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Measurement and simulation: A conceptual framework☆

Alessandro Giordani [a],*, Luca Mari [b]

[a] Università Cattolica di Milano, Department of Philosophy, L. Gemelli 1 – 20123 MIlano, Italy
[b] Università Cattaneo LIUC, Piazza Soldini, 5 – 21053, Castellanza, Italy

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ABSTRACT

The relationship between measurement and simulation is a key topic for both metrology and philosophy of science, posing fundamental questions about the epistemic status of empirical experimentation and computational modeling. With the aim of shedding light on this complex interplay, an analytical framework is proposed for understanding the general structure of measurement and simulation. The analysis shows that simulation is appropriately interpreted as a possible component of the computation module of indirect measurement, and not as a kind of measurement in itself. This clarification allows us to offer important insights into the epistemic status of both measurement and simulation, to operationally relate them in their functional roles as information-production processes, and ultimately to emphasize the staying meaning of measurement in our data-flooded society.

0. Introduction

For centuries, measurement has been understood as a process aimed at producing information about empirical entities, and as such it stands at the cornerstone of this endeavor. However, the widespread adoption of digital systems in our society is prompting us to reconsider how empirical and information activities differ, and how they relate to each other. A key issue on this matter is *the relationship between measurement and simulation*, that is becoming an important topic in both metrology and philosophy of science, posing fundamental questions about the epistemic status of empirical experimentation and computational modeling. With the growing complexity and sophistication of simulation methods, the question arises in particular whether simulation can be appropriately considered a kind of measurement, and therefore whether some processes performed by computational means solely can be appropriately considered measurements. While "measurement" is not a trademarked term,[1] the tradition we inherit assigns it a privileged role among information-production processes. Therefore, knowing that a value of a property is the outcome of a measurement, and not, say, of a guess or a prediction, gives it a trustworthiness that may justify the resources spent to obtain it. This paper aims at shedding light on this complex interplay by disentangling its various dimensions and proposing a framework for analysis. In developing the framework, we introduce:

1. a new setting for framing the problem;
2. a modular way of studying the structure of measurement;
3. a principled solution to the question whether blurring the distinction between measurement and simulation, and more generally between measurement and computation, is appropriate.

The paper is structured into five sections. The first is devoted to delineating the problem space, by defining four different questions that can be sensibly posed regarding the connection between measurement and simulation, and then to introducing the strategy to address these questions by developing a structural analysis of the two processes. In the second section the basic blocks of the proposed framework are introduced, that in the third section are combined to achieve a specific understanding of direct measurement, indirect measurement, prediction, and simulation. In the fourth section two examples are discussed in some details for arguing whether the position that simulation is a genuine kind of measurement is justified: this allows us to conclude that, if we want to maintain a concept of measurement that is recognizably connected with our tradition, simulation should be viewed not as *a kind of*, but possibly as *a part of* a measurement process. Finally, the conclusion provides a concise summary of the key findings.

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* Corresponding author.
E-mail addresses: alessandro.giordani@unicatt.it (A. Giordani), lmari@liuc.it (L. Mari).

[1] As a matter of fact, several technical standards dealing with measurement provide differing definitions, and various scientific schools of thought support diverse perspectives on what measurement actually is.

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1. The relationship between measurement and simulation

It is widely acknowledged that measurement is an *experimental activity* [1–5] with an *epistemically distinctive status* [3,5–8]. Due to the widespread adoption of computational models and digital systems in the last decades, some scholars have started asking whether and under what conditions computer simulation can be appropriately considered a measurement method [9–14]. Indeed, computer simulation seems to be analogous to indirect measurement, in which calculation plays a central role in attributing a value to the quantity under measurement. However, the conclusion that, under given conditions, simulation is a kind of measurement would be a substantial revolution in the understanding of measurement, and this not only in a philosophical perspective. Indeed, stating that something is a measurement has societal implications – in terms of the possibility of the explicit justification of the results it produces about empirical entities – that other sources of information, like opinions and guesses, do not guarantee. Are we claiming then that computer simulations have reached an analogous epistemic status as measurement? Such a bold hypothesis requires a careful analysis.

In order to clarify the conceptual framework in which the problem of the relationship between measurement and simulation can be addressed, we distinguish four related questions about measurement and simulation that are sometimes conflated [10,11]:

- **Q1**: We know that measurement is experimental activity: is simulation also an experimental activity?
- **Q2**: We know that measurement is epistemically distinctive: is simulation also an epistemically distinctive activity?
- **Q3**: If simulation is an epistemically distinctive activity, is it epistemically similar to measurement?
- **Q4**: If simulation is epistemically similar to measurement, is it a kind of measurement?

In this section we aim to show that the first two questions are to be answered positively. To substantiate this conclusion, we propose a characterization first of measurement and simulation, and then of the type of simulation that constitutes the best candidate to be considered a kind of measurement.

1.1. On the notion of measurement

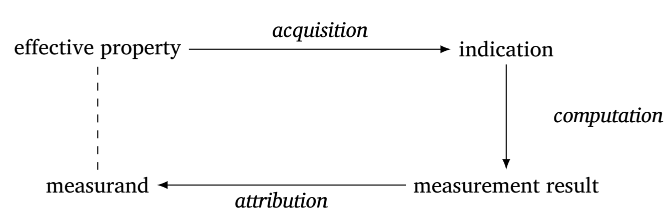
In what follows, we rely on a definition of measurement that is currently used in metrology, and that is best understood in the light of the following preliminary assumptions.

1. Measurement is an activity which is designed
   (a) by someone
   (a measurer)
   (b) to be performed by means of something
   (a measuring instrument)
   (c) that is supposed to be able to interact with something
   (an object under measurement)
   (d) with respect to some property of that something
   (a property intended to be measured)
   (e) in some conditions
   (the circumstances in which the measurement is performed).
   (f) for producing information as values of that property.[2]
2. The property that the measurer intends to measure and to which the produced information is attributed, called the *measurand*, is in principle not to be identified with the property with respect to which the measuring instrument actually interacts, that we call the *effective property* (in the sense of: the property that produces an effect on the measuring instrument). Indeed, the measurand is presented by a definition, which typically involves a reference to both the object under measurement and the conditions in which the measurement is expected to be performed, which could differ from the conditions that occur when the measuring instrument is applied.
3. Due to its required interaction with the measuring instrument, the object under measurement could be changed as a side effect of the measurement, a second reason of the possible difference between the measurand and the effective property.

According to the *International Vocabulary of Metrology* (VIM3, [15]), definition 2.1, measurement is a *process of experimentally obtaining one or more quantity values that can reasonably be attributed to a quantity*. By abstracting from the details, performing a measurement consists then in three basic steps:

- Step 1 (*the setup step*): the measurers decide what they want to measure by defining, or assuming a definition of, the measurand, and contextually decide the measurement procedure, so jointly establishing the measuring instruments to be used and the conditions of their usage and a measurement model.
- Step 2 (*the empirical step*): the measurers prepare the object under measurement and the measuring instruments, and couple them, in accordance with the conditions specified in the definition of the measurand and in the measurement procedure; as a result, they acquire the information produced by the measuring instruments, i.e., the instrument indications (VIM3, definition 4.1).
- Step 3 (*the computational step*): given the acquired information and the available information on the conditions in which measurement is performed, obtain a measurement result in the form of values attributed to the measurand (VIM3, definition 2.9) by applying the measurement model they chose, i.e., a mathematical relation among all quantities known to be involved in the measurement (VIM3, definition 2.48).

