# Physical learning analytics: a multimodal perspective

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## ABSTRACT

The increasing progress in ubiquitous technology makes it easier and cheaper to track students' physical actions unobtrusively, making it possible to consider such data for supporting research, educator interventions, and provision of feedback to students. In this paper, we reflect on the underexplored, yet important area of learning analytics applied to physical/motor learning tasks and to the physicality aspects of 'traditional' intellectual tasks that often occur in physical learning spaces. Based on Distributed Cognition theory, the concept of Internet of Things and multimodal learning analytics, this paper introduces a theoretical perspective for bringing learning analytics into physical spaces. We present three prototypes that serve to illustrate the potential of physical analytics for teaching and learning. These studies illustrate advances in proximity, motion and location analytics in collaborative learning, dance education and healthcare training.

## CCS CONCEPTS

• **Information systems** → Data analytics; • **Human-centered computing** → Visualization design and evaluation methods

## KEYWORDS

physical spaces; mobility tracking; motor learning; classroom; wearables; indoor positioning; internet of things

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## 1 INTRODUCTION

Learning is ubiquitous; hence it goes beyond students' interacting with a particular digital interface. It may for example occur while students interact face-to-face (f2f) with peers or their teachers. Some asks may require students to interact with an ecology of non-digital tools; use the physical space indoors and outdoors; or learn in ways that cannot be mediated by typical user interfaces as they involve the psychomotor domain. However, a large number of data-driven educational innovations that offer some sort of adaptation, personalisation or automated feedback mainly rely on the analysis of logged learner's interactions (e.g. clickstreams) with particular user interfaces [16]. This can inadvertently lead to overlooking at least two dimensions of learning which are also crucial for the full development of a lifelong learner: 1) physical/motor learning tasks aimed at promoting the development of kinaesthetic skills (e.g. dancing, playing an instrument, learning a clinical procedure, improving athlete's technique), and 2) the physical aspects of 'traditional' intellectual tasks (e.g. f2f group work, classroom dynamics, teacher's activity). Some exceptions beyond this centre of interest can be found in multimodal (generally conducted under lab conditions so far) and affective learning analytics approaches (see reviews in [1] and [2] respectively).

Similarly to the paradigm of Internet of Things (IoT), *physical computing* innovations pursue the idea that almost any object and person within a physical space can be embedded with computational capabilities to connect them with each other in such a way that the communication is always available [3]. Besides the clear potential for supporting learning across different spaces (e.g. [9]), these capabilities can also be used to sense physical aspects of learning. These include *proximity* (e.g. the relative distance to a particular section of the classroom or to peers and objects), *motion* (e.g. body movements performed in kinaesthetic activities), and *location* (e.g. the position of students or teachers in the learning space). This means that students' data can now include these physical aspects, which can lead to a broader, richer understanding of learning experiences. These physical aspects can be considered in different learning situations such as: 1) face-to-face collaborative learning [18]; 2) tracking location and motion while carrying out the learning activities [14, 15]; 3) augmenting the learning content within the physical context [13]; and 4) supporting learning motor skills [17].

This paper suggests a theoretical perspective for bringing physical learning analytics into the physical learning space. Whilst multiple streams of data could be sensed (e.g. speech/noise, gestures, gaze, etc.) in this paper we particularly focus on three dimensions directly associated with the use of the learning space: proximity, motion and location. We discuss the foundations underpinning our theoretical perspective, namely Distributed Cognition theory (DCog), the concept of physical computing/IoT, and Multimodal Learning Analytics (MMLA). We have made in-roads towards this perspective with three prototypes deployed in authentic settings and through which we illustrate the potential of such analytics for teaching and learning.

The paper is structured as follows. Next section discusses the connection between DCog and IoT and a brief discussion of current advancements in the area of physical learning analytics in MMLA.


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Sections 3 and 4 present the theoretical and applied sides of our physical learning analytics perspective. The paper concludes with a brief discussion of current and future implications.

