IoDEP: Towards an IoT-Data Analysis and Event Processing Architecture for Business Process Incident Management

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***Abstract*—IoT is becoming a hot spot area of technological innovations and economic development promises for many industries and services. This new paradigm shift affects all the enterprise architecture layers from infrastructure to business. Business Process Management (BPM) is a field among others that is affected by this new technology. To assist data and events explosion resulting, among others, from IoT, data analytic processes combined with event processing techniques, examine large data sets to uncover hidden patterns, unknown correlations between collected events, either at a very technical level (incident/anomaly detection, predictive maintenance) or at business level (customer preferences, market trends, revenue opportunities) to provide improved operational efficiency, better customer service and competitive advantages over rival organizations. In order to capitalize the business value of data and events generated by IoT sensors, IoT, Data Analytics and BPM need to meet in the middle. In this paper, we propose an end-to-end IoT-BPM integration architecture (IoDEP: IoT-Data-Event-Process) for a proactive business process incident management. A case study is presented and the obtained results from our experimentations demonstrate the benefit of our approach and allowed us to confirm the efficiency of our assumptions.**

***Keywords*—Business process management; internet of things; machine learning; complex event processing; data analytics**

I. Introduction

Nowadays, Business Process Management (BPM) is a well-established discipline in both academia and industry. It is considered as a powerful solution that helps organisations adapt to strategic, tactical and operational changes and gain more visibility and control over their business processes, so that they can continuously improve and optimise their activities and resources. Organizations use Business Process Management systems as an activity-based workflow manager that allow them to track the optimized functioning of their activities in order to gain in terms of agility, efficiency and performance. This method is mainly based on the concept of business processes. A business process is the structure of activities and actions as they occur in the real world. It defines all the possible paths in the real process and the rules that determine the path to follow and the actions to perform.

In most cases, business processes are isolated either from each other or from the organization's external ecosystem. Thus they don't benefit from the different added values that could be created from sensor data for example, and the useful knowledge that could be extracted from event logs and historical data from previous executions. Further, BPM works in a reactive way [1] which is not sufficient when facing new radical or incremental changes. Early anticipation is crucial to either avoid the occurrence of the problem or respond to it quickly, with no latency, and in an efficient way. This lack of proactivity and predictability is remarkable in three main steps of the BPM life cycle [2] [3]: the design and redesign step, the implementation step, and the execution step. To address this problem, proactive-oriented concepts start to be used in the BPM glossary such as proactive business process management [1] [4], process forecasting or future-oriented BPM [3] and context-aware business processes [5]. Therefore, switching from a reactive to a proactive and adaptable business processes becomes mandatory for every organization. With this new digitization of industrial processes, comes also the age of assistance, which mean that companies should be focused on customers, in order to offer a personalized and adaptable services, and even predict their needs in almost real time. Dealing with such a continuous changing environment requires an intelligent, adaptive and flexible business processes. As a result of all these new changes, organizations nowadays find that the traditional BPM systems present several limitations [6]. In the literature, different approaches have bean proposed to improve business process by applying diverse techniques and technologies such as recommended systems [7] [8], Ontologies [9], data analysis, data mining and process mining [10] [11], complex event processing [1] [12], Ubiquitous Computing [13], Internet of things - IoT [14] [15], just to name few.

Processes are executed within application systems belonging to the real world, where humans, cooperative computer systems and even physical objects are involved. In fact, connected objects are becoming progressively more prominent in the business process execution environment. IoT represents the inter-networking of physical objects [16] (also referred to as ”things”, ”connected devices”, ”smart devices”, ”ubiquitous devices”), vehicles and other items embedded with sensors, electronics, actuators, and network connectivity that enable these ”things” to collect and exchange data when interacting and sensing their environment. At the execution level, Business processes can be classified into Person-to-Person (P2P), Person-to-Application (P2A), and Application-to-Application (A2A) processes [2]. Recently with the emergence of these IoT devices, new Business process interactions are emerging such as Person-to-Thing, Thing-to-person, and Thing-to-Thing due to the advent of Internet of things (IoT) technologies [17]. However, IoT-BPM integration is still at its infant age. Most of the current research work on BPM-IoT integration, propose new approaches that target a specific aspect of the BPM life-cycle. For example, updating business process models by enriching business process model and notation (BPMN) with new elements that correspond to IoT domain and that can explicitly define IoT devices within a business process [18], improving resource Optimization and monitoring and task execution via IoT context-specific knowledge provisioning [19], improving business process execution via an IoT-aware business process execution that exploits IoT for BPM by providing IoT data in a process-aware way [20], or proposing an architecture for IoT-BPM integration in order to cope with the issues and limitations raised by the recent case studies in both industry or academia.

In this paper, we focus on how to improve BPM through IoT integration via an end-to-end architecture. This integration will help us to proactively manage the business process instances, that are launched by different IoT devices, based on their priority level. Although academia and industry have taken an interest in this integration, there is still a lot of research work to be done in order to propose effective methodologies, design patterns and architectures to ensure efficient and smooth integration and communication between the IoT domain and BPM.

In the literature, several research works are paving the way for BPM and IoT combination and integration, in order to optimize BPM using IoT and allow BPM to benefit from this new advanced technology. To go into more detail about our proposal related to IoT-BPM integration/Communication, it is appropriate to ask some research questions in order to define our problem in more concrete way.

- **Q01** : What is the state-of-the art regarding the integration/communication between IoT and BPM?
- **Q02** : What design strategy or methodology can we follow in order to achieve a successful integration/communication between IoT and BPM?
- **Q03** : What are the encountered issues when integrating IoT and BPM?
- **Q04** : And given that data and event are the common points between IoT and BPM, to what extent can the functionalities offered by data analysis and complex event processing be exploited for an end-to-end IoT-BPM architecture?

The reminder of this paper is organized as follow. Section 2 presents our context of work, illustrated with a real-life scenario. Section 3 overviews BPM, IoT and the integration of these two technologies. In Section 4, we present in more details our approach. In Sections 5, 6 and 7 we present an overview of our proposed IoDEP architecture from different perspectives. In Section 8 we describe the implementation of our approach (via an initial block validation), and we discuss and evaluate our results. And finally, we conclude our paper and present some future perspectives in Section 9.

II. Context and Motivating Scenario

In this section, we present a real-life scenario to illustrate our problematic and highlight the challenges we are trying to solve with the proposed approach.

