Human-Centric Processes: Where IoT and People Meet

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Abstract. "Human-centric processes" (HCPs) heavily involve human beings. Humans can partake in an HCP by *observing* and *interacting* with some socio-technical system, such as a supply chain or a hospital. These two actions are also at the core of IoT, where digital systems observe *things* by using sensors and interact with *things* utilizing actuators. Human-centric processes bring together observations and interactions from both humans and IoT.
HCPs can be studied from different points of view. In light of the increasing adoption of process technologies (in particular, process mining), we argue that it is crucial to study how existing process lifecycles can be adopted in the context of HCPs.
This chapter will focus on the challenges and opportunities emerging in modeling, discovering, checking for conformance, and enacting human-centric processes. Two case studies will be used to describe the opportunities, one referring to logistics and the other referring to personalized medicine. Based on these, we will provide a vision of the lifecycles of human-centric processes and the role of IoT in them.

Keywords: BPM · IoT · Process Mining · Conceptual Framework · Case Studies

1 Introduction and Background

Traditional workflow management systems (WfMS) made it easier for humans to participate in business processes and to manage and control them. To this end, humans were required to explicitly interact with computers through dedicated user interfaces. The workflow reference model [32] identified two main user interfaces of WfMSs for this purpose: the work list shows available work items to the humans, who have the authority and capability to work on them. When available, the human can then pick a work item from the work list, and this way start the respective activity; the activity itself is associated with an application, which will automatically be started by the WfMS, when human picks a work item; and the user interface of this application is then used to do the actual work on the activity.

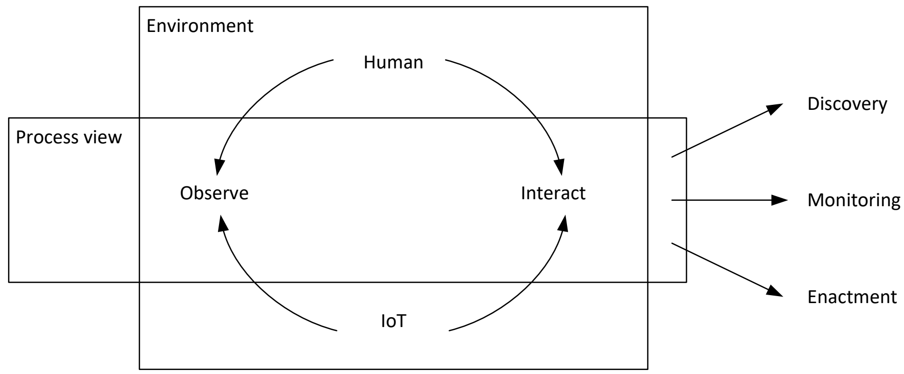

Fig. 1. Overview of the interplay between humans, IoT, and business processes

The idea of the Internet of Things (IoT) is that humans no longer need to explicitly provide information and interact with a computer, but that IoT devices would collect that information automatically [4]. In this way, humans can knowingly or unknowingly be part of business processes without actively or explicitly interacting with computers or communication devices; their participation could be by some IoT devices providing them with some information and by IoT devices perceiving the human behavior; humans could just "be themselves" and part of some processes. We call such processes human-centric processes (HCPs).

Figure 1 gives an overview of the interplay between humans, IoT, and business processes. Both humans and IoT devices are immersed in an environment, which they both can observe and interact with. In addition, framing the actions of observing and interacting with the environment in the context of BPM makes possible to use existing tools and techniques in this discipline. For instance, the observations being collected can be used by process discovery algorithms to determine the causal relations of events. Such observations can also be used by process monitoring tools to identify deviations between the expected execution of a process and the real one. Interactions can be coordinated by a Process Aware Information System (PAIS) so to ensure the enactment of a process to happen as specified in a process model.

This overview can then be refined as shown in Figure 2. In particular, we distinguish the environment into a set of perceivable things (e.g., the weather) and a set of actionable things (e.g., the ideas that emerged during a meeting). It is worth noting that the two sets can overlap, as things can be both actionable and perceivable (e.g., a self-driving car). IoT devices, similarly to humans, can then sense perceivable things and actuate actionable things through sensors and actuators, respectively. On top of that, IoT devices can communicate with a PAIS to provide information on the status of a process and to request a specific action to be taken.

It is worth noting that humans do not communicate directly with the PAIS. Instead, they do so by sensing and actuating the environment. In this view, IoT

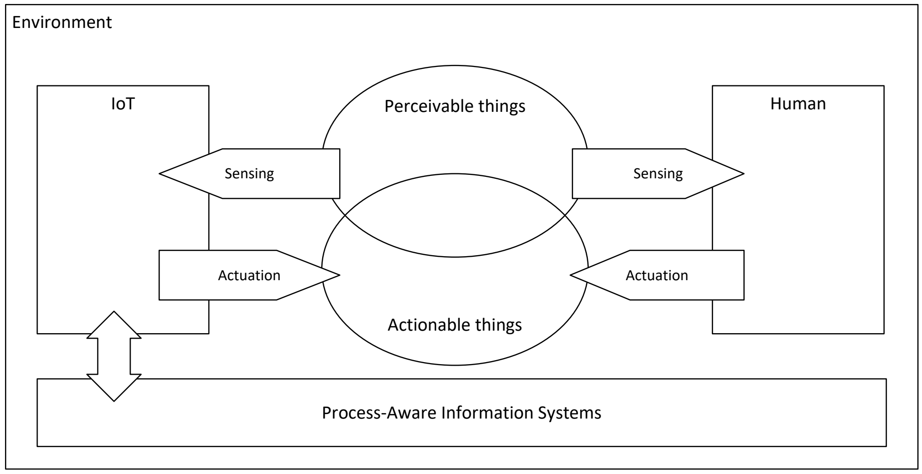

Fig. 2. Actionable overview

becomes the main interface between the PAIS and the human. It is also worth noting that, in IoT, we also include any device capable of interfacing with the human and the PAIS through the environment. For example, an IoT device could simply be a light bulb to tell the human to take a specific action, or a switch to be pushed to inform the PAIS that a task has been completed.

In this chapter, we discuss how IoT can be incorporated into the conventional BPM and PAIS landscape to make processes human-centric, based on the original idea of WfMs from the 90s. We do that in two steps. We provide a conceptual model for the relationship between IoT and BPM, and then we provide two use cases.

