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IS ROBOTICS IN EDUCATION THE RIGHT TOOL TO FACE THE FUTURE PIVOTAL CHALLENGES OF SOCIETY?

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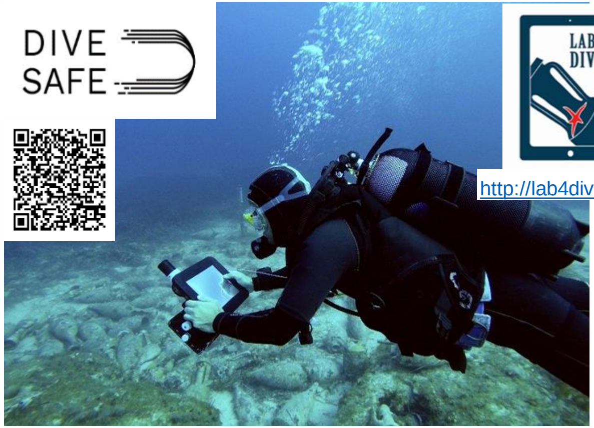
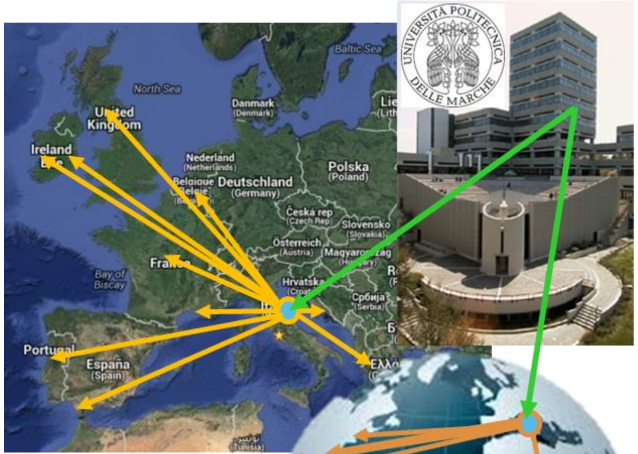
LabMACS (Laboratory of Modelling, Analysis and Control of Dynamical Sistems) @ UnivPM (Università Politecnica delle Marche)

Marine Robotics



http://lab4dive.eu

Educational Robotics



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Summary

- Background: Robotics in Education (RiE) is a broad area of robotics applications in education, but is it helpful to equip men and women with future critical competencies?
- Robotics in Education (RiE) or Educational Robotics (ER)?
- Educational Robotics: Challenges *and* outcomes
- Where is the learning system model?
- Can we use learning tools as sensors for collecting educational data?

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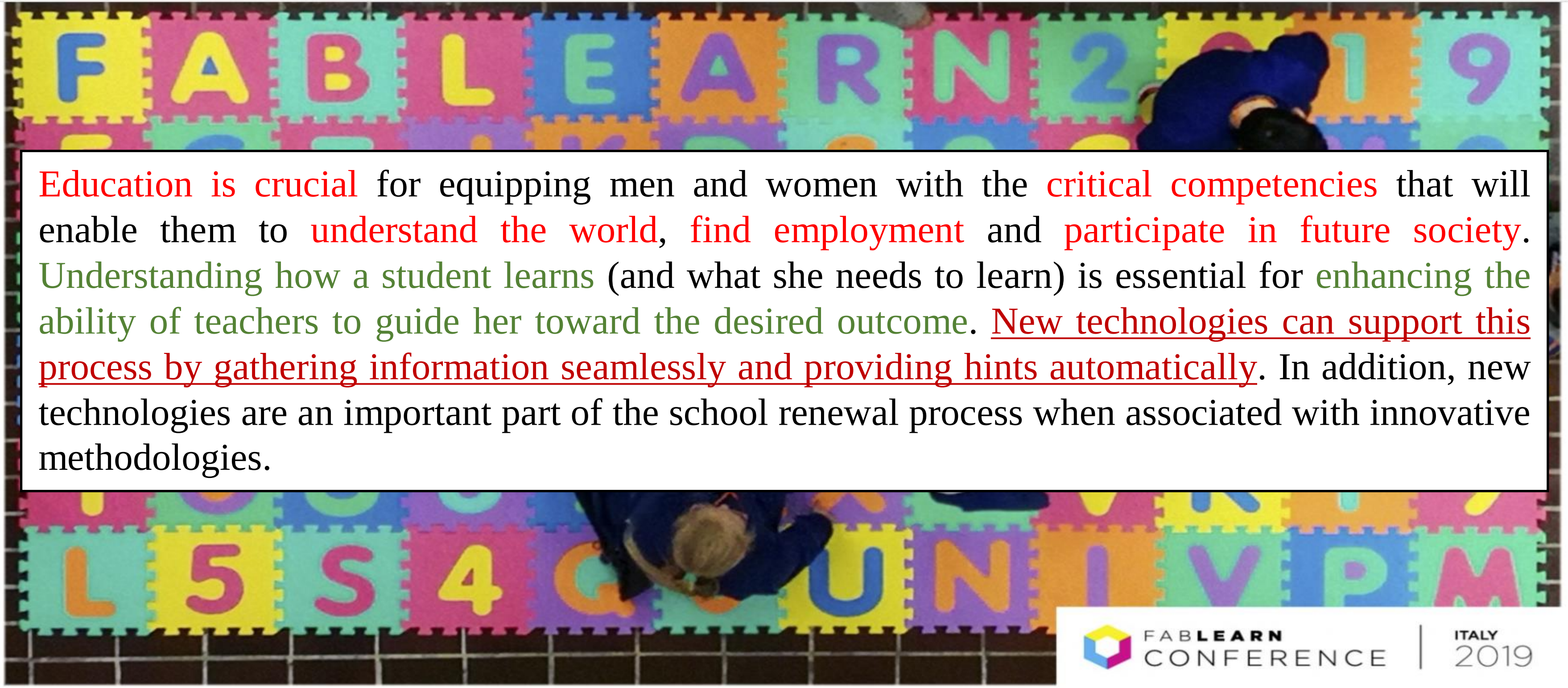
BACKGROUND



Education is crucial for equipping men and women with the critical competencies that will enable them to understand the world, find employment and participate in future society. Understanding how a student learns (and what she needs to learn) is essential for enhancing the ability of teachers to guide her toward the desired outcome. New technologies can support this process by gathering information seamlessly and providing hints automatically. In addition, new technologies are an important part of the school renewal process when associated with innovative methodologies.

Book: Scaradozzi et al., *Makers at School, Educational Robotics and Innovative Learning Environments, Lecture Notes in Networks and Systems Robots*. Springer.

Summary

- Background: Robotics in Education (RiE) is a broad area of robotics applications in education, we know that it is helpful to equip men and women with future critical competencies
- Robotics in Education (RiE) or Educational Robotics (ER)?

Even if some literature uses “Robotics in Education” and “Educational Robotics” as synonyms (Benitti, 2012; Eguchi, 2017), a distinction should be made between the two labels.

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Robotics in Education (RiE) or Educational Robotics (ER)

Educational Robotics **(ER)** is not **R4E** **or RiE**

~~CODING~~

Robots 4 Education (R4E)

- Robots that help students with relationship difficulties
- Robots that help children with physical impairments
- Robots used as educational tools to increase interest
- Robotic tools used in general for learning by educators
- Robotics / robotic tools to develop skills on a particular topic and transversal skills
- Robot as a mediator for learning STEM or other subjects

ER:

- Robots / robotic kits as a mediator for learning the basics of robotics

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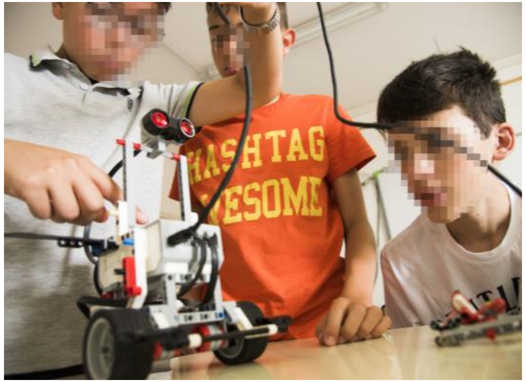
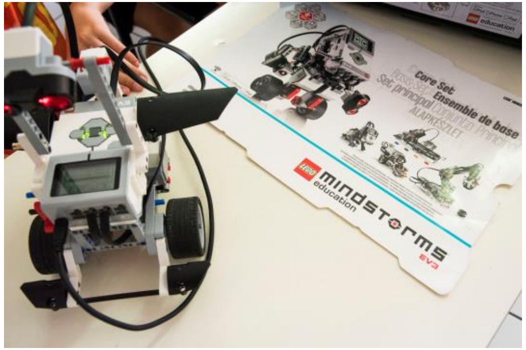
Educational Robotics DEFINITION





But how can we define ER?

It is not enough introducing robots in an educational setting to propose an ER activity (Scaradozzi, Screpanti & Cesaretti, 2019)!

ER is characterized by a workflow that allows students to **design**, **build** and **program** robotic artefacts, creatively solve problems and carry out meaningful projects.

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Educational Robotics DEFINITION

- Educational Robotics (ER) builds on the work of Seymour Papert, Lev Vygotsky, Jean Piaget (Ackermann, 2001; Mevarech and Kramarski, 1993; Papert, 1980; Vygotsky, 1968) to bring not just robotics in education, but to understand Robotics since an early age.
- ER is made of robots allowing a construction/deconstruction and programming activity, teachers/experts facilitating the activity, methodologies enabling students to explore the subject, the environment, the content of the activity and their personal skills and knowledge.

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- To benchmark ER activities, a framework is needed.
- Four different features can be identified to describe a RiE experience or project: the learning environment, the impact on students' school curriculum, the integration of the robotic tool in the activity, the way evaluation is carried out.
- Regarding how the robotic tool is integrated into the activity we can distinguish ER as a subset of RiE

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Robotics in Education: classification of experiences

Book: Daniela, L. *Smart Learning with Educational Robotics: Using Robots to Scaffold Learning Outcomes*. Springer.

- **Learning environment** (formal/non-formal)
- **Type of activity** carried out: curricular/not curricular activities (organized and purposefully designed activities carried out regularly during an entire cycle of compulsory school/scattered activities inside or outside the classroom)
- **How to assess** performance and evaluate outcomes. V&V model. KPIs. Evaluation methods.
- **How robots are integrated in class**:
  - As a companion (socially assistive robotics) -> robots helping children with social impairments
  - As an aid for students with disabilities (assistive robotics) -> robots helping children with physical impairments
  - As a mediator for learning STEM or other subjects (educational assistive robotics) -> robots designed to help students learn other subjects than Robotics
  - As a mediator for learning STrEM (educational robotics) -> robots designed to help students learn Robotics and other related subjects

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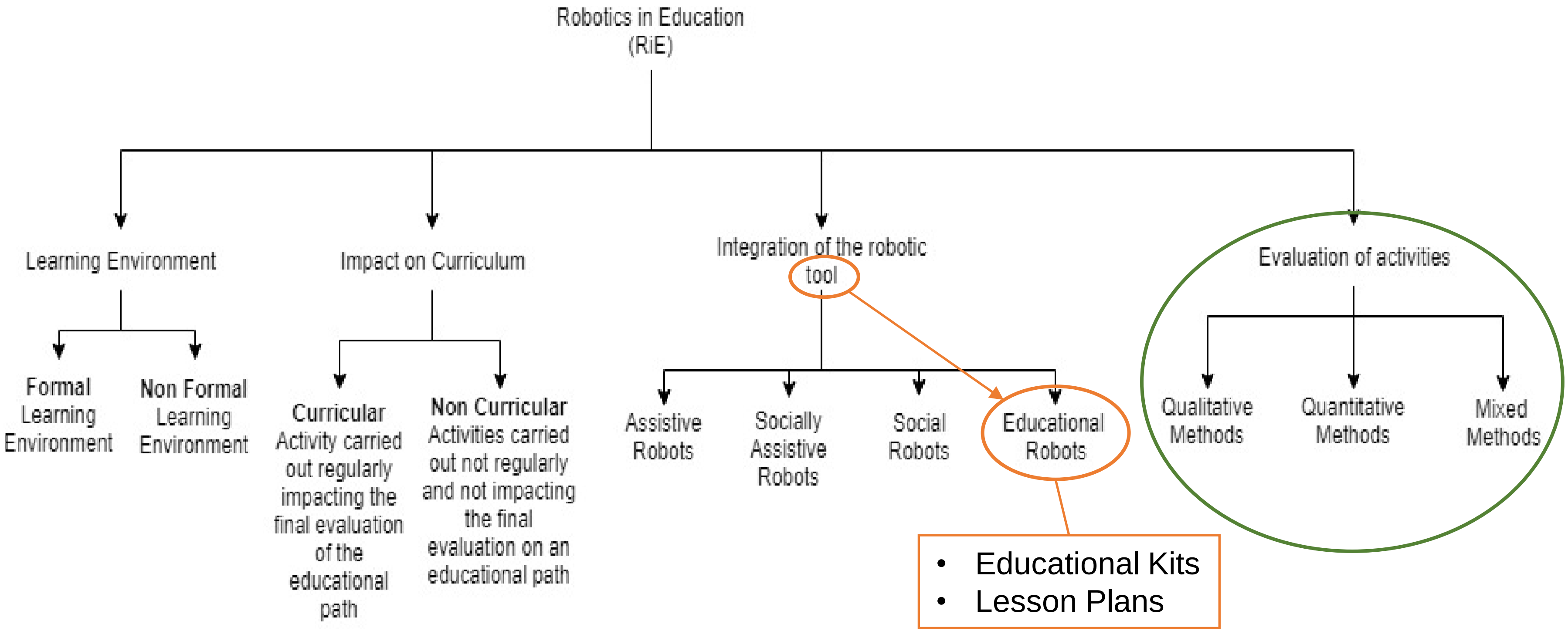
Robotics in Education: classification of experiences



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Why this research project?