The following diagram summarizes some key components of the process:



This highlights that the empirical step is surrounded by a large amount of theoretical activity, both in the setup step and in the computational step[3]:

[2] In the last decades the metrology community has more and more widely and consistently agreed that measurement is also characterized by producing information about the trustworthiness of such values, typically in some form of measurement uncertainty. Though clearly an important subject per se, uncertainty does not have a specific role in the present analysis.

[3] This conclusion essentially agrees with the analysis of the epistemology of measurement in [16], whose main outcomes are that (i) the specification of an empirical model, that is an abstract and idealized representation of a portion of the empirical world, is the basic condition for the possibility of measurement, and that (ii) to measure a physical quantity is to make coherent and consistent inferences from the final state(s) of a physical process to value(s) of a parameter of the model. While the idea of measurement as a kind of model-based inference is interesting, we prefer to avoid the conclusion that such an inference has propositions about states as premises and propositions about values as a conclusion, primarily because states are given to us through values, that is positions in some state space.

- the possibility of obtaining a measurement result is grounded on a measurement model that encodes a mathematical relation among the measurand and the quantities affecting it;
- the possibility of constructing a measurement model is grounded on an underlying theory that provides the justification for assuming that specific mathematical relation.

It is of some interest to compare this account with a characterization of the measurement process that is developed in the current philosophical context, in particular by van Fraassen who, by combining the representational approach and the emergent model-based approach to measurement, presents an extensive analysis of measurement that involves the following elements[4]:

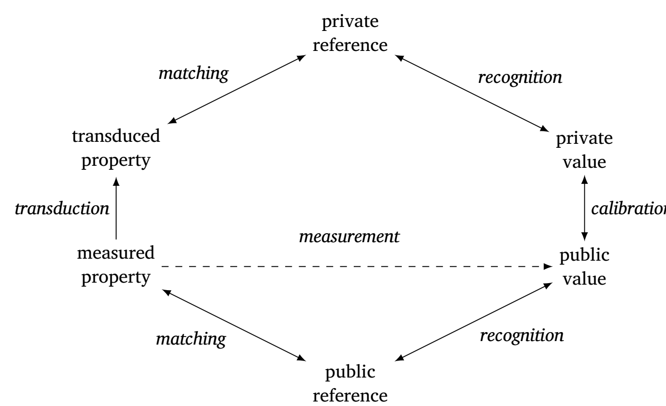
1. measurement is based on a physical interaction;
2. measurement is a model-based process;
3. measurement is a purpose-driven process;
4. measurement provides a representation of the entity measured;
5. measurement provides values for variables that represent that entity;
6. the variables that represent the entity are selected based on a theory;
7. the variables that represent the entity are related in a model;
8. that model is a model of the measurement process.

As a consequence, according to van Fraassen, the aim of measurement is to acquire enough information to locate the object in a certain logical space, with a location that it does not have a priori ([17], 177), the logical space being the state space defined by the variables whose values we intend to measure.[5] While the convergence between the metrological definition and this philosophical account is plain, it is worth noticing that in this account the fundamental notions of measurand and measurand definition play no role: to locate an object in a logical space of values is different from providing information on a defined measurand by means of a measured value. This becomes particularly evident by considering how the object is located within that space. The measurand is supposed to be the property by virtue of which the object can interact with an instrument, and therefore be located in a specific position, or be assigned a specific value, but this element seems to be missing in this model-based characterization. And we will see that *the possibility of invoking measurand-related interaction with the object under measurement is a crucial aspect for assessing whether simulation can be considered a kind of measurement.*

1.2. On direct and indirect methods of measurement

For understanding the role of simulation in measurement the distinction between direct and indirect methods of measurement is pivotal, given the fact that those who support the idea that simulation is a kind of measurement assume, more or less explicitly, that it is a kind of indirect measurement: let us remind it, and compare it with the tripartition of measurement into direct, derived and complex measurement proposed in [13].

Direct measurement. A measurement is direct when the measuring instrument interacts with the object under measurement under the respect that characterizes the measurand. The general structure of a direct measurement can be then represented as follows (see [18] for a more complete presentation):



Without entering into any detail, a direct measurement is typically performed by using a measuring instrument that incorporates an element able to transduce the property to be measured into a property that can be directly associated with a private value via a classification module, i.e., the indication of the instrument. When such a private value is provided, a public value is then obtained based on the calibration of the instrument.[6] Note that the diagram presents the simplified situation in which the measurand and the effective property coincide: when this assumption is dropped, the measurement model must take the distinction into account, and the value to be attributed to the measurand has to be identified by solving the equation that relates the effective property with the measurand, as encoded in the model itself.[7]

[4] See, in particular, [17], chapters 6 and 7, and [8], 781–783. Van Fraassen's general conclusion is that both what is measured and what counts as a measuring procedure are essentially theory dependent. In his perspective, whether a procedure counts as a measurement procedure depends on whether there is a quantity of the theory — that is a quantity that appears as a variable in a model provided by the theory — that meets a criterion of consistency with what the theory predicts and a criterion of correspondence with what exists based on the theory. While we are not fully convinced by the arguments proposed by van Fraassen on this point, we still acknowledge the significance of such an account for the current debate on what is measurement.

[5] A generalization of this account is proposed in [13], and can be summarized as follows. Measurement is an empirical information-production activity, involving physical interaction with the measured entity, which locates the entity in a logical space. Especially in contemporary measurement, this locating activity often involves some form of model-based inference: an inference from the state(s) of one or more physical processes to the value(s) of one or more variables thought to characterize the entity under study, where this inference is guided by a model of the measurement process. Assumptions about the model should cohere with background knowledge as much as possible, not just with relevant background theory but also with knowledge of interfering factors, limitations of instruments and human perception, and so on. The inferred parameter value(s) constitute a selective representation of the measured entity. Measurement outcomes, when complete, include not only a best-estimate value for a parameter but also a well-motivated uncertainty estimate; the latter indicates the degree to which the measuring process is expected to be informative. When measurement is successful, its outcomes are statistically consistent with those obtained in other measurement processes ([13], 279). Again, the fact that measurement is a model-based process is strongly stressed, and this gives rise to a tension concerning the genus of the concept of measurement: model-based process involving an empirical interaction *vs* empirical process involving a model-based interpretation.

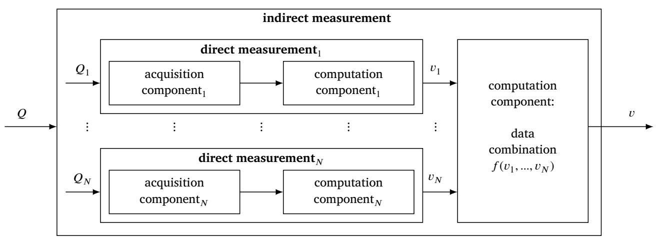
[6] As an example, consider an alcohol thermometer, that transduces the property to be measured (the temperature of a certain body) to an instrument-specific property (the length of the column of alcohol) that is then classified by comparison with a graded scale. This length is associated with a private value, that is relative to that particular thermometer that we are using. From that value of length a value of temperature can be obtained through the information provided by the calibration of the thermometer, which associates values of temperature with values of length.