The case study of our research work belongs to silver economy domain, which is a new industrial sector officially launched in 2013 in France. The aim is to create personalized services and new technologies to improve disability-free life expectancy and to help dependent elderly people as well as their care-givers on a day-to-day basis. Most countries all over the world live the demographic transition of aging population. According to the united nations, the number of people with 80+ years old will triple between 2015 (126.4 millions) and 2050 (446.6 millions). If we take France as an example, in 2015 the number of people with more than 60 years old is 12 thousands, which represents 18% of the French population and they will represent more than 1/3 of the population by 2060[1]. Since the demographic change is becoming a global phenomenon, several companies are focusing on developing products and services to create age-friendly societies.

The risk of diseases, loss of capacity and falls increase with age. Losing physical capacities due to age or some kind of accidents can lead to serious falls of elderly people and those falls can have adverse repercussions. In fact, The physical consequences of a fall differ from one individual to another. They can represent a decrease in mobility and an increase in daily life activities dependency. Falls have also some psychological consequences such as a loss of self-confidence, which can accelerate functional capacities decline. Falls among seniors result in a significant number of hospitalizations, with hip fractures being the main cause. Besides, falls are the leading cause of injury-related death.

Several studies have been conducted in the field of silver economy, in order to determine a standard definition of a fall and the number of falls over a specific period to consider an old person as a repetitive case. In [25] [21] [22] [23][24] a fall represents “an unintentional change in position resulting in coming to rest at a lower level or on the ground”. To characterize the repetitive aspect of a fall, we must determine the number of falls and the time interval between falls. As we can see in Table I, the majority of published studies consider at least two falls to retain repetitive character, with an interval between two falls ranging from 6 to 12 months on average. Quick intervention after a fall, using a fall detector for example, could avoid 26 % of hospitalizations, i.e. 160 M Euros and 9,400 deaths per year. There are several solutions for Fall Detection such as:

- Passive Solutions: where the senior must press a beeper to notify in case of an incident.
- Active solutions: these solutions require the use of sensors (Accelerometer, biological signals) or environmental detectors (presence, ground, doors...). In case of a particular variation of the signals, the device triggers an alert.

[1] https://www.insee.fr/fr/accueil

TABLE I. REPETITIVENESS ASPECT OF A FALL

References	Data Collected	Participants	Study plan	Falls repetition
[21]	Questionnaire A follow-up period of one year	N = 730 Age >= 55 years	Transversal	Yes >= 2/12 months
[22]	Postal questionnaire A follow-up period of one year	N = 1660 Age >= 70 years	Transversal	Yes >= 2/12 months
[23]	Telephone questionnaire Interval : 6 weeks A follow-up period of 36 weeks	N = 311 Age >= 70 years	Observational cohort	Yes >= 2/9 months
[24]	A follow-up period of 3 years Participants report their falls weekly on a fall calendar Phone contact in case the person is incapable of filling in his calendar	N = 1365 Age > 65 years	Observational cohort	Yes >= 2/6 months
[25]	Participants interviews Retrospective (12 months)	N = 377 Age =78 +− 3 years	Transversal	Yes >= 2/12 months

- Video-surveillance Solutions: the camera sensor analyzes the senior's behavior and triggers the alert accordingly.

Some of these solutions (bracelets, presence detectors, active floors...) are "blind". This means that they do not allow to know if a fall is a serious one or not, based on the received alert. Only the image delivered by the video fall detectors, allows us to remove doubt about the incident and therefore avoid unnecessary interventions and therefore minimize the overall cost of the service. Predicting and preventing falls among elderly, is the main objective of our case study, in fact to apply our approach, we will use a data set and a business process model from a Video surveillance company. This company edits an automatic falls detection system for elderly people and offers a 24/7 automatic alert solution and a quick rescue without the intervention of the person in danger.

Fig. 1 depicts our incident management process, using BPMN, which aims to manage falls alerts from detection to assistance and resolution. This incident management process is based on an analysis in real-time of alerts received from 24/7 streaming cameras (IoT devices) for detecting elderly people's falls. Waiting too long (sometimes even for few minutes) can be so risky as it can complicate the situation and also it can be so painful for the person. That is why a quick rescue is mandatory to assist the person after a fall or an incident. To achieve this prompt intervention, smart video surveillance cameras are installed at client's home or patients rooms at geriatric services. These devices detect suspicious scenes that may be a fall or an incident, take a picture of the scene and then send automatically an alert to the video-surveillance center. This received alert is handled by a human agent, who qualify the alerts into four categories, as described below, and after that he/she determines whether an assistance action is necessary or not according to the criticality level of the alert. That is why, each alert received requires a quite vigilant treatment, in order to be sure of its category, because the margin of error in this type of system must be very small, as those falls, in case of a delayed intervention or an incorrect qualification, may have an adverse impact on the person concerned: 1) False alerts (level 0): Empty place. 2) False alerts (level 1): Active person. 3) Alerts with average level (level 2): Seated person. 4) High level alerts (level 3): Person lying down.

Video-surveillance systems have proven their efficiency, as they can detect hundreds of falls and risky situations and then assist the person in danger in less than five minutes. However, these ambient cameras videos generates a lot of false alerts, triggered by an active person or a moving curtains for example, that are send to the back-office alert workflow management system. Given that the human agent handles the received alerts in a first in first out (FIFO) order, sometimes true and critical alerts may stay on a waiting list for few minutes until the agent handles all the false alerts or less critical ones that were received before the true one, as the incoming events are intercepted, queued and launch the process instances . So if we do not integrate a mechanism to help the human intelligence by prioritizing the event generated by a (very) serious case, high latency will induce delays that can be disruptive, depending on the severity of the case.

III. BACKGROUND AND LITERATURE OVERVIEW

In the literature, several research works are focusing on combining BPM and IoT. We start this section with a general BPM and IoT background. Then we present a literature Overview about BPM and IoT integration.

A. *Introduction to Internet of things*

Smart objects swept in our life to facilitate it in so many ways and in different domains such as transportation, health care, hospitalization, civil protection, smart home, smart cities, emergency, and individual automation. From smart phones to new smart objects that interact not only with people but with other machines (Machine to machine communication). The concept of the "Internet of Things" first emerged in a presentation by K. Ashton, on the connection of Radio Frequency Identification (RFID) to the supply chain of Procter and Gamble in 1999. Since then, IoT has been exploding and invading our daily lives in different aspects (smart phones, smart door locks, self-driving smart cars, smart cameras, smart medical devices, etc.). This new technology started to thrive right after the development of the web in the 1990's and mobile Internet in the 2010's. The internet of things (IoT) is growing by leaps and bounds. It is made up of billions of smart devices that use wireless technology to communicate with each other and with us. IoT infrastructures can range from connected, instrumented devices providing data to intelligent, standalone systems. IoT enables "a world where things can automatically