# 2 BACKGROUND

## 2.1 DCog, IoT and the Physicality of Learning

There has been an emphasis in learning analytics research and development in carefully connecting the technological and data-related aspects of learning analytics with wider strong educational theories [4] or with the pedagogical intent made explicit as a learning design [10]. In terms of learning in the physical space, there exist alternative theories aimed at explaining human activity situated in a specific context (e.g. situated cognition, activity theory, etc – see brief review of these theories applied to ubiquitous computing systems in [12]). Particularly, one of these theories, DCog, considers how the boundaries of cognition are not limited to the learners' minds but is rather expanded through external representations (e.g. metaphors, language) and interactions with other people situated in a sociocultural context [8]. In education, DCog has served to explain how students interact with other **people** (e.g. learners, teachers, learning designers - at different *planes* namely, individual, small group, class, etc) and **artefacts** (digital and physical: tools, resources, content, etc), in the physical **space** (environmental conditions, digital spaces, the notion of the body using the space, furniture) and across **time** (considering previous experiences and forward-oriented actions).

The recent and rapid progress in pervasive and ubiquitous computing technologies has made the DCog perspective of learning very relevant for learning analytics. IoT or physical computing innovations can become the technological counterpart to theoretical views of learning that embrace the complexity of the learning space understood as an interconnected network of people and artefacts [3]. Particularly, the three main dimensions of IoT can serve as a means to provide analytics support in physical learning spaces: 1) any **thing** (people and artefacts in DCog) connection (human-to-human, human-to-thing, thing-to-thing); 2) any **place** connection (the physical space in front of a personal computer, indoors, outdoors); and 3) any **time** connection (day, night, on the move) [5].

In short, the confluence of strong situated learning/human activity theories (such as DCog) and the IoT technological capabilities to ubiquitously sense the physical world can be of key importance for modelling critical physical aspects of learning and the learning spaces. Fig. 1 summarises how the "anywhere, anything, anytime" connectivity offered by IoT matches the notion of DCog. We emphasise that digital spaces and artefacts belong to the physical realm (e.g. digital artefacts and virtual spaces are accessed via physical devices situated in physical spaces).

## 2.2 Multimodal learning analytics

MMLA approaches are aimed at combining multiple data processing technologies (e.g. image processing, text mining, signal processing, biosensing, machine learning, etc) to gain a more holistic understanding of complex learning behaviours [1]. In the last few years, there has been an increasing interest in applying MMLA techniques in quite varied ways that the mere definition of MMLA has broadened. Most of these efforts have focused on enabling researchers to build more complete models about the actions that learners perform with a richer set of indicators (e.g. facial expressions, verbal intonations cues, eye gaze, content of dialogue/writing, physiological and emotional reactions, etc.). Less attention has been given to including other contextual aspects of learning associated with the physical space, such as location and proximity - with some exceptions such as the preliminary work in [7]). As of yet, most MMLA studies have been conducted under controlled laboratory conditions (e.g. see recent preliminary attempts in [1, 13]) and, still, some rely on complex set ups that often make them impractical for immediate deployment in classrooms under realistic conditions (e.g. without the support from a human experimenter). Thus, our work sits in a design space where much work is still needed to find ways in which MMLA approaches can solve challenges in realistic, mainstream scenarios.

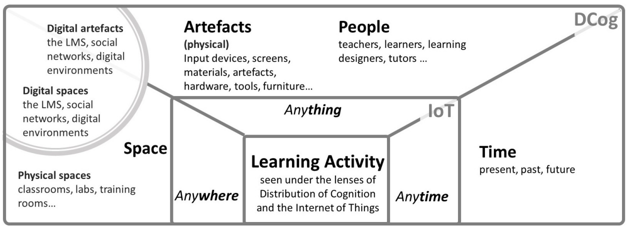


**Figure 1: Aligning DCog and IoT to see learning activity as an opportunity for multimodal physical learning analytics.**