[7] Thus, if we want to measure the temperature of a gas at a given pressure and we discover that the pressure during the interaction with the thermometer was different from the specified one, we must apply a correction determined by the equation that relates the pressure and the temperature of a gas in given circumstances, and of course the equation can vary depending on the model of the gas we select. Whether this correction makes the process a prediction instead of a measurement is discussed below.

In [13], a direct measurement is defined as a process that produces an instrument indication without involving explicit calculations, which is then associated with a value of the variable we are measuring. The process is interpreted in light of a model about the interactions that give rise to the indication and the corrections to be performed to obtain the final property value. Hence, the two accounts are essentially in agreement.

Indirect measurement. In an indirect measurement the value of the measurand is inferred from the values of other properties, which ultimately are measured in a direct way, via a computation component that reflects the relations between the properties that are directly measured and the measurand as provided in the definition of the measurand itself.

A general diagram of this process is:



where Q is the measurand, $Q_1, \ldots, Q_N$ are the properties on which Q depends according its definition or to a theory, $v_1, \ldots, v_N$ are the values of these properties obtained by direct measurement, and $v = f(v_1, \ldots, v_N)$ is the value attributed to Q, where f encodes the relation between $Q_1, \ldots, Q_N$ and Q.

In [13] an indirect measurement is defined as a process that produces a measured value that is derived from other values, which are ultimately directly measured, using dependable theoretical principles or definitions. Again in [13] the distinction is then introduced between synchronic and diachronic indirect measurements, where a diachronic indirect measurement allows us to acquire information on properties that an object possesses at a time that is different from the time when the measurement occurs. Finally, a complex measurement is defined as a process of that combines values that are directly or indirectly measured by using a number of different instrument.[8] Accordingly, the following classification can be derived:

(i) direct;
(ii) indirect – combination by definition;
(iii) indirect – combination by synchronic relations;
(iv) indirect – combination by synchronic and diachronic relations;

where in [13] all these methods are considered to be of measurement, under the assumption that there is no principled difference between deriving a value by computations based on synchronic theoretical connections and deriving a value by computations based on diachronic theoretical connections. Still, allowing for such generality has as a consequence that it is possible to measure something that does not exist, and this strikes us as peculiar.[9] In this respect, for the moment we stick to the idea that measurement implies acquisition of information through empirical interaction with an object under measurement and with respect to properties that are connected to the measurand based on definitions. Since interactions are local, meaning that the object under measurement and the measuring instruments interact in a confined spacetime region, classifying indirect diachronic methods as measurements is problematic. In addition, this gives us a principled justification to preserve the distinction between measurement and prediction, as is commonly accepted in science.

[8] This type of measurement is again a kind of indirect measurement is our scheme, since the fact that the values that are combined to derive a value for the measurand are obtained by using a number of different instruments does not seem to be an essential characteristic of the process.

[9] This consequence is indeed considered in [13], with the conclusion that some of these objections do have some force. So perhaps measurement should be limited to properties at times that are already past ([13], 283).

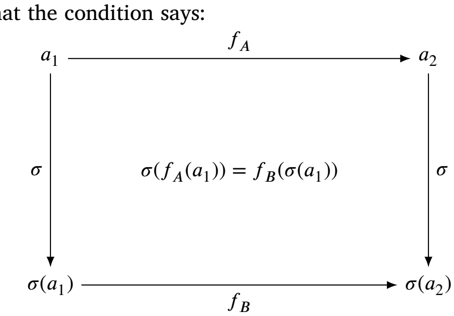
1.3. On the notion of simulation

In order to characterize the notion of simulation let us start by introducing the concept of a dynamical system: intuitively, a system that has a state that can change in time. Hence, a dynamical system is defined by a set of states and a dynamics, that is, a function that returns the state of the system as time goes by. In what follows we will focus on autonomous discrete-time deterministic dynamical systems, since this class of systems is sufficient for exemplifying all the issues related to the debate we are considering, while allowing us to avoid a number of inessential mathematical issues.

Definition 1. An autonomous discrete-time deterministic dynamical system is a pair $\mathbf{S} = (X, f)$, where X is a set of states and $f : X \to X$ is the dynamics of the system.

Definition 2. Let $\mathbf{S}_A = (A, f_A)$ and $\mathbf{S}_B = (B, f_B)$ be autonomous discrete-time deterministic dynamical systems. Then, a simulation of $\mathbf{S}_A$ through $\mathbf{S}_B$ is a morphism from $\mathbf{S}_A$ and $\mathbf{S}_B$, i.e., a function $\sigma : A \to B$ such that $\sigma(f_A(a)) = f_B(\sigma(a))$ for all $a \in A$.

The basic idea behind this definition is the following. Suppose we want to model the dynamics of a system $\mathbf{S}_A = (A, f_A)$ by means of a system $\mathbf{S}_B = (B, f_B)$. We observe that the current state of $\mathbf{S}_A$ is $a \in A$ and map it to the corresponding state $\sigma(a)$ of our model. What we want is our model to be able to follow the history of $\mathbf{S}_A$, that is to be able to predict all the successive states of $\mathbf{S}_A$. The state following a is $f_A(a)$, and therefore we want our model to be such that the state following $\sigma(a)$, which is $f_B(\sigma(a))$, be the image of the state $f_A(a)$, which is $\sigma(f_A(a))$. This is what the condition says:



A few comments on this. First, both $\mathbf{S}_A$ and $\mathbf{S}_B$ are dynamical systems: the fact that $\mathbf{S}_A$ is a *target* system and $\mathbf{S}_B$ is a *model* system, i.e., an intended model of $\mathbf{S}_A$, depends on a choice of who introduces the model. In principle, there is nothing intrinsic to $\mathbf{S}_A$ or $\mathbf{S}_B$ that forces us to treat $\mathbf{S}_A$ as a target and $\mathbf{S}_B$ as a model. Second, σ is required to map states of the target system $\mathbf{S}_A$ to states of the model $\mathbf{S}_B$, but nothing prevents this map to be many to one. Hence, nothing prevents the states of the model to be less fine-grained with respect to the states of the target, since what is crucial in a simulation is not how faithful a state is, but how faithful the dynamics is. Finally, the definition we are proposing is general enough to capture the main intuitive accounts of simulation that are discussed in the literature on the present topic.[10]

[10] See [19], 82 about the fact that simulations are closely related to dynamic models. In that work it is assumed that a simulation occurs when the equations of the underlying dynamic model are solved; the model is designed to imitate the time evolution of a target system; hence, a simulation imitates one process by another process. A similar definition is proposed in [20], chapter 4. See also [20], especially ch. 4, and [13], 284: “in a computer simulation study, an agent uses a digital computer to execute a special kind of algorithm, designed to repeatedly solve dynamical equations, at least some of whose variables are understood to represent properties of a real or imagined system, the target system. Such an algorithm, when implemented on a particular digital computer, is a computer simulation model. From a specification of values for the model’s variables at an initial time, t_0, the computer solves the dynamical equations to produce values for a later time, t_1, from the values for t_1, it calculates values for t_2, and so on for some number of time steps”.