When focusing on the relationship between IoT and BPM, it is important to mention that one key aspect of HCPs is flexibility: IoT provides an interface between human actors and the BPM system, which means that the need to have fixed rules that organize the work of human actors is not a hard requirement anymore; instead, it is expected that human actors perform their activities and the system reacts to them.

In the use cases part, we present different ways for processes to be human-centric (cf. Fig. 3). Specifically, the first use case, which is in the logistics domain, heavily relies on humans as they have a very active role in the process. In the second use case, focusing on healthcare, the human *is* the actual process under investigation. The two use cases complement each other and offer a comprehensive overview of human-centric processes.

Related works. To reflect on the various relationships between IoT, process management and mining, and, ultimately, human-centricity, we briefly discuss

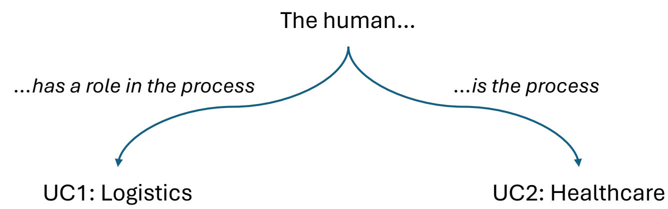

Fig. 3. Visual representation of the two classes of use cases reported in this chapter.

some recent works in these areas that may be relevant to the subjects covered in this chapter.

Conceptual Models for BPM in relation to IoT. Our investigation can start from the basics of conceptual models for BPM (and its extensions), including *why* we need such models (e.g., UML diagrams are crucial when implementing WF management systems/ PAIS).

A paper by Leotta et al. [42] discusses a BPM engine architecture capable of capturing and processing exogenous, unexpected events using IoT sensors so that executed processes can have higher degrees of adaptivity and reactivity. In Section 3, the paper discusses a conceptual architecture of their framework, highlighting how to automatically adapt processes at run-time when unanticipated exceptions occur in IoT-based environments and how to avoid explicit recovery specifications. Becker et al., in [7], propose a conceptual model to describe the digital shadows of manufacturing processes. The conceptual model, in this case, includes traces generated from multiple sources, as well as different types of process models. The role of the human is limited to a data source, not considering its influence on the operation of the process. [30], by Frigo et al., introduces the notion of *building blocks* and *building block implementations* for IoT processes. Building blocks are general structures that can be later refined for physical devices, network protocols, or software applications, among others. Such building blocks will contain a software artifact defining its operation. Building blocks are later orchestrated by a process management engine. However, no notion of humans in the loop is presented in this work. Berges et al., in [8], present an ontology that captures how the sensors relate to indicators about the performance of an industrial machine. This ontology focuses on the sensing aspects and does not consider the human in the loop. In [60], Vila et al. describe the Connectivity Management Tool Semantics (CMTS), an ontology aimed at allowing digital tools for monitoring physical infrastructures through the use of IoT devices: gateways, nodes, and sensors. The focus is more on the sensing aspects, and there is no mention of the implications of human participants in the process. Differently from the previous works, [3] introduces a conceptual architecture that handles both self-awareness and IoT sensors. This architecture considers both sensing and actuating phases, as well as the role of models in the reasoning and execution of processes. The impact of humans is not explicitly mapped, although one can see that its impact could be mapped into external sources in an environment.

Human-centricity in BPM. One of the recent surveys [61] identifies the human-centricity in IoT as "an approach that can meet the needs of communities served by IoT technology and that helps to find out what technically works best for humans and society first and foremost." While, as the same survey suggests, there is no agreement in the scientific communities studying IoT what "human-centricity" actually stands for, the BPM community has considered human-centricity in two major contexts. First, human-in-the-loop is a standard approach in workflow automation scenarios where domain experts can intervene at specific stages to resolve errors, make decisions, and guide the process execution [34]. Second, approaches that allow the development of systems and solutions that are proactive and can anticipate or accommodate the needs of human actors have been extensively studied by the BPM community [19]. Finally, Lee et al, in [41], discuss ethical aspects of human-sensing frameworks, including those driven by IoT.

IoT and BPM and Process Mining. It has been acknowledged that the integration of the Internet of Things with Business Process Management can enhance business processes by increasing flexibility, efficiency, and responsiveness by collecting and acting upon real-time data with the help of IoT sensors and actuators. In fact, the recent "BPM meets IoT" manifesto [35], suggests that BPM and IoT domains can mutually benefit from each other: BPM can rely on IoT as a data-centric and data-intensive technology that can improve business processes, both at design- and run-time; IoT can use well-defined processes and event data to improve automated decision-making.

Following the aforementioned manifesto, [51] studies an industrial use case showing how process adaptation and process mining - a sub-discipline of BPM that focuses on interpreting event data to understand and improve business processes - can be applied in the context of Industry 4.0, whereas [16] presents a systematic literature review on the adoption of IoT-aware BPM solutions as well as their maturity through the prism of challenges identified in the manifesto.

Recent research in both BPM and Process Mining reveals a growing interest in IoT adoption in these fields. [11] proposes a conceptual model that mixes the event-data realm with data coming from physical IoT devices. The model can then be used in developing new and/or adopting existing process mining techniques for scenarios involving IoT. Diamantini et al., in [20], propose an ontology for process-aware scenarios in the Industrial Internet of Things, where raw sensor data is augmented with details about process activities and the physical production environment.

Some of the works also propose extensions of existing conventional process modeling formalisms and notations with specific IoT elements, where some of the approaches propose well-defined conceptual extensions of BPMN with location-aware elements [53], while others propose concrete extensions of the BPMN 2.0 metamodel [39,40] and show how such extensions can be employed in complex decision-making tasks driven by DMN [38]. Other works focus on more generic frameworks for adopting IoT in process-aware systems (e.g., [31] proposes a framework for process-aware cyber-physical systems allowing the integration of IoT environments and human actors into higher-level process-oriented systems).

Moving closer to Process Mining topics, [12] proposes an approach for multi-perspective trace clustering that is applied to logs enriched with time series sensor data; [29] addresses the topics of monitoring and conformance checking in IoT-driven PAIS, and suggests a conceptual event-centric metamodel which only assumes observability of low-level events from IoT devices that can be easily linked to a concrete process. Some of the recent works propose IoT-aware extensions of event data by either building on top of existing formats like XES [45] or by proposing new, conceptually well-defined solutions [11,9] with their further adoption and validation in practice [10].