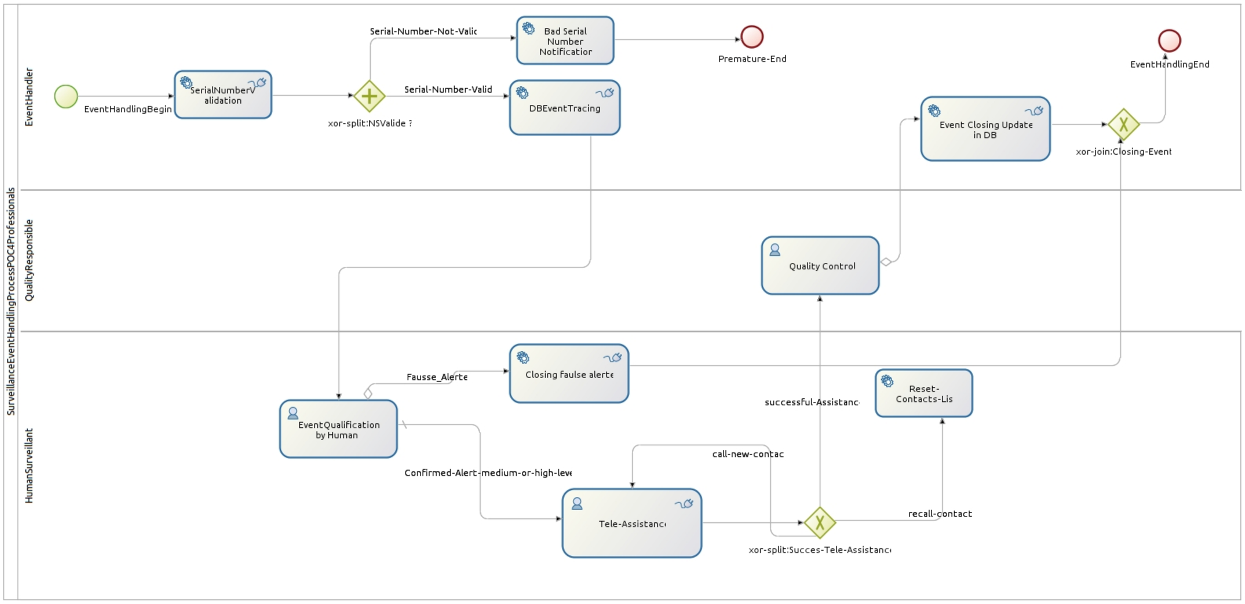

Fig. 1. Motivating Scenario: Qualification and Assessment of the Risk Level of Incidents Process.

communicate to computers and each other providing services to the benefit of the human kind" [26].

Connected devices collect data by sensing their environment, and exchange data with other devices and humans. All devices (things) act locally withing their environment. Whereas, the IoT allows them to be remotely monitored via existing network infrastructures, including the Internet [19]. IoT contribute to continuously feeding "big" data to every node [27]. Besides, the evolution of the IoT invokes significant opportunities for private data exchange enabling new business models across heterogeneous networks [28]. However, it cannot generates value. That is why, it is necessary to couple it with other technologies to transform this huge amount of data into useful knowledge, in order to make meaningful decisions.

B. Introduction to Business Process Management

The Process approach has been increasingly adopted by companies since the 1980s, leading to a new organizational model and a new way of operating in different organizations. Faced with a changing and competitive environment, traditional approaches that treat the company as a closed environment are no longer appropriate. Indeed, the process approach is a systemic approach that aims to transform the hierarchical and vertical structure of an organization into a transverse structure whose ultimate goal is the satisfaction of external and internal customers. It is a method of analysis and modeling intended to ensure collaborative work in order to control and improve the efficiency and smooth running of an organization.

This method is mainly based on the concept of business processes. A business process is the structure of activities and actions as they occur in the real world. It defines all the possible paths in the real process and the rules that determine the path to follow and the actions to perform [29]. The International Standards Organization (ISO) defines processes as a set of interrelated or interacting activities that transform inputs into outputs elements. For Harrington in [30], he presents business processes as an activity or set of activities that uses an input, adds some value to it, and delivers it as an output to an internal or external customer. Dumas et.al [31] represent a business process as a collection of inter-related events, activities, and decision points that involve a number of actors and objects, which collectively lead to an outcome that is of value to a customer. All these definitions and many others present business processes as a set of activities and tasks that exploit the different resources (human and/or machine) of the organization to achieve one or more objectives previously defined, in order to satisfy an internal or external customer. Each business process is attached to a single enterprise, but in some cases it may interact with other business processes belonging either to the same organization or to other organizations. In order to achieve its objectives and ensure efficient performance, the organization must subject its business processes to a continuous improvement mechanism. This mechanism represents the BPM life-cycle [31]. In fact, BPM life cycle is about discovery, modeling/(re)desing, executing, analysis and monitoring of business processes in a perpetual repetition in order to optimize and automate these processes as much as possible, and also to accommodate the ever-changing business requirements.

Business processes therefore occupy a very important place in the field of information systems, because they play a core role within every organization. Moreover, the performance level of any organization is indirectly linked to the efficiency of its processes and the quality of their models. In fact, a proper management of business processes within an organization can have a very positive impact on the efficiency and smooth running of its activities, as it allows this organization to have a clear vision of its objectives in order to better meet the requirements of competitiveness that are constantly increasing.

BPM provides already different methods and solutions to manage and analyse data and events. Among these methods we have Business Process Intelligence (BPI). In fact BPI systems provides solutions to enhance decision making throughout a wide range of business activities, by analysing, predicting, monitoring, controlling and optimizing business processes [32]. Although, BPI has proven to be efficient for post-execution prediction of future process behavior, it is unable to manage and process huge amounts of real-time data and events that are generates from different sources [33]. This becomes more difficult when integrating IoT devices in a BPM architecture. Another solution provided by the BPM field, when dealing with real-time event data is Business activity monitoring (BAM). In fact, BAM is used in order to analyse data related to activities that have been executed. It complements ex-post analysis of process execution by continuously identifying specific situations at run-time and responding to them by triggering specific actions [34]. However, this technology remains less effective in use cases that includes IoT generated events. The limitations of traditional BAM in IoT case studies can be seen from two aspects: prediction and proactivity. The first aspect is manifested in the complex event correlation identification [35]. In fact, by sensing their environment, IoT devices generates a massive volume of event data that need to be processed and analyzed in order to extract useful information and to detect (complex) event patterns in real-time. However, traditional BAM does not provide rule-based engines. This limitation becomes more apparent when the events are generated from diverse data sources, because BAM lacks flexibility in integrating multiple heterogeneous data sources [33] [36] [37]. The second aspect is linked to the absence of proactivity in BAM solutions. In fact, using BAM in a reactive way is no longer sufficient, especially when we have this huge amount of real life data and events.