Educational Robotics (ER) is increasingly spreading in schools all over the world (Miller & Nourbakhsh, 2016), thanks to teachers and educators that are using this approach during the course of their standard lessons.

And the academic community?

Angel-Fernandez and Vincze (2018) showed how the number of scientific papers using the words "robotics" and "education", or the expression "ER" <u>has significantly increased</u> in the last two decades.

Miller, D. P., & Nourbakhsh, I. (2016). Robotics for education. In B. Siciliano, & O. Khatib, Springer Handbook of Robotics (pp. 2115-2134). Springer, Cham.
Angel-Fernandez, J. M., & Vincze, M. (2018) Towards a Formal Definition of Educational Robotics. In Philipp Zech, Justus Piater Eds., Proceedings of the Austrian Robotics Workshop 2018. Conference series, Innsbruck university press.

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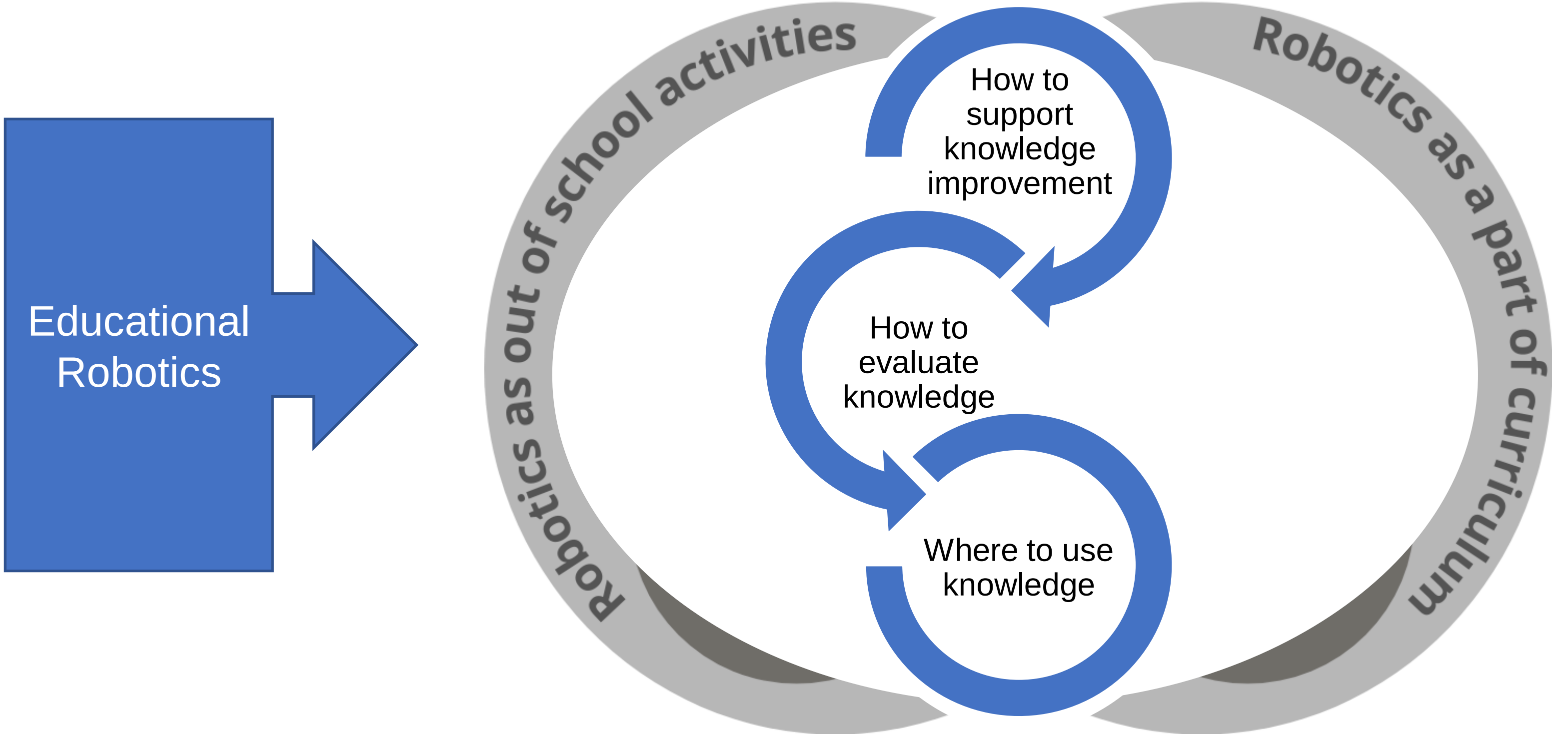
- ~~Robotics in Education (RiE) or Educational Robotics (ER)?~~

- Educational Robotics: Challenges *and* outcomes

  (credits: Linda Daniela, Dean of the Faculty of Education, Psychology and Art, Chair of the Council for Promotion in Pedagogy of the University of Latvia)

Educational Robotics: Challenges versus outcomes



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Challenges for educational robotics activities

- For teachers
- For students
- For planning of learning activities

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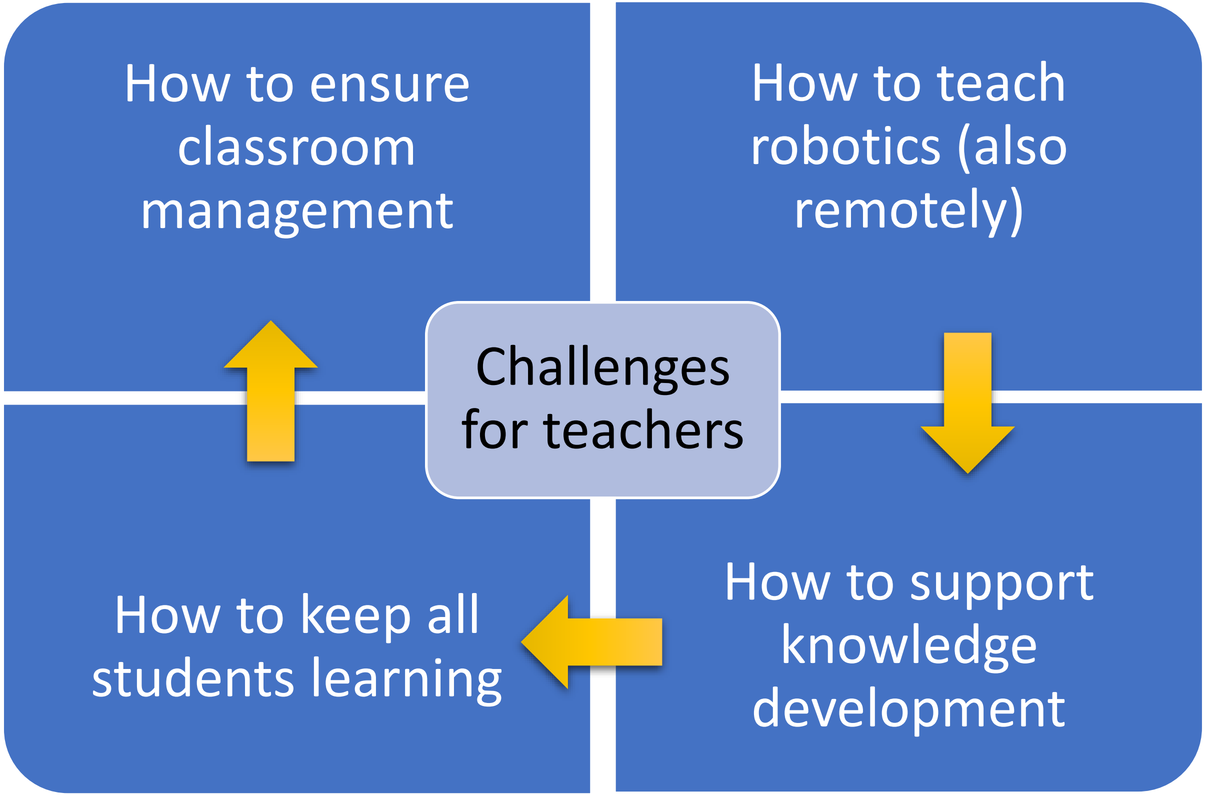
Challenges for educational robotics activities: teachers' side



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Challenges for educational robotics activities: students' side

Challenges for students

How to keep learning in own pace?

How to understand what should be done?

How to conceptualize knowledge?

How to apply knowledge?

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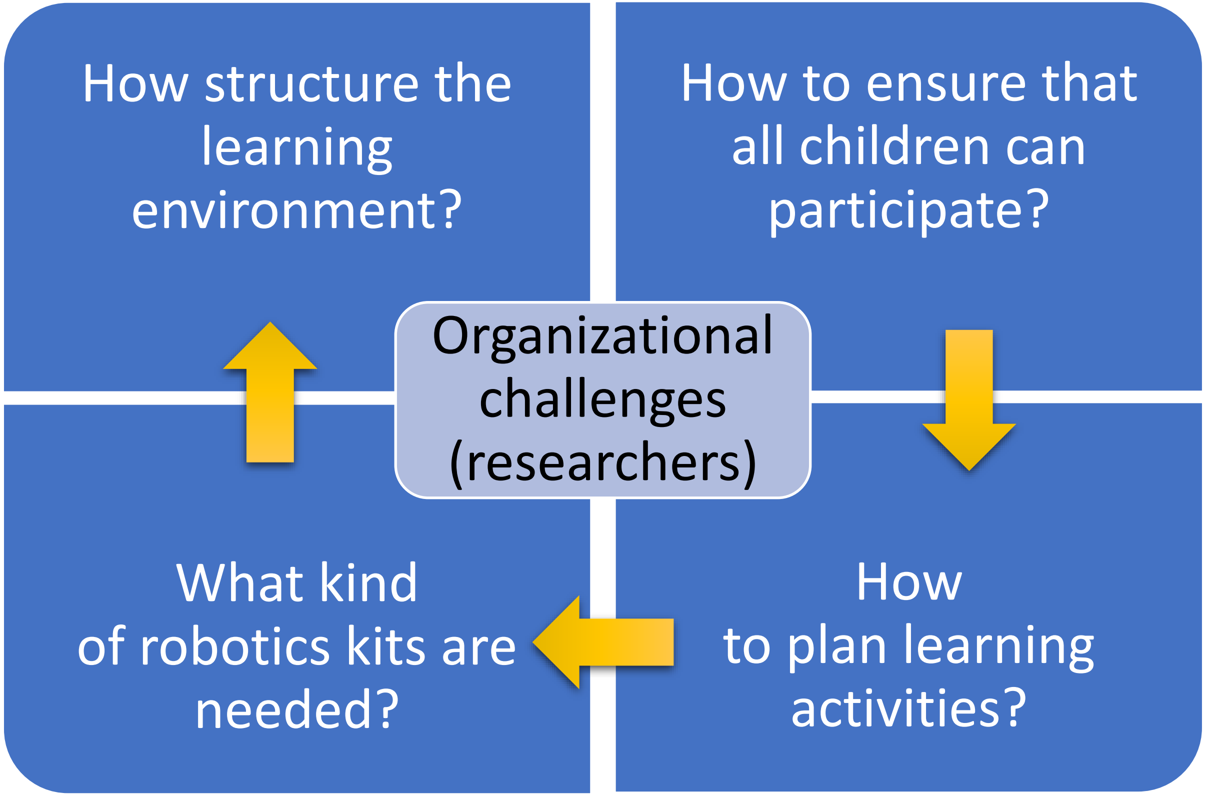
Challenges for educational robotics activities: planning new learning activities