2 Human-Centric Conceptual Model of BPM Using IoT

In this section, we discuss the concepts of business process management, IoT and their relation, and how IoT helps make business processes more human-centric. The result is a conceptual model, which then is used to present the opportunities and challenges of IoT and BPM to help humans to more seamlessly use, work, and interact with Processes Aware Information Systems (PAIS).

Traditional workflow management systems (WfMS) as reflected by the Workflow Reference Model of the Workflow Management Coalition (WfMC) [32,33] suggested two user interfaces for humans (end users), to participate in and to interact with workflows: the work list, where the humans can manage and pick their work items, and the applications where the actual work on a work item is done. In Processes Aware Information Systems [21], interactions of humans became much more flexible. And with IoT, the human might not even need to explicitly interact with information systems anymore to participate in a process. Using IoT devices, the behavior of the human or changes in attributes or conditions of involved goods or equipment can be automatically detected and events relevant to the execution and progress in a given process can automatically monitored and aggregated, which then drive the process.

We start with introducing the core concepts of business processes, following the workflow reference model of the WfMC [32] and our own AMFIBIA approach [5]. A business process, which we call process for short, consists of different tasks that need to be done to achieve a certain goal. The process typically defines in which order these tasks need to be done. Each different execution (or instance) of such a process is called a case of that process. And each time performing a task in a case of that process is called an activity. The process and its tasks are the conceptual ideas of the business process. When this idea of a process is made explicit in a more or less formal and graphical way, this is called the model of the process. The cases and activities are the manifestations of this idea; and, when there is a process model, each case is considered an execution of this process model in the real world.

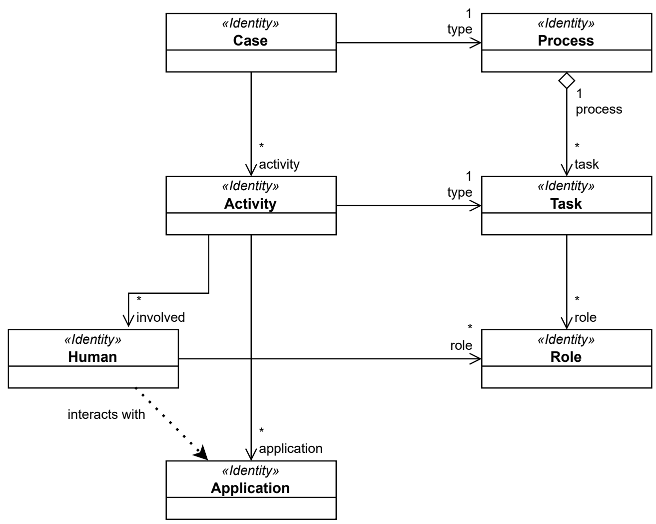

Fig. 4. Core concepts of BPM

Figure 4 shows these concepts and their relation as a UML class diagram — an excerpt of and slightly adapted from the AMFIBIA model [5]. On top of these core concepts, Fig. 4 shows the humans who are involved in cases and activities; the counterpart of the concrete humans participating in a process in the process model are the roles, which define who is required or allowed to do a certain task. This is part of the organizational aspect of a business process and can be much more involved than in our simple model. At last, the actual work on an activity is done with the help of some application, such as general-purpose software like Word or dedicated software for a specific task. The dashed dependency between the human and the application indicates this interaction, and the application might make all kinds of changes to data and documents in the process, which, however, are not in the focus of this paper and, therefore, are not included to the conceptual model discussed here.

Note that Fig. 4 reflects the paradigm of traditional business process and workflow management, where each activity belongs to exactly one single case and is associated with one task of a specific process. In the paradigm of object-centric processes [58], this view is relaxed, so that the same activity can belong to different cases (or, in the object-centric terminology, objects) and reflect tasks of different processes. For this paper, however, we stay with the traditional paradigm of "case-centric processes" in order not to blur the conceptual model of BPM and IoT with the additional paradigm shift toward object-centric processes, which is not too relevant to our discussion.

Figure 5 extends the core concepts of BPM from Fig. 4 and brings them together with IoT to help make BPM more human-centric. First of all, this conceptual model acknowledges that modern PAIS will not only have applications which humans can interact with but might also use IoT devices for letting humans interact with the system. Therefore, applications are generalized to any kind of information technology (IT), which can be classical applications but also IoT devices as an explicit part of the PAIS.

And the human might interact with the environment and cause all kinds of effects in the environment through IoT devices. In turn, the environment (which is not an explicit part of the PAIS) could detect all kinds of events and changes by IoT devices. A part of what is going on in the environment or internally in the PAIS might be recorded as events. These events will typically not have a direct meaning in the PAIS, which is why we might also call them raw events. But, by filtering and combing some of the raw events into aggregated events, these aggregated events could bear some importance or meaning for the processes running in the PAIS; such aggregated events, we call BPM events. For example, a human adding some items or goods into the basket in a supermarket might start a new case of a shopping process.

With this conceptual model, we want to put attention to two components that are needed for this: Event monitoring and configuration for collecting data or, actually, events from the environment; and event aggregation and configuration for aggregating these raw events to higher-level BPM events. Today, the collection and aggregation are mostly done programmatically in some specific setting. However, we believe that this could and should be done by configurations as an integral part of setting up PAIS without programming, much like workflow models were used for enacting workflows without programming them anymore.

The classes in the conceptual model in Fig. 4 and 5 do do not have any attributes, since these are not too relevant to the discussion in this paper. But, we included the nature and characteristics of some classes. The most important characteristics are indicated in the diagram by the two stereotypes «Identity»and «Entity».

The concepts with the stereotype «Identity» indicate that these objects have an identity that can somehow be traced and identified across different systems, and they are permanently stored somewhere in the PAIS. This applies to most of the BPM concepts, where the processes, tasks, cases, and activities and some of their relevant attributes and history need to be stored permanently for legal and documentation purposes. In particular, for activities these attributes could be the start and end time.