In business environment where every single event is important and need to be processed, Event Driven Architecture (EDA) needs to be adopted. Now with the emergence of IoT, events are becoming increasingly important for the current information systems (SI), especially for organizations that integrate IoT devices and senors in their business operations (video surveillance, Health care, ...). EDA is the successor of service Oriented Architecture (SOA). The idea behind this paradigm is that everything is an event, all the different components of this architecture interact with each other by events. In this architecture each component is either an event consumer or an event provider. Event consumers subscribe to an intermediate event handler, and providers publish to that handler. When the event handler receives an event from a providers, the handler forwards it to the consumer [38]. The difference between EDA and SOA is that SOA is based on the *"request/response"* concept where the consumer of the service sends a request to the producer, and the producer sends a response that contains either the result or feedback. While EDA is based on the *"publish/subscribe"* concept where the communication pattern between the consumer and the provider is reversed. So in this architecture consumers do not start the communication channel, but they receive the events published by the event providers, which means that the communication is made in an unidirectional way [39].

The main interest of the EDA is to manage real-time process events and data in an efficient way. This message-driven architecture enables the introduction of a higher level of event processing using the Complex Event Processing (CEP) engine. CEP is used to exploit and correlate large event streams generated by heterogeneous data sources in order to produce useful information.

C. Event-Driven Business Process Management

Although, IoT is becoming the hot spot area of technological innovations and economic development promises for many industries and services, it still at its infant age, as we have seen previously. During the last years, both academic and industrial world have been interested in this field and its integration with other domains. However, there is still a lot of research work to do to propose methodologies, design models and architectures in order to ensure an efficient and smooth integration and bidirectional communication between IoT field and BPM. Dealing with event in BPM field is not recent. Event-Driven Business Process Management (EDBPM) concept represents an enhancement of Business Process Management, by including other concepts such as SOA (Service Oriented Architecture), EDA (Event Driven Architecture), SaaS (Software as a Service), BAM (Business Activity Monitoring) and CEP (Complex Event Processing) [40]. This concept was first used in 2003 in a white paper of Bruce Silver Associates in connection with the FileNet P8-BPM platform [41]. The idea behind EDBPM was limited to a single event processing, because the concept of CEP was not well known back then. So early applications of EDBPM was mainly focused on business process monitoring and on Key Performance Indicators (KPIs), or metrics measurement [42]. Despite the fact that the concept of CEP was used for the first time in 2002 by David Luckham is his book "the power of events" [43]. It was until 2007 that an integration of CEP in BPM field has been considered for the first time [44]. The integration of CEP technology within BPM is then known as EDBPM.

Recently, the EDBPM research area has been growing significantly again due to the omnipresence of IoT devices. We find applications that integrate IoT, CEP and (ED)BPM in several research area and business sectors such as Health-care, logistics, manufacturing, banking, smart cities/homes, cultural heritage, agriculture, etc. ([45], [46]). Hence the interest to propose an architecture that integrates all these technologies side by side, in order to achieve a proactive event/instance management.

D. Integration BPM with IoT: Literature Overview

During the last years, both academic and industrial world have been interested in this field and its integration with other fields. However, there is still a lot of research work to do to propose methodologies, design models and architectures in order to ensure an efficient and smooth integration and bidirectional communication between IoT and BPM.

We discuss this related work from two perspectives. The first perspective is the impact of IoT on business process. The second one is the different problems and difficulties encountered when we try to integrate IoT and BPM.

1) How IoT Can Impact Business Process?: The alignment of IoT and BPM is the focus of several research works. However, this alignment comes with various challenges that

TABLE II. BUSINESS PROCESS RELATED LIMITATIONS, ADDRESSED VIA IOT INTEGRATION

BPM Limitations	BPM Life-cycle phases				References
	Process modeling	Process analysis	Process execution	Process monitoring	
Physical surrounding	X		X		[18] [47] [48]
Context-insensitivity			X		[47] [20] [49] [50] [51]
Data-input			X		[51] [16] [20] [47]
Models complexity	X		X		[51]
Transparency				X	[51]
Latency			X		[51]
Event-logs quality		X			[51] [52]
Context-awareness	X	X	X	X	[53] [54]
Knowledge feedback loop	X	X	X	X	[55] [56]

need to be tackled. Both technologies will affect and of course benefit from each other [19] [51]. However, in this paper, we focus only on the influence / benefit of IoT on BPM.

The integration of IoT can provide several benefits for BPM. Besides, it can also address some business process related limitations. Among these limitations we have:

- **Physical surrounding:**Business processes have no access (or limited access) to physical surrounding, as they operate in a cyber surrounding. Taking into consideration the physical surrounding at modeling phase can lead to correct resolution and execution of business processes [18] [47] [48].
- **Context-insensitivity:** Business processes are insensitive to context, they are considered as blind and stateless, which mean that in each business process execution we do not take into consideration neither the results from last process instances nor the context (a context-aware business processes execution). So they need to know the conditions and situations in which IoT operates, given that IoT is by default context sensitive through devices/sensors [47] [20] [49] [50] [51].
- **Data-input:** Business processes have no direct access to data generated by different devices ans sensors. This data could be exploited to BP execution to progress via taking actions (e.g., IoT-based trigger events/alerts, IoT-based decisions...) [51] [16] [20] [47].
- **Models complexity:** Integrating IoT technology can reduce the complexity of process models (for example, replace elements or patterns, ...). It Can also extend and enrich process models. As a result, we have more precise process definitions that accurately reflect the operational reality [51].
- **Transparency:** Integrating IoT technology enhances business process monitoring by increasing BP transparency through data provided by IoT sensors [51].
- **Latency:** The incorporation of IoT technology can ultimately lead activity run time reduction and significant latency that can result in an overall performance enhancement [51].
- **Event-logs quality:** IoT sensors produce a huge amount of data that enrich process event logs. Given that event logs are the fuel of process mining technology enriched event logs provide enriched process models [51] [52].

Table (II) summarises and classifies these Business process related limitations according to the different phases of BPM life-Cycle.

2) Problems Encountered in IoT/BPM Integration : The integration of IoT with BPM certainly contributes to business process improvement. However, this integration comes with several issues and challenges. In [57], authors present the challenges that need to be addressed in Business Process Management Systems (BPMS) to achieve an efficient integration of IoT, such as the absence of direct interaction between the business layer and the edge network, or the problem of complex and inflexible business process models due to a lack of standardization and interoperability when modeling IoT elements and components in BPM. The unexploited potential of extracted data from sensing environment represents a challenging issue when integrating IoT with BPM [58]. Security and data privacy represent another level of IoT/BPM integration concerns [19]. Many other challenges exist and need to be tackled when dealing with an IoT and BPM integration and alignment, these challenges have been summarized by C.Janiesch et.al in their manifesto [19].