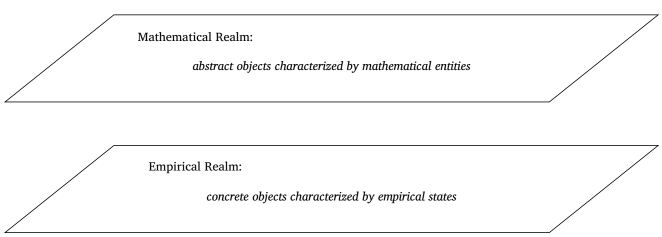
1.4. Types of simulation

Having defined the notion of simulation, let us classify simulations in light of two distinctions. The first is between reality-oriented and non-reality-oriented simulations: a simulation is *reality-oriented* when the target system is a real system, not a fictional one. The second distinction is between reality-based and non-reality-based simulations: a simulation is *reality-based* when the states of the model system are determined by observing the states of the target system, not by a free selection of the modeler. In terms of σ, a simulation is reality-oriented when $\mathbf{S}_A$ is real, so that we are interested in capturing some aspects of a real portion of the world, and it is reality-based when σ involves measurements, so that the state space of $\mathbf{S}_B$ is defined in terms of the dynamical properties we want to model.[11]

On the basis of these distinctions we are able to answer in the positive the first two questions posed at the beginning. Concerning **Q1**: simulation can be an experimental activity. In fact, a reality-oriented and reality-based simulation can only be performed by empirically interacting with the target system, by measuring some of the properties that determine the state of the system. Concerning **Q2**: a reality-oriented and reality-based simulation can be an epistemically distinctive activity, precisely because measurement is epistemically distinctive and measurement is involved in such a simulation. So, half of the initial problem is positively solved. All that is left now is addressing the other two questions.

2. Structural elements of the Framework

In both measurement and simulation, we use mathematical models to produce information about empirical objects.



The two realms — the mathematical one and the empirical one — are characterized and related via different kinds of functions which constitute the building blocks for studying and understanding the structure of both measurements and simulations. The aim of this section is to introduce four kinds of functions that connect mathematical entities and empirical states and then propose a structural analysis of the various types of measurement and simulation discussed before so as to highlight their main differences. In addition, with the aim of demonstrating the applicability of the framework across the sciences, several examples about physical processes are mentioned and an example about the evaluation of the proficiency of students is more extensively presented in these two sections.

[11] As an example, consider the development of a population of bacteria in an environment rich of nutrients. The state space of the system is the set containing the possible numbers of the members of the population, while the dynamics determines the growth of the population. A possible model of this system has the same state space and a dynamics based on a certain growth rate. This model is reality-oriented, but it is reality-based only if the state in the model that corresponds to the population state is obtained by counting the number of bacteria, a direct measurement, or by deriving that number by measuring the mass of the population or the region it occupies, an indirect measurement.

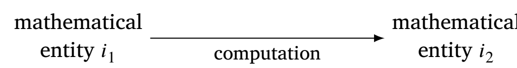
2.1. The basic building blocks

Let us start with the basic blocks.

- **Transition functions**: from empirical states to empirical states, capturing the dynamics of concrete objects.

For example: an iron bar changes its temperature; two physical particles change their distance.

- **Computation functions**: from mathematical entities to mathematical entities, capturing the process of deriving information.



For example: a number is scaled by a factor of 2; two numbers are added.

- **Classification functions**: from empirical states to mathematical entities, capturing the process of acquiring information on concrete objects.

For example: an iron bar is classified based on its temperature.

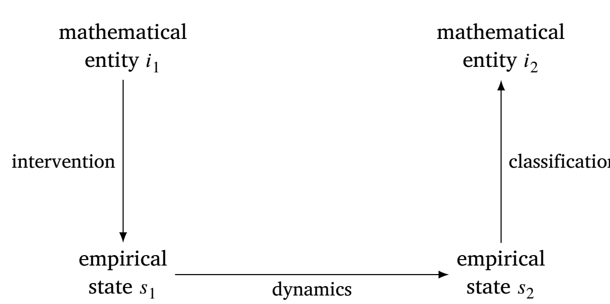
- **Intervention functions**: from mathematical entities to empirical states, capturing the process of acting on concrete objects based on information.

For example: the temperature of an iron bar is set to 20 C° based on some specification.

2.2. The basic modules obtained from the building blocks

These functions combine to give rise to two structural modules that are essential tools for an in-depth analysis of the measurement process.

- **Interaction module**:



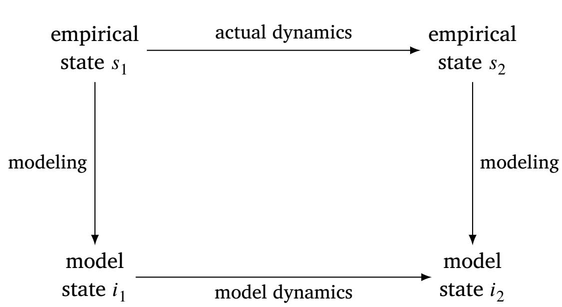
This allows us to understand how experiments and empirical models work. An interaction module captures the basic structure of an intentional action. Suppose we want to open a window to ventilate a room. Such an action is defined by a pair of states, the initial one, when the window is closed, and the final one, when the window is open. The action is intentionally performed when the agent has an abstract representation of both the current and the wished states, corresponding to i_1 and i_2, intervenes on the current state, corresponding to s_1, so as to trigger a dynamics that results in the intended state, corresponding to s_2, and gets an abstract representation of the consequences of the action, corresponding to i_2. In general, performing an experiment follows the same scheme: we design the experiment, by devising a set of experimental conditions, i_1; we initialize the experiment, by setting the conditions, s_1; we let the experiment run until a certain outcome is achieved, s_2; and then we learn the outcome of the experiment, i_2.

Example 1. Suppose we want to measure the proficiency of math students by using the Rasch model.[12]

1. The first stage of such measurement consists of an interaction module, that involves four steps. (1) designing a test (i_1), i.e., a set of items that target the skills of students; (2) administrating the test (s_1): this is the implementation of an intervention function, where the test is written and coupled with the objects under measurement, in this case, students; (3) letting the students produce the responses (s_2): this is the implementation of a transition function, where the state of the measuring system changes, as the responses are marked; (4) and, finally, classifying the responses in terms of correct and incorrect answers, thus obtaining a set of raw scores (i_2)—this is the implementation of a classification function, where the final state of the measuring system is connected to a mathematical entity, in this case, the pattern of correct and incorrect answers and possibly the number of correct answers.
2. A second stage consists in a sequence of computation functions, applying Rasch analysis to assess both item difficulty parameters and item fitness, and therefore to calibrate the model.
3. The final stage consists again in a sequence of computation functions, and is aimed at estimating the proficiency of students in terms of their estimated probability of correctly answering items of varying difficulties.

Hence, measurement of proficiency involves an interaction module, complemented with a sequence of computation functions. Indeed, we will see that it is a case of indirect measurement.

