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The ethical acceptability of personalization via intelligent systems in education

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Abstract
Technological implementations in the educational context seem to contribute to competence acquisition through personalized learning. For instance, intelligent systems are embedded in the learning environment in smart classrooms. Implementing these systems is widely accepted, and different technical solutions have been proposed, but the educational context still needs to be thoroughly scrutinized. The examined approaches fail to capture the complexity of the learning experience and underdetermine the pedagogical aspect. Therefore, directions are indicated and discussed to clarify the educational context of technological implementations and show how intelligent systems can support personalized learning in an ethically acceptable way.

Keywords Behaviorism · Personalized learning · Autonomy · Human–system interaction · Smart classrooms

1 Introduction

In smart learning environments, intelligent systems are embedded in the learning environment. Smart learning environments are spaces that are enriched with tools and technologies to sense, analyze, and react to learners. They encompass "features such as adaptive and personalized, efficient, effective, scalable, engaging, flexible, conversational, reflective, and innovative" (Tabuenca et al. 2021, p. 139/140). Implementing these systems is widely accepted to introduce a more personalized learning experience, but the educational context still requires thorough scrutiny. Approaches in previous research under the title "smart classrooms" fail to capture the complexity of the learning experience and underdetermine the pedagogical aspect. A "smart classroom" is a "technology-assisted closed environment" (Saini and Goel 2019) where "data from the environment, students and teachers" is used to enhance or improve teaching and learning (Figueroa et al. 2024). "A typical smart classroom has tools for better presentation, student engagement enhancement, better interaction, and better physical environment" (Saini and Goel 2019). However, it is questionable what "better" means. Particularly, this evaluative or normative dimension is overlooked in smart classrooms, which encompass four dimensions: "smart content," "smart interaction and engagement," "smart assessment," and "smart physical environment" (Saini and Goel 2019).[1] Nevertheless, as another literature review examines, it seems that the focus is on "how sensor technology improves the physical classroom environment, monitors physiological and behavioral data" in order "to boost student engagements, manage attendance, and provide personalized learning experiences" (Zhang et al. 2024). Furthermore, other literature reviews locate participation and engagement mainly in the context of sensor use (microphones, cameras, etc.) (Saini and Goel 2019), (Kaur and Bhatia 2024). Such surveillance of learners is used to condition or "drill" (Jia et al. 2020, pp. 6–9) them. This seems to hint that a behavioristic framework underlies such approaches that are mainly discussed in the literature under the term "smart classroom." In that meaning, I use the term here throughout the paper. Behaviorism must therefore also be discussed in this paper as a means of addressing this issue because it is mainly the educational background for technological implementations in so-called "smart classrooms." However, such approaches fail on an educational and ethical

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1 Slightly differently named in (Kaur and Bhatia 2024): "smart material," "smart interaction and engagement," "smart evaluation," and "smart physical surrounding." For instance, creating smart "educational material" using agentic AI simulation is undertaken in a pilot project by (Ma and Wang 2024).

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level to provide acceptable learning experiences as will be examined in the next sections. "Smart learning environments," on the other hand, is a term that also encompasses constructivist and competence-based approaches (Tabuenca et al. 2021)[2] that open the learning experience. As I argue here, constructivist approaches can increase the learner's autonomy, while behavioristic approaches diminish it or make it impossible for learners to develop autonomy.

1.1 Educational background

In pedagogy (Trabandt and Wagner 2020, p. 114), but also, for instance, in higher education (Aalborg University 2015), (Tecnológico de Monterrey 2018), (University of Twente, n.d) a refinement of behavioristic toward constructivist or cognitive theories has taken place. In particular, the introduction of competence-based educational models in recent decades (Raithel et al. 2009, pp. 36–45; Trabandt and Wagner 2020, pp. 65–75) stems from a constructivist tradition (see, e.g., Vygotsky 2012; Piaget 2015)). Moreover, the "pedagogical context" of smart learning environment seems to support the claim that there is a trend toward "competency-based education," "problem-based," and "project-based learning," where learning is enabled in "unconventional settings that offer new opportunities to learners" (Tabuenca et al. 2021, p. 137/138). Constructivist theories also promise some kind of personalization of the learning experience by designing or constructing the learning environment while even considering the "heterogenous learning preconditions" (Trabandt and Wagner 2020, p. 75) of the learner. The students learn autonomously under the teacher's guidance and develop their learning progress. However, the focus is on the interaction between persons (teacher and learner) and less on the implementation of intelligent systems that can also personalize, to a certain degree, the learning experience. Hence, it is argued here that the use of intelligent systems within a constructivist framework can personalize the learning experience that goes beyond behavioristic notions under the heading "smart classrooms," not only because constructivism surmounts the shortcomings of behaviorism but also because the learning experience is personalized in an ethically acceptable way since the autonomy of the learner is preserved.

1.2 Ethical issues regarding the implementation of intelligent systems in education

Even though information about the learner has always been collected (for instance, via exams, projects, participation, etc.), personalized learning through collecting large amounts of data or even the implementation of sensors to monitor the learner poses a threat not only to the learner's privacy but also to her autonomy. This is even more pressing when the intelligent system is integrated into the lifeworld and is ready-to-hand so that it no longer appears as an object or artifact that is visible or identifiable to the learner. Hence, intelligent systems for smart classrooms seem problematic from three perspectives: (1.) the underlying pedagogical theories, (2) the diminishment of the learner's autonomy, and (3.) the intrusion into the privacy of the learner.[3]

But how can using intelligent systems lead to a personalized learning experience without diminishing the learner's autonomy? One intention of introducing personalized learning is to make education fairer since it might enable weak learners to catch up and foster gifted students. Usually, justice and fairness are discussed either from an egalitarian point of view or as a matter of moral desert. Should we give everyone the same or more to some because they need or deserve more? As commonly described in the literature, implementing smart classrooms will result in somewhat dystopian learning scenarios despite the proclaimed promise of fair and personalized learning experiences. That is why other ways of personalizing the learning experience need to be sought to make education not only fairer but also, first and foremost, establish normative criteria to judge the ethical acceptability of technologies in the field of education.

In recent years, Value Sensitive Design (VSD) has been used to develop technology and AI-based systems in an ethically aligned way. VSD is based on an "iterative methodology that integrates conceptual, empirical, and technical investigations." In a first step, conceptual clarifications of the involved values must be outlined. Here, conflicting values (autonomy vs. privacy) are identified. Empirical investigations, in a second step, include stakeholders and their prioritization of values to resolve value conflicts. In the last step, the technological investigation focuses on how certain technologies might facilitate or hinder the implementation of specific values. Moreover, a particular "value hierarchy" might be used in the background, whereby the preference for a certain value overrides the preference for other values

[2] I am thankful to an anonymous reviewer for the suggestion of additional literature in that field (see also Sect. 2.2) and for pointing out to clarify this distinction.

[3] Here, only the first and second perspectives will be discussed because they have an intricate connection. The last perspective is located in a legal framework and will only be mentioned briefly. For Europe, the "General Data Protection Regulation" regulates the sphere of privacy. (I am thankful to an anonymous reviewer for pointing this out.)

(Friedman et al. 2008, pp. 71–73). However, VSD is criticized for lacking integration or discussion of a normative or moral framework. Reijers and Gordijn have proposed to use it based on virtue ethics (Reijers and Gordijn 2019, p. 199). VSD has also been adopted for AI-based systems and how they can embody values (van de Poel 2020; Umbrello and van de Poel 2021). Others have suggested designing AI for the social good (Floridi et al. 2020). Nevertheless, we are not only faced with a value pluralism but also with ethical pluralism. So, choosing one theory (like virtue ethics (Reijers and Gordijn 2019)) is just another preference, although it might be well justified. However, I will argue that based on a tripartite model of autonomy, technological implementations in smart classrooms can be classified as either ethically *acceptable* or not, which establishes a normative frame; otherwise, *accepted* value heuristics are solely based on mere stakeholder preferences, which "leads to an arbitrary and potentially dogmatic heuristic" (Reijers and Gordijn 2019, p. 199). Or it is even irrational and inconsistent (Hubig 2007, p. 19).

This paper makes three contributions. First, the underlying pedagogical framework of smart classrooms is scrutinized and analyzed. Behaviorism is the underlying pedagogical framework. Based on this analysis, it is shown that developing autonomy is not possible within such a framework. Second, levels of autonomy are distinguished to discuss, on a constructivist and competence-based approach, possible implementations of intelligent systems that, on the one hand, allow a certain personalization of the learning experience and, on the other hand, do not diminish the learner's autonomy. Third, the advantage of the proposed approach is that certain implementations of such systems can be assessed either as ethically acceptable or as ethically unacceptable; this is demonstrated by analyzing various technologies in the field of education.

