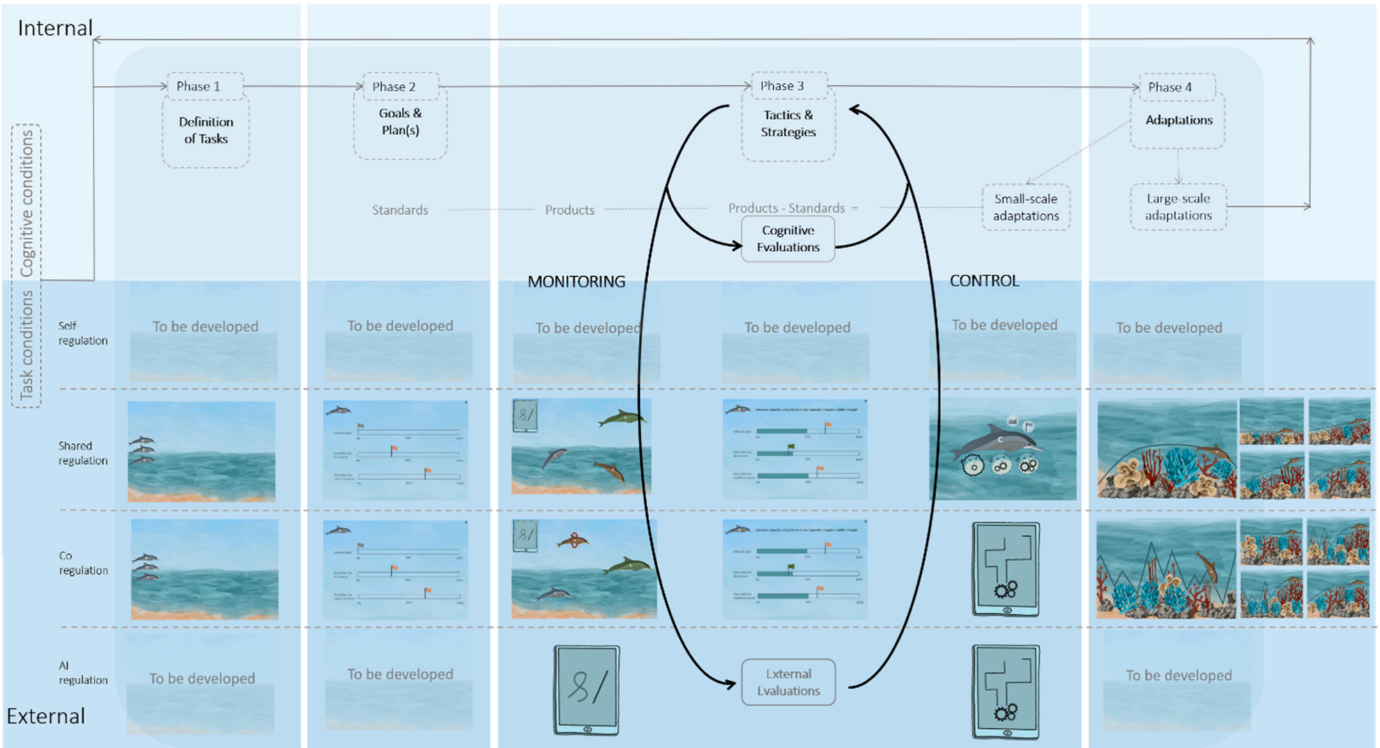

Fig. 2. Hybrid Human-AI regulation conceptualized.

in the HHAIR approach (Dignath et al., 2008). In line with this argument, it has been emphasized that in order to engage in accurate cognitive evaluations, learners need reliable, revealing, and relevant data to draw valid inferences about their own regulation process (Molenaar et al., 2021). Learner-facing dashboards have been used as external cues to help learners make those inferences and our approach is to further develop these dashboards.