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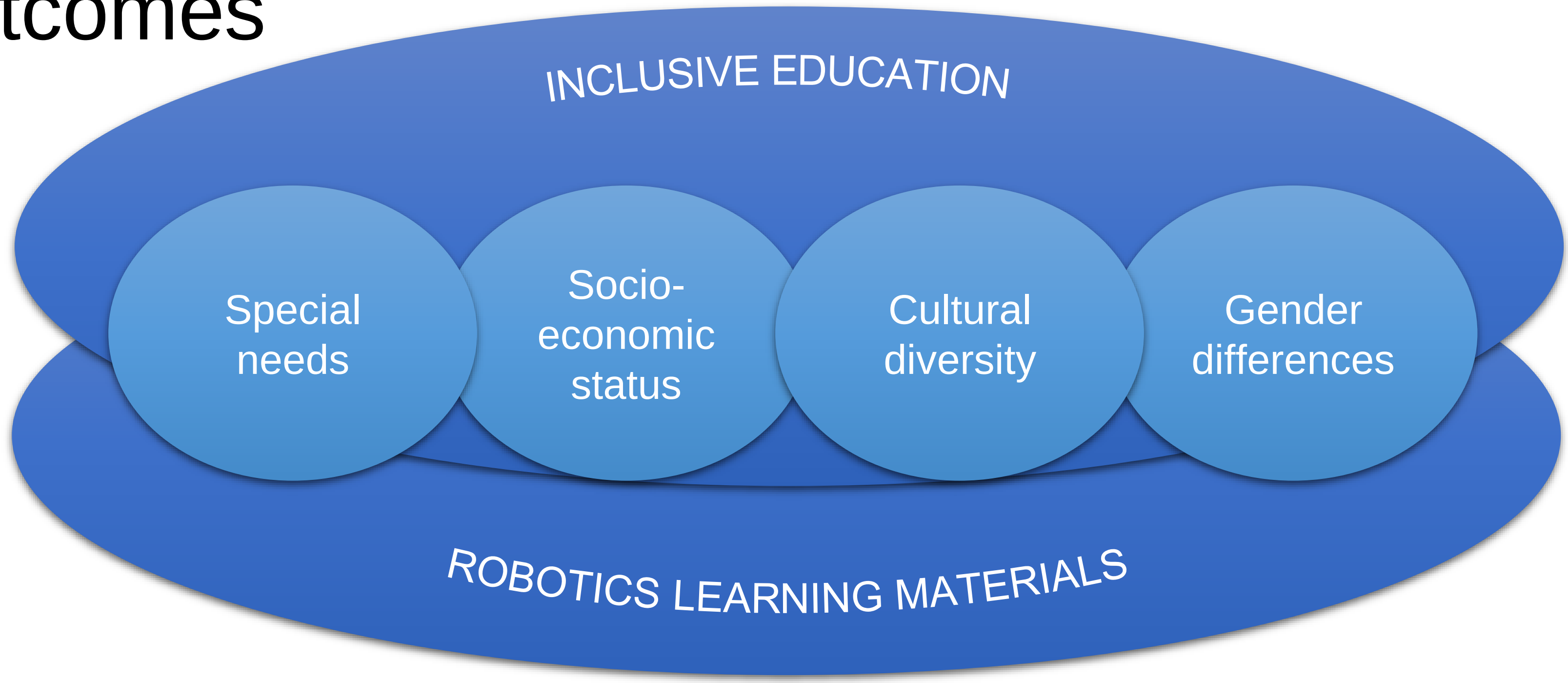
Outcomes



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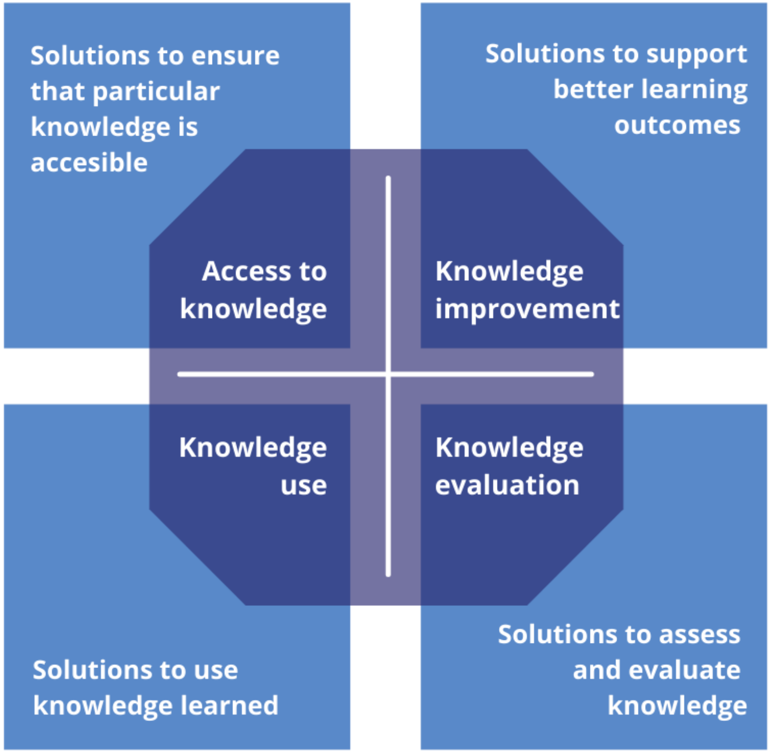
Outcomes



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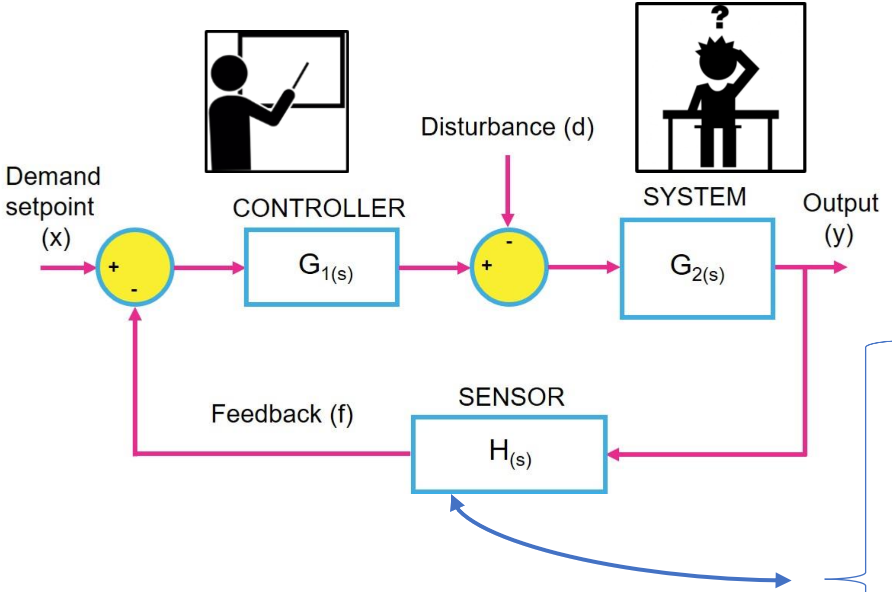
Modelling learning systems



STUDENT ACTIVITY METER

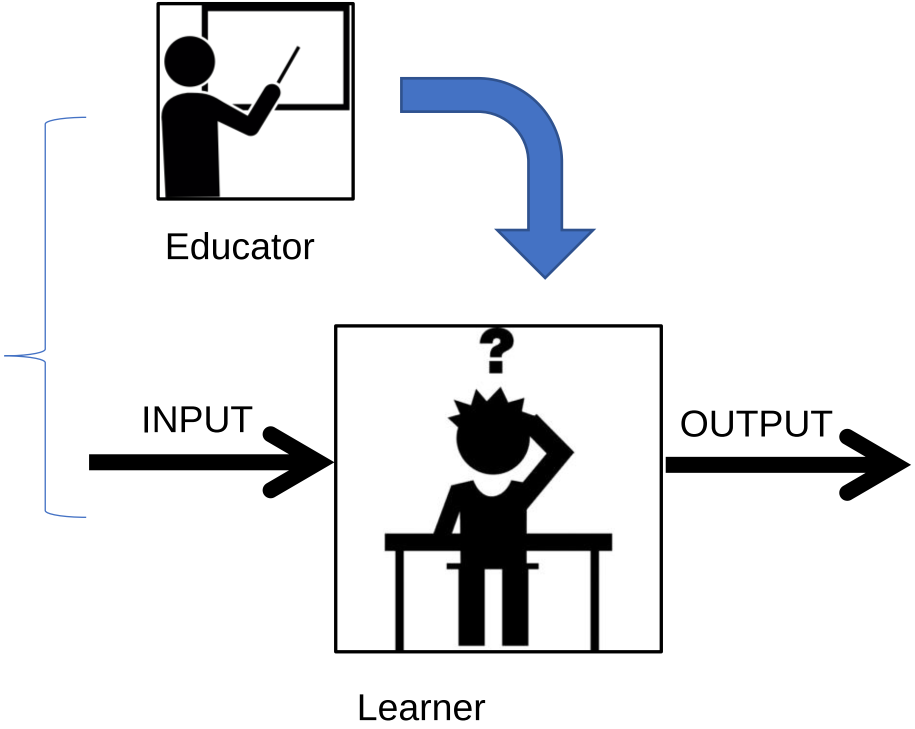
Source: https://tinyurl.com/ya5as4kj

© Can Stock Photo

A system theory approach to Educational Robotics

Modelling learning systems: the system theory approach

- A system is a group of **interacting** or **interrelated entities** that form a unified whole. It can be **natural** or **artificial**.
- A system is delineated by its **spatial** and **temporal boundaries**, surrounded and influenced by its **environment**, described by its **structure** and **purpose** and expressed in its **timing** or **event functioning**.



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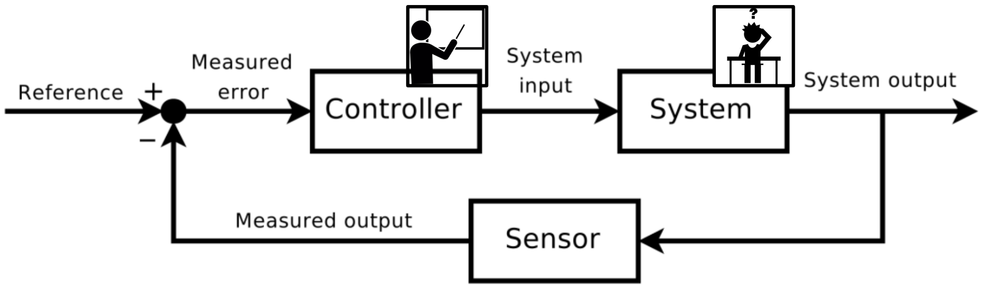
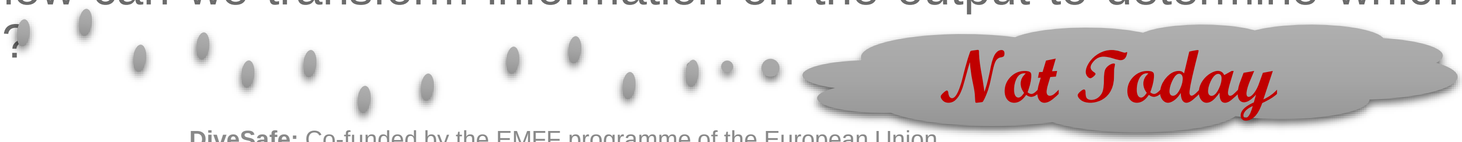
Modelling learning systems: the system theory approach



Four phases in modeling

- How can it be studied the learning process? What is learning? Which variables should be included in the model?
- Is it possible to establish the causality principle (i.e., given an input at a time t (or an event), we have a certain output at the time t (or a trigger))?
- Metrology: how can we measure the intended variables?
- Cybernetics: how can we transform information on the output to determine which input to provide?