2 Education and autonomy

The pedagogical background of implementing AI-based systems in so-called "smart classrooms" is mostly behavioristic. Consequently, the theoretical foundations need to be discussed by examining the main ideas of behaviorism. Furthermore, learning theories have already been refined from behaviorism toward cognitive approaches (Trabandt and Wagner 2020, p. 114). In the course of the so-called "cognitive revolution," where behaviorism was criticized in various disciplines (Miller 2003), constructivist approaches in education gained broad influence (Jones and Brader-Araje 2002). Both points must be discussed to find ways of enriching learning environments with technologies that are ethically acceptable because they do not diminish or inhibit the development of the learner's autonomy. Hence, to scrutinize the critique of smart classrooms, it must be shown that in behaviorism, autonomous development is not possible. At the same time, it needs to be demonstrated that in cognitive or constructivist approaches, the levels of autonomy are part of the learning process and thus allow a personalization of the learning experience that, in the end, is ethically acceptable.

2.1 Educational background of smart classrooms—behaviorism and its limitations

In behaviorism, the circumstances and the environment evoke stimuli. The environment is, therefore, the condition, along with the stimuli, whereby the environment can be constructed or influenced by (learning) techniques or technology. They represent sufficient means to elicit reactions (an individual's behavior) (Richter 2016, p. 109). In smart classrooms, multimodal action environments are created that synthesize different streams of data (Jia et al. 2020, p. 5/6). The data can also be from different independent sensors, such as eye-tracking (Liu and Peng 2021), monitoring (via cameras) (Wang 2021; Mohammed Ali and Nihad 2021; Zhang 2021), or biosensors (Timms 2016, p. 709). Leaving problematic issues like privacy and surveillance aside, it seems that such environments are, at first glance, value-neutral. Still, the introduction of reinforcement and conditioning[4] presupposes specific criteria of goodness, i.e., to what end should the behavior be manipulated, and what is considered good and bad behavior? Conditioning to increase engagement and concentration is the underlying behavioristic idea of smart classrooms. As mentioned above, a "typical smart classroom" should provide tools for various educational improvements (Saini and Goel 2019). However, the criteria of goodness lie primarily in boosting engagement, managing attendance (Zhang et al. 2024), or increasing concentration; even using "drill" by checking how fast answers are typed (Jia et al. 2020, pp. 6–9).

In behaviorism, as in smart classrooms, the behavior is controlled through sanctioning. This should not be understood as mere "punishment" but instead as the construction of a particular environment to elicit a specific behavior, either via "negative reinforcement" or "positive reinforcement." Constructing a specific social environment can also lead to behavior that can be considered morally right. Of

[4] Even by desisting from the concrete conditions of success for individual behavior (the primary concern of behaviorism), i.e., how behavior can successfully be trained and internalized to be performed under certain circumstances, it also needs to be considered how a particular behavior can be preferred over another and why it should be preferred. Behaviorism excludes intentions and preferences, which weakens its explanatory force. Choosing and preferring are already intentional actions that go beyond a behavioristic explanation.

course, the correct or "moral" behavior in a smart classroom is a higher degree of engagement and concentration. The learner's behavior is regulated by the teacher using technological tools. According to Skinner, control is hidden and only leads to a subjective feeling of freedom (Skinner 1974, pp. 208–227). The learner does not have to be aware of the regulation of behavior, since it is in her interest, at least from the standpoint of the person who is in control. Behavioristic theories, therefore, do not have to deal with the so-called "Kantian paradox" (Pinkard 2002, p. 226) or the "pedagogical paradox" (Nordström 2009, p. 23), i.e., how the learner can become an autonomous being under the guidance of a teacher. In a behavioristic setting, the teacher controls or regulates the learner's performance, but does not have to be concerned with the learner's autonomy.

Although Skinner is concerned with the abuse of control by teachers, it is unclear how countermeasures could be established that would even lead to a kind of liberation, which he envisions. He hints at a specific evolutionary development of culture that can only be reached by planning, but this is also intentional (Skinner 1974, pp. 208–227). This shows that the behavioristic framework is inconsistent. Autonomy is a supervisory authority that all humans should exercise. Such an instance of control does not exist in a behavioristic framework. Consequently, it should also not be considered an underlying theory for implementing intelligent systems in education. Unfortunately, it is the underlying theory for technological implementations under the heading "smart classrooms."

2.2 Educational background of smart learning environments—constructivist approaches

Constructivist (Jones and Brader-Araje 2002) and competence-based approaches have a broad influence in the field of learning theories and on an institutional level, for instance, via the Bologna process in European universities. It is functional, instrumental, and outcome-oriented (Trabandt and Wagner 2020, p. 73). AI-based systems can be used to achieve learning goals and to acquire skills and competencies. Problem- (Martínez et al. 2016) or project-based learning approaches are often used to support a competence-based education, as promoted by various universities (Aalborg University 2015), (University of Twente, n.d), (Tecnológico de Monterrey 2018). Game-based learning appears to be a consequent application since the acquisition of competencies can also be understood as reaching levels in a game. Moreover, it can help cater to the needs of different learner types (Barata et al. 2015). Game-based learning, for instance, has been used in the medical context for problem-solving and acquiring skills, where engagement and motivation should be increased (Pesare et al. 2016). Gamified options could be, to a certain degree, considered ethically acceptable, also because they can be designed in a way that would not be an intrusion into the learner's privacy (as in behavioristic approaches). However, gamification can lead to a strong immersion in the virtual world through competition and rewards, without further reflection on other learning goals and techniques necessary to master a skill or competence.

Another area of intelligent or smart technologies is the personalization of learning, for instance, in massive online courses (Paquette, et al. 2015) or to give immediate feedback to the learner (Serral et al. 2016). It might also be possible to use non-intrusive assessment "solely on characteristics of the natural language interaction between students and conversational Intelligent Tutoring Systems" (Rus and Ştefănescu 2016). Although explicit assessment (via exams) might increase stress, it is usually a transparent and predefined task for the learner. Taking cues from the learner's language or behavior might not be transparent to the user, i.e., which system strategies are used and, hence, might threaten the strategic autonomy of the learner.

Competence-based education has the advantage that other informal contexts (apart from traditional classrooms) can be used to acquire skills, for instance, to learn languages in a kitchen (Preston, et al. 2015) or in the so-called "maker movement" where platforms can serve as smart learning environments (Toivonen et al. 2018). Another advantage of constructivist learning is that it supports, contrary to behavioristic learning, self-regulated learning. Smart learning environments and technology can be helpful by "providing support for setting goals, setting aside time to learn, tracking study time and monitoring the progress" (Tabuenca et al. 2015), which aligns with competence-based and constructivist education. Even though a literature review concluded that, for instance, learning analytics dashboards do not provide for metacognition, nor do they "offer any information about effective learning tactics and strategies" (Matcha et al. 2019, p. 227). Other technological means could be developed to do so, for instance, a Socratic assistant that helps students form stronger arguments and challenge their own judgments (Lara and Deckers 2020). Another crucial dimension of self-regulation is self-efficacy, i.e., to actually pursue the goals. Hence, strategic autonomy might also be supported and enhanced by smart technologies when employed in the right way. However, humanistic approaches to education criticize that a competence-based model transforms, in the end, the learner's autonomy into skillful self-organization with respect to preset goals (Erpenbeck and Heyse 2021, p. 75). Hence, the learner is not able to set herself goals; only finding efficient and effective means (strategies) to reach them.

2.3 The foundational role of autonomy for education

Users of technological devices have expectations about how the device should function and how they would use it. In the field of acceptance research, such expectations are investigated (sometimes, it can also have an ethical dimension). Additionally, developers expect how the device will be or should be used. The expectations of both groups are aligned in the research and development phase of a device. It is based on relations between persons (developers and users) that align their expectations and interests. In contrast, such an alignment procedure cannot describe the human–system interaction, where systems behave autonomously on an operational or strategic level. Autonomous systems collect user data by tracking or monitoring them, thus creating relevance rankings, establishing routines, or ascribing roles to the user (or stereotypes) (Hubig 2015, pp. 134–145). A recommendation system in the educational context could, for example, track learners to create recommendations about learning content (relevance ranking).

