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Experimental analysis of behavior assisted by artificial intelligence: Towards a multidisciplinary paradigm shift

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The main purpose of *Behavioral Science*[1] (BS) is to explain and predict ontogenetic or individual behavior, understood as a system of interdependent relationships between states and patterns of activity of the organism and its ecological-social environment.

BS's seminal works were distinguished by the creativity involved in developing situations for systematic observation, as well as their incorporation of the cutting-edge technological advances of the day (for a detailed review, see Watson, 1914). These observation situations were aimed at various patterns of organismic activity, such as the manipulation or operation of objects in problem boxes, movement patterns in learning situations under appetitive or aversive stimulation, and orientation patterns, among others.

As is well known, after a period of maturation of BS, operant conditioning (Skinner, 1938), also called *experimental behavior analysis* (EBA), established itself as the dominant paradigm, and one of the reasons for this was the parsimony of its explanatory and predictive system, derived to a large extent from the distance taken from concepts that: (a) could not be operationalized, (b) did not correspond to observed behavior, or (c) appealed to unobservable entities as the *cause* of the behavior.

Complementarily, this paradigm prioritized the development of a methodological system that would make possible: (a) the systematic and objective recording of behavior, (b) the controlled presentation of stimuli, (c) the identification and analysis of the functional relationships between the organism's behavior and the *reinforcement schedules*, and (d) the control of those variables that could interfere with the observation of the phenomenon of interest.

The above was materialized in the ingenious development of an instrument that marked the history of BS: the *operant conditioning chamber* and the implementation of the *cumulative record*. With this revolutionary methodological paradigm, behavioral recordings were made in an automated manner through mechanical and electronic switches, while data analysis and representation focused on the frequency and temporal distribution of the activation of those switches. This gave rise to the paradigmatic dependent variable of operant conditioning: the *response rate.*

Although the scientific achievements of the *operant conditioning* paradigm (OC) cannot be overlooked, it naturally has not been free of criticisms. The sharpest are those that arise from within the disciplinary community –or internalist criticisms–, among which we can cite, for example, that this paradigm: (a) limits the analysis of complex interactions

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1. "Behavioral science" is used by economics to refer to the "science of individual behavior" or "scientific psychology." The concept "psychology" is not used due to its well-known disciplinary ambiguity in terms of phenomena of interest and research methods. The well-reputed concept of "experimental behavior analysis" in its standard usage is fundamentally tied to the "operant conditioning" paradigm. The "experimental analysis of behavior" is considered as an instance, perhaps the most outstanding and commendable of "behavioral science".

between different response patterns (see Henton & Iversen, 1978); (b) neglects the relevance of the spatial dimension in the organization of behavior (see León et al., 2020; León et al., 2021); and (c) disregards the ecological dimension of behavior (see Timberlake, 2004).

These limitations have been pointed out as a consequence of the intrinsic characteristics of what was once the methodological exemplar that revolutionized BS (Henton & Iversen, 1978). But, let us be fair, in the 1930s, the EBA represented the scientific and technological vanguard in BS. The question is: more than eighty years later, can that still be the case? The answer is a resounding no.

The subsequent natural question is whether the limitations referred to above can be overcome, either in the particular framework of the EBA or in the general framework of BS; of course, considering that overcoming them would imply integrating: (a) the recording of multiple discrete responses; (b) the moment-to-moment recording of the animal's movement (c) the development of appropriate apparatus given the bioecological characteristics of the organisms; (d) the moment-to-moment analysis of multidimensional data; (e) the integrative representation of multidimensional data; and (f) the explanation and prediction of multidimensional data.

Integrating all the aspects listed in a methodological paradigm is a scientific aspiration that until very recently could have been considered unattainable. However, the advances achieved during the last decade by artificial intelligence (AI) –computer vision, machine learning, deep learning techniques– and mechatronics (MT) –3D printing, sensors, actuators and low-cost microcontrollers such as Arduino™– today make it affordable, even for laboratories with modest budgets, such as those in our region, Latin America. Based on these advances, it would be possible to perform both the recording of multiple discrete responses (a) and the design of suitable devices given the bioecological characteristics of the organisms (c), especially if *ad hoc* interfaces developed with low-cost components, such as Arduino™, are used (Escobar & Pérez-Herrera, 2015).

In fact, one of the areas with the greatest development in recent years has been the *tracking* of objects by *computer vision*. Until very recently, the standard tool for monitoring organisms was proprietary software that was not easily accessible to many researchers > €4,300 in 2018 for *tracking* a single organism. However, today the most robust *tracking* systems are free and even open source (Datta et al., 2019; Mathis et al., 2018; Mathis & Mathis, 2020; Walter & Couzin, 2021), and allow not only tracking and recording the position of one organism (b) but of several organisms, moment by moment, based on their center of mass, as well as making direction records, pose estimation and activity sequence records. All this in an automated way and with reliability similar to or greater than that of a trained observer.

Although there are some incipient advances, the integration of discrete responses and continuous data obtained with the organism's *tracking* systems is still meager. However, advances in *machine learning* such as *t*-SNE, PCA, UMAP, and *Variable Ranking* provide robust and useful tools to implement a multidimensional approach that integrates these two types of data (for a more detailed description, see León et al., 2021). Such multidimensional analyses, in addition to integrating different behavioral variables as a unitary system, have shown that, in such a system, variables embedded in the spatial dimension –e.g., location entropy– can be even more sensitive to *stimulus schedules* than discrete responses typically considered as dependent variables.

Now, so far, EBA –with few exceptions– has not benefited from the tools described above, and this is so not only in our region but also in the English-speaking community of *experimental behavior analysts* –see, e.g., the special section of *Perspectives on Behavior Science* (Jarmolowicz et al., 2021), in which fellow analysts are urged to "think outside Skinner's (sic) box"–.

This editorial is a proposal and an open invitation to participate in the novel multidisciplinary approach of experimental behavior analysis (EBA) with artificial intelligence (AI) and mechatronics (MT), which could be called computational-experimental analysis of behavior (CEAB), and its purpose is to motivate Latin American researchers to make contributions to the journal *Acta Colombiana de Psicología*, so that, together and through critical discussion based on methodological developments and data, we delineate the future of our paradigms, and also contribute, among other things, to: (a) broaden the scope and reach of EBA; (b) deepen our understanding of behavioral phenomena; (c) crystallize a more integrative, comprehensive and encompassing methodological approach; (d) open up new research possibilities; (e) push the methodological and conceptual boundaries of EBA; and (f) conduct genuinely cutting-edge research in EBA.

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