By contrast, the concepts with stereotype «Entity» are concepts where the particular attributes would depend on the domain in which the processes are running. This concerns the payload of events. But, all kinds of event objects will have a timestamp. An additional characteristic of «Entity» is that the amount of them might be so high that not all of them could or should be stored in a PAIS in the long run. So these might not be stored for longer periods. These objects might have all kinds of attributes that cannot be defined upfront since they depend on the domain. Therefore, there needs to be a way to handle the attributes of these objects more dynamically, such as entities with attribute-

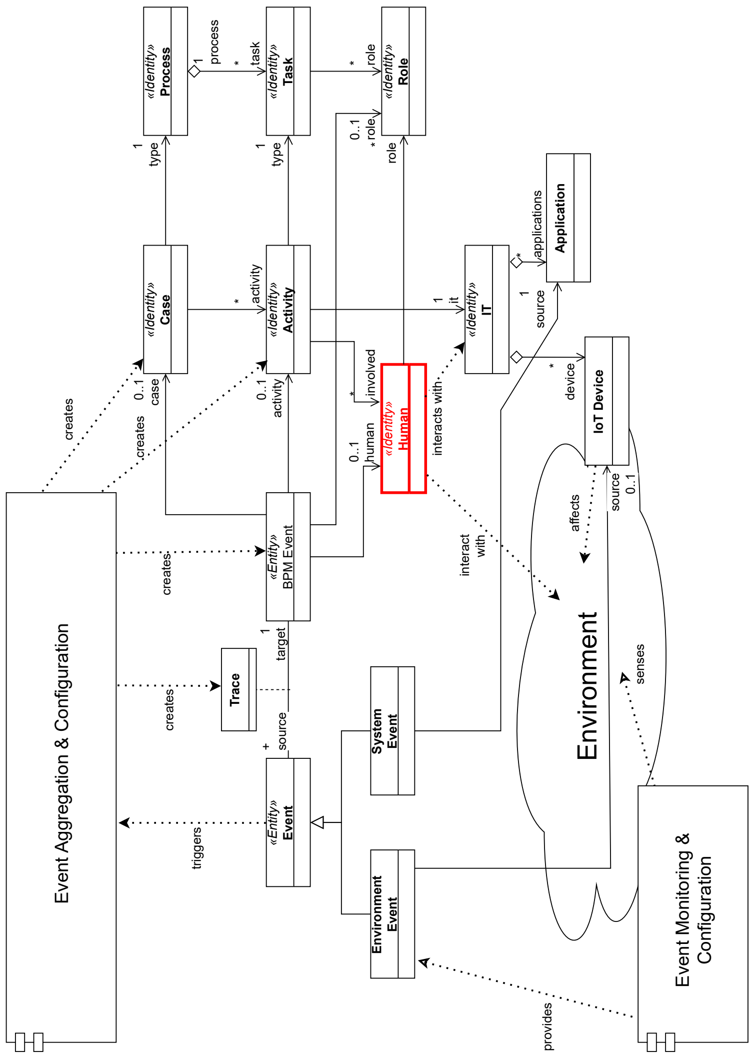

Fig. 5. BPM IoT Conceptual model (complete)

value pairs. This is the reason why we call it «Entity» stereotype; but we do not dwell on this since the model we present here is just a conceptual model and not a data model. For now, events (or objects of using stereotype «Entity») can have any kind of property and they have a timestamp.

Figure 6 shows which parts of the conceptual model relate to the areas of BPM (blue) and IoT (orange), and it shows that the human (red) is at the intersection of both. The dashed lines show areas, where we currently do not see or want to assign to which area they belong. This, in particular, applies to the area that we indicated by the components for the event aggregation and its configuration, which is responsible for combining and aggregating the raw events from IoT to some meaningful BPM events. As mentioned above, this part is often programmed specifically for some dedicated application. This, however, would need to be programmed by software developers who have a very good understanding of the domain and the processes, or it would require Complex Event Processing (CEP). But, we believe that this could and should be done by domain experts themselves (who typically are not software developers), eg. by defining rules for combining and aggregating raw events to meaningful events, which we call event monitoring and event aggregation configurations. And these configurations should be part of modeling the business process.

The way how these configurations could be done in an appropriate way for domain experts who are not software engineers and programmers or IoT experts is still a research issue, which is of great importance for making processes more human-centric – right at the intersection of BPM, IoT, and CEP. This also applies how to adequately integrate IoT devices to PAIS just by configuration.

3 Use Case UC1: Detecting deviations in logistics processes at runtime

3.1 Motivations

Business processes belonging to the logistics domain are multi-party, that is, they require multiple organizations to cooperate for the process to be successfully executed. This implies that no organization has full control over the whole process, but only on the portion that the organization is responsible for. For example, the BPMN model shown in the upper portion of Figure 8 represents a (simplified) logistics process, where some goods are loaded into a shipping container, which is then shipped, and finally the goods are unloaded. In this process, the manufacturer would be responsible for loading the goods. However, (s)he would not be able to control how the container is shipped and the goods unloaded, since these tasks are performed by the shipper and the customer, respectively. In particular, (s)he cannot guarantee that the container will never be overheated.

In this setting, being able to continuously monitor how such processes are executed, and to detect when a case deviates from the expected execution, becomes critical. However, monitoring processes that are distributed among multiple participants poses significant challenges. Existing monitoring solutions typically rely