Since such a recommendation can also come from a teacher, it does not seem as mere nudging from an intelligent system that might diminish the learner's autonomy. Nevertheless, education is also sometimes seen as a process that should foster the development of autonomy and self-reflection, as it is emphasized by some who base learning more on a humanistic and liberal arts model of education (see, e.g., (Leuphana Universität Lüneburg 2006; Harvard College 2024)). On the other hand, competence-based education focuses on the "results" (Trabandt and Wagner 2020, p. 73) laid down in learning outcomes or goals. Both models have benefits that become shortcomings when attacked by the adversary's view. A competence-based model may provide more effective measurement standards by establishing proficiency levels. However, this can also be considered a drawback because not everything in the educational process might be quantifiable or measurable. (Trabandt and Wagner 2020, pp. 68, 75) Even worse, a competence-based model might transform the learner's autonomy into a competence of organizing and assessing one's output with respect to given tasks and goals (Erpenbeck and Heyse 2021, p. 75). Thus, the learner might not be able to act and think autonomously. She will only be able to regulate her behavior to obtain a given goal, but not be able to set her own goals. Even though the debate between a humanistic approach and a competence-based approach cannot be settled, the debate lacks a further analysis of the concept of "autonomy."

2.4 Levels of autonomy

In ethics or philosophy, autonomy is commonly distinguished by the area where it is discussed: personal, moral, or political autonomy (Gottschalk-Mazouz 2019, p. 238). Here, however, operational, strategic, and moral autonomy will be distinguished to analyze learning experiences and how to implement personalized learning via intelligent systems. This classification is taken from Christoph Hubig (2019, p. 282/283) and adapted to learning via intelligent systems. This classification enables a more fine-grained discussion of the learner's autonomy, but also of the intelligent system's autonomy.

Moral autonomy plays a foundational role since it enables subjects to set themselves in relation to others and themselves, i.e., experiencing themselves as subjects. Education is hence essential in guaranteeing the social structures that enable undogmatic forms of self-constitution and development. Besides the difficulties in evaluating what constitutes an undogmatic education, the importance lies in the possibility of orienting oneself within normative frameworks (Hubig 2007, p. 142). Therefore, this value plays a foundational role. Autonomy can, moreover, be operationalized via different criteria (self-determination, self-control, and independence) that allow for the establishment of indicators (see Table 1). The table does not represent an exhaustive list. Nevertheless, it develops the proposed classification conceptually further to obtain operationalizable criteria.

Such indicators can be used to assess the ethical acceptability of smart learning environments at each level (see below). Increasing the leeway for decisions gives the learner

Table 1 Operationalization of autonomy through criteria and indicators

Criteria	Indicators
Self-determination	*Which choice options are available?* Operational level: Can exercises be skipped? Strategic level: Does a learning system offer other learning paths that are presented to the learner based on her preferences?
Self-control	*How can the learner regulate her learning process?* Operational level: Are incentives mainly set extrinsically, or is the learner guided to intrinsically motivate herself? Strategic level: Does the system give feedback about the learning progress, and which goals should be preferred?
Independence	*To what degree can the learner be independent?* Moral level: Is the learner encouraged to defend pertinaciously her own standpoint with adequate justifications? Strategic level: Can the use of systems be rejected without being punished with lower grades?

more autonomy, where the leeway is determined by the adequacy of selecting means (operational level), goals (strategic level), and principles (moral level).

2.4.1 Operational autonomy

Within this type, there are certain degrees of freedom for the system in selecting the means for an objective, thereby improving the effectiveness and efficiency of an action. For example, driver-assistance systems (in the car) have operational autonomy. Responsibility of this type can be almost wholly delegated to systems under certain limits (Hubig 2019, p. 282/283). An example is the generation of exercises by a system, the help of a virtual assistant or a social robot in learning vocabulary, or the recommendation of exercises for students to increase the efficiency of solving mathematical problems.[5] The system selects the means or necessary resources to improve the learner's performance under a given objective. Nevertheless, the selection of means to improve the learner's performance can also be considered ethically unacceptable. For instance, increasing the attention span by monitoring the learner's biodata, etc., is an intrusion into their privacy. Hence, a value like privacy conflicts with a more technical value like efficiency (increasing the attention span). However, we could consider such an intrusion into the learner's privacy ethically acceptable if it helps to improve the student's mental health. Here, the value "well-being" would be prioritized. The selection of adequate means stands ethically within a value pluralism where prioritizations must be made. Additionally, moral autonomy also plays a role in assessing the ethical acceptability since the learners must commit themselves to opt for the intrusion in their privacy without negative repercussions for them.

2.4.2 Strategic autonomy

Within this type, certain degrees of freedom exist in selecting the optimal ends or objectives within a general framework of goals, for example, prioritization, duration, or deviation. For an autonomous vehicle, the goal is to reach a destination, and the system can select a detour to get there faster because there is more traffic on the shorter route. It is an example of prioritization, duration, and detour. Responsibility of this type can be delegated in part to the systems if interventions are possible, as well as options of action to interrupt the processes. Hence, there is still the possibility of acting or intervening for humans (Hubig 2019, p. 282/283). One form of prioritizing, where the intelligent system operates on a strategic level, is the recommendation of learning paths to arrive at a specific learning outcome. The system reduces the complexity for the learner by selecting goals within a framework of preset learning objectives. Different approaches might be possible, such as forms of gamification. Some forms can be considered as nudging the learner toward a certain outcome. Here, the system must also provide a level of transparency on how the learner can adapt strategies to learn or how she can commit herself to certain strategies. Otherwise, the systems would be paternalistic and hence, not ethically acceptable. For instance, a gamified application for language learning could state the learning outcome to which the learner can commit.

2.4.3 Moral autonomy

It represents a freedom that not only entails knowing the goals but also recognizes them and their principles: "I recognize the principle as a reason for my action." That is a self-attribution of recognition and a recognition of oneself as a person. Ethics is oriented here on the ideal of human dignity and based on human rights. Moral autonomy entails a responsibility that cannot be delegated to an intelligent system because it only exists between autonomous persons who understand and recognize that they are responsible for their thoughts and actions (Hubig 2019, p. 282/283). It is expressed in a normative and deontic vocabulary (commitment, entitlement, responsibility, (moral) norms) (Brandom 1994). The first two levels of autonomy could be expressed in alethic modal vocabulary. The system might be *able* to choose means and ends, which could be described as reactions of dispositions it possesses. There are specific possible means or ends available and form a realm or space of possibilities that can be expressed in counterfactual statements: "If systems S would have chosen means M, it would have resulted in output O." Dispositions of intelligent systems express whether they are reliable and make "good" discriminations or inferences, "*ranges of counterfactual robustness*" (Brandom 2008, p. 103).

This might seem to suggest that technology conflicts are merely "conflicts about technical means and instruments;" however, they are "normative conflicts" (Grunwald 1999, p. 176). Grunwald discusses this normative underpinning of "Technology Assessment" by relating it to "Technology Ethics." A participatory approach—in "Responsible Innovation" (Van den Hoven 2014, p. 5) or "Technology Assessment"—must consider the moral convictions of the stakeholders, i.e., their commitments and how they are entitled to them. Investigating ethical acceptability implies considering the stakeholders via qualitative and quantitative empirical studies (scenario writing, vignette experiments, etc.) to make explicit the commitments they are entitled to, i.e., what they consider as ethically acceptable. Participatory research is

[5] A further analysis of the technological implementations and their connections with the levels of autonomy will be discussed in the next section.

essential here, as it seeks to respect the moral autonomy of each individual as a competent participant in shaping the discourse about technological implementations.

3 Assessment of virtualized learning contexts

Acceptance studies do not examine normative or ethical issues but rather influence factors on the acceptance of technology within the domains of, for instance, usability or functionality. In contrast, questions surrounding acceptability establish normative criteria to assess the risk of technologies (Hubig 2007, p. 105/106; Grunwald 2005, p. 54; Petermann and Scherz 2005). For establishing such criteria, the conceptual and theoretical framework needs to be clarified. The different levels of autonomy are consolidated with a constructivist approach because autonomy can be preserved within this pedagogical framework. To operationalize the conceptual structure, various educational applications are discussed and critically examined. Thereby, the autonomy levels help clarify which applications should be considered ethically acceptable.