In this article, we focus mostly on the challenges linked to event processing and also learning aspect withing an IoT-BPM architecture. The next section details this proposed approach.

IV. PROPOSED APPROACH

Event-driven business process management is mainly adapted in organizations that have a real-time based activities which involved some sensors or some IoT devices that collect data and generate new events by sensing their environment [55]. However, a real-time system must have three main characteristics to ensure better functioning inside any organization [59]: 1) *High availability*, 2) *Low latency* and 3) *Horizontal scalability*. Those three characteristics are mandatory to achieve a real-time and efficient scheduling and event management in BPM.

So in order to ensure a (near) real-time priority-based business process instances management, we resort to an integration of four concepts: IoT (to sense the environment), CEP (to detect situations of interest since it is considered as the standard course for real-time analysis and situation detection [60]), Machine Learning (to analyse our data, find patterns in it and then make predictions, to facilitate decision making), and BPM (to manage our business processes). The idea behind this integrated quaternity of technologies (see Fig. 2) is: 1) to accompany data an event explosion resulting from IoT, 2) to

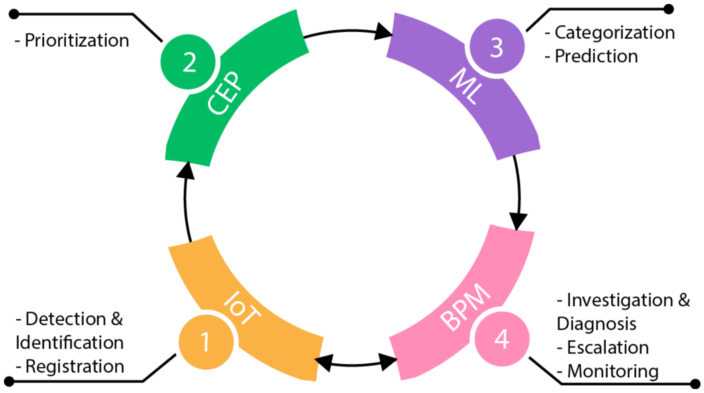

Fig. 2. Quaternity View of BPM, IoT, Machine Learning and CEP.

examine large data sets in order to uncover hidden patterns, unknown correlations between collected events, either at a very technical level (incident/anomaly detection, predictive maintenance) or at business level (customer preferences, market trends, revenue opportunities) 3) to capitalize business value from data generated by IoT sensors, 4) to provide improved operational efficiency, better customer service, competitive advantages over rival organizations.

To turn this conceptual integrated quaternity of technologies into a concrete reality, we propose an end-to-end IoT-BPM architecture (IoDEP: IoT-Data-Event-Process). This integration architecture follows Haze Architecture and Cascading Analytics [61], incarnated by a DIKW (Data Information Knowledge Wisdom) discovery pattern crossing the architecture from device then Fog/Edge to the cloud, and a learning feedback loop that feeds forward insight to adjust either Fog/Edge or device algorithms [55]. IoT-BPM integration involves bi-directional communication. It is possible to acquire data/event from sensors (e.g., monitor and control IoT devices) to manage business process instances and to send instructions to those devices (e.g., reset, adjustment or shut them down). One of the requirement of our proposed architecture is scalability without imposing an architecture redesign. That is the reason behind using Haze Architecture and Cascading architecture as it ensures fluidity and dynamism.

A. Research Design / Modeling Methodology

As we said previously, in order to handle the challenges faced by BPM when dealing with IoT objects, IoT and BPM need to meet in the middle. The Incorporation of two heavy paradigms such as IoT and BPM generates, with no doubt, a modeling methodology issue. This issue becomes more complicated when this integration involves other technologies (CEP and ML in this case). There are three types of modeling methodologies: - The Top-down approach, - The Bottom-up approach, - and the Meet-in the- middle approach. We propose in this article a meet-in-the-middle approach, to facilitate the integration of IoT and BPM. In fact, The meet in the middle approach is considered as a method of refinement going alternately from top to bottom to bottom to top. The combination of deductive and inductive iterative sprints in this approach allows both re-use/mutualization and disruptive thinking. In this paper, we propose an integration of IoT and BPM via an end-to-end architecture aiming to provide a meet-in-the-middle environment capable to capture data and event from IoT sensors, when they are sensing their environment, create actionable and useful knowledge, and allow this knowledge to be used in the business layer through business processes.

B. Functional Requirements

Business processes are supposed to be smoothly executed under different business situations and context. This constantly changing environment, requires having business processes that can easily be adapted to the appropriate action taken. However, without being coupled to other technology, business processes are still deficient regarding the critical ability to provide assistance to their users [62] due to a lack of two important aspect:

- **Context-awareness**: The emergence or even the omnipresence of IoT solutions in different businesses forces organizations to adapt their processes to a high level of connectivity. Context-awareness is a fundamental characteristic of ubiquitous computing [53], and it is the key to benefit from sensors collected raw data, as it allows to store contextual information related to these raw data and to decide which data should be processed, in order to facilitate the interpretation [54] especially at the level of business processes.

- **Knowledge feedback loop**: Traditional BPM systems present different limits, as they do not facilitate the use of knowledge extracted/generated from data by business processes after their execution. As a result, tremendous amount of data and event data that are constantly collected within the organization is not exploited to improve business processes. As a matter of fact, these data represent for enterprises a real engine of growth. However, a large amount of raw data is not valuable; data must go through a whole process to extract value from it [63]. The analysis of huge data helps organizations to extract information and then knowledge, because the real value is in how organizations will use that data and turn their organization into an information-centric company that relies on insights derived from data analyses for their decision-making.

To accompany data an events explosion resulting, among others, from IoT, data analytic processes combined with event processing techniques, examine large data sets to uncover hidden patterns, unknown correlations between collected events, either at a very technical level (incident/anomaly detection, predictive maintenance) or at business level (customer preferences, market trends, revenue opportunities) to provide improved operational efficiency, better customer service, competitive advantages over rival organizations. In order to capitalize business value of data and events generated by IoT sensors and business process execution, IoT and BPM need to meet in the middle, as we said previously. One critical use case for IoT is to warn organizations when a product or service is at risk. Early detection is essential to either remedy the issue before it becomes a real problem or quickly do cleanup when failure

		IoDEP Architecture				
		IoDEP Architecture Front-End		IoDEP Architecture Back-End		IoDEP Architecture Continuum
		Connected Device/Sensor Processing & Analytics	Fog/Edge Processing & Analytics	Cloud Data Processing & Analytics	Human Processes	Learning Feed back loop
Incident Management Process Functions	Detection/Identification	X	X			X
	Registration		X	X		
	Categorization		X	X		X
	Prioritization			X		X
	Investigation & Diagnosis				X	X
	Escalation			X	X	
	Resolution & Recovery				X	
	Closure				X	

Fig. 3. ITIL Incident Management Process Functions vs IoDEP Architecture Analysis Matrix.

hits[2].