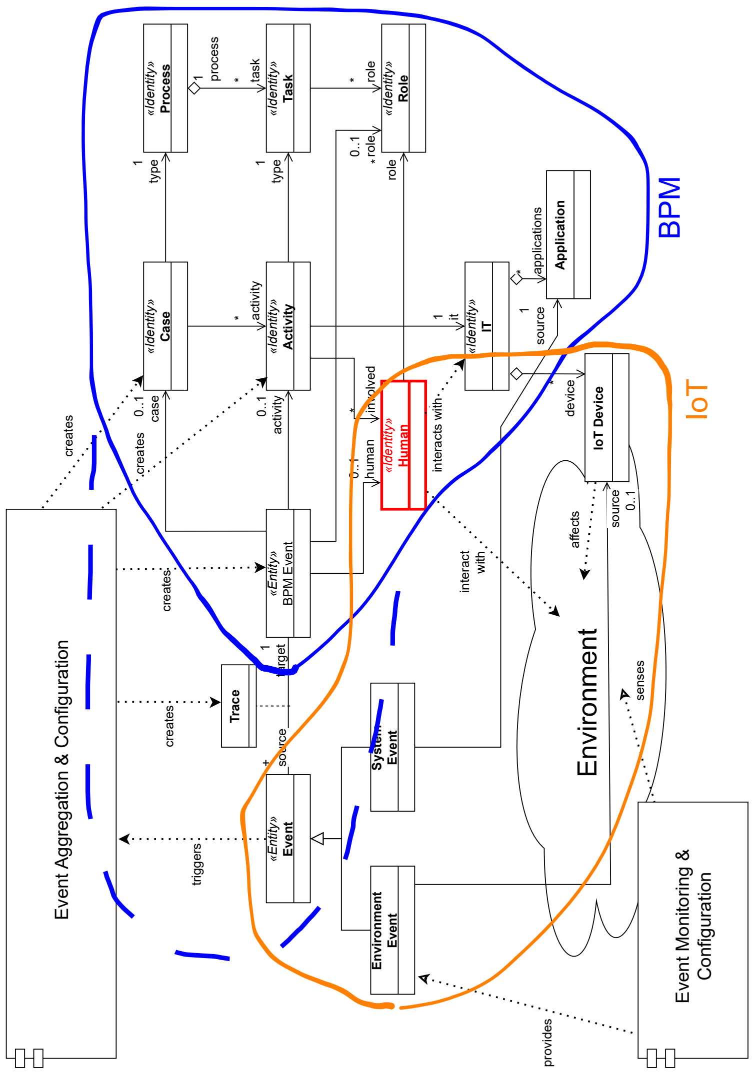

Fig. 6. BPM IoT Conceptual model (areas)

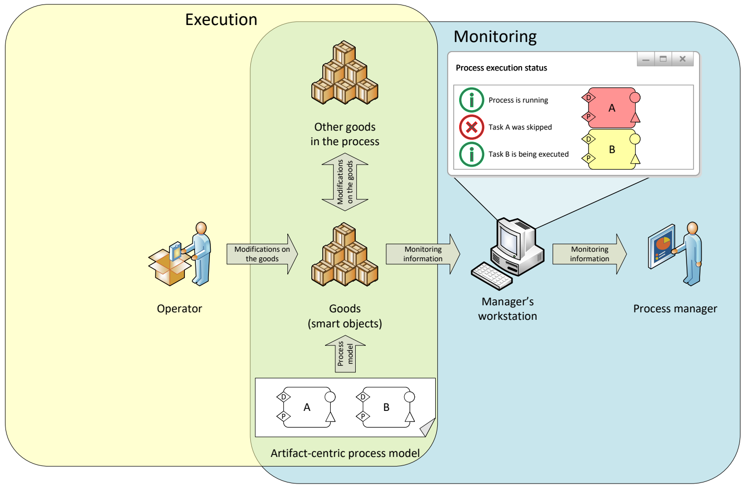

Fig. 7. Key idea behind artifact-driven process monitoring. Figure from [48].

on BPM events which - As discussed in Section 2 - are generated by a Business Process Management System (BPMS), which is usually confined within organizational boundaries. Thus, monitoring collaborative processes may require federating such systems, a daunting task, particularly for short-term collaborations.

Another significant challenge in process monitoring is ensuring the accuracy, timeliness, and reliability of events related to process execution. While monitoring automated processes through a single software component like a BPMS may involve collecting and analyzing execution logs generated by these systems, the presence of manual tasks complicates obtaining reliable monitoring information. In this setting, the human responsible for executing the activity related to that task has to interact with an application to notify that the activity was started and completed. As such, this person may forget to send, delay, or forge this information, leading to incorrect monitoring results. In addition, doing so disrupts that human from his/her working routine.

Lastly, continuously and autonomously detecting deviations from the process model is far from trivial. Conformance-checking techniques typically operate post-mortem with complete event logs, providing monitoring information only after process completion. Conversely, compliance-checking techniques can operate in real time with partial event logs, but they often only indicate whether a constraint was met or violated without pinpointing the exact discrepancies. Breaking down the model into multiple constraints may alleviate this issue, but it also significantly increases the complexity of compliance checks if all potential discrepancies must be accounted for.

3.2 Key idea

To address the aforementioned challenges, artifact-driven monitoring was introduced [48]. As shown in Figure 7, the key idea behind this monitoring technique is that, by observing the changes in the artifacts – physical or virtual objects involved in a process – one can infer how the process is executed. Specifically, artifact-driven monitoring adopts the IoT paradigm to make physical artifacts taking part in a process 'smart'. Being equipped with sensors, computing devices (such as single board computers), and communication interfaces, physical artifacts become IoT devices aware of their own conditions and of the environment in which they reside. Also, they can autonomously exchange this information with other IoT devices.

The main benefits of artifact-driven monitoring are the following:

– Manual notifications are no longer required. Manual tasks inherently alters the state of one or more artifacts. For instance, delivering a package alters its position. Consequently, if the conditions of these artifacts are automatically monitored by IoT devices, they will produce external events. If an event aggregation between events and BPM events has been defined, operators overseeing such activities no longer need to interact with an application to manually report on their execution details.
– Ease of monitoring collaborative processes: Physical artifacts are in close contact with the processes they are involved in, even if such processes cross the boundaries of a single organization. Hence, they can independently collect information relevant for that process, without the need for this information to go through applications belonging to external organizations.
– Deviations in the process model can be promptly identified: Artifact-driven monitoring adopts an artifact-centric view of the process, treating task dependencies as descriptive rather than prescriptive. This approach allows to achieve runtime conformance checking and, in case a deviation is detected, to identify which portion of the process is affected.

3.3 Modelling language

Most business processes are modeled with imperative models, such as Business Process Modeling Notation (BPMN) process diagrams. While such models are fine to document how the process is executed and to instruct a BPMS, they do not allow flexibility in process monitoring. Indeed, all control flow dependencies are expected to always hold. In addition, such languages lack the possibility to express conditions on data to determine when activities are started or completed. For example, the BPMN model in the upper part of Figure 8 shows a simplified delivery process consisting of three manual tasks (Load goods, Ship container, and Unload goods). This model would not allow for a container to be shipped without the goods being loaded first. However, being all three tasks manual, such behavior may happen and it would not be captured by that model.