Technology enriches, transforms, and virtualizes (Hubig 2007, p. 45) the learning context where "smart learning can be regarded as learning in interactive, intelligent, and tailored environments, supported by advanced digital technologies and services" (Tabuenca et al. 2021, p. 129): (1.) Sensors or systems collect and analyze data about the learner (Tabuenca et al. 2021, p. 145). Here, the controlling and monitoring of the student is used to increase the attention span or concentration. The history of the user or generated stereotypes serves to optimize the system's behavior as well as the learner's behavior. (2.) Learning platforms are virtualized contexts (or virtual realities) within which specific steps for users/learners are simulated, such as recommendations of exercises, literature, etc. The interaction is limited to the degree of the strategic design preset by the developers. (3.) A further form of virtualization is the interaction with a social robot or a chatbot to obtain (personalized) information. This might be possible because such systems can achieve a type of generality beyond the preset learning contexts of platforms. Although large language models are valuable tools for such tasks, they must be used with caution since there are no tools to check whether large language models "hallucinate" in certain situations and thus fail to provide correct answers or feedback to learners who might not be able to assess the answer as incorrect.

The following discussion presents various types of use cases and is not meant to be a systematic literature review. I will describe in each type of use case, technological applications, and problematic issues regarding a behavioristic conception of education. Based on this description, ethical concerns regarding the autonomy of such applications will be developed to demonstrate how autonomy can be operationalized (based on the above-described criteria), and technical applicability can be sought for non-behavioristic approaches.

3.1 Smart environments—sensors

Data from the movement of students' mice and keyboards can be collected, and this input is used to evaluate their attention and engagement. Jia et al. "designed and developed a web-based multimodal human–computer interaction system, MMISE (Multimodal Interaction System for Education)." The "program deals with the capture, detection, and recognition of various input signals on the one side, on the other side generates the synthesized voice and avatar animation" (Jia et al. 2020, p. 5/6). This system can process speech and monitor whether the learner is absent. The output can also be speech or text. They hope it can "improve the student's concentration on the learning content displayed on the screen, such as a video lecture on demand or a live video lecture" (Jiaet al. 2020, p. 6). Other system implementations are an emotional mimicry of the students' emotions by an avatar or controlling the learner's input. If there is no input after some time (via speech, keyboard, mouse, or the learner is not at all in front of the screen), then an output (voice, text) is emitted to ask the learner where she is or to remind her to continue with the exercise. Additionally, in a "drill" (sic!), there can be a reminder that the student needs to be faster to meet the objective (Jia et al. 2020, pp. 6–9). The speech recognition and facial expression recognition systems are AI-based (Jia et al. 2020, p. 9), and they were applied in graduate and undergraduate courses at Peking University and in a mathematics system for school pupils (Jia et al. 2020, p. 11).

Moreover, monitoring the students via cameras to "keep" control over the whole classroom is not only an idea that was presented (Timms 2016) but has already been implemented. Such a system tracks the "user concentration" via "the fusion of face recognition technology and [an] eye-tracking system" (Liu and Peng 2021). Approaches to designing and implementing smart classrooms mainly focus on monitoring the students (Wang 2021; Mohammed Ali and Nihad 2021; Zhang 2021). Other ideas involve collecting "more fine-grained data that could help to monitor individual learners rather than the classroom as a whole." This can include even "[d]ata from biometric sensors" to track the "blood volume pulse and galvanic skin response," hence, to "detect changes in mood and how focused a student is" (Timms 2016, p. 709).

Such devices, sensors, and measurements pose a threat to the learner's privacy and autonomy. However, even from a pedagogical standpoint, they are highly questionable.

Attention span and concentration increase via such methods or controlling the learner resembles a kind of training or drill within a behavioristic framework. As argued above, such a framework makes it impossible for the learner to develop autonomy. Hence, such methods are not ethically acceptable. Nonetheless, there are other ways to use biosensors than increasing concentration, for instance, to improve the well-being or mental health of learners by monitoring them (Adomako Gyasi et al. 2025). However, this is also sensitive information that, in certain situations, should not be shared with teachers or institutions. Conversely, it could be used to help learners regulate stress and increase their autonomy by giving them adequate recommendations to study or to determine the best time.

Contrary to behavioristic frameworks, constructivist learning can also be used to form an environment where attention is increased via problem-based learning in groups. Social robots could be used to interact with the learners to learn vocabulary (Randall 2019), or blended learning could be used in the form of escape room games, where the learners have to solve puzzles to reach another level (Veldkamp et al. 2020). In these learning environments, learners' autonomy is respected. The social robots and the escape room game scenarios provide gamified ways to increase engagement. Learners may also get feedback from the system about their learning level, which gives them the opportunity to reflect on their learning trajectory and to adjust their own learning goals. Hence, they will be taught to regulate their own behavior. Moreover, it might be possible to present different choice options to learners by letting them skip exercises that inhibit drilling them. Providing learners with choices or different learning paths also reduces stress in situations where she might not be able to answer questions due to a level of difficulty.

3.2 Virtual realities—learning platforms

Learning platforms employ and establish learning paths for students, sometimes in accordance with the class syllabus (for instance, through uploaded presentations and literature), but also through exercises. Such simulations can also be personalized and constitute a virtualized reality. The recommendation of learning paths to prioritize a route to achieve a specific learning outcome is an example where the intelligent system operates on a strategic level of autonomy. Such functions of learning platforms can make education fairer due to the personalization of the learning path.[6] However, implementing recommendation systems in education is problematic from a data privacy standpoint if they are built on "implicit feedback" from the learner, i.e., recommendations are taken from monitoring the user's behavior. As in smart classrooms, the learner needs to be tracked for that purpose. This might be even more concerning in the case of AI-based systems and their black box character. So even for developers, it may not be clear which strategies the system employs. Moreover, it can lead to effects like those on social media platforms where implicit feedback is used to provide users with similar content to what they have read or watched, thus creating so-called "filter bubbles." Such a technological implementation would mainly be constructing the environment to condition the users' behavior. Hence, it is a behavioristic strategy.

However, recommender systems can also be built on "explicit feedback" from the learner. It has been shown that there is not truly a difference in the performance of a recommender system depending on which form of feedback it is built on (Jawaheer et al. 2010; Zhao et al. 2018). It is usually seen as a weakness of explicit feedback that it needs effort and engagement from the user (Isinkaye, et al. 2015). But in fact, it is the crucial point because, in that way, the autonomy of the user is not diminished; hence, it is ethically acceptable.

A recommendation system could, for example, give suggestions regarding which literature for a thesis might be appropriate. Instead of recommendations from a teacher or mentor, the "responsibility and accountability" is shifted "toward the user collective" (Buder and Schwind 2012, p. 208). Unlike a "teacher-centered education," such an approach would foster a "peer-centered education" (Buder and Schwind 2012, p. 208). In the latter type of education and "in recommender systems, a power structure with flat hierarchies emerges" (Buder and Schwind 2012, p. 208) although it is far from some kind of "distributed expertise" among peers (yielded, for instance, through the "jigsaw method") (Brown et al. 1993). In a way, this is similar to what has been discussed under the term "social recommender systems," where recommendations are based on the preferences of peers and friends (Shokeen and Rana 2020).

The conceptual background does not always need to be explicit to the learner. For instance, learning a language does not always entail full explicit knowledge of the grammar. A recommender system for books does not need to explain why a specific book might be helpful to a student. Part of the learning experience can be the student discovering this after reading the book herself. Furthermore, a "book that is suggested by a recommender system differs from a book that is a mandatory part of a course syllabus. Our student has the choice to follow the recommendation or not. Recommender systems preserve user autonomy" (Buder and Schwind 2012, p. 208). One aspect of the conceptual model of autonomy

[6] Of course, this claim assumes that such platforms help the learners that struggle for example because of their social background. Yet, it is still difficult to say whether they are helpful because such systems are mostly still under development and a further evaluation of their implementation is missing.

is that "self-determination" can be made observable by an indicator that captures the choice options. By giving users choices or the option to refrain from suggestions, their autonomy is respected on an operational and strategic level.

A recommender system can also be based on explicit feedback, thus offering a personalized learning experience (Buder and Schwind 2012, p. 209). Additionally, social and psychological factors need to be considered to adapt recommender systems to the educational field, i.e., personalization should not be based on taste but on knowledge and activities (Buder and Schwind 2012, pp. 210–217). For this purpose, learning goals and proficiency levels that go beyond the learner's mere taste or interest need to be established; otherwise, the learners will be stuck in a bubble. For instance, a system that recommends movies could learn that the user only likes comedies and no other genres, thus only recommending comedies, but in the end, the user will not develop an esthetic judgment about movies. For that purpose, the aspect of "independence" plays an essential role because the learner must also be able to reject common opinions without punishment to form her own judgment. In developing competence, such as critical thinking, obstacles must be part of the learning experience to challenge the learner and to build a specific resistance that the learner needs to overcome.