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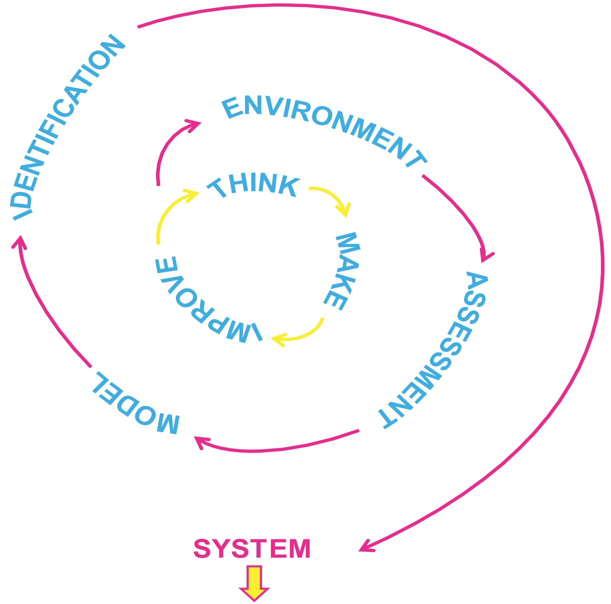
Model the learning process in an ER activity

Educational Robotics



Creating better innovation measurement practices
Errors and feedbacks
Success
Ethics

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Model the learning process in an ER activity

Lesson topic

Learner's development

Actions and Reactions

Cyber-Human-Physical system Model of the Human Learning Interactions

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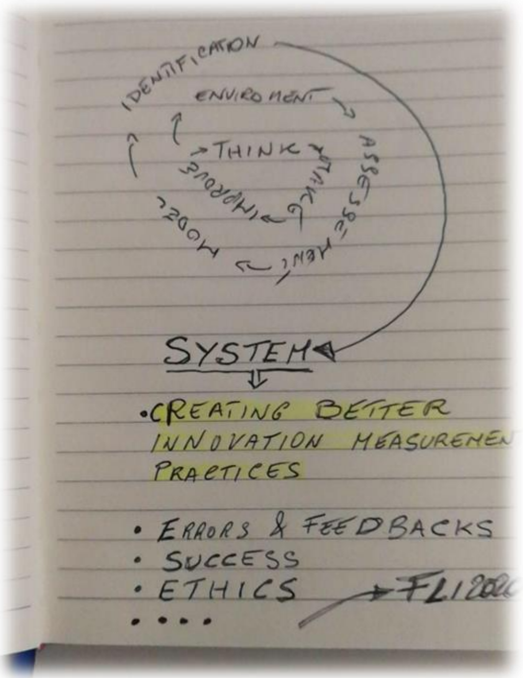
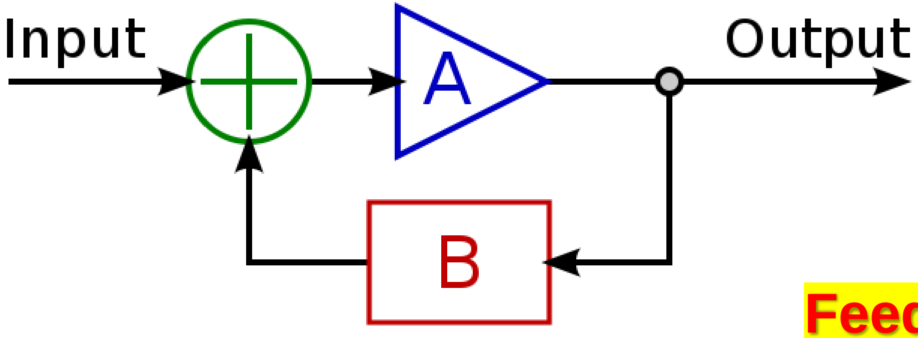
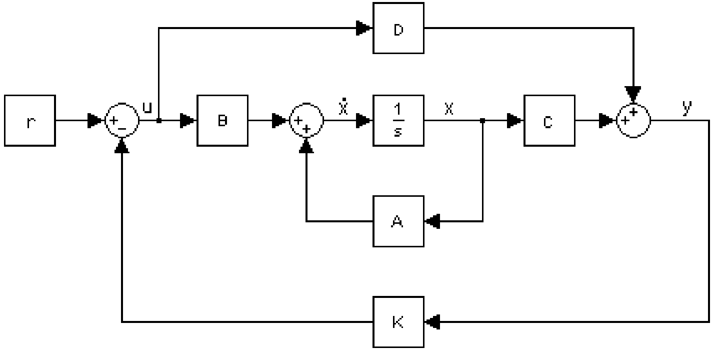
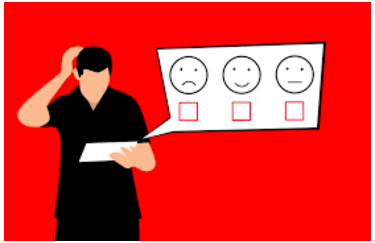
Model the learning process in an ER activity







Feedback!!!!!!



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Modelling learning systems: the system theory approach

What is learning? | Causality principle | Metrology | Cybernetics

Not Today

- **Learning is** the process by which an individual assimilates information, ideas and values and thus acquires **knowledge**, **know-how**, skills and/or **competences**.
- **Competence is** the "combination of knowledge, **skills** and **attitudes** appropriate to the context" .
- **Learning occurs** through **personal reflection**, **reconstruction** and **social interaction.** It may take place in formal, non-formal or informal settings.

Source: Cedefop (2014). **Terminology of European education and training policy:** a selection of 130 terms. 2nd ed. Luxembourg: Publications Office. Available at https://www.cedefop.europa.eu/en/events-and-projects/projects/validation-non-formal-and-informal-learning/european-inventory/european-inventory-glossary#

Richard Gross, Psychology: **The Science of Mind and Behaviour** 6E, Hachette UK, ISBN 978-1-4441-6436-7.

Modelling learning systems: the system theory approach

What is lear
Causality
Metrology
Cybe tics
Nety

Define Constructs

- Learning is ... on, ideas and values and th ... tences.
- Competenc ... ppropriate to the context" .
- Learning o ... and social interaction. ...

Source: Cedefop (2014). **Te ogy of European education and training policy:** a selection of 130 terms. 2nd ed. Luxembourg: Publications Office. Available at https://www.cedefop.europa.eu/en/events-and-projects/projects/validation-non-formal-and-informal-learning/european-inventory/european-inventory-glossary#

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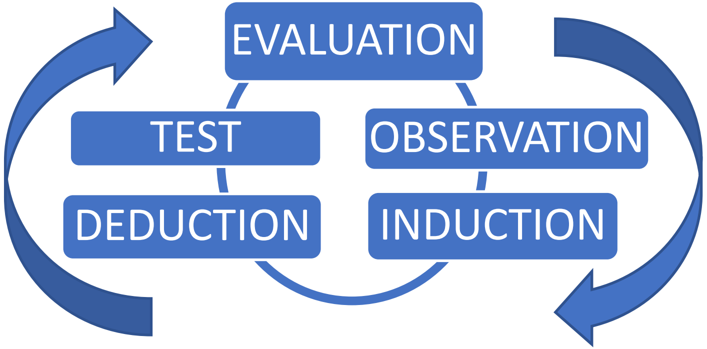
Modelling learning systems: the system theory approach

What is learning? | **Causality principle** | Metr

Conclusions of the study are strictly drawn from concretely empirical evidence



		Level	Contrasting stances	
Theoretical stance		**Ontology** Beliefs about the nature of being or reality	There is one objective reality	There are multiple realities
Theoretical stance		**Epistemology** Belief about the nature and scope of knowledge (how we come to know the world)	You uncover the reality – there is one true explanation	Meaning is culturally defined
Approach		**Methodology** Based on paradigmatically different ontological and epistemological assumptions	**Quantitative** Positivist, Objectivist, Empiricist, Nomothetic	**Qualitative** Hermeneutic Interpretivist
Approach		**Design**	Overarching strategy for collecting data, such as: Experimental Quasi-experimental Random Controlled Trials	Case study Action research Ethnography
Approach		Emphasises	deductive reasoning	inductive reasoning
Approach	**Data** (numerical or non-numerical)	**Methods**	Techniques for collecting data, such as: Survey/questionnaire; Interview/Focus group; Document analysis; Observation	
Approach	**Data** (numerical or non-numerical)	**Instruments**	Specific data collection tools, such as: a specific questionnaire or interview schedule	
Approach	**Data** (numerical or non-numerical)	**Analysis**	How the data are processed in order to make sense of them (to answer your research questions)	

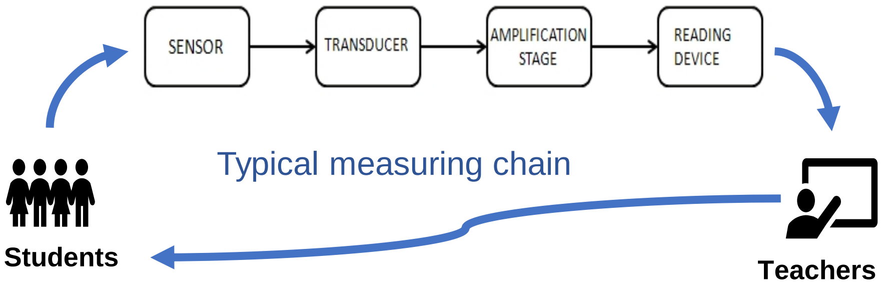
Twining, P., Heller, R. S., Nussbaum, M., & Tsai, C. (2017). **Some guidance on conducting and reporting qualitative studies.** Computers & Education, 106, A1-A9. doi: 10.1016/j.compedu.2016.12.002

Causality principle

Metrology

How can we measure learning?

- Development of the proper **sensors** to capture the **variables of interest** (Knowledge, Skills, Attitudes, Competences).
- Identification of the adequate **sampling period** and **quantization**.
- Demonstration of their **validity** and **reliability**.

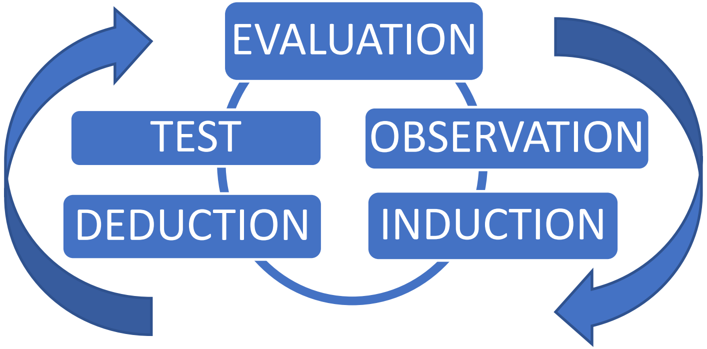


Causality principle

Metrology

How can we measure learning?

The scientific method – empirical cycle



Conclusions of the study is strictly drawn from concretely empirical evidence

"verifiable" evidence

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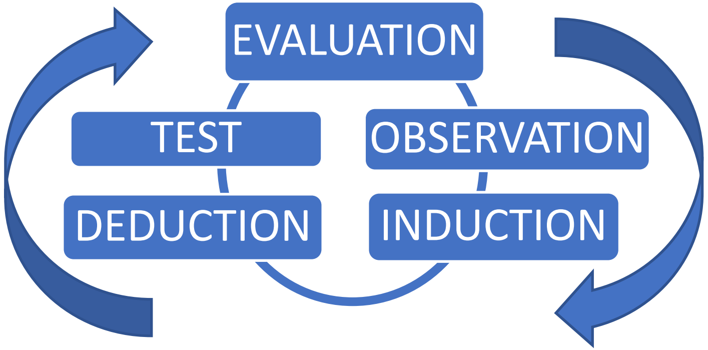
Modelling learning systems: the system theory approach

Causality principle

Metrology

The scientific method – empirical cycle



We must formulate hypotheses that are:

- empirically testable
- replicable
- objective
- transparent
- falsifiable
- logically consistent

To ensure the effectiveness, researchers need to be critical of their own studies and those of others; they should be **open** and **transparent**.

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Causality principle

Metrology

How can we measure learning?
The scientific method – empirical cycle

- Respect for participant's autonomy
  - voluntary consent vs. coercion
  - Well-informed consent vs. deception (active – cover story or passive – omission, false feedback and perseverance effect)
- Beneficience
  - participants should not be harmed
  - cost/benefit for individuals and for society as a whole
  - Privacy (ex.: European GDPR)
- Justice
  - costs and benefits of research should be divided reasonably, fairly and equally over potential participants.

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Causality principle

Metrology

How can we measure learning?
A good research of Answers…

Quantitative

- Internal validity
- External validity
- Reliability
- Objectivity

Qualitative

- Credibility / Trustworthiness
- (Transferability)
- Confirmability, dependability
- Engagement, reflexivity

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Causality principle

Metrology

How can we measure learning?
A good research of Answers…

Trustworthiness

- Member checks: recycling interpretation back to the key informants
- Searching for disconfirming evidence
- Triangulation; multiple data sources and multiple methods
- Thick description_ a thorough description of the context of the study

Qualitative

- Credibility / **Trustworthiness**
- (Transferability)
- Confirmability, dependability
- Engagement, reflexivity

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Causality principle

Metrology

How can we measure learning?
A good research of Answers…

Confirmability

- Data collection so that audit could be carried out (audio recordings, full transcripts of interview, …)
- Team approach
- Independent auditors

Qualitative

- Credibility / Trustworthiness
- (Transferability)
- **Confirmability**, dependability
- Engagement, reflexivity

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Causality principle

Metrology

How can we measure learning?
A good research of Answers…

Reflexivity

- Document beliefs, framework, theories underlying approach to the problem before beginning the data collection
- Document reflections and limitations explaining how to overcome it
- Team analysis

Qualitative

- Credibility / Trustworthiness
- (Transferability)
- Confirmability, dependability
- Engagement, **reflexivity**

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Causality principle

Metrology

How can we measure learning?
A good research of Answers…

Quantitative

- **Internal validity**
- External validity
- Reliability
- Objectivity

Internal validity

- How well an experiment is done, especially **whether it avoids confounding** (more than one possible independent variable [cause] acting at the same time).
- The less chance for confounding in a study, the higher its internal validity is.

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Causality principle

Metrology

How can we measure learning?
A good research of Answers…

Quantitative

- Internal validity
- **External validity**
- Reliability
- Objectivity

External validity

- how well data and theories from one setting apply to another.