# 3 THEORETICAL PERSPECTIVE

Following a top-down approach for bringing learning analytics into the physical world may allow us to build some theoretical grounding that can drive the technology development. Our proposed physical learning analytics theoretical perspective is depicted in Fig. 2. Based on DCog, and to facilitate clarity, the figure depicts an individual (e.g. a learner, a teacher, a tutor, etc.) situated in the **physical learning space** (e.g. a classroom, a science lab, a training room, outdoors space, a dance studio, etc. – represented in Fig. 2 as the larger upper bounding rectangle). Within the actual physical space, we can have other **people** and **artefacts** (both digital and non-digital: devices, screens, materials, tools, furniture etc.). Some of these artefacts can serve as the 'portals' to the **digital space** (or spaces). For example, a personal computer or a mobile device (a physical artefact) can provide a range of functionalities (via digital artefacts such as software programs, tools, websites, etc.) to allow individuals or cohorts to connect with other people remotely, to have access to digital resources and services such as documents, tools, media, etc. via a formally institutionalised learning management system or a set of heterogeneous (connected or isolated) personal learning environments. This digital realm is represented in Fig. 2 as the smaller lower bounding rectangle. **Time** is also a critical element because products of earlier events can shape the meaning of present and future events. Thus, temporality is a critical aspect for learning analytics sense-making.

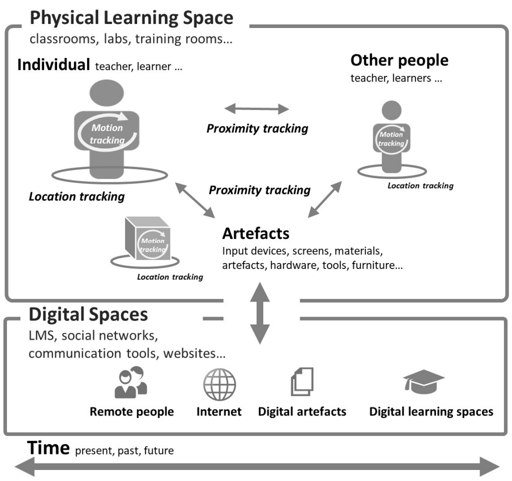


**Figure 2: A DCog/IoT perspective for bringing learning analytics into physical spaces through location, motion and proximity tracking.**

As the individual interacts with other people and artefacts in this physical learning space, **proximity** tracking, along with additional contextual data, can provide a way to deepen understanding of the cognitive processes distributed across learners and educators; and the material or digital infrastructure. MMLA techniques (such as **motion** tracking and others) can shed light on the embodied actions that people perform during the learning activity whilst interacting with people and artefacts. This kind of 'inner' tracking, when performed ecologically across people and artefacts, can make visible the coordination of the enactment (for example of the learning design) among people and artefacts. The **location** of people and artefacts can also be tracked to understand the role that each play within the learning space, understand the space usage, and map the journey of each individual and artefact in the space.

This paper is focused on activity occurring at one physical space at a time due to space limitations. Additionally, our examples illustrate activity happening in particular learning spaces. However, a deeper analysis of activity across learning spaces (e.g. connecting learning happening at home, at the library, etc) and the bridge between the physical and digital realms can be hinted in this perspective, since that is the ultimate goal in both DCog theory and IoT technical perspectives.

## 4 PHYSICAL LEARNING ANALYTICS PROTOTYPES

In this section, we present three prototypes that illustrate the feasibility and potential of 1) proximity analytics in a collaboration classroom; 2) motion analytics for dancing education; and 3) location and stress analytics for life support training. Each prototype is developed to support teaching and learning in distinctive classroom arrangements. Each is divided into three parts describing: i) the learning setting in terms of DCog; ii) the IoT sensors; and iii) an illustrative analytics scenario (with an interface prototype and its context of use).

### 4.1 Proximity Analytics for Classroom Teaching

**Learning setting**. The first prototype is useful for classrooms that favour tasks where students construct a learning situation in small groups. For example, Fig. 3 (left) shows one type of furniture arrangement pervasively present in classrooms in some higher education institutions. In these classrooms, the teacher(s) commonly walks around, monitoring and assessing team-based tasks, and providing feedback to the whole class or to one group at a time. The teacher generally has access to a personal computer (located at the middle of the classroom in our example). In other words, this example depicts how distribution of cognition happens across the **people** involved in the classroom at multiple planes (individual, small groups, and the whole class); and the **physical artefacts** (e.g. screens, computers, materials and devices) which can also facilitate access to **digital** artefacts (e.g. teacher's tools and materials as well as those used at each table). One of the critical challenges for any teacher in this type of environment is deciding how to assist students evenly, while supporting the students that need most attention and, at the same time, keeping awareness of the overall state of the classroom.