Recently, some have proposed developing artificial moral experts that could dialogically scrutinize the moral judgments of human agents. Such a Socratic assistant could help learners to develop critical thinking in moral domains and still not interfere with their autonomy (Lara and Deckers 2020). Even in "Explainable AI" (XAI), giving adequate reasons could be considered as an ethically acceptable form of persuasion, although there might be a thin line "between persuasive UX practices and manipulative designs" (Sanchez Chamorro et al. 2023). The hope behind XAI is to increase trust in AI-based systems, the transparency of such systems (Fiok et al. 2021), and the understandability of decisions made by the systems (Chaushi et al. 2023). Moreover, it should make systems fairer, for instance, by preventing discrimination against protected groups (Fiok et al. 2021). "XAI can aid teachers in explaining to students how AI systems generate their recommendations or decisions, thereby enhancing the efficiency and personalization of learning experiences for individual students. XAI can aid in the creation of efficient and personalized learning environments for students" (Chaushi et al. 2023). The understandability of system decisions for learners can also increase their autonomy since they can adjust their own learning goals and trajectories when using a learning platform.

However, attempts in Explainable AI to increase trust also fail because users in certain contexts underweight AI predictions (Agarwal et al. 2023). Several studies seem to show, for instance, that radiologists have low trust in computer-based systems (Jorritsma et al. 2015). So, it seems also context-dependent which kind of explanations can be considered as adequate reasons and which influence on trust they might have. Much work remains to be done before a full understanding of recommender systems in different contexts is established. In XAI, visual or textual information is used for giving reasons in Explainable AI (Schwalbe and Finzel 2024), e.g., certain systems "adapt the level or type of instruction for each student." This can be used to give "*automated feedback*" on the quality of reviews that peers must give their colleagues (Rachha and Seyam 2023). Here, it is important to consider the design of the interface and which options are presented to the learner. Does the learner just overwrite her poor review with suggestions from the system, or does the system give strategies to improve the review? In the second option, it is possible to learn from the system feedback. Nevertheless, "generic explanations provided by XAI systems" might not be helpful and must be personalized by taking "into account individual differences such as abilities, traits, cognitive and affective states, and preferences" (Rachha and Seyam 2023). Moreover, such systems should give choice options on a strategic level to increase autonomy. For that reason, the design of systems must be adjustable so that "cognitive and metacognitive tactics and strategies to guide learners about how to approach their learning" are possible (Rachha and Seyam 2023). Since "educational systems that utilize AI, particularly in areas such as student evaluation and grading, raise concerns about potential biases and ethical consequences," future direction of research has been particularly identified in the "implementation of ethical and regulatory frameworks that address the unique challenges of AI in education, such as student privacy and data security" (Chaushi et al. 2023).

3.3 Virtual actualities—social robots and virtual agents

"Virtual actualities" yield "virtually induced effects" (Hubig 2007, p. 45). Social robots and virtual agents provide a different form of interaction with intelligent systems. Experiments show that virtual agents' positive emotions might affect learners' "intrinsic motivation" (Liew et al. 2017). However, it seems rather difficult to measure intrinsic motivation by external factors. At least, it appears that the learners' "positive emotions were affected by the agent's enthusiastic verbal and nonverbal cues, such as smiling facial expression, highly animated gestures, enthusiastic vocal tones" (Liew et al. 2017). Using (social) robots might even "provide more social interaction that fits our biological predispositions in learning" (Timms 2016, p. 702). These technological implementations also focus on increasing, capturing, or retaining "the attention of learners in the classroom" (Timms 2016, p. 703). Of course, this might be useful since "attention is a precursor to learning" (Timms 2016, p. 703).

However, results of literature reviews show a more indistinct picture of the success of using social robots (Randall 2019; van der Berghe et al. 2019). Nevertheless, Timms states that children who were engaged with a robot called Rubi lost attention after 20 min, but "when the robot was programmed to react to their gaze and [to] look at them, the attention span skyrocketed. We are biologically wired by evolution to respond to facial cues in interpersonal interactions" (Timms 2016, p. 706). Additionally, Randall (2019) states that in the field of robot-assisted language learning (RALL), positive effects have been shown and that "[u]tilizing robots in this area has been shown to increase engagement during the task, interest in learning with technology, and motivation in learning the language. They also demonstrate effectiveness in this regard when used as an addition to human instruction, in addition to increasing confidence and decreasing anxiety when communicating" (Randall 2019).

However, Randall also expresses concerns about "whether these effects will still prove prominent in comparison in the long term" (Randall 2019). In another review from van den Berghe et al., it is stated that "[a]t least some results on learning-related emotions and learning gains obtained in previous robot studies are likely to stem from the initial excitement when learners work with a robot for the first time" (van der Berghe, et al. 2019). That means that "motivation could, at least in part, be due to the initial novelty effect of robots, which soon disappears" (van der Berghe et al. 2019). The presumed loss of interest in the long term is problematic since the learner may only be excited and motivated in the beginning due to the new learning situation with the social robot. The construction of the environment to condition the learners mainly via exciting, extrinsic motivations has its limits. Self-control and -regulation in learning also come with the transition from extrinsic incentives to intrinsic motivation. Gamification has its limits when learners are solely nudged to perform certain tasks without the learner acquiring aspects of autonomy, such as self-control.

Another problematic issue is that a "robot showing social behavior, such as producing the child's name, can increase children's engagement in learning tasks. At the same time, the social behaviors of the robot can distract children from learning and, as a consequence, result in poorer learning outcomes" (van der Berghe et al. 2019). The demonstration of social behavior by the robot needs to be adjusted so that it does not distract the learner from her learning tasks. A robot could thus even be "too social." The humanistic notion of education emphasizes interactions between humans. The use of robots that are too social or simulate too human-like behavior may not only elicit the uncanny valley effect but also have certain effects on human interactions and expectations of learners in education. For instance, the around-the-clock availability of robots or chatbots might make learners incapable of organizing themselves in an established schedule, believing that they can get answers at any time. However, learning during a set time also establishes a certain kind of self-control in organizing oneself. Further research is needed to understand such implications and how around-the-clock availability conditions learners.

Furthermore, it seems that "few studies examining reading skills, grammar learning, and sign language showed quite positive results, while the evidence concerning speaking skills is more mixed." (van der Berghe et al. 2019). Additionally, "[m]ost studies focused on word learning and did not clearly show whether robots are effective for word learning. More research is needed to determine the most effective role for the robot (e.g., teaching assistant or peer learner), the age-groups for which robots are most beneficial (e.g., preschool children, school-aged children, or adults), and the optimal number of sessions for word learning (one or multiple)" (van der Berghe et al. 2019). Although, hence, the main idea of social robots in the field of education is to keep the learner engaged, motivated, and focused on the task, learning a language can be supported by intelligent systems, virtual agents, or social robots without diminishing the autonomy of the learner as long as it is used as an assistance system (like the ones in cars) that help on an operational level. Responsibility could also be delegated partly to the system. This is rooted in acquiring basic language skills on the so-called "preoperational level." Thereby, actions are internalized, which leads to a conceptualization of action schemes and their representation; for example, the child is capable, among other things, of elementary conclusions and classifications, that is, objects are endowed with predicates (for instance, a pencil is described as red) and permanent relations. These representations do not have to be verbalized. Piaget, therefore, speaks of preliminary terms, as a conceptualization of logical operations has not yet been fully developed, and representations have not yet been separated from actions (Piaget 2015, pp. 31–43). Even though Piaget calls it the preoperational level, these abilities exhibit dispositional behavior on an operational level. A child becomes a "reliable reporter" (Brandom 1994, p. 219/220) of factual circumstances. Such acquisitions of basic language skills also resemble human–human interactions and do not diminish the learner's autonomy. Hence, using intelligent systems in the classroom is ethically acceptable for this purpose. However, it must also be accompanied by regular classes and not solely establish a kind of extrinsic motivation for the sake of keeping the learner engaged. Moreover, other options must be present to acquire vocabulary or language. Otherwise, aspects of autonomy like self-control and determination will be neglected.