To address these issues, the Extended-GSM (E-GSM) language has been proposed to model the process to monitor [49]. E-GSM is an extension of the

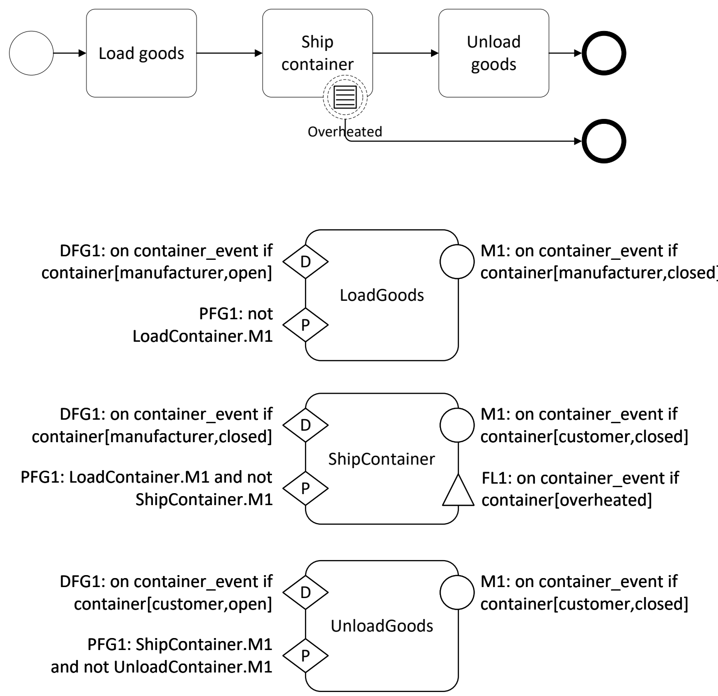

Fig. 8. BPMN model of a (simplified) logistics process (upper part) and equivalent E-GSM model for monitoring (lower part).

Guard-Stage-Milestone (GSM) language, originally designed for automating the execution of knowledge-intensive process models [14]. In GSM, tasks and process portions are represented by stages. Stages can be atomic to represent atomic tasks, or they can hierarchically nest other stages.

To determine under which conditions an activity starts and completes its execution, the stage representing the corresponding task is decorated with one or more data flow guards and with one or more milestones. Data flow guards and milestones are Event-Condition-Action (ECA) rules, requiring an event and a Boolean expression to be specified. When the specified event happens, the ECA rule is said to be fired. If an ECA rule is fired and its Boolean expression evaluates to true, the ECA rule is said to hold.

Stages can assume one of the following states: *unopened*, *opened*, or *closed*. When the monitoring starts, all stages are marked as *unopened*, denoting that they have not been executed. When a data flow guard holds, if the stage to which that data flow guard is attached is *unopened* or *closed*, that stage becomes *opened*. This indicates that the process element represented by that stage is running. When a milestone holds, it becomes achieved. Also, if the stage to which the milestone is attached is *opened*, that stage becomes *closed*. This indicates that the execution of the process element represented by that stage is completed. In addition, if that stage has any child stage which is *opened*, these stages become *closed* as well.

Thank to data flow guards and milestones, it is possible to define conditions on attributes of artifacts, thus allowing to automatically infer when activities are executed.

E-GSM extends GSM by introducing two additional constructs: process flow guards and fault loggers. To specify the control flow dependencies that are expected to hold for a task, the stage representing that task is decorated with a process flow guard. A process flow guard is a Boolean expression, which predicates on the other elements in an E-GSM model. Such expression is evaluated when at least one of the data flow guards of the attached stage holds, before the stage becomes *opened*.

To specify under which conditions, independently from control flow deviations, an activity would fail its execution, the stage representing the corresponding task is decorated with a fault logger. A fault logger is an ECA rule that is evaluated while a stage is *opened*.

To keep track on whether the execution of an activity deviates from the expected flow, E-GSM classifies stages as *onTime*, *outOfOrder*, or *skipped*. Initially, all stages are marked as *onTime*. Upon satisfaction of a data flow guard of a stage, if the process flow guard of that stage evaluates to true, the stage remains *onTime*. Otherwise, the stage is marked as *outOfOrder*. Moreover, if the process flow guard requires another stage to be *opened* or *closed*, and that stage is *unopened*, then that other stage is marked as *skipped*.

To detect if the execution of an activity is unsuccessful, E-GSM also classifies stages as *regular* or *faulty*. Initially, all stages are marked as *regular*. If, while a stage is *opened*, one of its fault loggers holds, that stage is marked as *faulty*.

It is important to note that process flow guards and fault loggers do not enforce control flow dependencies. A stage can still be *opened* even if its process flow guard evaluates to false, as long as at least one of its data flow guards holds. Similarly, a stage can remain *opened* even if one of its fault loggers hold. This capability facilitates continuous and autonomous process monitoring. Also, ECA rules effectively turn events into BPM events. Thus, they play the role of event aggregations.

The lower part of Figure 8 shows an E-GSM model capable of monitoring the logistics process previously inroduced, whose BPMN model is shown in the upper part of that figure. In particular, the atomic stages LoadGoods, ShipContainer and UnloadGoods represent the homonymous tasks in the BPMN model. Data flow guards and milestones on that stage are triggered by and predicate on events produced by the IoT device attached to the container being shipped, which is capable of providing the position, the condition of the doors (open or closed), and whether it is overheated or not. For example, LoadGoods.DFG1 requires the container to be at the manufacturer with the doors open to cause the stage LoadGoods to open, indicating that activity Load goods has started. Control flow dependencies are represented by process flow guards. For example, ShipContainer.PFG1 requires LoadContainer to be closed and ShipContainer not

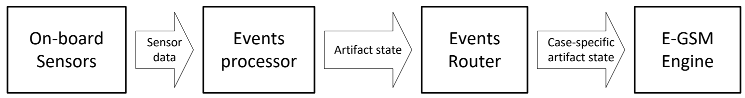

Fig. 9. Reference architecture of an artifact-driven monitoring platform.

to be closed, indicating that it must be executed after activity Load container and no more than once. However, if the container is shipped without loading the goods, this behavior can still be captured by the model. In this case, ShipContainer.PFG1 will not hold. Thus, ShipContainer will become outOfOrder and LoadContainer skipped. The non-interrupting boundary event Overheated in the BPMN model is represented by the fault logger ShipContainer.FL1.