Although SRL theory is the most common foundation for learner-facing dashboards (Bodily & Verbert, 2017), most of these dashboards visualize indicators of learner performance to support learners' regulation (Bodily et al., 2018). Performance feedback alone is not always enough to help learners to translate progress data into actions that improve regulation (Butler & Winne, 1995). Although there are some good examples of trace-data-informed progress charts (Arroyo et al., 2007) and intelligent tutor systems to support SRL (Roll et al., 2011), there has been limited work within learner-facing dashboards that use trace data to support SRL (Bodily et al., 2018). This lack of research may stem in part from challenges in understanding what trace data reveal about SRL (Azevedo, 2015; Malmberg et al., 2019) and in finding ways to visualize temporal and sequential characteristics of SRL that are meaningful to learners.

Hybrid Human-AI Regulation therefore combines two novel elements to overcome these issues: i) forward adaptive SRL support and transfer of control based on learners' SRL skills to overcome the sole dependency on learners to self-regulate, and ii) explicit reference to learners' regulation during learning on dashboards to help them to better understand their actions. This mirror function especially can support learners' inferencing and offers unique opportunities for the development of SRL. This mix of support features has the potential to produce a new generation of SRL support that focuses on the development of SRL skills over time as opposed to simply prompting or scaffolding regulation to improve learning.

8. Challenges

There are a number of scientific challenges that need to be resolved to develop a solution: i) to identify individual learners' SRL during learning, ii) to design degrees of hybrid regulation; iii) to confirm effects of HHAIR on transfer of learning, and iv) to validate effects of HHAIR on SRL skills for future learning. The conceptual model combines these challenges into one overview, see Fig. 3.

8.1. Challenge 1. identify individual Learner's SRL during learning

This MbMLC algorithm detects learners' SRL during learning and functions as a basis for the different degrees of hybrid regulation. However, this technique was only used *after* learners completed their learning process and needs to be adjusted for measurement *during* learning. Moreover, the technique was applied on data from one lesson and needs to be adjusted for use over multiple lessons. The challenge is to further develop techniques to measure SRL during learning.

8.2. Challenge 2. design hybrid Human-AI regulation

The role of dashboards as an interface between the learner and the AI that helps learners to develop the SRL skills needed to support their upward movement through the HHAIR model is a challenge. The challenge is to develop dashboards that raise awareness and model and develop new skills without learners becoming dependent on the different levels of support.

8.3. Challenge 3. evaluate effectiveness of HHAIR in optimizing transfer of learning

The third challenge is to test the effectiveness of HHAIR in supporting transfer of learning. Hybrid regulation supports learners to self-regulate more during learning. At the same time, learners need to maintain learning *efficiency* and improve learning *effectiveness*. Learning

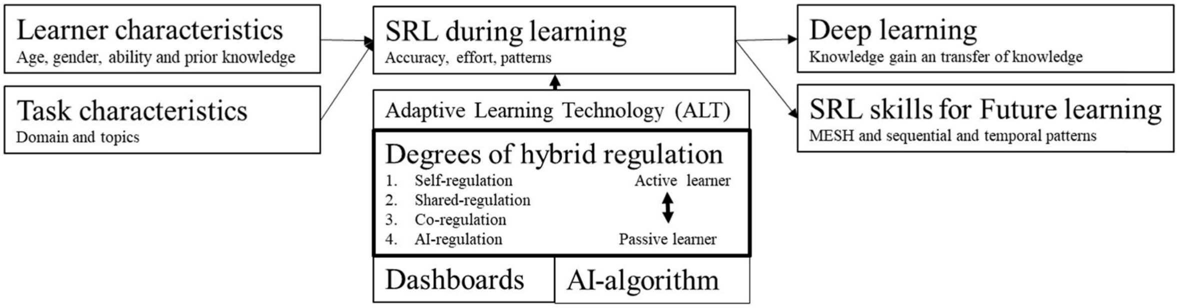

Fig. 3. Hybrid Human-AI Regulation conceptual model.