**IoT sensors**. Although the above challenges can be quite complex for the teacher, we aim for a first step towards making the traces of physical classroom usage visible to the teacher in real-time and for post-hoc enquiry. We intend to leverage the sensing capabilities of the classroom by embedding ultra-wide band (UWB) positioning tags (see Fig. 3-left the actual tag circuit) into tangibles (to be put inside a cardboard or 3D printed box) that can be located on furniture by the teacher(s) or be worn in their pockets). These tags can be placed by the teacher at the beginning of the class on the tables where there are students seated, thus automatically ignoring the empty ones.

**Analytics scenario.** Fig. 3-centre shows a low-fidelity prototype of the kind of teacher's dashboard we are building to exploit the location and proximity data automatically captured by the sensors in the classroom. The prototype shows a heatmap according to the teacher's physical presence in the empty space of the classroom. The size of a hexagonal dot on the classroom map corresponds to the time spent by one teacher at that location, while its colour can depict qualitative aspects such as speech detected (if a lapel microphone is used) at that location. Proximity data can be used to estimate the time the teacher attended specific groups working at the tables. This way, the most neglected tables can be highlighted (e.g. see tables 5 and 6 coloured in orange). Additionally, the prototype illustrates how we are designing pop-up suggestions or alerts that can be automatically triggered to recommend the teacher to walk around more often or distribute his/her presence more evenly across students. In terms of research and teacher's modelling

Fig. 3-right shows a transition diagram generated (from real data captured by an observer) in one of the classroom sessions where the teacher had to monitor four teams (1-4) using an analytics dashboard, detailed elsewhere [11]. The nodes correspond to the time the teacher dedicated to each team, to looking at her Dashboard, or to monitoring the Whole Class. The directed arrows between nodes represent the transitions recorded by an external observer (45 transitions registered in this example). The diagram indicates that the teacher devoted most time to the *third* team (32% of attention time) compared with the others (20%, 26%, and 21% for teams 1, 2 and 4). In fact, the teacher assessed the Team 3 as the only *low achieving* team in the class, therefore confirming that the attention in this class was not equally distributed. The teacher never attended to team 1 after looking at the dashboard (no transition line from *Dashboard* to *team 1* node). This can motivate further exploration to start uncovering patterns of teacher attention and also to measure the impact of teacher feedback. Further analytics about physical


**Figure 3: Left: IoT proximity/location sensors and a dashboard to be deployed in an authentic classroom. Centre: Low-fidelity prototype of a physical proximity analytics teacher's dashboard. Right: Example of a state diagram representing the teacher's tracked proximity data at an authentic small group classroom session.**

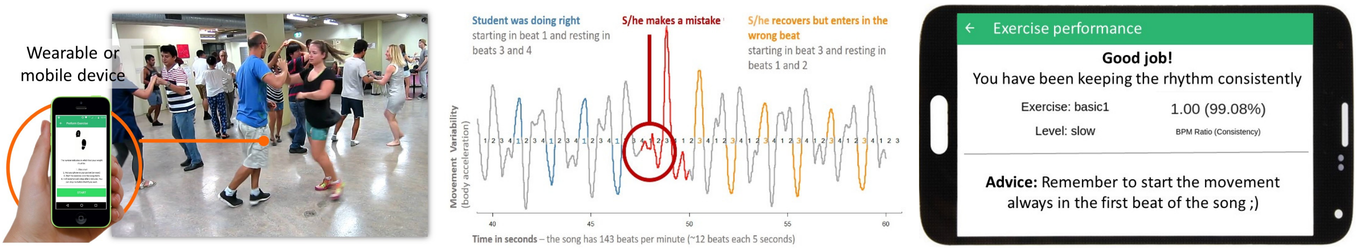


**Figure 4: Left: A wearable motion sensor or a mobile device used to track learner's movement while dancing. Centre: A motion time series representing a student shifting to the wrong beat of the music after making a mistake. Right: Prototype of the interface to provide narrative feedback on a dancing mistake.**

space usage could be explored by triangulating proximity/location data, with other sources of data such as the people counting devices already installed in our classrooms (see Fig. 3-right) or traces from the expected learning design that can help explain the data.