- **Representation module**:



This allows us to understand how theories and theoretical models are used to study the world, where theoretical models are usually mathematical entities. A representation module captures the basic structure of a step in a simulation: states of the target system are mapped to states of the model in order to observe whether the dynamics of the system is simulated by the dynamics of the model. Suppose we want to model what happens to a room when we open a window. Then, it is possible to produce an agent-based model that tracks the dynamics of many molecules as individual agents and then derive macroscopic states like temperature and pressure from their collective behavior.[13] Hence, the actual state of the room, corresponding to s_1, is modeled by a state of the model, corresponding to i_1, which according to the rules governing the dynamics of the agents evolves to a new state, i_2, that represents the final state of the room, s_2. In general, performing a simulation, here a computer simulation, follows the same scheme: we design a model, by devising a specific state space and a suitable dynamics on it, and a set of correspondence rules that allows us to pair states of an empirical system with states of the model. Since the model itself is a dynamical system, we say that a simulation is performed based on a *dynamical model*.

Example 2. Suppose we use the Rasch model to assess student proficiency in a middle-term exam and subsequently for simulating the results of a final exam.

1. In a first stage, we use Rasch analysis to calibrate item difficulties and assess student abilities based on their middle-term raw scores. This is the implementation of a classification function from an empirical state, which is the proficiency level of the students, to a mathematical state, the probability of correctly answering items of varying difficulties.
2. In a second stage, based on the proficiency estimates from the middle-term exam, we project student abilities for the final test. In this phase, we use the item difficulty parameters and the estimated student abilities to model the probability of correctly answering items for the final test, and therefore we implement a model dynamics which is typically defined with reference to the historical series of data at our disposal.
3. In a final stage, we track how student abilities evolve from the initial to the final test, by measuring the final proficiency of the students, and check the consistency of the estimates and the fit of the Rasch model to validate the simulation accuracy. In this phase, we assume that a certain learning dynamics occurred, and then we implement a classification function from an empirical state, the proficiency level of the students, to a mathematical state.

Hence, the simulation of future proficiency involves a representation module, complemented with a sequence of measurements. Indeed, we will see that it is a case of reality-oriented and reality-based simulation.

3. Combining the elements of the Framework

Based on this Framework, we are now in a position to discuss how measurement and simulation can be decomposed. This will enable us to distinguish between direct measurement, indirect measurement, computation in a strict sense, and various kinds of simulation: pure, reality-oriented, and reality-oriented and reality-based.

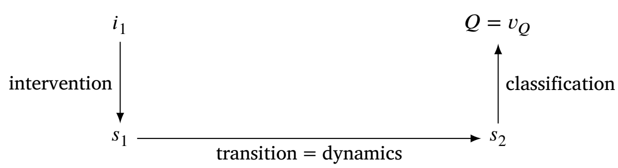
[12] Rasch models can be used to measure proficiency based on categorical data, such as responses to test items. They models the probability of a correct response based on the difference between two construct: the ability of a person and the difficulty of an item, both located on the same interval scale. This probabilistic measurement allows the Rasch model to estimate person abilities and item difficulties independently, which helps to measure proficiency independently of the items used. See [21] for a metrology-oriented introduction, and [22], for an in-depth presentation.

[13] While modeling an amount of 10^{25} molecules in a room is computationally impossible, an agent-based model can still simulate a much smaller, representative number of agents to capture essential molecular interactions and the dynamics of the main thermodynamic quantities. In this case, to overcome computational limits, a model can simulate fewer agents that represent clusters or statistical ensembles of molecules rather than every single molecule.

3.1. Elements involved in measurement

The first point we aim to defend here is that *direct measurement* basically consists of an interaction with an object under measurement that allows us to assign values to empirical quantities, while *indirect measurement* consists of performing one or more direct measurements and operating on their results by a computation function. A crucial outcome of this idea is that *computation is not measurement*. Let us see the details.

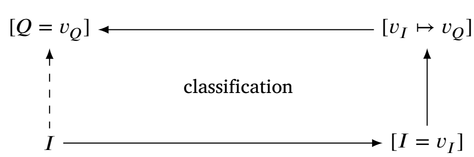
Direct measurement. Basically, direct measurement consists in an interaction module with a composite classification function:



In this diagram, the information in i_1 involves the definition of the measurand Q and the decision about an appropriate measurement procedure, thus including the measuring instrument; s_1 involves coupling the instrument with the object under measurement in the conditions specified by the definition of Q; s_2 is the state of the coupled system as a consequence of the dynamics; $Q = v_Q$, where v_Q is the value attributed to Q, is the information obtained as a result of the classification of s_2.

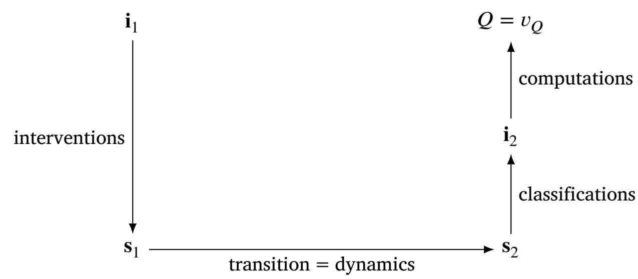
Remark 1. The first phase of the process in Example 1 is a direct measurement of the ability of a student to correctly answers the items in the test.

As said before, the operation of classification is non-trivial, as it typically comprises different steps:



In order to understand this process, note that the state s_2 of the coupled system includes the indication quantity I provided by the measuring instrument. It is this quantity that is directly classified and assigned a (private) value v_I. Then, this value is converted into a (public) value for v_Q, based on the calibration of the measuring instrument, a value that is finally attributed to the measurand Q, possibly following some corrections that account for the difference between Q and the effective quantity.[14]

Indirect measurement. Indirect measurement consists in a sequence of an interaction module with a composite classification function:



In this diagram, $\mathbf{i}_1, \mathbf{s}_1, \mathbf{s}_2$, and $\mathbf{i}_2$ are vectors, since the outcomes of one or more direct measurements are finally combined to compute the value to be attributed to the measurand. This diagram sheds light on two key points. First, computation is an essential component of indirect measurement, typically based on equations that relate the measurand to quantities that can be measured directly. Hence, indirect measurement is strongly dependent on models. Second, computation is only one step in a measurement, and this step is possible only when some information about the quantities related to the measurand is available, in the form of values of such quantities. This consideration is crucial: *computation is not measurement, as it lacks the essential empirical component that characterizes any measurement process.*

Remark 2. The entire process in Example 1 is an indirect measurement of the proficiency of a student in correctly answering items of varying difficulties about a subject.

Conclusion on direct and indirect measurement. Suppose a is an object and $q = Q(a)$ is a quantity that a has. Since any, direct or indirect, measurement of q involves some empirical interaction between measuring instruments and a, the following principles are satisfied.

- Since it is impossible to interact with non-existent objects, if we measure $q = Q(a)$, then a exists, or at least existed when the interaction took place.
- Since it is impossible to activate instruments via a non-existent property, if we measure $q = Q(a)$ directly, then a has the property q.
- Since it is impossible to activate instruments via a non-interacting property, if we measure $q = Q(a)$ indirectly, then a has some q-related properties.

Let us now consider some examples in order of increasing indirectness:

1. measuring the length of a bar;
2. measuring the volume of a bar;
3. measuring the density of a bar;
4. measuring the density of a star.