efficiency is indicated by the relation between learners' actions and learning outcomes, that is the amount of effort and time invested related to outcomes. Efficient self-regulators select those actions that yield the highest learning gain for the least time and effort. Efficiency of regulation is closely related to the control and monitoring of learning and indicators are learners' accuracy and effort. The degrees in HHAIR put higher demands on learners to maintain efficiency and their ability to do that will be an indicator of successful regulation. Learning *effectiveness* refers to the acquisition and transfer of new knowledge and skills (Koedinger et al., 2012). When learners engage in more control and monitoring, the integration of knowledge into existing cognitive structures is supported, which promotes learning and transfer (Bannert et al., 2009). Thus, increased human regulation is expected to support more effective and efficient learning. This hypothesis needs to be examined in short-term pre-post-test experimental studies and initial findings can be used to further refine HHAIR.

8.4. Challenge 4. evaluate effectiveness of HHAIR for future learning

The fourth challenge is to examine long-term effects of HHAIR on the development of learners' SRL skills to support future learning. SRL skills need time to develop and are known to be improved by gradually increasing learner control over regulation (Dignath & Büttner, 2008; Dignath et al., 2008). The degrees of hybrid regulation are ordered to gradually increase human control and hence develop SRL skills (see Table 1). Extant knowledge about the development of SRL skills is insufficient to determine how much time learners need to practise the different degrees and how stable SRL will be across domains and topics. Insights into these questions will drive the development of an AI-algorithm that progresses learners through the different degrees of hybrid regulation. Hence the detection of learners' SRL skills during learning needs to be attuned to different degrees of hybrid regulation. Based on our emerging understanding of how learners' SRL skills develop over time, the transitions between the degrees of hybrid regulation will be refined. This challenge can be addressed in long-term pre-post-test experimental studies. These studies should enable fundamental progress in our understanding of how young learners' SRL skills develop over time in interaction with AI.

9. Conclusion

The HHAIR concept is theoretically ground-breaking in proposing a hybrid system to train human SRL skills with AI. The research needed to develop such systems will foreground the complexity of human-AI interaction in educational applications and use systematic approaches to unravel this complexity to benefit learners. The proposed conceptual model provides a first framework for the development of HHAIR systems. This development has the potential to contribute to advancements in the application of AI in education; in particular, the measurement of SRL and application of hybrid systems for training purposes.

The paper articulates how hybrid human AI regulation is expected to make important theoretical and methodological contributions. This research seeks to illuminate how learners regulate their learning in ALTs and combines three research fields: self-regulated learning, learning analytics, and artificial intelligence. This approach aims to bring about a concerted interdisciplinary dialogue, combining insights from educational sciences with advances in computer sciences and artificial intelligence. Advancing the HHAIR concept in different HHAIR systems will develop novel ways to measure SRL with trace-data and use these measurements to develop new interventions, i.e. hybrid regulation. Pioneering this concept connects with efforts to advance measurement of SRL during learning. The development requires a combination of explorative studies, design studies and controlled short-term and long-term experiments to draw robust conclusions about the importance of understanding SRL during learning and its value for supporting SRL in HHAIR. In general, the findings should support evidenced-based use of ALTs in primary and secondary education.

The proposed approach may have societal impact on schools, publishers, and educational technology companies. It will allow advanced integration of research into educational practice, close collaboration with educational technology companies and it will support knowledge transfer between universities and private companies. This entails designing, developing, testing and refining AI for education with all stakeholders (schools, learners, publisher and technology developers). This is in line with the new recommendation of the European high expert group on AI. Many collaborating partners are to participate in this highly innovative approach that will support ALTs and education to be improved by Artificial Intelligence within a trustworthy and transparent partnership.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