Causality principle

Metrology

How can we measure learning?
A good research of Answers…

Quantitative

- Internal validity
- External validity
- **Reliability**
- Objectivity

Reliability

- In research, the term reliability means "**repeatability**" or "**consistency**". A measure is considered reliable if it would give us the same result over and over again (assuming that what we are measuring isn't changing!)

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Causality principle

Metrology

How can we measure learning?
A good research of Answers…

Quantitative

- Internal validity
- External validity
- Reliability
- **Objectivity**

Objectivity

- In social research it is the principle drawn from positivism that, as far as is possible, **researchers should remain distanced from what they study** so findings depend on the nature of what was studied rather than on the personality, beliefs and values of the researcher.

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Modelling learning systems: the system theory approach

What is learning? | Causality principle | Metrology | Cybernetics

Not Today

Measure Constructs

- Learning is the process by which an individual assimilates in … mation, ideas and values a … mpetences.
- Compet … es appropriate to the conte …
- Learnin … tion and social interacti … tings.

Source: Cedefop (2 … ublications Office. Available at https://www.cedefo … an-inventory-glossary#

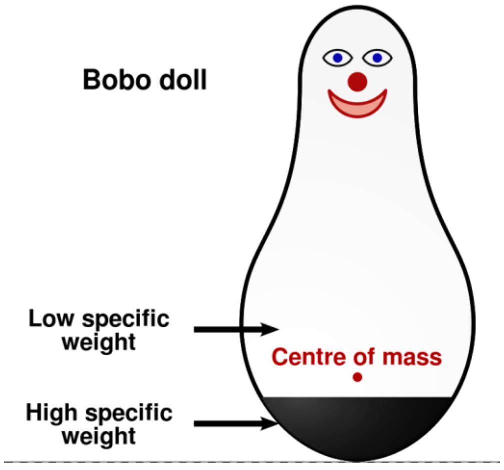
Richard Gross, Psy … The Science of Mind and Behaviour 6E, Hachette UK, ISBN 978-1-4441-0486-7.

Modelling learning systems: the system theory approach

Metrology

How can we measure learning?
A good measurement of constructs…

- We are measuring **constructs**: an explanatory variable which is not directly observable.
- For example, an object's **centre of mass** is certainly a real thing, but it is a construct (not another object).
- For example, the concepts of **intelligence** and **motivation** are used to explain phenomena in psychology, but neither is directly observable.



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Metrology

How can we measure learning?
A good measurement of constructs…

Are we measuring accurately?

Do our measurements reflect the construct we are interested in?

- The validity of an instrument or manipulation method is commonly referred to as **measurement or construct validity.**

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Metrology

How can we measure learning?
A good measurement of constructs…

How do we assess construct validity?

How do we determine if this score actually reflects the property?

- Face validity
- Predictive validity or criterion validity,
- Convergent and discriminant validity (multi trait and multi method matrix)

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Metrology

How do we assess construct reliability?

- **Measurement reliability** refers to the instrument's consistency or stability or precision.
- A reliable instrument will result in highly similar scores if we repeatedly measure a stable property in the same person.
- There could be three types of consistency:
  - over time (test-retest reliability),
  - across items (internal consistency) -> split-halves reliability
  - across different researchers (inter-rater reliability).
  - over time for the same observer (intra-observer consistency)

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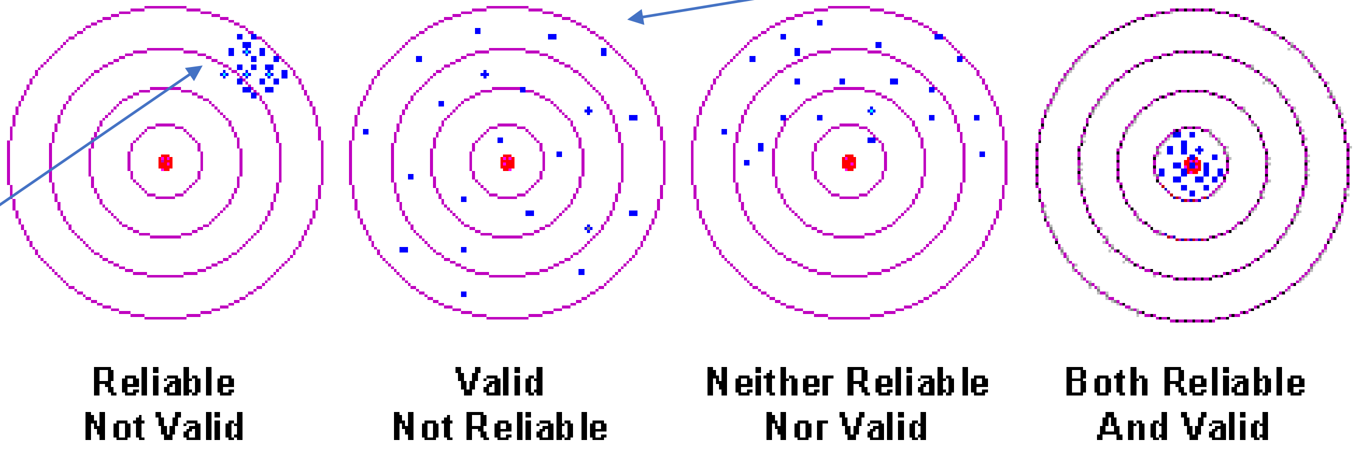
Metrology

A good measurement of constructs
A systematically measure of a construct…

- What we want is **true score** from **observed score**

Reliability is influenced by random error

Systematic error



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In the Educational Robotics (ER) field researchers have identified **lack of quantitative analysis** on how robotics can improve skills and increase learning achievements in students (Benitti 2012; Alimisis, 2013).

The **evaluation of designing and problem-solving activities could be difficult for teachers**: what students learn thanks to the ER approach is hardly detected via analysing scores obtained through standard tests (Berland, Baker and Blikstein, 2014).

BUT

We need a **deep (quantitative) analysis** of ER activities!

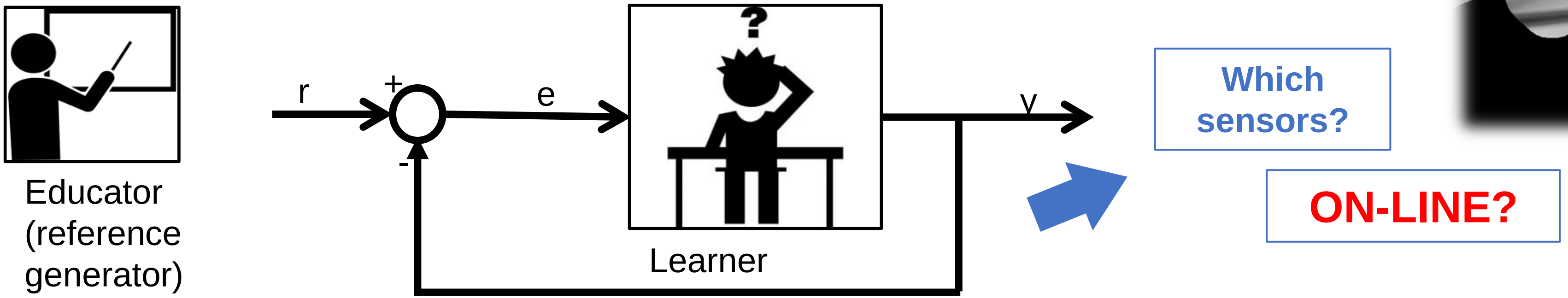
Alimisis, D. (2013). Educational robotics: Open questions and new challenges. Themes in Science and Technology Education, 6(1), 63-71.
Benitti, F. B. V. (2012). Exploring the educational potential of robotics in schools: A systematic review. Computers & Education, 58(3), 978-988.
Berland, M., Baker, R. S., & Blikstein, P. (2014). Educational data mining and learning analytics: Applications to constructionist research. Technology, Knowledge and Learning, 19(1-2), 205-220.

How can we measure learning? Classical Instruments (Sensors)

- '**Survey**' is a general term that can refer to a list of questions asking about biographical information, opinions, attitudes, traits, behavior, basically anything. Surveys generally cover a variety of topics.
- '**Questionnaire**' is used when the focus is on one construct, or a related set of constructs, usually psychological traits, emotional states or attitudes.
- '**Test**' is used when the aim is to measure an ability, such as general intelligence or math proficiency.
- Surveys, test and questionnaires all consist of a series of questions. We refer to the questions as **items**, usually accompanied by a set of discrete **response options** or a continuous range to choose from.

D. Scaradozzi, L. Screpanti, L. Cesaretti, M. Storti, E. Mazzieri (2019). Implementation and assessment methodologies of teachers' training courses for STEM activities. *Technology, Knowledge and Learning*. Springer. Doi: 10.1007/s10758-018-9356-1

How can we collect educational data? (On-Line Sensors)



FROM CLASSIC APPROACH
(questionnaires, multiple choice questions, etc.)

ONLINE APPROACH
(recording log files during students' activity)

Machine Learning in Education?

- Evaluation of complex activities → ER, programming, etc.
- Personalised paths and feedbacks

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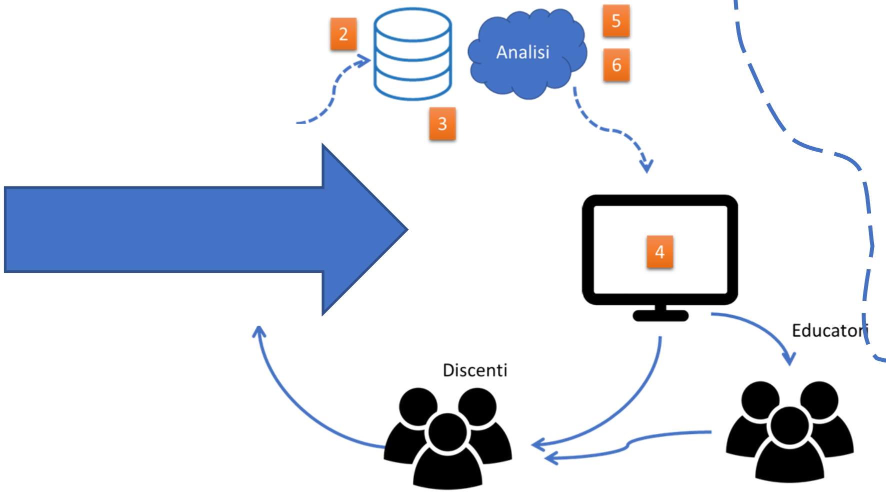
Modelling learning systems: the system theory approach

Educational Data Mining



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Case Study: Research Questions

Applying data mining and machine learning methods to data collected from the educational environments can allow to **predict** and **classify students' behaviours** and discover latent structural regularities to large educational dataset.

Our 3 research objectives:

- accurate **prediction** of students' team final performance
- identification of **different patterns** in the students' problem-solving trajectories
- **correlation of the discovered patterns** of students' problem-solving with the **evaluation** given by the educators

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Case Study: Research procedure

1. Software updated into Lego Mindstorms EV3 blocks
2. Data acquisition (ER activities in collaboration with 16 schools)
3. Algorithmic problem solving for input data transformation
4. Performance prediction and data clustering (problem-solving patterns analysis)
5. Cluster models' validation
6. Correlation results (Cluster analysis vs. Student performance)

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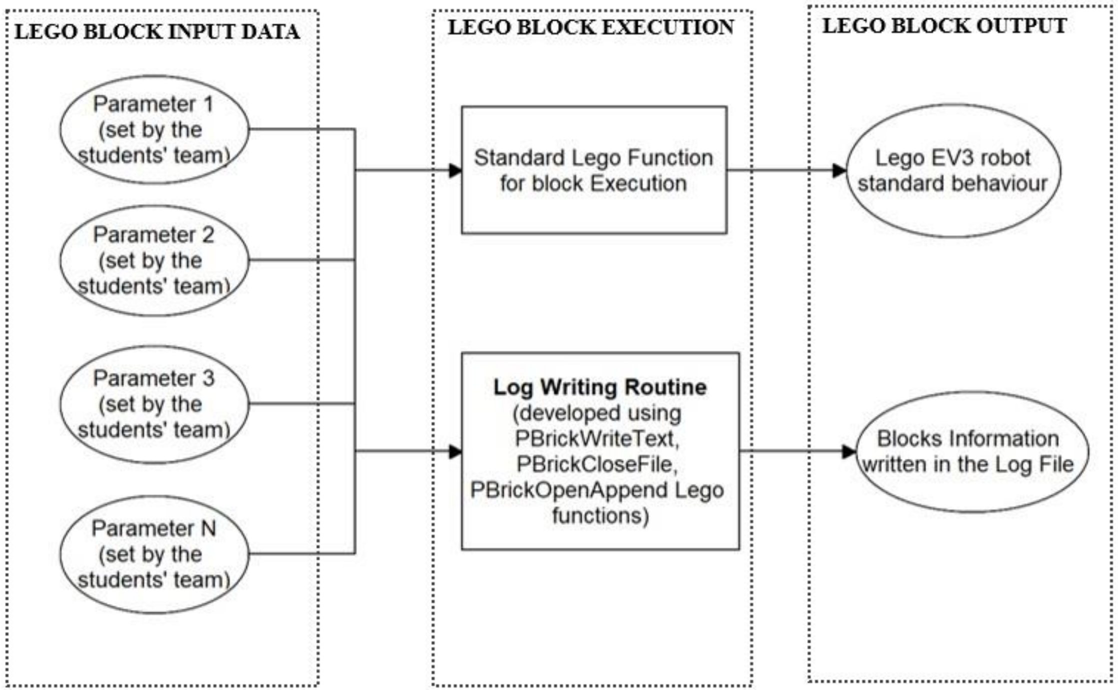
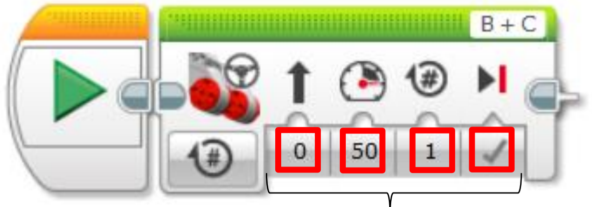
Case Study: Software update design