3.4 Software architecture

To implement an artifact-driven monitoring platform, the reference architecture shown in Figure 9 has been proposed, organized into four main modules:

- On-board Sensors Gateway: This module operates on each IoT device, responsible for periodically gathering events from the environment.
- Events Processor: This module receives events from the On-board Sensors Gateway, analyzes them, and determines the artifact's state. Depending on complexity and computing capabilities, it may run locally on IoT devices or remotely in an on-premises or cloud environment.
- Events Router: This module is responsible for keeping track of which IoT device participates in which case. In this way, it will forward only events relevant for a specific case to the corresponding E-GSM instance.
- EGSM Engine: Housing the EGSM model of the process to monitor, this module detects when each activity is executed and when the a case deviates with rexpect to the planned process. Upon receiving a new event from the Events Router, it triggers ECA rules in the EGSM model corresponding to that event.

This architecture was implemented in the SMARTifact platform [50], with specific technologies: Node-RED for the Events Processor, MQTT protocol for the Events Router, and Node.js for the EGSM Engine. The platform's modest computing requirements allowed deployment on an Intel Galileo single-board computer.

4 Use Case UC2: Understanding Deviations in Daily Routine for Healthcare Purposes

In the domain of human behavior, recurrent behaviors form what we commonly call *routines*. These routines, marked by repetitive actions, offer a sense of predictability and regularity in individuals' lives [36]. A person's daily routine encompasses the tasks of everyday life. Understanding these patterns sheds light on preferences and habits and enables us to observe how routines shift and develop over time. Delving into the intricacies of daily routines is crucial for a comprehensive grasp of human behavior.

A business process can be depicted through a process model, which offers a representation of the flow of tasks and decisions. This model provides a structured and abstract overview of the process, aiding in the comprehension and analysis of its execution.

Once we establish the ability to represent daily routines as process models, process mining techniques [59,57,13], typically employed for analyzing processes, can be repurposed to explore human behavior. Essentially, process mining involves analyzing and extracting valuable insights from data, operating under the assumption that any process with recordable events can potentially benefit from its application. This adaptability makes process mining a potent and widely applicable tool for gaining deeper insights into various processes.

In healthcare, utilizing individual patient data enables more personalized medical care, with the potential of leading to enhanced patient well-being. For example, individuals dealing with neurological conditions face numerous challenges in their daily lives. This is also due to insufficient tracking of cognitive and behavioral changes [55,37]. Investigating these challenges is crucial for clinical interventions, as a thorough understanding of deficiencies can improve therapeutic effectiveness. Since physiological functions are not easily quantifiable, information about a person's daily routine can help identify relevant health conditions. For example, let's consider a person suffering from dementia. If such a person is used to sticking to a structured routine (for example, during the evening, night, or when waking up) and this routine gets disrupted in an unprecedented way, it could be a signal of the worsening of dementia.

To benefit from process mining in the healthcare context, however, several challenges need to be addressed [52] first. Among these, when the human *is* the process (cf. Fig. 3), modeling human behavior as a process model and capturing data referring to daily activities are the most important ones.

4.1 Modeling Human Behavior

A process describing human behavior differs significantly from a business process in several aspects [25]. Specifically, human behavior blends intentions, perceptions, and states. Routines, on the other hand, represent intermediate structures comprised of aggregated tangible actions resulting from human behavior – that is, the actual sequence of activities undertaken during a day. For our investigation, we consider routines as a proxy for human behavior. Human behavior can be understood as a sequence of routines. A routine consists of a series of activities, which, at a lower level of abstraction, are sequences of observable units. The same routine can happen multiple times, thus resulting in several cases. As illustrated in Fig. 10, the structure of human behavior is hierarchical. A routine may comprise other routines, and an activity may consist of other activities.

When modeling human behavior and routines, psychological and external factors must also be considered, as they create a close interdependence between

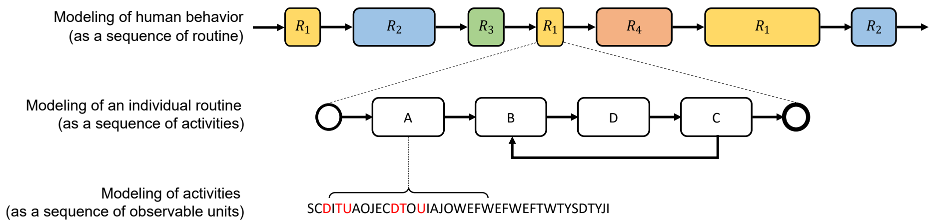

Fig. 10. A simplified hierarchical structure of human behavior. Figure from [25].

behavior and context [6]. Behavior is then guided by the person who decides how and when to perform certain actions, but it is also contingent on specific circumstances (or context). Thus, based on these variables, individuals choose how and which routine to implement.

A comprehensive list of requirements to model routines and how these are matched by existing process modeling languages is available in the literature [25,18]. However, it is important to mention that no single language is capable of capturing all shades and peculiarities of human behavior. A common approach, therefore, is to use a combination of multiple languages to describe the behavior from different angles. For example, to describe the general structure of the routine, an imperative language can be used (such as Petri nets or BPMN); local constraints among activities are better captured by declarative language (such as DECLARE or DCR) and, finally, statistics (such as frequency and absolute time distributions) can help to capture aspects otherwise neglected by the control-flow alone.

4.2 Capturing Human behavior

Ambient assisted living environments leverage technologies and services to support individuals with specific needs in living longer and independently in their natural surroundings [54]. These environments can capture individuals' daily routines using technologies such as Internet of Things (IoT devices) systems, which collect data on daily activities [6]. Process mining techniques can automatically derive a process model representing the typical daily routine of an individual from this data [22,27]. Such a model has the potential to offer a comprehensive representation of the human behavior manifested in the routine. Additionally, the person's behavior can be continually monitored using IoT systems and compared with the reference model to identify and explain deviations in execution. Detecting variations in behavior can serve as a tool for identifying critical health conditions and facilitating interventions.

Event and activity abstraction. In order to benefit from the ambient assisted living data, it is necessary to abstract these into more tangible activities, which can be fed to process mining algorithms via event aggregations. From the

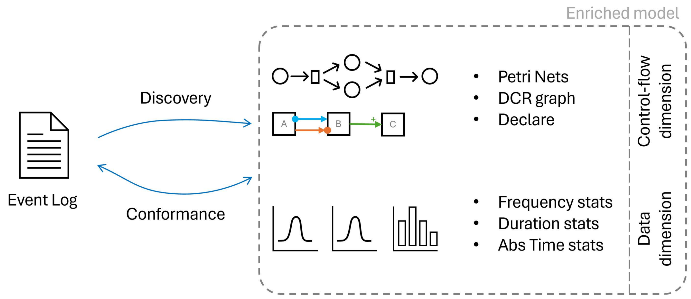

Fig. 11. Multi-dimensional approach. Figure from [18].

literature, we can distinguish two primary approaches to accomplishing such an abstraction: model-based and trace-based abstractions.