## 4.2 Motion Analytics for Social Dance Education

**Learning setting**. The second prototype is being developed to provide automated feedback to dance students whilst or after they practice Forró dance in a dancing studio or at home. In social dance learning, one key skill for students to learn is how to follow rhythm with their bodies. Teachers commonly demonstrate to the students how to move with the song (e.g. see Fig. 4-left); sometimes they explain what to do using words or physical contact with students. These different techniques require time and effort from the teacher, and do not scale up well for large classes. With current and easily available technology, it may now be possible to track students' **motion**, using wearable sensors, with high precision and accuracy. In this learning situation, the distribution of cognition occurs as learners connect visual and gestural practices (that they observe in other **people** such as peers or the teacher according to the **temporality** of music) with rhythmic and gestural structures of their **bodies** and support **artefacts** (e.g. the mobile learning application depicted in Fig. 4-left, and the music as an intangible artefact).

**IoT Sensors**. Motion data collected can generate information that can potentially help teachers and students reflect on possible mistakes and aspects that need to be improved [6]. A dance support mobile application that provides a series of exercises for improving rhythmic dancing skills illustrates this case. The accelerometer embedded in the mobile device tracks students' motion while performing dance exercises and provides feedback about the rhythm consistency. Due to the repetitive nature of the exercise, the data collected from the devices generate a wave with a periodic pattern that can reveal useful information.

**Analytics scenario**. Fig. 4-centre shows a motion time series obtained from real data representing the beat stream of a song (intangible artefact) interwoven with the learner's dancing movements in time. Forró songs have a quaternary tempo (1, 2, 3, 4) to which the dancers need to synchronise their steps. In this exercise, the student needs to perform a movement in an 8-beat pack associated to specific steps and weight transfers. Fig. 4-centre illustrates three patterns: the first part shows that the student performed the movement in correct rhythm, going forward in the first beat of the song (e.g. first peak contoured in blue), changing the weight on the second beat (a valley after the first peak) and resting the hips on beats 3 and 4 (double-peak). The second part, contoured in red, shows that the student stopped being in rhythm and moved out of beat. The third part, contoured in orange, shows that the student tried to recover from the mistake, by following the rhythm of the music again, but starting on the third (wrong) beat of the song. This is a common mistake for social dance students as they are progressively learning how to recognise the song beats. Using our in-house algorithm and rules to interpret the accelerometer data, we now can automatically detect this and other types of patterns and provide direct feedback about what actions students need to perform to improve (e.g. see the interface prototype in Fig. 4-right). With a more detailed analysis, other features can be extracted from these data that can provide dance teachers with a better understanding of their students' common mistakes and adapt or improve their classes.

## 4.3 Location Analytics in Healthcare Education

**The learning setting.** The third prototype is being rolled out in healthcare simulation classrooms equipped with 5-6 quite sophisticated patient manikins placed on clinical beds that produce various indicators of a patients' health, respond to and log actions performed on them, and can be pre-set to deteriorate over time. These manikins are commonly used for teaching medical procedures in scenarios such as emergency response situations (e.g. see nursing students enacting a simulated cardiac arrest scenario in Fig. 5-left). This scenario is quite complex in terms of DCog. **People** are commonly organised in small teams and have to apply their health care knowledge and skills (e.g. procedural, communication, teamwork) while enacting a role (e.g. a leader, a person responsible to bring medicine, etc.) and different procedures should be carried on by each one. Learners have to interact with several **artefacts**, including medical equipment, medicine, furniture (e.g. raising/lowering the bed or closing curtains to apply some procedure), paper-based patient's documents, digital devices (e.g. vital signs monitors, defibrillator machines, personal devices). The **time** dimension is critical too as nurses' cognition generated in one working shift gets physically represented on paper or digitally and passed to the nurses in the next shift. At a fine-grained level, **time**