Here, we only focus on the fundamental steps that lead from a direct measurement of the length of a bar to the highly indirect measurement of the mass of a star.

A first step, from 1 to 2, may involve using a geometric equation to calculate the value of a volume given some values of length, which is supposed to be measured directly. Thus, if the bar can be modeled as a cylinder, measuring the diameter of its section and its height provides enough information to calculate its volume. Hence, also in this very basic case a model is required, and its appropriateness has to be checked, in this case by verifying that the bar is sufficiently cylindrical, for validating the obtained result.

A second step, from 2 to 3, assuming that a spring is used to measure the mass of the bar in a gravitational field, may involve using an equation that corresponds to the physical law that models the behavior of the spring and allows us to calculate a value of mass from a value of length. An equation is then used to calculate the density of the bar from its volume and mass.

[14] This shows that, despite the name, direct measurement is not model-free, as a model must be used at least to calibrate the measuring instrument. For example, to construct the mapping from values of length to values of temperature in an alcohol thermometer, the instrument can be made interacting with a number of different objects whose temperature is known and the correspondence between those values and the obtained lengths of the column of alcohol recorded. In any case some sort of interpolation model is required, given that the measured temperature could be different from all temperatures exploited in calibration.

The final step, from stage 3 to stage 4, relies massively on theoretical physics: the equations used for the calculations are based on models that are so approximate that they make us question whether an actual measurement is possible, and in fact the density of a star is usually said to be estimated, rather than measured. To gain insight into how such process is performed, consider that we are first required to measure the mass and the volume of the star and that all we can directly measure to this purpose is the light emitted by the star as detected by using charge-coupled devices, i.e., light-sensitive circuits converting incoming photons into electrical charges. In brief, one of the simplest procedures to measure the mass and volume of a star, and therefore its density, when the star belongs to the main sequence and its distance d is known, involves the following steps.[15]

Step 1: acquire the star's spectrum.

– This is done by using a spectrograph.[16]

Step 2: classify the star's spectral type.

– This is done by using a classification scheme.

Step 3: measure the star's apparent magnitude m.

– This is done by using a charge-coupled device.

Step 4: use the star's spectral type to determine the effective temperature T.

– This is done by using a spectral type–temperature calibration table.

Step 5: use m and the distance d to compute the star's absolute magnitude M.

– The relevant equation is $M = m - 5\log_{10}(d/10)$.

Step 6: use M to compute the star luminosity L.

– The relevant equation is $L = L_{\odot} \cdot 10^{(M_{\odot}-M)/2.5}$.[17]

Step 7: use L to compute the star mass M_*.

– The relevant equation is $L/L_{\odot} = (M_*/M_{\odot})^{\alpha}$.[18]

Step 8: use T and L to compute the star radius R.

– The relevant equation is $L = 4\pi R^2 \sigma T^4$.[19]

Step 9: use R to compute the star volume.

– The relevant equation is $V = 4\pi R^3/3$.[20]

Step 10: use V and M_* to compute the star's density $d = M_*/V$.

These steps are justified by modeling decisions, abstractions, idealizations, and approximations that substantially influence measurement results and their associated uncertainties.[21] This notwithstanding, the general framework describing an indirect measurement still applies: the computational function incorporates all abstractions, idealizations, and approximations inherent in the process. This is an important point: *even though the computational component constitutes the predominant part in a measurement process, in terms of time and expertise required, it is the interaction component that ultimately defines the process as a measurement.*

[15] See [23], chapter 12, for an introduction to the problems concerning evaluating/estimating / measuring the properties of stars.

[16] This initial process, by itself, requires: (*i*) a non-trivial set up, incorporating a telescope, a dispersing element, like a prism, and a recording element, like a CCD, and (*ii*) a non-trivial computational component to process the data by subtracting background light, correcting for instrumental effects, and calibrating about wavelengths.

[17] Where $L_{\odot}$ and $M_{\odot}$ are the luminosity and the mass of the Sun.

[18] Where α is a parameter that depends on the spectral type of the star.

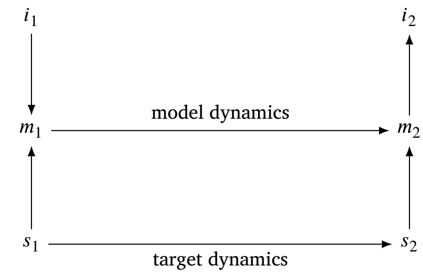
[19] This is the Stefan–Boltzmann law, where σ is the Stefan–Boltzmann constant.

[20] Where it is assumed that the star can be appropriately modeled as a sphere.

[21] See [24], especially Part III, for a thorough study of the processes involved in model construction.

3.2. Elements involved in simulation

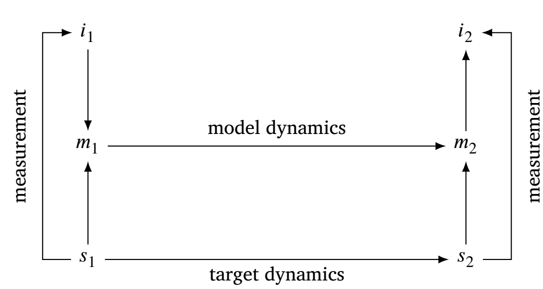
The kind of simulation that fits best with the conjecture that simulation is a kind of measurement is reality-oriented and reality-based simulation, which results from combining a representation module and an intervention module. In general, a reality-oriented simulation has the following structure:



The intervention module accounts for how a dynamical model is used: we set its parameters, run the model, and observe the outcome of its dynamics. The representation module accounts for the fact that the simulation is reality-oriented: the initial state of the model, m_1, is intended as a representation of a particular state of the system, s_1, and, similarly, the final state of the model, m_2, is intended as a representation of another particular state of the system, s_2. When considering a computer simulation of the dynamics of an abstract system that in itself is a model of a real system, nothing essentially changes. This is still not sufficient for the simulation to be reality-based. Indeed, in order to be so, the fact that m_1 represents s_1 has to be empirically justified, and here is where measurement is expected to be used.

Remark 3. The process in Example 2 is a simulation. The initial state of the model represents the proficiency that characterizes the students at the time of the middle-term exam, while the final state of the model represents their predicted proficiency at the time of the final exam. The model is used to simulate typical learning dynamics, and the alignment between the model's outcome and the actual outcome of the final exam can be used to check whether the class followed this typical learning trajectory, which is an aspect of significant interest.