Parameters set by students

Hiden keylogger

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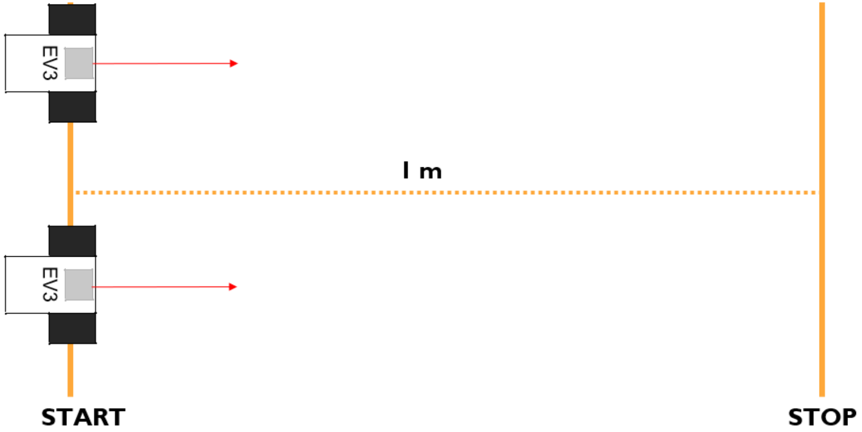
Case Study: Data acquisition

Exercise A

Program the robot so that it covers a given distance (1 m), trying to be as precise as possible.

Constraints:
- **the amount of time within students had to design and test their solution (15 - 20 minutes);**
- **the teams could test the programming sequence as many times as they wanted;**
- **they were allowed to use measuring instruments only to measure some robot's parameters (for example the radius of the wheel).**



EVALUATION
- **if the error was < 4 cm, the educator considered the challenge completed;**
- **if the error was >= 4 cm the educator considered the challenge not completed.**

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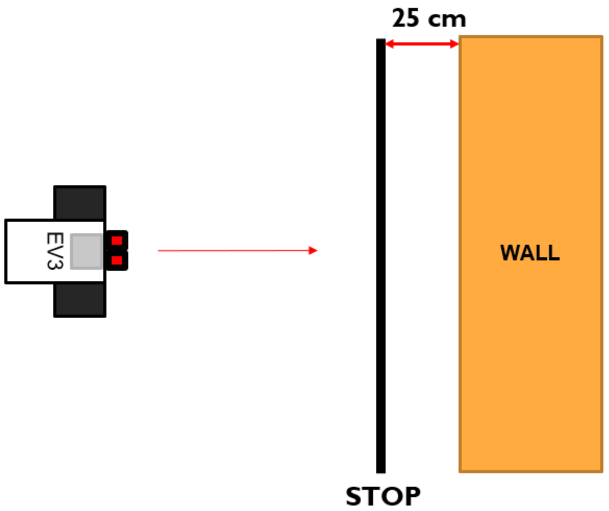
Case Study: Data acquisition



Exercise B

Program the robot so that it stops at a given distance from the wall (25 cm), trying to be as precise as possible.

Constraints:

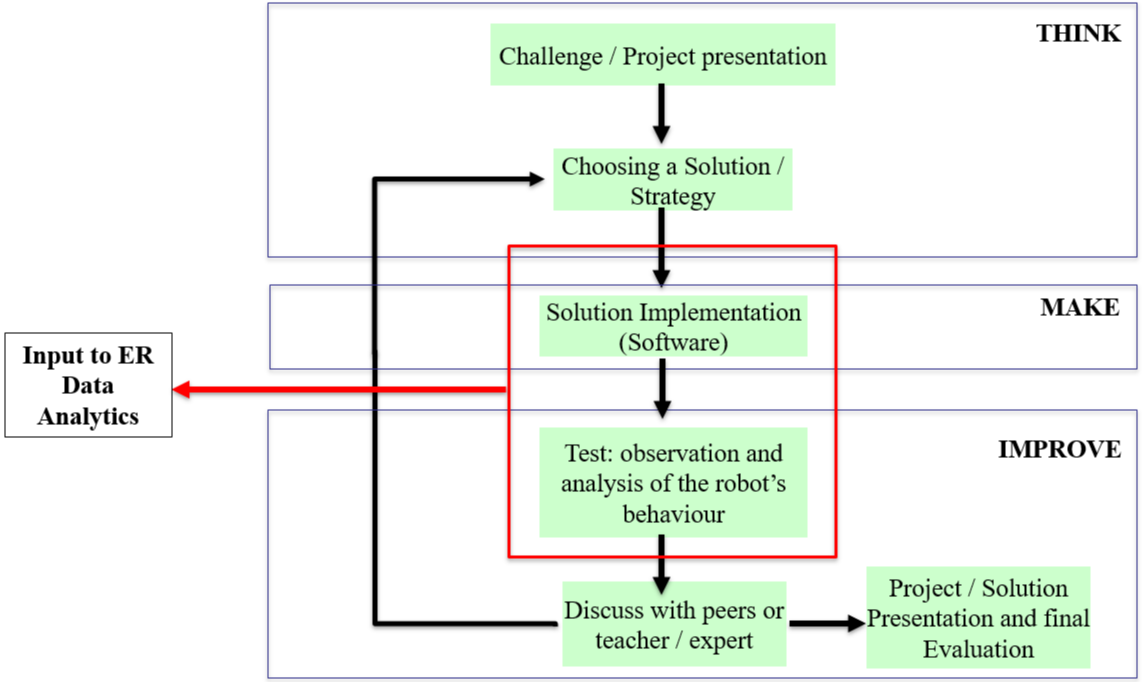
- **the amount of time within students had to design and test their solution (20 minutes for secondary school classes, 30 minutes for primary school classes);**
- **during the available time the teams could test the programming sequence as many times as they wanted.**

EVALUATION

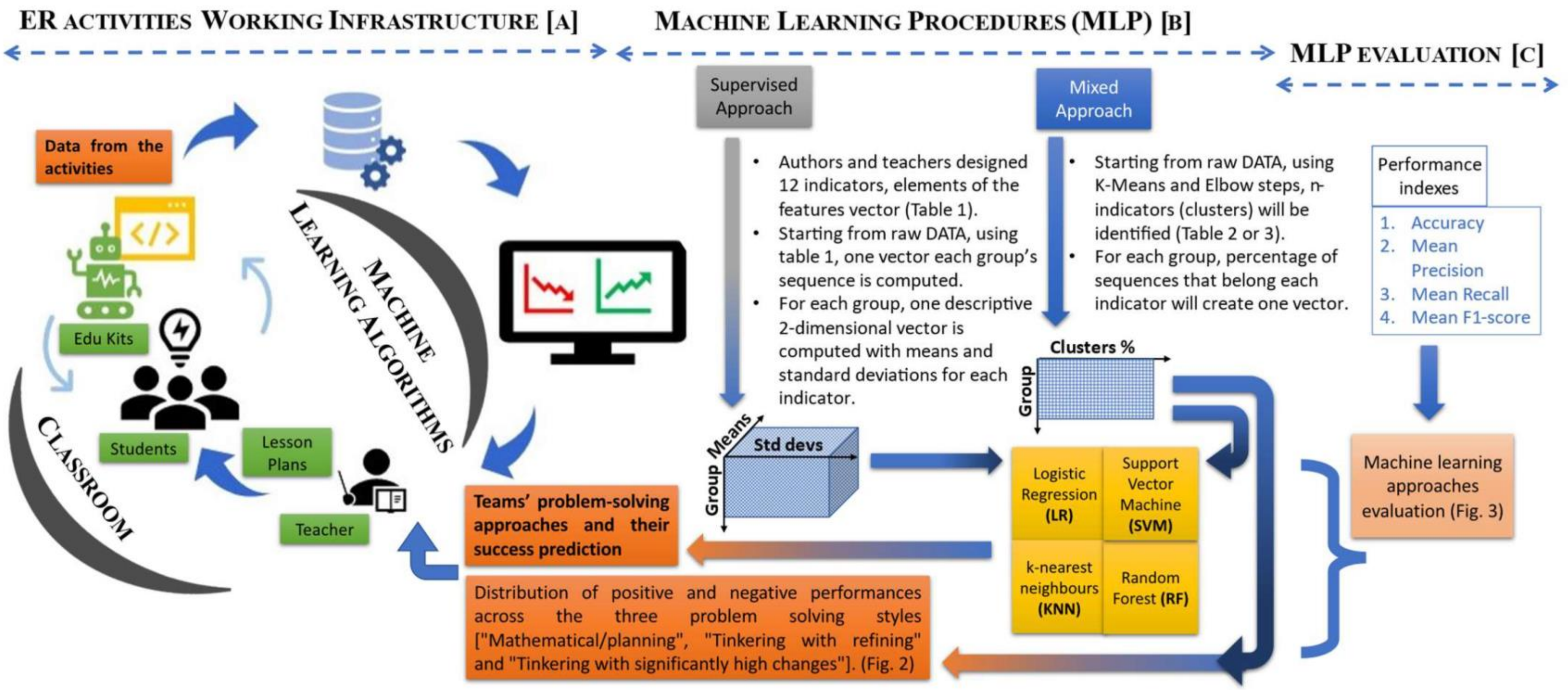
- **if the error was < 3 cm, the educator considered the challenge completed;**
- **if the error was >= 3 cm the educator considered the challenge not completed.**

Case Study: Data acquisition

Students from sixteen Italian primary and secondary schools, located in the Emilia Romagna, Lazio and Marche regions. The total number of students involved in this study is 455. The experimentation was carried out from March 2018 to October 2019.



Modelling learning systems: the system theory approach



Scaradozzi, D., Cesaretti, L., Screpanti, L., & Mangina, E. (2021). Identification and Assessment of Educational Experiences: Utilizing Data Mining With Robotics. IEEE Robotics & Automation Magazine.

Case Study: Input data transformation

Students' teams designed 2187 programming sequences to solve the Exercise A and 4252 programming sequences to solve the Exercise B . At first, for each programming sequences in each log files we calculated these 13 parameters:

- **Motors**: the n° of Motor blocks in the sequence
- **Loops**: the n° of Loop blocks in the sequence.
- **Conditionals**: the n° of Conditional and Sensors blocks in the sequence.
- **Others**: the n° of blocks in the sequence belonging to different categories than Motors, Loops and Conditionals.
- **High Values**: the n° of Motors blocks in the sequence with a Rotations parameter >= 20, or with a Seconds parameter >= 15.
- **Added**: the n° of blocks added, compared to the previous sequence;
- **Deleted**: the n° of blocks deleted, compared to the previous sequence;
- **Changed**: the n° of blocks changed, compared to the previous sequence;
- **Equal**: the n° of the same blocks, compared to the previous sequence;
- **Delta Motors**: amount of change in Motor blocks parameters (first, second or third parameter), compared to the previous sequence (calculated only for blocks of the "Changed" category);
- **Delta Loops**: amount of change in Loop blocks parameters, compared to the previous sequence;
- **Delta Conditionals**: amount of change in Conditional blocks parameters, compared to the previous sequence;
- **Delta Others**: amount of change in Other blocks parameters, compared to the previous sequence.