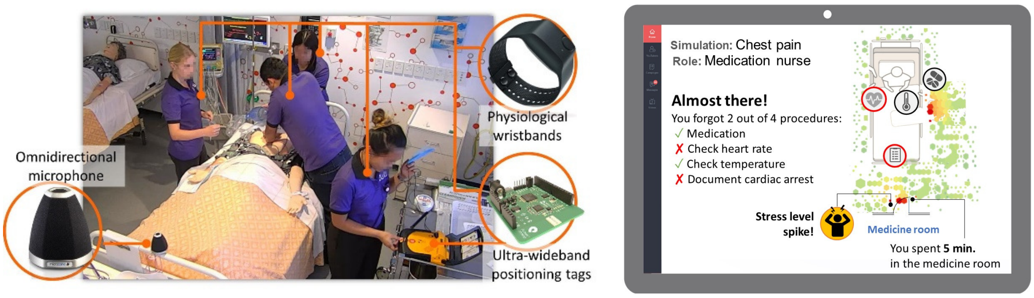


**Figure 5: Left: location, physiological and audio sensors deployed in a healthcare simulation classroom. Right: Prototype of a reflection tool tailored to provide feedback to a specific healthcare team member after completing the scenario.**

and **space** management can also be critical. In an emergency response scenario, nurses have to react according to a defined protocol so they need to perform specific actions and be at specific locations around the bed. For example, during a cardiac arrest, nurses need to perform actions such as the cardiac massage and airflow compressions timely whilst coping with the stressful situation of dealing with people's lives in risk. The challenge here is that, although students are required to reflect about the task, they do not have access to any evidence about how they performed.

**Sensors**. Besides the logs produced by the manikins, simulation classrooms can be equipped with ultra-wideband positioning tags can be worn by each student or attached to physical instruments to analyse how students interact with people and artefacts. Stress levels can be measured through physiological wristbands that can sense electrodermal and blood volume variations. From these sensors, we can synchronously calculate heart rate, sweating levels, temperature among others. Finally, audio can also be captured trough an array microphone located near the bed in order to analyse speech interactions among students and with the patient.

**Analytics scenario**. In a recent participatory design, students expressed the lack of personal and/or group feedback once they finished the simulation scenario. Students also commented that they would be keen to use these analytics if they could make visible procedural oversights or delays (e.g. long time spent to get medicines or special equipment such as defibrillator). Stress levels can be mapped to instances where the task becomes difficult. Furthermore, audio could help visualise student-patient verbal and non-verbal interactions with the aim of nurturing their communication skills. Fig. 5 (right) presents the interface prototype for a reflection tool as a result of these design conversations with students. This particular low-fidelity prototype is aimed at providing individual feedback to one student enacting the role of an auxiliary nurse who has the duty of helping the leading nurse during an emergency response scenario. The interface shows symbolic location information tracked by the positioning tags indicating where the nurse spent most of her time (see heatmap) and critical events recorded via proximity tags (see icons for each event). The location data can be contextually enriched by adding information captured by other sensors (e.g. see the stress spike symbols that can be identified using the physiological wristbands) and activity logs.

## 5 CONCLUSION AND FUTURE WORK

With the increasing availability of affordable mobile and pervasive devices, and multimodal sensors, we can make in-roads towards coupling different data science techniques for the rapid analysis of emerging large datasets. This opens the possibility that contexts in which learners' proximity, location and motion are important need not be invisible to computational tracking. While these exciting technologies can certainly enable new forms of educational research, theoretical foundations for aligning these analytics to the intended pedagogical goals will be also critical. In this paper, we have suggested a theoretical perspective for bringing learning analytics into classrooms and similar learning spaces. A theoretical foundation, such as DCog allied to the technical lens of IoT allowed us to embrace the complex relationships that exist between people, artefacts, space and time, in the physical and digital realms. This interconnection includes the role of data as a critical actor in making physical aspects of learning visible. The prototypes presented helped illustrate how the physical, epistemic and social dimensions of each learning situation strongly shape the kind of sensors, analytics and interfaces required in each physical space.

In sum, we see a challenging but exciting transdisciplinary space emerging. Our proposed perspective should be seen as a first step toward a more holistic, comprehensive view of learning analytics. Undeniably, there are challenges and obstacles lying ahead, requiring the cooperative engagement of the learning analytics community jointly with experts in the learning technology, data mining and machine learning communities, as well as the growing body of societies concerned with the ethics of algorithms (e.g. the Council for Big Data, Ethics & Society bdes.datasociety.net). The potential for inappropriate surveillance is clear, as is the risk that the algorithms used be opaque to questioning. Future work should not only focus on developing the tracking technologies and the analytics approaches, but also to build a sustainable data pipeline for collecting, processing and analysing data from multiple sensors and explore the ethical issues that can particularly emerge with physical learning analytics.

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