3.4 Virtual actualities—chatbots and feedback systems

Natural language processing (NLP) deals with verbal input and output and how intelligent systems can process it. Litman (2016) states: "Although education is arguably one of the oldest application areas of NLP research, new phenomena such as MOOCs and big data have triggered an explosion of current interest in this area, as well as increased already strong ties between researchers in NLP and in other areas of Artificial Intelligence" (Litman 2016, p. 4174). The applications and their uses are multifaceted. There are NLP-based applications that support teachers by "automatically generating multiple-choice, wordbank, and other types of test questions by processing texts in the subject domain" (Litman 2016, p. 4173). Of course, introducing powerful tools based on so-called large language models will further boost these developments. Empirical studies already have demonstrated the efficacy of chatbots when acquiring a language (Yuan 2023) and that such systems "contribute to improving language skills" (Polakova and Klimova 2024).

Some systems provide feedback to either teachers or students. Teachers can, e.g., obtain formative feedback from student answers to free-response questions by automatically grouping them "based on semantic similarity" (Comprehension SEEDING system) (Paiva et al. 2014). Other applications help assess learners' work to give either formative or summative feedback. Litman states that many feedback systems "often achieve high *reliability* in replicating human scores using only features that are easily computable (e.g., essay length) but that bear little relationship to the human scoring rubric" (Litman 2016, p. 4172). To not only achieve high reliability but also to obtain "*validity*," the "dimensions of the rubric need to be well represented by the features used in the automated scoring system, and the features should not be irrelevant to the rubric" (Litman 2016, p. 4172). Different methods of automated scoring are examined by (Loukina et al. 2015), and for the assessment of texts by rubric-based automated scoring, see (Rahimi et al. 2017). Automated evaluation of writing can range from grammatical evaluation to semantic similarity to textual entailment (Chapelle et al. 2015; Dzikovska et al. 2016; Foltz and Rosenstein 2015; Leacock et al. 2014).

Of course, feedback is also crucial to keep the students engaged, as shown in (Papageorgiou and Lameras 2017), but a "system with validity has greater potential to generate useful formative feedback to students and teachers." However, "much work remains to be done to improve the utility of such systems" (Litman 2016, p. 4172). The next step will then be tutoring systems such as chatbots that serve as learning assistants (Mathew et al. 2021). Litman states that concerning dialog tutors, "most research has focused on STEM and other domains where knowledge correctness is well-defined," such as biology, computer sciences, physics, etc. (for an overview of the literature, see (Litman 2016, p. 4172)). Another example is "Watson Tutor," which "is a 'one-on-one' virtual tutoring system" (Afzal, et al. 2019). They state that the "dialog strategy followed by Watson Tutor is inspired by Socratic dialog" (Afzal, et al. 2019, p. 47). Nonetheless, it is based on teaching facts, while Socratic dialog is about discussing concepts and their meaning. The method focuses on learning objectives and the mastery of different levels, but it is not transparent how the tutoring system functions and how its success can be evaluated. Although much work remains to be done in the research on NLP-based tutoring systems, there seem to be specific directions for providing valuable feedback for learners beyond correcting mistakes and keeping them motivated or concentrated. As empirical studies with pilots suggest, personalized chatbots can be helpful to achieve learning objectives (Chen et al. 2025).

Feedback systems provide a fruitful ground for non-behavioristic approaches. However, certain aspects must be considered to increase the learner's autonomy. For instance, writing analytics tools "guide students through strategies to address well-defined constructed response writing tasks" (Khosravi et al. 2022). "AcaWriter" provides feedback about so-called "rhetorical moves", such as summarizing, contrasting ideas, and whether they are missing in the text (Knight et al. 2020). Such strategies are helpful in structuring texts. Nevertheless, different genres have their own style and form of argumentation; hence, it is context-dependent which strategies are provided. On a certain level, handling different strategies to write a text is also important. At this higher level, different choice options for strategies could be available for the user to avoid uniformity of texts. Even though such systems can transcend a behavioristic framework of learning and teaching, it is important to design systems that generate feedback or texts in a way that prevents the text from being copied without further reflection on the part of the learner. For instance, such systems might make it impossible to copy and paste texts. Nonetheless, the transformative power of large language models and their various possible uses in education cannot yet be fully foreseen, and the impact they have on the learner's autonomy, since learners can outsource tasks that are part of their learning trajectory (such as translating or generating texts). Much research remains to be done to understand the impact of large language models on education.

4 Limitations and outlook

4.1 Limitations

Ethical acceptability is discussed here from a theoretical standpoint. Yet, it needs to be empirically investigated how implementing intelligent systems on different levels (operational, strategic, and moral) influences the learner's behavior. Studies have shown that technology influences users on a strategic level (Krügel et al. 2023a; b), but also on a moral level (Krügel et al. 2023a; b). Hence, more empirical studies that take the theoretical side of acceptability as a starting point to assess intelligent systems in the classroom are needed.

So far, the constructivist approach has been presupposed without critical questioning. The findings of Piaget are, of course, not uncontroversial, but most points of critique can be seen as adjustments to some of the statements of the theory. One does not have to give up the whole theory just because some statements are considered not valid anymore (see chapter 5.5 of (Schurz 2014)). This idea is based on Willard van Orman Quine's thoughts on the philosophy of science. He claimed that the statements form a "field of force" with experience at its periphery (Quine 1980 [1953]). As argued here, such a constructivist or learner-oriented approach has the advantage that specific tasks can be delegated to intelligent systems without diminishing the learner's autonomy. Despite these limitations, this research can be seen as a first step toward integrating two lines of research, pedagogy and technology ethics, which have not been directly linked regarding the implementation of intelligent systems.

4.2 Outlook—educational justice

To establish a competence-based approach, objectives need to be implemented that are transparent and institutionalized, allowing for the measurement and evaluation of the acquired competence. The degree to which learners should know about the objectives and participate in the institutional framework must also be scrutinized because it has implications for educational justice. However, this can only be outlined. The interplay in acquiring behavior or learning is much more complex than behaviorism suggests. Not only the circumstances or the environment, but also the interests and individual talent shape the produced behavior. While behaviorism focuses on the environment, empirical pedagogy focuses on latent variables to analyze learners' talents (Nagengast and Trautwein 2015). The circumstances only play a role if there is a talent that allows the circumstances to be realized and to be converted into achievements of the individual (see also Amartya Sen's discussion of the concept "capability" (Sen 1995)), but even the combination of all three underdetermines the competences of learners.

Competence can only be measured by the products that are achieved through them. The ability to play the piano can only be demonstrated by playing the piano, and the competence of critical thinking can only be demonstrated in a product like a presentation or a written text. The products can demonstrate either a "stronger energy of the will," which makes it difficult to measure the quality of a product, or they only demonstrate accidental differences that depend on the "richer nature," i.e., more favorable circumstances such as growing up in a more affluent neighborhood or country, or specific individual talents. Both circumstance and talent are only accidental, i.e., they could have also been different and not in our favor. Consequently, doing justice to a learner by either reconstructing her circumstances to explain her development or by basing her development on her individual talents—may they be advanced or underdeveloped—will not lead to measurements that can be compared because it will lead to a portrayal of the personal biography of the learner and how can there be a comparison of different biographies of learners for the sake of fair evaluation? This reconstruction is based on Hegel's analysis of abilities in his *Phenomenology of Spirit* (Hegel 2008, pp. 294–311). Furthermore, "the distribution of talents given by nature is no less arbitrary" than distributing shares "based on social status or accident of birth (as in aristocratic or caste societies)" (Sandel 1994, pp. 1782–1789). To do "justice" to each learner—an extreme version of personalization!—would make it impossible to set standards to evaluate the learners. Hence, Hegel states that in addition to the circumstances, the interests and the talent (which he calls "*inner means*"), also "*real* means" ("*wirkliche* Mittel") are needed (Hegel 2008, p. 297). They are not just tools that are means to build something, but also intellectual techniques that fall under it. They help to evaluate the performances by establishing the conditions of success for performances and the criteria of goodness of actions.

These means transcend individual performances. For example, the competence of mastering a practice, such as speaking a language, implies applying concepts and structures, including the language's grammar. We acquire our native language without explicit knowledge of these structures (real intellectual means). However, although it is implicit knowledge, criteria of goodness can be established to distinguish levels of proficiency, as in the guideline "Common European Framework of Reference for Languages," to recognize different aspects that go beyond a pure application of the structures. Someone can make mistakes, i.e., form syntactically wrong sentences, but can still be understood, i.e., the communicative aspect is fulfilled. Such guidelines usually undergo phases of discussion and implementation until they are institutionalized. For example, one can obtain a certificate from an official institution (e.g., the Goethe Institute for German) to apply to a university in another country. The conditions of success for performances and practices are based on discursive practices that establish specific guidelines that transcend individual performances. (Another aspect of speaking a language is the matter of style, which plays an important role but is bound more to taste and regional differences.)