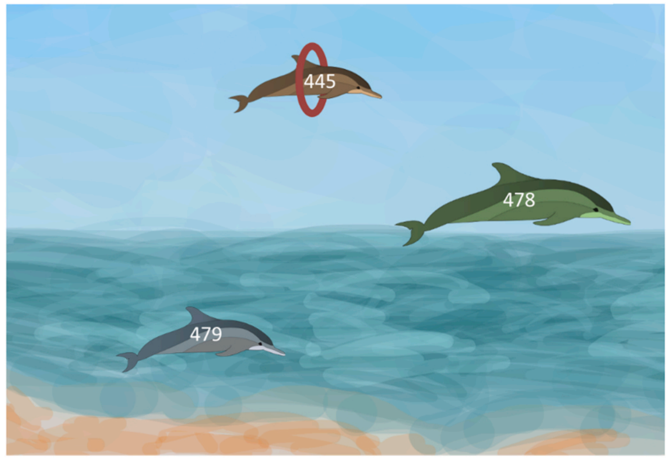


Fig. 4. Overview screen .

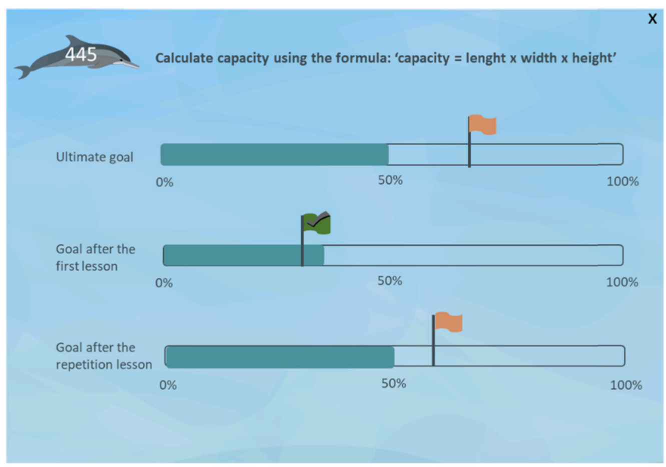


Fig. 5. Goal-setting screen .

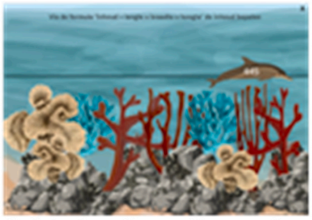
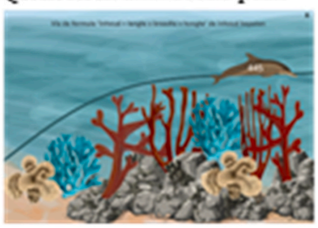
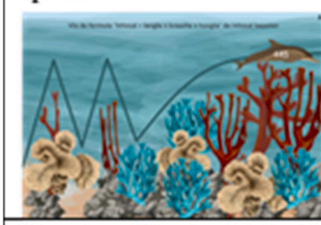
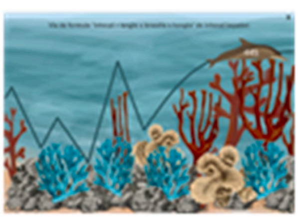
Personalized dashboards	Planning	Monitoring
High swimmer: Immediate drop 	You already know this skill. → Please practice a different skill.	Your accuracy is high, well done!
Quick riser: Immediate peak 	You have learned this skill quickly after the teacher explained it. → You can practice until you have reached proficiency (green dolphin) and then continue on the next skill.	Your accuracy is high, well done!
Riser in two stages: Double Spikes 	You have learned this skill in two stages during guided instruction and class wide practice. → Please practice until you have reached proficiency.	→ Please monitor your accuracy during practice. → Do you feel that you can put in a little more effort? Try to become a quick riser!
Slow riser: Close multiple spikes 	You are learning this skill somewhat slowly. → Please continue to practice in adaptive mode until you have reached proficiency.	→ Please monitor your accuracy during practicing. → Do you feel that you can put in a little more effort? Try to become a riser in two stages!
Riser and descender: Separate multiple spikes 	You are learning this skill quite slowly. → Please continue to practice in adaptive mode → If you cannot master this skill please notify your teacher	→ Please monitor your accuracy during practicing. → Do you feel that you can put in a little more effort? Try to become a slow riser!

Fig. 6. Learning path screens with recommendations..

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