Model-based approaches seek to recognize activities by representing them through process models, such as "local process models" expressed using Petri nets. Examples of these approaches are reported in [43,46,47,56] Trace-based approaches, on the other hand, focus on identifying activities at the trace level: these try to transform a trace into another trace, where events are now at a higher level of abstraction [23,24,44,15].

Routine discovery and conformance. In the literature, we can find that two main approaches have been used to discover routines and verify the adherence of new behavior with existing routines. These have implications in terms of how the discovery is performed as well as how the conformance is computed.

Since human behavior is multifaceted, leveraging only the control flow is insufficient. To comprehensively understand personal behavior processes, a possible approach is to adopt a multi-dimensional process discovery and conformance approach [22]. This not only considers control flow but also incorporates a data dimension. Figure 11 gives a graphical intuition of the idea: it starts with an abstracted event log, where activities are already aggregated at the process level. The control flow is then captured using both declarative and imperative languages, whereas the data flow is captured by computing statistics. Adequate algorithms are used for each notation to compute the conformance of these models. For example, alignment algorithms are used for Petri nets [13]. Rule checkers are employed for declarative models [17]. For the statistical aspects (i.e., frequencies), the normal distribution function is employed. By considering the mean frequency as the reference value, it is possible to interpret the probability density function as the likelihood of the mean frequency value in the trace being close to the reference. This likelihood is then returned as the fitness value. All these fitness values are aggregated to a final conformance value.

An alternative approach to multi-dimensional models is to consider models that embed both data conditions and the process aspects, such as E-GSM, which has been introduced in Section 3.3. In Figure 12 an overview of a possi-

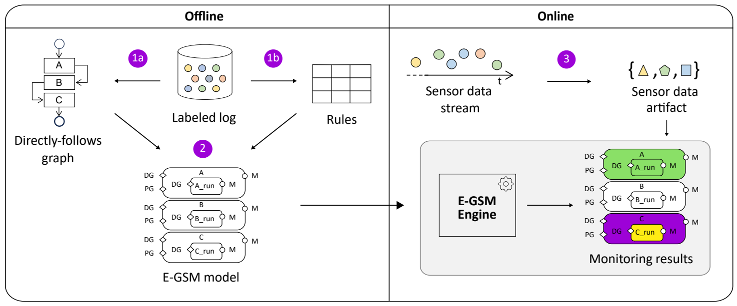

Fig. 12. Overview of the single-model approach based on E-GSM. Figure from [27].

ble approach is provided, consisting of two phases: the offline phase (where the model is derived) and the online phase (which includes streaming conformance). The peculiarity of this approach is that the identification of activities and conditions is fully automated. To compute the conformance, the existing E-GSM engine evaluates the conditions on the different activities and extracts conformance properties on them, such as activities executed when expected (on time), activities that are not compliant with control flow constraints (out of order), or activities that are skipped.

4.3 Evaluation

Results on synthetic [28] as well as real data [26] have shown that it is possible to leverage the presented techniques to discover deviations in human behavior when a process representation is leveraged. These results, combined with visual analytics techniques [1,2], have the potential to empower non-expert users to better understand human behavior. While tests on patients affected by dementia are sill very limited [18, Sec. 10.2], this family of techniques shows the potential to closely monitor patients affected by the disease, with the ultimate goal of spotting as early as possible signs of worsening of their disease.

5 Conclusion

In this chapter, we focused on the challenges and opportunities that the IoT would offer in the context of human-centric processes, that is, business processes heavily involving and centered around interaction with humans. To this aim, we discussed related work in this area and we designed a conceptual model that captures the interactions between the IoT, BPM, and humans. Finally, we then presented two different use cases of IoT-enabled human-centric processes discussing how these can be framed within the proposed model.

The first use case relied on the IoT to monitor the bahavior of humans involved in a process, and their impact on the correct execution of the process. The second use case relied on IoT to observe the daily routines that humans perform – which can be seen as business processes – and to detect changes over time. Despite being two very different use cases, with humans having, respectively, an active and passive role in the process, the proposed model was capable of describing them.

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Glossary

activity An activity is the execution of some task of a process in a specific case.

application In traditional workflow management, the applications are assigned to certain tasks or the activities, which will be used by a human actor to perform the tasks. And via these applications humans will make changes to the state of the case and the data and documents in it (where we do not dwell on concepts involving the information aspects of a process in the context of this paper).

BPM event Some events from the environment in aggregated might have meaning in the BPM process and can be used tp as input and to control the execution of a case. These are called BPM events, which can be associated with a case, a activity, a human or role. .

case A case is single instance of the execution of a process..

event All things that occur in environment of a workflow system or PAIS can be perceived by a events. A single raw event, might not have a meaning from a process perspective. But, a combination of them might have a meaning be useful to control the process.

event aggregation Event aggregation derives higher-level BPM events from low-level or is established the raw events. The provenance of this high-level BPM event and raw events it was derived from can represented by a trace..

human In a process activities are performed by or need the participation or authorization of human actors (notwithstanding the fact that some activities can be performed automatically, here we focus on the human actors). In the process model, there is typically an organizational aspect or perspective, which defines an organization model, and defines roles, assigns humans to these roles, and defines which roles a human needs to have to perform a certain task.

IoT device In modern PAIS, activities can be performed not only by applications, but also by IoT devices, which can be an explicit part of the PAIS; or and implicit part by using events from environment.

process A process is a business process executed in some organization for achieving certain goals. The process is actually the conceptual idea (often called the model), how each individual execution of this process would look. A process consists of the different tasks that need to be done to achieve the goal; and the processes typically defines in which order these tasks need to be done. Each different execution (or instance) of this same process is called a case of that process.

role In a process, their different roles and these roles defines which activities can be performed by which humans.

task A defines task are the different units of work that need be done to execute a process. The instance of the execution within a specific case is called an activity.