Supervision and incident management processes, especially in health-care domain, are considered as an event-driven business process. The instances of these processes are: In some cases, launched by IoT generated events ('Big' data push paradigm: i.e. data is triggering processes). In order to handle incident management in IoT-BPM architecture, Information Technology and Infrastructure Library (ITIL) repository has been considered. In fact, according to ITIL V3 [64], incident management processes are composed of the following functions:

- **Detection / Identification:** Detect the incident and identification of first elements of classification.
- **Registration:** Record basic details of the incident and propagate the incident alert as necessary.
- **Categorization:** Categorize incidents, Assign impact and urgency, and thereby define priority and match against known errors and problems.
- **Prioritization:** The incident is prioritized for better utilization of the resources and the Support Staff time
- **Investigation and Diagnosis:** Assess the incident details, Collect and analyse all related information, and resolve, (including any work around) or route to online support.
- **Escalation:** Escalate (functionally or hierarchically) where/when necessary.
- **Resolution and recovery:** Resolve the incident and take recovery actions.
- **Closure:** When the Incident has been resolved, the system should ensure that details of the action taken to resolve the incident are concise and readable, classification is complete and accurate according to root cause, resolution/action is achieved.

[2]https://www.informationweek.com/big-data-analytics/when-internet-of-things-meets-big-data

Beside incident management process, IoT-BPM Architecture integrates additional features to target highest IoT maturity levels. Among those features, we have:

- **Monitoring and Communication:** All information, metrics, and key performance indicators applicable to the incident are assessed, recorded and reported (time spent on the incident, support actors, date and time of closure, number and type of reoccurring incidents, average time to achieve incident resolution, percentage of incidents resolved at first line support that meet the Service Level Agreement, etc.).
- **Prediction:** Predicting an incident before happening, will enable anticipatory incident management. This may help avoiding the incident by actionning problem management, or at least, this moves the predicted incident resolution closer to the incident detection insuring proactive incident management. Thus, by collecting and combining connected devices/sensors data with historical context data, IoT-BPM Architecture could provide a wide variety of ad hoc, proactive and anticipatory incident, anomaly, and problem management.

Fig. 3 represents these functional requirements according to each layer of our proposed architecture.

V. Overview of the Layered Architecture

This section provides a high level overview about the different layers of our proposed IoDEP architecture.

Fig. 4 presents the layers of our architecture. In fact, the purpose of this layered architecture is to meet the requirements detailed in the previous section. Our proposed architecture requires five layers (see Fig. 4). IoT sensing layer or Edge Layer, IoT sensor data acquisition Layer, Detection, identification and registration Layer, Categorization and Prioritization Layer, and Cloud layer. In the following we will present a detailed explanation of each layer of this architecture.

A. The Edge Layer

This layer concerns all IoT sensors and devices, each one of these have a precise role depending on their environment, location and the purpose behind using them, such

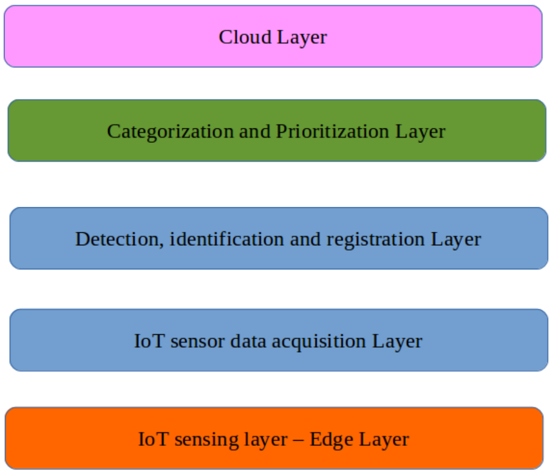

Fig. 4. The Architecture Layers.

as hospital, home, geriatric services, retail store, facilities. IoT devices collect data and generate new events by sensing their environment, after that those events could launch specific business process instances according to the particularities of the detected situation.

As we have seen before, early detection is essential to either remedy the issue before it becomes a real problem or quickly do cleanup when failure hits [65]. The time lapse between sensing the environment and sending a notification, a message or a signal is very critical. In fact, latency is one of the most challenging requirements for connected IoT devices. One of the most effective solution to reduce this lapse of time, is putting some computing on the device or at least bringing computing near the device (edge computing). Pushing data to the edge eliminates long-distance data transmissions to the cloud, which reduces network congestion and latency. Edge nodes are endowed with fall detection capabilities. In fact, these nodes implements several advanced algorithms for image processing and interpretation ([66], [67]). However, this is out of scope of this paper. These algorithms allow the automatic detection and qualification of risky events, following these steps:

- **Image Qualification**: This step allows to qualify the captured image of the camera. Several types of errors are identified at this stage (Error of recovery of the image, Image of incorrect size ...).
- **Movement detection**: This step allows to identify the movements captured by the image, and then render the behaviors of these movements. Mathematical features are identified and extracted from the images and videos. Their exploitation allows to model the behaviors and the events.
- **Movement tracking**: This step consists of tracking objects in their attention zones. Tracking their evolution allows to recognize an abnormal event or behavior and to make a decision.
- **Decision**: At this step a decision about launching an alert or not is taking, based on the results of the previous steps.
- **Pre-qualification**: This step is reinforced with the learning feed back loop [55], by learning from past decisions, mainly false alerts. This final step will consider and exploit the overall context to correct future risk assessments.

At the end of these steps, the detected alerts/events are sent to the cloud. Intercepted events are queued in order to be qualified by a human resource.

B. The Fog Layer

When dealing with IoT devices and sensors, the cloud by itself cannot connect, process and analyze data from thousands and millions of objects and devices of different type and nature spread out over vast areas. To overcome this issue, Fog layer was introduced by Cisco in 2012, in order to offload the cloud through the injection of smart devices at the network layer to provide limited computational resources at the edge of the device layer [68]. Fog computing and edge computing seem similar since they both consist of bringing intelligence and processing closer to data creation. However, the location of the intelligence, processing and computing power is the key difference between these two layers. Generally, intelligence and computing power are placed in devices such as Smart Cameras with embedded vision software (used in our case study). While in the fog layer intelligence and computing facilities are placed at the local area network (LAN).

In our proposed architecture, the fog layer is dedicated to real-time stream processing with CEP as we can see in Fig. 6.

a) Complex Event Processing - CEP: An event is a record of an activity in a system [69] and it represents any change that occurs or will occur in this system, whereas a complex event is a set of events that are related to each other by aggregation, causality or time [70].