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LOG-FILES AND DATA MINING

Thanks to the **Log-files** produced by the students, it is possible to extract the data useful for the development of the project:

- ➔ Data-mining process extrapolated
  - ➔ 1113 code sequences relating to Exercise A
  - ➔ 1785 code sequences relating to Exercise B
- ➔ The final evaluation expressed by the teacher for each of the two tests was used as a **label** for the subsequent data-labeling process

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LOG-FILES AND DATA MINING

The log-files of the student groups were collected, the various datasets were grouped to train and refine the machine learning algorithms:

- ***LR*** *- Logistic Regression*
- ***SVM*** *- Support Vector Machine*
- ***KNN*** *- K-nearest neighbor classifier*
- ***RF*** *- Random Forest*

the project authors adopted two different approaches in data analysis:

➔ Supervised Approach

➔ Mixed Approach

The Supervised Approach creates a matrix of characteristics by <u>manipulating data based on what the authors consider relevant.</u>

The Mixed Approach, thanks to the preliminary division into clusters, attempts to <u>focus attention on the presence of homogeneity between elements</u> or specific intrinsic patterns in the composition of the dataset.

The Mixed Approach, initially released from any conditioning, lays the foundations for a second interpretation (this time supervised) of the data, producing a matrix of characteristics very different from that proposed by the supervised approach.

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SUPERVISED APPROACH

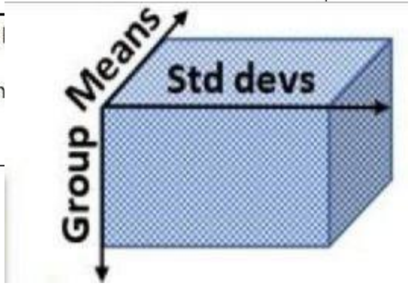
Analyzing the code sequence produced by the students, the authors of the experiment identified 12 indicators, thus managing to synthesize the elaborate of each group as a vector of the characteristics of 12 components.

Since each group of students produced a log-file for each of the two exercises, it was possible to calculate the mean and standard deviation of each indicator thus obtaining a two-dimensional sample.

The dataset that will be provided as input to the learning algorithms is therefore composed of the two-dimensional samples of each group of students.

Name of the indicator	Meaning
Motors	The number of Lego Motor blocks in the sequence
Loops	The number of Lego Loop blocks in the sequence
Conditionals	The number of Lego Conditional and Sensors blocks in the sequence
Others	The number of Lego blocks in the sequence belonging to different categories than Motors, Loops and Conditionals
Added	The number of Lego blocks added in sequence i+1 if compared to the sequence i
Changed*	The number of Lego blocks in sequence i+1 that has different parameters if compared to the sequence i
Deleted**	The number of Lego blocks deleted in sequence i+1 if compared to the sequence i
Equal	The number of the unchanged Lego blocks, compared to the previous sequence
Delta Motors***	The amount of change in Motor blocks parameters (first, second or third parameter) in sequence i+1 if compared to the sequence i
Delta Loops***	The amount of change in Loop blocks parameters in sequence i+1 if compared to the sequence i
Delta Conditionals***	amount of change in Conditional blocks parameters in sequence i+1 if compared to the sequence i
Delta Others***	amount of change in Other blocks parameters in sequence i+1 if compared to the sequence i

*how many blocks with same Block Name and same Block Option, but different
comparing two contiguous sequences.
**how many blocks in a specific sequence have been deleted in the next sequen
as "Changed").
*** only for blocks of the "Changed" category



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MIXED APPROACH

In this case, the code sequence present in the log-files has been clustered using the K-means method, supported by the Elbow method.
The clustering algorithm has identified precise patterns within the documents of the various groups of students by grouping the data into optimal subsets

Esercizio A:

	Name	Number of sequences	%	Description
1	SMALL MOTORS PARAMETERS CHANGE	231	20,7	The team is refining its Motors parameters.
2	STRATEGY CHANGE	17	1,5	The team is changing its strategy (1 block is deleted, 1 block is added).
3	TEST MOTORS SEQUENCE	799	71,8	The team is testing the same previous programming sequence (with only Motors blocks).
4	HIGH MOTORS PARAMETERS CHANGE	30	2,7	The team is strongly changing its Motors parameters.
5	OTHERS BLOCKS CHANGE	1	0,1	The team is changing something not connected to the challenge.
6	SMALL LOOP PARAMETERS CHANGE	2	0,2	The team is refining its Loop parameters.
7	TEST LOOP SEQUENCE	21	1,9	The team is testing the same programming sequence (with Loop and Motors block).
8	TEST OTHERS BLOCKS SEQUENCE	12	1,1	The team is testing the same programming sequence (with Others and Motors block).

Esercizio B:

	Name	Number of sequences	%	Description
1	TEST COMPLETE SEQUENCE (WITH LOOPS)	393	22,02	The team is testing the same previous programming sequence (with Motors, Loops and Conditional blocks).
2	SMALL CONDITIONALS PARAMETERS CHANGE (NO LOOPS)	676	37,87	The team is refining its conditionals parameters, in the Wait block (there aren't Loops blocks in these cluster).
3	HIGH CONDITIONAL PARAMETERS CHANGE	48	2,69	The team is strongly changing its Conditional (Wait or Switch block) parameters.
4	DOUBLE PARAMETERS CHANGE (OTHERS AND MOTORS)	6	0,34	The team is changing Others and Motors parameters.
5	LOOPS PARAMETERS CHANGE	1	0,06	The team is changing its Loops parameters.
6	HIGH MOTORS PAMERATERS CHANGE	32	1,79	The team is strongly changing its Motors parameters.
7	TEST COMPLETE SEQUENCE (NO LOOPS)	234	13,11	The team is testing the same previous programming sequence (with Motors and Conditional blocks (Wait block), and without Loop blocks).
8	TEST COMPLEX COMPLETE SEQUENCE	103	5,77	The team is testing the same previous and complex programming sequence (with Motors, Loops, Others and Conditionals blocks)
9	ADDING BLOCKS	85	4,76	The team is adding some blocks in the sequence.
10	SMALL CONDITIONALS PARAMETER CHANGE (WITH LOOPS)	136	7,62	The team is refining its Conditional (Switch) parameters (with also Motors and Loops blocks in the sequence).
11	DELETING BLOCKS	71	3,98	The team is deleting some blocks in the sequence.

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MIXED APPROACH AND PROBLEM SOLVING STYLES

The difference in the number of clusters is due to the nature of the exercises themselves: the former is less complex than the latter and requires a simpler code sequence.

By analyzing the data in this way, the presence of each type of cluster within the files produced for each of the two exercises was assessed at a percentage level, thus obtaining a one-dimensional sample.

The dataset that will be provided as input to the learning algorithms is therefore composed of the one-dimensional samples of each group of students..

Side analisys:

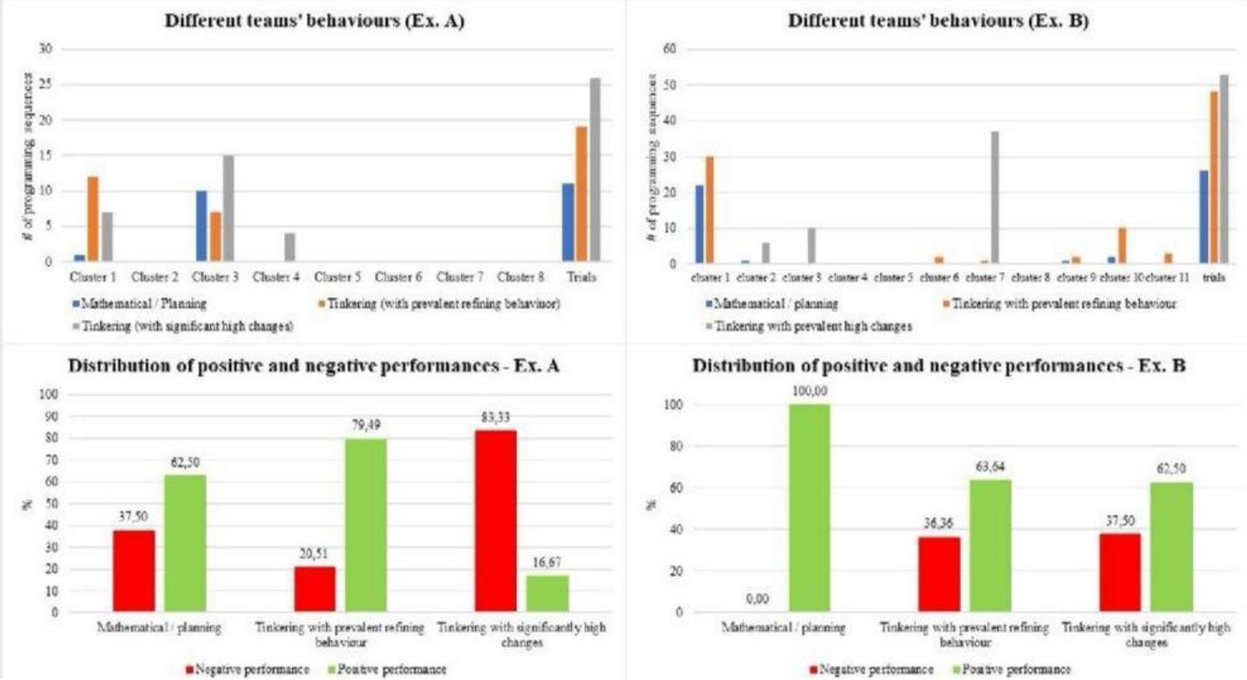
The way in which the students attempted to solve the two exercises can be classified into three macro categories:

The authors of the experiment, in collaboration with the same teachers who participated in the project, **associated key elements present in each cluster to a specific type of "problem-solving".**

- **Mathematical / planning:** reduced number of tests with minimal changes to the product code; the robot parameters were derived analytically.
- **Tinkering with refining:** the robot parameters are assigned in a heuristic way, refining them on the basis of the feedback generated by the robot itself.
- **Tinkering with significantly high changes:** the robot parameters are assigned in a heuristic way, but there is a high number of tests and a distortion of the code due to an incorrect interpretation of the *robot feedback*.

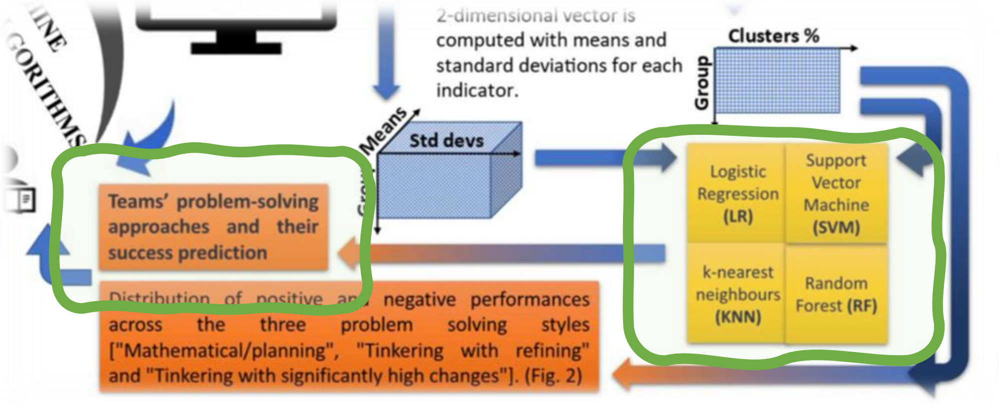
MIXED APPROACH AND PROBLEM SOLVING STYLES: I result

- Distribution of the different types of problem-solving in the two assigned exercises (upper part);
- distribution of successes and failures related to the different types of problem-solving (lower part).



Using the mixed approach as an exploitation of a clustering method for data manipulation (**typical of the unsupervised approach**) and combining it with the observation-interpretation of the results (**typical of the supervised approach**), thus relating cluster and classification of the problem-solving.

MACHINE LEARNING TECHNIQUES AND PERFORMANCE FORECAST



After preparing the datasets according to the two approaches, we move on to **training the machine learning models** to make them able to predict the "success" or "failure" of a group of students in solving an ER exercise.

Goal:

- decree **which of the four methods is more accurate in predicting the final result** of the single exercise;
- **performances** of each individual model in relation to the two different dataset management approaches, establishing which feature space is best in the training phase.