Thus, we define a reality-oriented and reality-based simulation as a simulation where the dynamics of the model is intended to represent the dynamics of a real system, so that the model is oriented to reality, and the initial state of the model is determined by setting the values of the relevant parameters based on values that are obtained by measuring properties of the target system, so that the model is also based on reality. The corresponding diagram is as follows:



Hence, a first set of measurements allows us to set the initial state of the model and a second set of measurements allows us to check whether the final state corresponds to a state of the system, thus witnessing that the model is appropriate. As a consequence, a first connection between simulation and measurement shows up, as *measurement is essential to characterize the very notion of reality-based simulation.*

4. Measurement and simulation

On the basis of the Framework we introduced and the previous analysis, in this section we address the problem of the relationship between measurement and simulation, by presenting two examples that seem to support the thesis that simulation is a kind of measurement. One example is about the prediction of the existence of an object with a given quantity, which could be interpreted as an indirect measurement of that quantity once the object is discovered to exist. The other example involves measuring a quantity at a certain space–time region to predict the values of related quantities in different space–time regions, which could be interpreted as an indirect measurement of these other quantities. The analysis of these examples will lead us to the main contribution of this paper: the rejection of the conjecture that simulation is a kind of measurement, in favor of the thesis that *simulation can be a functional part of the computational step that characterizes a specific kind of indirect measurement*. This thesis sheds light on the four questions presented at the beginning of this paper, since it turns out that simulation:

1. can be an experimental activity;
2. can be an epistemically distinctive activity;
3. is similar to measurement in being an epistemically distinctive activity;
4. but is not a kind of measurement, being possibly only a part of a process of indirect measurement.

This answers the initial problems and presents a positive assessment of the epistemic status of both measurement and simulation.

4.1. Determination of a quantity of a hypothetical object

The existence of Neptune was predicted before the planet was directly observed, and the prediction was the result of solving the inverse problem of determining the parameters of a mathematical model from observations. A simplified version of the modeling process that led to the discovery of Neptune is as follows.

- Assume a solar system with 8 planets.

Given the fact that at that time only 7 planets were known, the hypothesis of the existence of a new planet is therefore incorporated in the model.

- Simulate the dynamics of the system:
  - *known (measured) parameters*: the masses of the 7 known planets and their positions and velocities at a given point in time;
  - *unknown (guessed) parameters*: the mass of the unknown planet and its position and velocity at the same point in time;
  - *dynamics*: Newton's second law and the law of gravitation;
  - *output*: the orbit of Uranus with its known perturbations (under the hypothesis that Uranus orbit is the one most affected by the presence of the eighth planet).
- Observe the actual orbit of Uranus.
- Compute the distance between the predicted and the observed orbit of Uranus.
- Change the unknown parameters to minimize this distance.

This description highlights the critical role of simulation in the process: by implementing the model as an autonomous discrete-time deterministic dynamical system, with a sufficiently small time step to obtain a suitable approximation of the original differential equations, and running the model, an orbit for Uranus is computed and the perturbations caused by the presence of the hypothesized eighth planet determined. The simulated orbit can be then compared with the observed orbit, and their distance minimized by iterating the simulation and adjusting the values of the relevant model parameters, such as the position, velocity, and mass of the hypothetical new planet. Suppose that a set of values is obtained that makes the simulated orbit closely match the observed one and that according to these values an unknown planet is discovered, which is indeed what actually happened. The conclusion could be drawn then that the process of simulation through which the parameters were determined is actually a measurement of the mass of the planet. Is this argument sound?

Assessing the argument. Let us see what we have obtained. Let C be a proposition that describes the conditions determined at the end of a simulation. Hence, in our example C is the proposition that the solar system contains 8 planets, that the orbit of the seventh planet exhibits perturbations and these perturbations are the effects of the presence of a gravitational interaction between the seventh and the eighth planet, and that the orbit of the eighth planet is such and such. Let Q be the mass of the eighth planet and let v_Q be the value of this mass in some units. Then, it is sensible to accept that a reality-oriented and reality-based simulation can be used:

1. to know a conditional statement like $C \rightarrow Q = v_Q$;
2. to know that $Q = v_Q$, given the knowledge that C;
3. to measure Q, given the knowledge that C.

Is this equivalent to saying that a reality-oriented and reality-based simulation is a kind of measurement? The answer should be in the negative. In the case we are considering, simulations are used as tools to compute values, not as measurements. Indeed, simulations are used as parts of the computational step of a specific process of indirect measurement. Therefore, in this case too, we conclude that even though the computational component is the predominant part in the process, it is the interaction component — *what makes the simulation reality-based* — that ultimately defines the process as a measurement. Indeed, without the availability of the values of the relevant parameters of the seven known planets, as obtained by measurements, this would have been only a simulation, not a measurement.

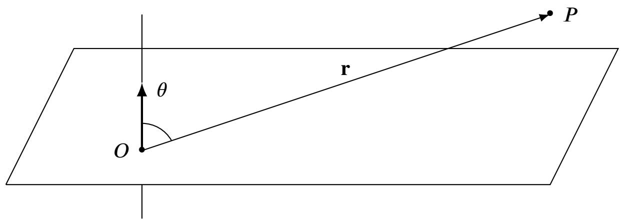
4.2. Determination of a quantity at a distant space–time region

The second example we consider is more subtle, as it might suggest that even diachronic indirect measurements could count as a genuine kind of measurement, thus blurring the distinction between measuring and predicting the value of a quantity.[22] As an example, one might assume that data assimilation processes, like four-dimensional variational assimilation, are indeed indistinguishable from measurements.[23] To focus on the core issue, we study a simplified case where no simulation is involved: this approach allows us to isolate and understand the fundamental aspects of the problem without additional complexity—cases that include simulations can be addressed in a similar way.

[22] See [13], p. 283: "Including diachronic derived measurement — and thus some predictive and retrodictive practices — as a species of measurement is a departure from earlier discussions. However, diachronic derived measurement seems to differ from ordinary synchronic derived measurement only in relying on principles or definitions that relate parameters at different times, rather than at the same time. As long as such a process can deliver estimates of parameter values whose accuracy can be specified reliably, it seems reasonable to consider it a species of derived measurement".

[23] See [13], sections 4 and 5 for an extensive discussion of this topic. Let us remind that data assimilation processes combine information from numerical models and observations to produce the best possible estimate of the state of a dynamic system, by minimizing a cost function that evaluates the difference between the model prediction and observations distributed over a time window. Hence, this approach incorporates the time dimension explicitly.

Suppose we have a charge q oscillating in a certain direction at point O and we are at point $O + \mathbf{r} = P$ such that both the distance $\overline{OP} = r$ and the angle θ between direction of observation and axis of oscillation are known.



Suppose further that q is oscillating vertically according to the equation $z(t) = A\cos(\omega t)$, so that its acceleration is given by $\ddot{z}(t) = -\omega^2 A\cos(\omega t)$. In general, the electric field produced at P by the charge is proportional both to a field that goes inversely as the square of the distance—a velocity field associated with the instantaneous position and velocity of the charge—and to a radiation field that goes inversely as the distance—an acceleration field that is responsible for radiation.[24] Therefore, if P is sufficiently distant, we can abstract from the influence of the first field and only focus on the radiation field. Finally, if q is oscillating with a sufficiently small amplitude, the field at θ can be modeled always at right angles to the line of sight and in the plane containing both the acceleration and the line of sight. The resulting equation for the intensity of $\mathbf{E}$ is then the following:

$$E(t) = -q\frac{\ddot{z}\left(t - r/c\right)\sin\theta}{4\pi\epsilon_0 c^2 r} = q\frac{\omega^2 A\cos\left(t - r/c\right)\sin\theta}{4\pi\epsilon_0 c^2 r}$$

where ϵ_0 is the permittivity in vacuum and c is the speed of light. The equation is not difficult to understand: it simply says that the electric field at P is directly proportional to the charge and acceleration of the moving source, and inversely proportional to the distance of P; in addition, the electric field decreases by a factor $\sin\theta$, so that the field is null when P is on the line of oscillation and maximum when P is a right angle with respect to the line of oscillation. Now, suppose we are at P and are equipped with a instrument that allows us to measure the intensity of the oscillating field $E(t)$. Then, it is possible:

1. to measure the frequency of the oscillating charge f and solve for ω:

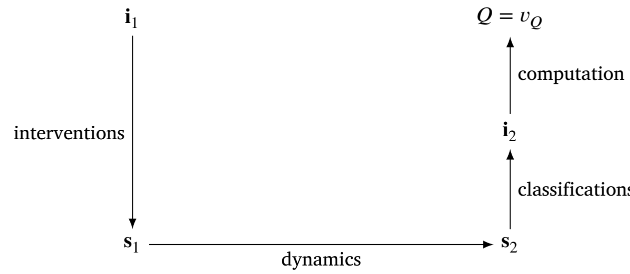
   $$\omega = 2\pi f$$

2. to measure the amplitude of the radiation field E_0 and solve for q

   $$E_0 = \frac{qA\omega^2\sin\theta}{4\pi\epsilon_0 c^2 r} = \frac{qA\omega^2\sin\theta}{4\pi\epsilon_0 c^2 r} \quad\Rightarrow\quad q = \frac{4\pi\epsilon_0 c^2 r}{A\omega^2\sin\theta}E_0$$

Hence, when equipped with appropriate measuring instruments we are able to determine both the frequency and the charge of an oscillating object at a point at a distance r, provided that the distance is sufficient to screen the effects of the velocity field. The question now is: does this sequence of computations counts as a measurement of ω and q

Assessing the argument. One may suggest that the whole process can be classified as an indirect measurement, since it instantiates the general structure:



The hard work is done here in the computational step. In fact, the sequence of values obtained by direct measurement is $\mathbf{i}_2 = (f, E_0)$, while the values of ω and q are computed using a model of the system, based on assumptions about what we measure and in what condition we measure it, and a set of equations, incorporating assumptions about the laws of electromagnetic radiation and approximations about what parameters can be neglected. In this respect, the similarity with an indirect measurement is evident. Despite this, we argue that such a process should be distinguished from measurement. As anticipated, the reason is that measurement should involve *local interactions with the object under measurement under the respect of the measurand*—meaning that the object under measurement and the measuring instruments must interact within a confined spacetime region. In contrast, in the present case, we use equations to determine the values of quantities characterizing an object in a distant spacetime region O based on quantities measured at P. To justify the assumption that measurement should only involve local interactions, consider the following: when determining the values of quantities that characterize an object in a distant spacetime region, we generally cannot ascertain whether those values have been influenced by interactions occurring in the intermediate regions. This is why we consider that those values are determined or estimated, rather than measured, and when the quantities are presumed to characterize an object in the future, we say those values are predicted.

As a final remark on this topic, let us observe that the criterion of local empirical interaction is typically met by both direct and indirect measurements, and therefore allows for computational based inferences to be legitimate component within measurement processes, provided that basic metrological principles are respected. As an example, the present Framework is completely consistent with the position according to which psycho-social quantities can be rigorously measured through test-based interactions, as our examples related to psychometry demonstrate.[25]

5. Conclusions

Let us summarize our results.

1. We distinguished between direct and indirect methods of measurement, highlighting that indirect measurement is characterized by a computation component playing a crucial role in obtaining measured values.
2. We distinguished between indirect measurement and simulation, arguing that simulation is not a kind of indirect measurement, but can be a part of an indirect measurement, typically when the equations in the computation component are solved in a numerical and algorithmic way.
3. We characterized measurement, either direct or indirect, as a specific kind of estimation, arguing that measurement is based on local interaction, so that quantities characterizing objects in a distant spacetime region are not measurable.

[24] See [25], Volume 1, chapters 28–29. To compute the field at P at time t we have to take into account the values of the velocity field and the acceleration field at time $t - r/c$, where r/c is the time the radiation needs to get to P.

[25] We thank two anonymous referees for encouraging us to clarify this point more thoroughly and to highlight the applicability of the framework in different scientific domains. In this regard, see [26,27] for the development of a unified notion of measurement across science.

This allows us to conclude the study, with the following answers.

- **Q1**: Simulation can be an experimental activity, when it is reality-oriented and reality-based; in this sense, simulation is similar to measurement.
- **Q2**: Simulation can be an epistemically distinctive activity, in the same conditions as before; in this sense too, simulation is similar to measurement.
- **Q3**: Accordingly, simulation is epistemically similar to measurement, and in fact can be used as a part of an indirect measurement.
- **Q4**: Still, simulation is not a kind of measurement, since the process that involves a simulation is an indirect measurement only because it is based on direct measurement.

Accordingly, the diachronic estimation should not be considered a kind of measurement, due to the impossibility of empirical interaction with quantities characterizing an object in a distant spacetime region. This, of course, does not imply that we cannot estimate the value of a property of an object not currently interacting with a measuring instrument; rather, it clarifies that such estimation is typically classified as a prediction, not a measurement. In this respect, we maintain that measurement is a process whose empirical stage crucially involves local interactions, that is, a process anchored to the world through actual connections with the object possessing the property we aim to measure. This condition holds true for measurements in both the physical and psycho-social sciences, where instruments are designed to interact appropriately with the objects of interest. Indeed, a crucial step of measurement in both fields involves coupling the instrument — whether a sensor or a test — to the object under measurement, thereby triggering the interaction that leads to the measurement result.

In conclusion, while the primary objective of this paper is essentially theoretical, the practical consequences of the thesis we critically addressed and challenged — that simulation is a kind of measurement — are significant, given our view that measurement remains *the primary process for acquiring objective and intersubjectively validated information about the world*. What we suggest is that, in measurement:

1. *intersubjectivity* is warranted by anchoring the measurement result to a primary measurement standards, by means of a *metrological traceability chain*[26];
2. *objectivity* is warranted by anchoring the measurement result to the measurand, by means on an *empirical traceability chain*.

In the empirical chain, the measurand is connected to the indication of the instrument either causally only (direct measurement) or also computationally (indirect measurement), thus ensuring that the measurement result can be referred to it properly.

Therefore, blurring the distinction between measurement and simulation risks implying that simulation is as dependable as measurement in conducting research and testing theories, a claim that is not necessarily justified. As Parker succinctly observed in [28] on the question whether a simulation system that produces results about the future can be regarded as measuring properties of entities in the actual world: “An affirmative answer would indeed mark a significant conceptual change. It seems better to simply characterize such results as predictions. But they might be considered measurements at some later date, once the future has arrived”.

In focusing on these conceptual challenges and acknowledging the potential risks of equating measurement and simulation, the present Framework offers a structured foundation designed to support and stimulate further inquiry aimed at exploring and advancing an evolutionary concept of measurement in the digital age.

[26] See VIM3, definition 2.41.

CRediT authorship contribution statement

Alessandro Giordani: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Luca Mari:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that there are no conflicts of interest related to the content of this work. No financial, personal, intellectual, or professional relationships exist that could have influenced the outcomes or interpretations presented in this document.

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Data availability

No data was used for the research described in the article.

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