Consequently, forms of personalized learning via technology fail if they only focus on tailoring education to the needs of each learner because learning objectives and proficiency levels are conditions for success in learning. Additionally, applications that only measure the strength of engagement or the output's quantity will not help form autonomous learners because they remain in a behavioristic framework and will not teach to master practices. The formation of competence is only possible through the acquisition of specific techniques. It is the main task to develop criteria and indicators that enable the differentiation of proficiency levels. The qualitative and quantitative measurement of the development of competence (observables) can only be clear if the criteria, as levels of proficiency, are made explicit (e.g., in the "Common European Framework of Reference for Languages").

It has been shown that personalized learning within a behavioristic framework is not ethically acceptable because the autonomous development of the learner is not possible. Nevertheless, it is possible to integrate intelligent systems that support the learner's development, even if intelligent systems operate on certain levels of autonomy. Hence, certain kinds of personalization of the learning experience are ethically acceptable. Nevertheless, the institutionalized framework, conditions of success, and possible ways of evaluating and comparing learning need to be considered; otherwise, even in a constructivist framework, fair education will be far-fetched. This, however, requires further research to shed light on the issue of educational fairness.

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References

Aalborg University (2015) Problem-based learning. [Online]. Available at: https://www.en.aau.dk/about-aau/aalborg-model-problem-based-learning/

Adomako Gyasi P et al (2025) Nano-biosensors for continuous cognitive and stress monitoring: applications in learning and mental well-being. Nano Select

Afzal S et al (2019) The personality os AI systems in education: experiences with the Watson tutor a one on one virtual tutoring system. Child Educ 95(1):44–52

Agarwal N, Moehring A, Rajpurkar P, Salz T (2023) Combining human expertise with artificial intelligence: experimental evidence from radiology. NBER Working Paper No. w31422 (https://ssrn.com/abstract=4505053)

Barata G, Gama S, Jorge J, Gonçalves D (2015) Gamification for smarter learning: tales from the trenches. Smart Learn Environ 2:1–23

Brandom R (1994) Making it explicit: reasoning, representing, and discursive commitment. Harvard University Press, Cambridge (Mass.)/London

Brandom R (2008) Between saying and doing. Oxford University Press, Oxford

Brown A et al (1993) Distributed expertise in the classroom. In: Salomon G (ed) Distributed cognitions: psychological and educational considerations. s.n., New York, pp 188–228

Buder J, Schwind C (2012) Learning with personalized recommender systems: a psychological view. Comput Hum Behav 28(1):207–216

Chapelle C, Cotos E, Lee J (2015) Validity arguments for diagnostic assessment using automated writing evaluation. Lang Test 32(3):385–405

Chaushi B, Selimi B, Chaushi A, Apostolova M (2023) Explainable artificial intelligence in education: a comprehensive review. In: Longo L, (ed). Explainable artificial intelligence. xAI 2023. Communications in computer and information science. Springer, Cham

Chen D, Aaltonen K, Lampela H, Kujala J (2025) The design and implementation of an educational chatbot with personalized adaptive learning features for project management training. Tech Know Learn 30:1047–1072

Dzikovska M, Nielsen R, Leacock C (2016) The joint student response analysis and recognizing textual entailment challenge: making sense of student responses in educational applications. Lang Resour Eval 50(1):67–93

Erpenbeck J, Heyse V (2021) Die Kompetenzbiographie: Wege der Kompetenzenticklung. 3 ed. Münster/New York

Figueroa E et al (2024) The use of artificial intelligence techniques in smart classrooms is in its infancy. IEEE Access 12:125179–125193

Fiok K, Farahani F, Karwowski W, Ahram T (2021) Explainable artificial intelligence for education and training. J Def Model Simul 19(2):133–144

Floridi L, Cowls J, King T, Taddeo M (2020) How to design AI for social good: seven essential factors. Sci Eng Ethics 26(3):1771–1796

Foltz P, Rosenstein M (2015) Analysis of a large-scale formative writing assessment system with automated feedback. L@S 2015 - 2nd ACM Conference on Learning at Scale, pp. 339–342

Friedman B, Kahn P Jr, Borning A (2008) Value sensitive design and information systems. In: Kimma K, Tavani H (eds) The handbook of information and computer ethics. Wiley, New Jersey, pp 69–101

Gottschalk-Mazouz N, (2019) Autonomie. In: Liggieri K, Müller O (eds) Mensch – Maschine – Interaktion: Handbuch zur Geschichte – Kultur – Ethik,. Stuttgart: s.n., pp 238–240

Grunwald A (1999) Technology assessment or ethics of technology? Ethical Perspect 6(2):170–182

Grunwald A (2005) Zur Rolle von Akzeptanz und Akzeptabilität von Technik bei der Bewältigung von Technikkonflikten. TATuP 14(3):54–60

Harvard College (2024) Mission, vision, & history. [Online]. Available at: https://college.harvard.edu/about/mission-vision-history

Hegel GFW (2008) Phänomenologie des Geistes. s.n, Frankfurt am Main

Hubig C (2007) Die Kunst des Möglichen II: Ethik der Technik als provisorische Moral. s.n, Bielefeld

Hubig C (2015) Die Kunst des Möglichen III: Macht der Technik. s.n, Bielefeld

Hubig C (2019) Haben autonome Maschinen Verantwortung?. In: Hirsch-Kreinsen H, Karacic A (eds) Autonome Systeme und Arbeit: Perspektiven, Herausforderungen und Grenzen der Künstlichen Intelligenz in der Arbeitswelt. Bielefeld, pp 275–298

Isinkaye F, Folajimi Y, Ojokoh B (2015) Recommendation systems: principles, methods and evaluation. Egypt Inform J 16(3):261–273

Jawaheer G, Szomszor M, Kostko P (2010) Comparison of implicit and explicit feedback from an online music recommendation service. In: Proceedings of the 1st International Workshop on Information Heterogeneity and Fusion in Recommender Systems (HetRec '10). Association for Computing Machinery, New York, NY, USA, pp 47–51

Jia J, He Y, Le H (2020) A multimodal human-computer interaction system and its application in smart learning environments. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol 12218 LNCS, pp 3–14

Jones M, Brader-Araje L (2002) The impact of constructivism on education: language, discourse, and meaning. Am Commun J 5(3):1–10

Jorritsma W, Cnossen F, van Ooijen P (2015) Improving the radiologist–CAD interaction: designing for appropriate trust. Clin Radiol 70(2):115–122

Kaur A, Bhatia M (2024) Smart classroom: a review and research agenda. IEEE Trans Eng Manag 71:2430–2446

Khosravi H et al (2022) Explainable artificial intelligence in education. Comput Educ: Artif Intell. https://doi.org/10.1016/j.caeai.2022.100074

Knight S et al (2020) Acawriter: a learning analytics tool for formative feedback on academic writing. J Writ Res 12(1):141–186

Krügel S, Ostermaier A, Uhl M, (2023) ChatGPT's inconsistent moral advice influences users' judgment. Sci Rep 13(4569)

Krügel S, Ostermeier A, Uhl M, (2023) Algorithms as partners in crime: a lesson in ethics by design. Comput Human Behav 138

Lara F, Deckers J (2020) Artificial intelligence as a Socratic assistant for moral enhancement. Neuroethics 13:275–287

Leacock C, Chodorow M, Gamon M, Tetreault J (2014) Automated grammatical error detection for language learners. Synth Lect Human Lang Technol 7(1):1–185

Leuphana Universität Lüneburg (2006) Eine Universität in Freiheit und Verantwortung. s.n, s.l.