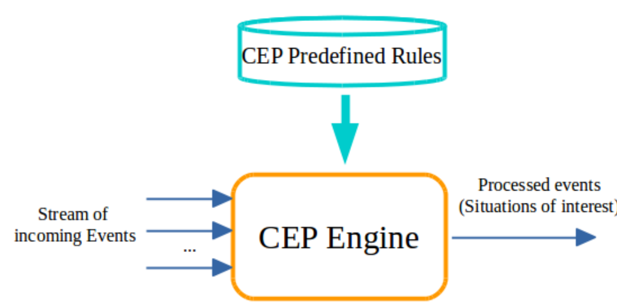

Fig. 5. CEP Basic Architecture.

Complex event processing is a widely used technology, it becomes an increasingly active research field [71] especially with the popularity of publish/subscribe systems in 1997 [72] as stated in [1]. Complex Event Processing (CEP) represents a set of methods, techniques, and tools for processing events while they occur [73]. It aims to process and analyze events generated from different sources in order to extract useful information [74]. CEP is widely used to detect and deal with different business anomalies, threats and opportunities [74] by analyzing event streams instead of traditional static data stored in databases. CEP engines provide the scalability and the (near) real-time processing to filter, to combine and to extract actionable knowledge, known as situation of interest, from a stream of events (see Fig. 5).

Complex situation of interest can be easily expressed using CEP engines and rules. For example, in our case study, queries such as: *prioritize a case if the patient has some particular needs (Wheelchair, walker, etc.)* or *trigger an alert if the patient is a recidivist faller*.

The combination between CEP and BPM is not recent. In fact, it has been widely used to control and monitor business processes in real time in order to improve the effectiveness of business operations by keeping track of what is happening now and raising awareness of issues as soon as they can be detected [75]. CEP helps to monitor not only process instances and activities during run time, but also different events that are related to business process but not necessarily generated from the process instances [76]. Several approaches and solutions based on the integration of CEP with BPM have been proposed for run time or design time ([77], [78], [79]) just to name a few.

The starting point of this incident management approach is the real time analysis of the incoming generated events, using CEP engine to detect the events with the highest priority withing all the incoming ones, that will launch our business process different instances. And based on this estimated priority we can schedule those instances. In fact, the business process instances triggered by those events will then have the highest priority to be assigned to the available human resources. In order to process the incoming events and then detect meaningful patterns concerning the important situation of interest (which represent for us the events with the highest priority), CEP engine needs a set of rules that are determined in advance. A rule for us in this approach represents a condition (IF...THEN ...) that characterizes the event source (the different sources that generate each event). So in the processing step, whenever a condition is satisfied by the event, the priority of this event increases.

CEP strength relies basically on concept of rules and operators. CEP engines are mainly based on a set of rules provided by a rule engine. A rule engine represents a part of a CEP engine that generates rule models. These rules are used in order to create and/or modify business logic in a Business Process Management System (BPMS) [80] for example. CEP rules are based on CEP operators. Among these operators we have: *aggregation operators, sequencing operators, logic operators, single-item operators, windowing operators, and flow management operators*. Those rules are, in most of the time, manually predefined by domain experts, and after that implemented in CEP systems such as Esper, Siddhi, FlinkCEP[3], or Oracle. Since defining these rules manually can be error prone and time consuming, there are many recent approaches that propose an automatic CEP rules learning and generation [1] [81] [74]. However, the automatic CEP rules learning and generation is out of the scope of this paper, because the main purpose of this paper it to pave the way for the use of CEP in order to achieve a real-time analysis of incoming events in order to detect situations of interest, about the priority of the business process instances that need to be executed.

C. The Cloud Layer

Both fog and edge computing are extensions of cloud networks. The majority of enterprises are already familiar with cloud since it is the de facto standard in most industries. The concept of "cloud" was used in several contexts in the 1990s, but only in 2006 when it became associated with offering services over the internet [82]. Cloud computing is "a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction." [83]. Cloud layer facilitates storing and accessing data and programs over the internet (as a service) rather than on servers of the enterprise as we can see in Fig. 6. In fact, it offers the ability to drastically outgrow an organization's normally available storage, without having to host any additional servers. In our IoDEP architecture, Data and intelligence are pushed through layers from edge to cloud in order to be analysed and processed. The knowledge produced goes through a learning feedback-loop that feeds forward insight to adjust either Fog/Edge or device algorithms. To produce this knowledge, we use machine learning algorithm. In the following, we introduce this technology and present in more details the algorithm used in our approach.

a) Machine Learning: Integrating IoT in a BPM environment generates several challenges, among these challenges, we have the huge amount of data and event data that are continuously gathered. Data and event data are the key to get a better understanding of the functioning of business processes. This data represent for enterprises a real engine of growth. However, a large amount of raw data is not valuable; data must go through a whole process to extract value from it. In fact, pre-processing and exploring data before using it help to get correct assumptions and insights in order to make correct predictions and finally take correct and accurate actions and decisions such as instances scheduling, resources management, or business process models redesign. The analysis of this huge generated data helps organizations to extract information and then knowledge, because the real value is in how organizations will use that data and turn their organization into an "information-centric company that relies on insights derived from data analyses for their decision-making"[4]. Hence integrating data analysis techniques, process mining, data mining, machine learning algorithms or even deep learning in each step of business process life cycle is very crucial for the process improvement. In our approach, we have chosen to exploit the machine learning algorithms in order to enhance one aspect of business process life-cycle, which is the instance management.

Machine learning is a branch of the artificial intelligence research domain. Using mathematical methods, Machine learning enables systems to learn from data and generate knowledge from experience. With time and more experience, the system can learn and improve and sharpen a model that can be used to predict outcomes of questions using previous learning

[3] https://nightlies.apache.org/flink/flink-docs-release-1.14/docs/libs/cep/

[4] https://datafloq.com/read/3vs-sufficient-describe-big-data/

[84]. Machine learning algorithms are organized into different categories based on the learning type: supervised learning, unsupervised learning, semi-supervised learning, Reinforcement learning, and Transduction learning. Supervised learning and unsupervised learning algorithms are the most used in real world problems. They can be further grouped into different categories that we can find in real world machine learning problems. However, the choice of the appropriate algorithm depends on your case study, the type of data manipulated, and the purpose of your analysis.