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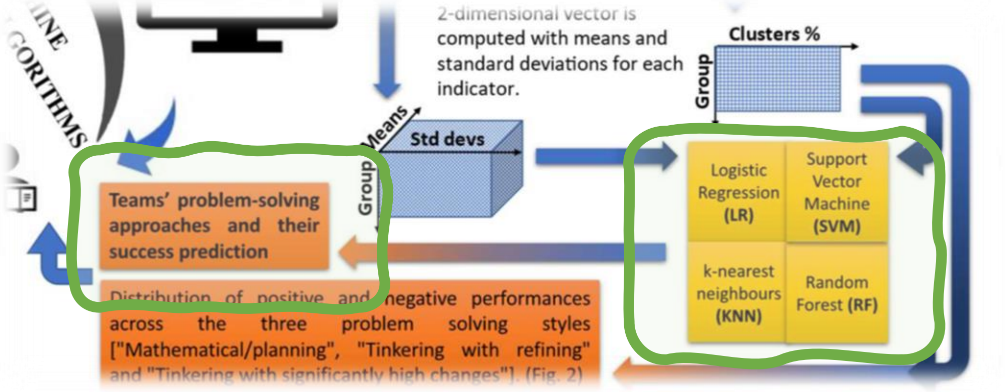

Learning algorithms used and **results:**

- The **Support Vector Machine**, which features a high degree of accuracy.
- The **Logistic Regression**, with good performance in terms of speed of prediction.
- The **K-nearest neighbor**, based on storage and characterized by low to medium computational complexity
- The **Random Forest**, with a clear interpretation of the data provided as output

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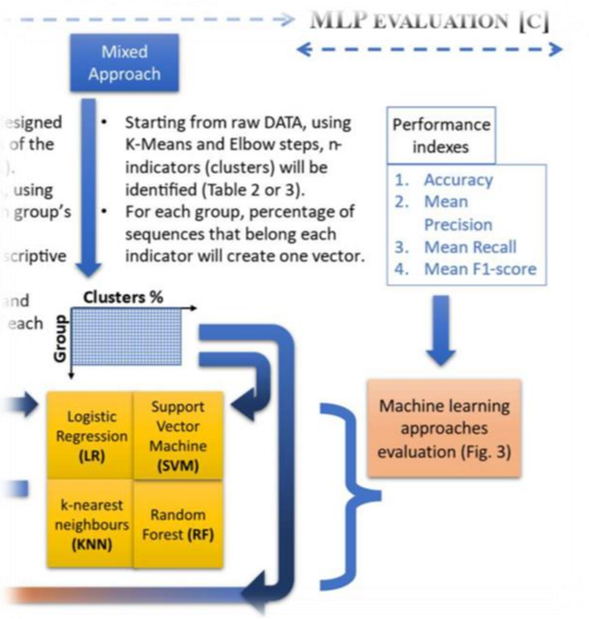
PERFORMANCES OF MACHINE LEARNING TECHNIQUES



SVM, **LR**, **K-NN,** and **RF** are evaluated on the basis of four parameters:

- ➔ ***Accuracy:*** *the ratio of correct predictions to total predictions.*
- ➔ ***Mean Precision:*** *the average value between the precision in establishing a student's success and his or her failure*
- ➔ ***Mean Recall:*** *the average value between **recall** in predicting a student's success and his or her failure. The term recall indicates the percentage of samples classified correctly with respect to the total number of samples belonging to that same class.*
- ➔ ***Mean F1-score:*** *the mean value of the **F1-score** of each prediction, that is a parameter that depends on the precision and recall of each sample.*

For each of the methods, through a **10-fold cross-validation method**, the mean and standard deviation are determined and the results obtained by the four machine-learning methods subjected to the two different data analysis approaches are compared.

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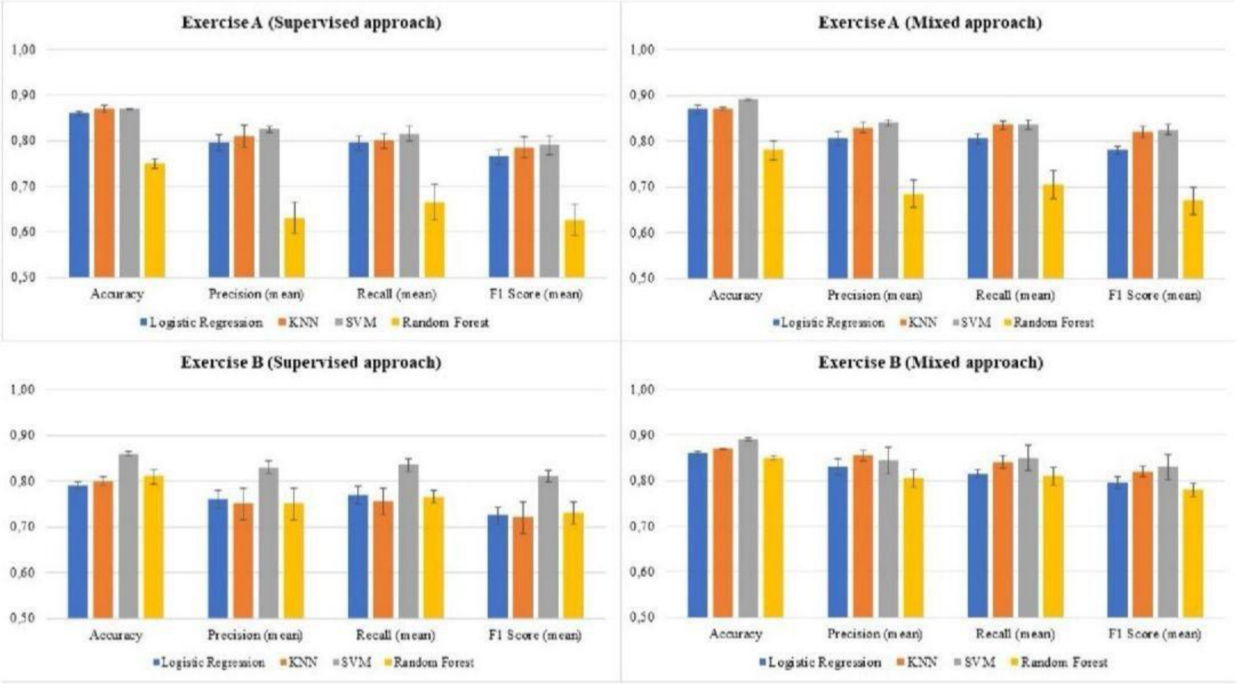
Performances in the predictions of the four Machine Learning algorithms relating to Exercises A and B, obtained by applying the Supervised Approach (left) and the Mixed Approach (right)



The **Support Vector Machine** features a high degree of accuracy.

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	SVM (supervised) Ex. A	SVM (mixed) Ex. A	SVM (supervised) Ex. B	SVM (mixed) Ex. B
Accuracy	0,80	**0,82**	0,83	**0,84**
Mean Precision	0,76	**0,80**	0,77	**0,82**
Mean Recall	0,72	**0,76**	0,76	**0,79**
Mean F1 Score	0,71	**0,76**	0,75	**0,79**

To obtain these results a repeated 10-fold cross validation was performed, so that the average value and standard deviation of the four indicators (Accuracy, Precision, Recall, F1 Score) repeating the 10-fold validation multiple times were calculated.

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Conclusions

1- For the **first time** an experimentation involving a fair number of students (455) has been conducted gathering programming sequences designed by students during Educational Robotics activities and automatically analysing them, using machine learning techniques (Scaradozzi, Cesaretti, Screpanti & Mangina, 2020).

2- We consider very important from a pedagogical point of view the **recall indicator for the students' groups who showed a negative performance**. Recognizing in advance those teams with difficulties in the exercise resolution could allow teachers to give them some suggestions to solve the challenge; the MLP neural network algorithm reached very high performance also for this indicator (Ex. A = 0.92, Ex. B = 0.97):
We are quite close to identify each **students' group that is struggling with the Educational Robotics challenge**, and this result is very important for further developments of the system, implementing a **real-time use of the tool by teachers and educators**.

3- The results presented our research project seem to show connections with previous research, in terms of **problem-solving patterns**.

D. Scaradozzi, L. Cesaretti, L. Screpanti, E. Mangina. Identification of the students learning process during Education Robotics activities. Frontiers In Robotics and AI. doi: 10.3389/frobt.2020.00021.

Further developments

Some planned improvements are:

- **Applying our approach to a larger set of Robotics exercises (in order to obtain more general results).**
- **Including time tracking in the log files generated by the system.**
- **Using recurrent neural network, in particular the long short-term memory autoencoders (a structure specifically designed to support sequences of input data), in order to translate the programming sequences created by students into fixed-length vectors (compress representation of the input data), maintaining high level of information content.**
- **Performing a sequential analysis (lag sequential analysis, sequential pattern mining) of the programming sequences created by the participants.**
- **Updating the current system design with a personalised e-learning system.**

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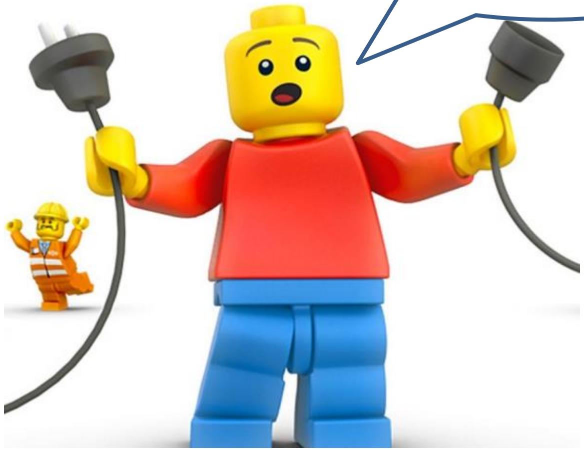
- ***Nihil est in intellectu quod prius non fuerit in sensu***

- *Nihil est in intellectu quod prius non fuerit in sensu* ***nisi intellectus ipse.***

  (Nouveaux Essais, II, 1, 2) <Leibniz>

Thank you!
Questions?



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Related work

<u>Journal:</u>

1. **D. Scaradozzi, L. Cesaretti, L. Screpanti, E. Mangina (2020). Identification of the students learning process during Education Robotics activities. *Frontiers In Robotics and AI*.**
2. **D. Scaradozzi, L. Screpanti, L. Cesaretti, M. Storti, E. Mazzieri (2019). Implementation and assessment methodologies of teachers' training courses for STEM activities. *Technology*, *Knowledge and Learning*. Springer. Doi: 10.1007/s10758-018-9356-1.**
3. **L. Screpanti, L. Cesaretti, M. Storti, E. Mazzieri, A. Longhi, M. Brandoni, D. Scaradozzi (2018). Advancing K12 education through Educational Robotics to shape the citizens of the future, *Mondo Digitale*, ANNO XVII, N.7, Giugno 2018. AICA.**
4. **L. Cesaretti, M. Storti, E. Mazzieri, L. Screpanti and D. Scaradozzi (2017). An innovative approach to School-Work turnover programme with Educational Robotics, *Mondo Digitale*. AICA**
5. **D. Scaradozzi, L. Cesaretti, L. Screpanti, E. Mangina (*submitted*). Utilising data mining for assessment with Educational Robotics. *IEEE Robotics and Automation Magazine*. IEEE.**

Related work

International conference:

1. **L. Cesaretti, L. Screpanti, D. Scaradozzi, and E. Mangina (*in press*). Analysis of Educational Robotics activities using a machine learning approach. *2nd FabLearn Italy conference (FLI2019)*. 20-22 November, 2019. Ancona, Italy.**
2. **L. Screpanti, L. Cesaretti e D. Scaradozzi (*in press*). Educational Robotics and social relationships in the classroom. *2nd FabLearn Italy conference (FLI2019)*. 20-22 November, 2019. Ancona, Italy.**
3. **M. Valzano, C. Vergine, L. Cesaretti, L. Screpanti and D. Scaradozzi (*in press*). Ten years of Educational Robotics in Primary School. *2nd FabLearn Italy conference (FLI2019)*. 20-22 November, 2019. Ancona, Italy.**
4. **D. Scaradozzi, L. Screpanti, L. Cesaretti (2019). Active learning tools for teaching Marine Robotics, IoT and Control strategies since the primary school. *1st International Conference “Scuola Democratica – Education and Post-Democracy”*. 6-8 June 2019. Cagliari, Italy.**
5. **L. Screpanti, L. Cesaretti, E. Mazzieri, L. Marchetti, A. Baione, D. Scaradozzi (2018). An educational robotics activity to promote gender equality in STEM education. In *Proceedings of the 28th International conference on Information,Communication in Education (ICICTE)*. 5-7 July, 2018. Crete, Greece.**
6. **D. Scaradozzi, L. Screpanti, L. Cesaretti, E. Mazzieri, M. Storti, M. Brandoni, A. Longhi (2016). “Rethink loreto: we build our smart city!” A stem education experience for introducing smart city concept with the educational robotics. *9th annual International Conference of Education, Research and Innovation (ICERI2016)*. 14-16 November, 2016. Seville, Spain.**

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Related work

Other types of publication:

- **Book chapters:**
  1. **Scaradozzi, D., Cesaretti, L., Screpanti, L., Costa, D., Zingaretti, S. and Valzano, M. (2019). Innovative tools for teaching marine robotics, iot and control strategies since the primary school. In: Daniela, L. (Ed.), *Smart Learning with Educational Robotics - Using Robots to Scaffold Learning Outcomes*, Springer.**
  2. **Scaradozzi, D., Screpanti, L., Cesaretti, L. (2019). Towards a definition of educational robotics: a classification of tools, experiences and assessments. In: Daniela, L. (Ed.), *Smart Learning with Educational Robotics - Using Robots to Scaffold Learning Outcomes*, Springer.**
- **INDIRE National platform for teachers' training:**
  1. **L. Cesaretti (2019), Educational Data Mining e Robotica Educativa.**
  2. **L. Cesaretti (2019), Robotica educativa ed educazione ambientale: un esempio per la scuola primaria.**

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