Leuphana Universität Lüneburg (2024) Leitbild. [Online]. Available at: https://www.leuphana.de/universitaet/entwicklung/leitbild.html

Liew T, Mat Zin N, Sahari N (2017) Exploring the affective, motivational and cognitive effects of pedagogical agent enthusiasm in a multimedia learning environment. Hum Cent Comput Inf Sci 7:9

Litman D (2016) Natural language processing for enhancing teaching and learning. In: Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence (AAAI'16). AAAI Press, pp 4170–4176

Liu L, Peng N (2021) Evaluation of user concentration in ubiquitous and cognitive artificial intelligence-assisted English online guiding system integrating face and eye movement detection. Int J Commun Syst 34(6)

Loukina A, Zechner K, Chen L, Heilman M (2015) Feature selection for automated speech scoring. In: Proceedings of the Tenth Workshop on Innovative Use of NLP for Building Educational Applications, pp 12–19

Ma X, Wang J (2024) WIP: Active learning through prompt engineering and agentic AI simulation-A pilot project in computer networks education. IEEE Front Educ Conf (FIE) Washington, DC, USA 2024:1–5

Martínez F, Montiel H, Valderrama H (2016) Using embedded robotic platform and problem-based learning for engineering education. Smart education and e-learning. Springer, Cham, pp 435–445

Matcha W, Uzir N, Gašević D, Pardo A (2019) A systematic review of empirical studies on learning analytics dashboards: a self-regulated learning perspective. IEEE Trans Learn Technol 13(2):226–245

Mathew A, Rohini V, Paulose J (2021) Nlp-based personal learning assistant for school education. Int J Electr Comput Eng 11(5):4522–4530

Miller G (2003) The cognitive revolution: a historical perspective. Trends Cogn Sci 7(3):141–144

Mohammed Ali S, Nihad M (2021) Internet of things for education field. J Phys: Conf Ser. https://doi.org/10.1088/1742-6596/1897/1/012076

Tecnológico de Monterrey (2018) Tec21: Educational Model. [Online]. Available at: https://internationalfaculty.tec.mx/es/our-differenciator

Nagengast B, Trautwein U (2015) The prospects and limitations of latent variable models in educational psychology. In: Corno L, Anderman E (eds) Handbook of educational psychology. Routledge/Taylor & Francis Group, New York, pp 41–58

Nordström K (2009) Autonomie und Erziehung: Eine ethische Studie. Freiburg/München

Paiva F et al (2014) Comprehension SEEDING: comprehension through self explanation, enhanced discussion, and Inquiry generation. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Volume 8474. LNCS, pp 283–293

Papageorgiou V, Lameras P (2017) Multimodal teaching and learning with the use of technology: meanings, practices and discourses. In: 14th International Conference on Cognition and Exploratory Learning in the Digital Age, CELDA 2017, pp 133–140

Paquette G, Mariño O, Rogozan D, Léonard M (2015) Competency-based personalization for massive online learning. Smart Learn Environ 2:1–19

Pesare E, Roselli T, Corriero N, Rossano V (2016) Game-based learning and gamification to promote engagement and motivation in medical learning contexts. Smart Learn Environ 3:1–21

Petermann T, Scherz C (2005) TA und (Technik-)Akzeptanz(-forschung). TATuP 14(3):45–53

Piaget J (2015) Genetische Erkenntnistheorie (L'épistémologie génétique). Kindle Edition ed. Stuttgart

Pinkard T (2002) German philosophy, 1760–1860: the legacy of idealism. s.n, Cambridge

Polakova P, Klimova B (2024) Implementation of AI-driven technology into education—a pilot study on the use of chatbots in foreign

language learning. Cogent Educ. https://doi.org/10.1080/2331186X.2024.2355385
Preston A et al (2015) Can a kitchen teach languages? Linking theory and practice in the design of context-aware language learning environments. Smart Learn Environ 2:1–19
Quine WVO 1980 [1953] Two Dogmas of Empiricism. In: From a Logical Point of View. Harvard University Press, Cambridge (Mass.), pp 20–46
Rachha A, Seyam M (2023) Explainable AI in education: current trends, challenges, and opportunities. SoutheastCon 2023, Orlando, FL, USA, pp 232–239
Rahimi Z et al (2017) Assessing students' use of evidence and organization in response-to-text writing: using natural language processing for rubric-based automated scoring. Int J Artif Intell Educ 27(4):694–728
Raithel J, Dollinger B, Hörmann G (2009) Einführung Pädagogik: Begriffe, Strömungen, Klassiker, Fachrichtungen. 3 ed. Wiesbaden
Randall N (2019) A survey of robot-assisted language learning (RALL). J Hum-Robot Interact 9(1):1–36
Reijers W, Gordijn B (2019) Moving from value sensitive design to virtuous practice design. J Inf Commun Ethics Soc 17(2):196–209
Richter F (2016) Der Status des Normativen: Ein Beitrag zur aktuellen Debatte im Ausgang von Hegel. s.n, Darmstadt
Rus V, Ştefănescu D (2016) Non-intrusive assessment of learners' prior knowledge in dialogue-based intelligent tutoring system. Smart Learn Environ 3:1–18
Saini MK, Goel N (2019) How smart are smart classrooms? A review of smart classroom technologies. ACM Comput Surv 52(6):1–28
Sanchez Chamorro L, Bongard-Blanchy K, Koenig V (2023) Ethical tensions in UX design practice: exploring the fine line between persuasion and manipulation in online interfaces. In: Proceedings of the 2023 ACM Designing Interactive Systems Conference (DIS '23), pp 2408–2422
Sandel M (1994) Political liberalism. Harvard Law Review, pp 1765–1794
Schurz G (2014) Einführung in die Wissenschaftstheorie. 4 ed. Darmstadt
Schwalbe G, Finzel B (2024) A comprehensive taxonomy for explainable artificial intelligence: a systematic survey of surveys on methods and concepts. Data Min Knowl Discov 38(5):3043–3101
Sen A (1995) Inequality reexamined. New York/Cambridge (Mass.)
Serral E, De Weerdt J, Sedrakyan G, Snoeck M (2016) Automating immediate and personalized feedback taking conceptual modelling education to a next level. In: IEEE Tenth International Conference on Research Challenges in Information Science (RCIS), Grenoble
Shokeen J, Rana C (2020) A study on features of social recommender systems. Artif Intell Rev 53(2):965–988
Skinner BF (1974) About behaviorism. s.n, New York
Tabuenca B et al (2021) Affordances and core functions of smart learning environments: a systematic literature review. IEEE Trans Learn Technol 14(2):129–145
Tabuenca B, Börner D, Kalz M, Specht M (2015) User-modelled ambient feedback for self-regulated learning. In: Design for Teaching and Learning in a Networked World: 10th European Conference on Technology Enhanced Learning, EC-TEL 2015, Toledo, Spain, Volume Proceedings 10, pp 535–539
Timms M (2016) Letting artificial intelligence in education out of the box: educational cobots and smart classrooms. Int J Artif Intell Educ 26(2):701–712
Toivonen T, Jormanainen I, Montero C, Alessandrini A (2018) Innovative maker movement platform for K-12 education as a smart learning environment. In: Challenges and Solutions in Smart Learning: Proceeding of 2018 International Conference on Smart Learning Environments, Beijing, China, pp 61–66
Trabandt S, Wagner H-J (2020) Pädagogisches Grundwissen für das Studium der Sozialen Arbeit: Ein Kompendium. Opladen/Toronto
Umbrello S, van de Poel I (2021) Mapping value sensitive design onto AI for social good principles. AI Ethics 1(3):283–296
University of Twente (n.d.) Shaping2030: Mission, Vision & Strategy
van de Poel I (2020) Embedding values in artificial intelligence (AI) systems. Minds Mach 30:385–409
Van den Hoven J (2014) Responsible innovation: a new look at technology and ethics. Responsible innovation 1: innovative solutions for global issues. Springer, Dordrecht, pp 3–13
van der Berghe R et al (2019) Social robots for language learning: a review. Rev Educ Res 89(2):259–295
Veldkamp A, Van De Grint L, Knippels M, Van Joolingen W (2020) Escape education: a systematic review on escape rooms in education. Educ Res Rev. https://doi.org/10.1016/j.edurev.2020.100364
Vygotsky L (2012) Thought and language (Revised and expanded edition). Cambridge (Mass.)/London
Wang H (2021) Linear algebra online interactive guiding innovation based on big data and eye movement monitoring. In: Proceedings - 5th International Conference on Intelligent Computing and Control Systems, ICICCS 2021, pp 924–927
Yuan Y (2023) An empirical study of the efficacy of AI chatbots for English as a foreign language learning in primary education. Interact Learn Environ 32(10):6774–6789
Zhang K (2021) Design and implementation of smart classroom based on internet of things and cloud computing. Int J Inf Technol Syst Approach 14(2):38–51
Zhang X et al (2024) Smart classrooms: how sensors and AI are shaping educational paradigms. Sensors. https://doi.org/10.3390/s24175487
Zhao Q, Harper FM, Adomaviciu G, Konstan JA (2018) Explicit or implicit feedback? engagement or satisfaction? a field experiment on machine-learning-based recommender systems. In: Proceedings of the 33rd Annual ACM Symposium on Applied Computing (SAC '18). Association for Computing Machinery, New York, NY, USA, pp 1331–1340