The first step of our approach aims to ensure an efficient acquisition, filtering, and analyzing incident/event data generated by IoT devices. The second step consists on scoring the generated events from IoT devices, based on the result of the first step, using unsupervised machine learning algorithm. We opted for clustering algorithms to discover groups in our dataset, in order to achieve a categorization of the event sources that trigger our process instances. We choose K-means clustering algorithms, which is a partitioning technique used to analyse data based on the distance between different data points in the input dataset. This algorithm was described by Hartigan in 1975. The idea behind K-means algorithm is to divide a dataset composed of M data points in N dimensions into K clusters, in such a way that the within-clusters sum of squares is minimized [85]. The most complicated part of this algorithm is the determination of the right value of K which represents the number of clusters. In the literature, we can find several methods for selecting the most optimal number of clusters for this algorithm such as: The Elbow method [86]: The Average Silhouette method [87], or the GAP statistic method [88]. When applying K-means algorithm in our approach, we have used the Elbow method to determine the value of K. The basic steps of K-means algorithm are shown in the following pseudo-code:

Algorithm 1 K-Means Clustering Algorithm

Input:
S = s_1, s_2..... s_m // list of data points (list of sources which generate the different events)
K //Number of clusters

1: choose K Random data points from S as initial clusters centroids
2: **repeat**
3: Assign each data point s_i to the cluster which has the closest centroids.
4: Calculate the new centroids of each cluster.
5: **until** Convergence //no more changes for centroids
Output: Set of K clusters

We tested several criteria such as the frequency of falls or total number of falls, in order to have the most representative clustering for our data. We apply K-means algorithm on a set of events sources in order to classify those sources on different clusters using a score that we calculate for each event's source (a patient in our case) based on the frequency of previously generated events and their criticality value given previously by the agents (human resources) in the qualification step.

VI. Overview of the Front-end and Back-end of the Architecture

From a front-end and back-end perspective, our architecture can be seen as follows (see Fig. 3):

The IoDEP Front-end architecture is composed of two parts:

- **Connected Device/Sensor Processing and Analytics:** insure acquisition of incident data, and incident data filtering and Simple classifier.
- **Fog/Edge Processing and Analytics:** insure the following functionalities:
  1) **incident data processing**: Detection of anomaly incident.
  2) **incident data analytics**: Pattern recognition/correlation/scoring (advanced supervised time-based analysis algorithms here need smaller training set but may need more performance resources like GPU).
  3) **incident data routing**: Transmission of the anomaly information through an Edge Spooler.

The IoDEP Architecture Back-End is represented by several components insuring cloud side processing and analytic of incident management:

- **Cloud Data Processing and Analytics:** Ensure the following functionalities:
  1) **incident data routing**: Transmission of the anomaly information to the relevant back end processing and analytics system – ESB/CEP.
  2) **incident data analytics and intelligence**: Extraction, cleaning and annotation, Integration, aggregation and representation, Modelling and analysis Pattern recognition/correlation/scoring (more sophisticated supervised machine learning algorithms (e.g. deep learning) may here need big training sets) (Big Data).
  3) **incident data processing**: Anomaly Human Processes (Human qualification of the anomaly information) and Enterprise Business Processes (BPMS based on Big Data analytics), and Interpretation: Through on Reporting incident KPI Scoreboards based on (Data Warehousing and Data visualisation).

VII. Application Architecture Overview

In this section, we present a concrete application of our architecture (see Fig. 6). The content of the Edge layer can differ from one case study to another. For our case study, IoT devices were represented by smart cameras that detect the falls of patients. In other context, these devices and sensors could be either Smart locks, Fire and smoke alarms, or smart wristband, etc.

Our Fog layer represents the real-time stream processing layer using CEP technologies. We propose the use of Apache Flink framework as it facilitates complex event processing

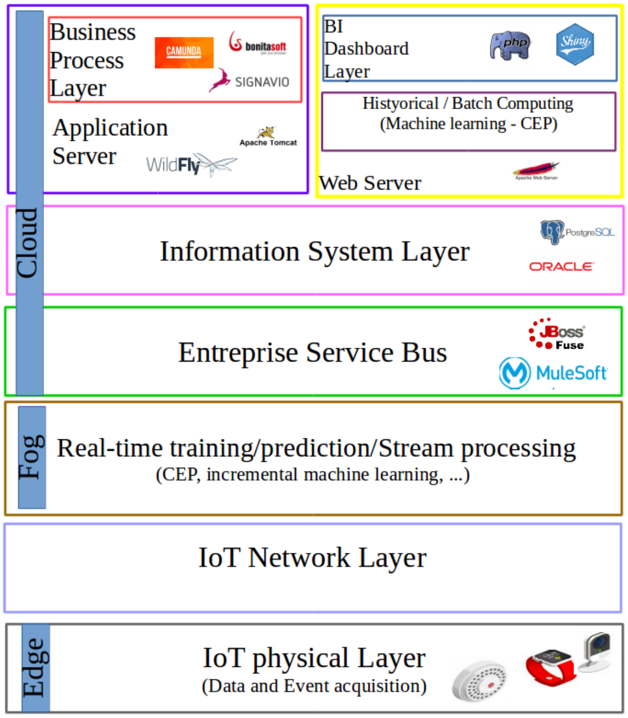

Fig. 6. IoDEP Applicative Architecture.

for real time analysis. Our choice is based on the benchmark that we have conducted. The Enterprise Service Bus layer represents a message broker. It is an integration solution implementing a totally distributed architecture where the applications or services to be integrated are distributed on different machines or information systems, and its role is to ensure communication and interoperability between these different applications whatever their communication protocols. ESB is mostly adapted to asynchronous communications, publish/subscribe messaging, and message queues. Solutions such as Mule ESB, PEtALS, JBoss ESB, Glassfish ESB, or Apache Camel, could be used in this architecture. Historical data in our architecture are stored in a PostgreSQL database. However other Data Base Management System (DBMS) can be used. For the Business Process Layer, several Business Process management Systems can be used such as Bonitasoft[5] (that we have used in our case), Signavio, or Camunda. As an application server, solutions such as Apache Tomcat, or WildFly can be used in this architecture. As a web server to distribute web content, examples such as Apache web Server, can be integrated in this architecture. And finally, for communicating results a BI Dashboard layer, interactive Dashboards can be build using PHP, or Shiny R package given that we have used R language in our experiments.

VIII. Experiments and Results

We opted for à block validation in order to conduct an initial validation of the efficiency of our IoEDP architecture.

Experimental settings:

We worked with a dataset of patients falls (from 01-02-2016 to 12-06-2017), this dataset contains 238228 observations generated by 81 patients.The historical data in this dataset are gathered from our incident management process past instances, and they are partitioned as follows: 89312 alerts are of level 0 (low), 148466 of level 1(average), 275 of level 2 (serious) and 175 of level 3 (very serious). Since that the serious and very serious alerts are the most important in our study, we have applied our clustering algorithms on these two levels only.

The dataset was stored in a PostGreSQL database and all analyses and algorithms implementation were conducted using R and different R packages[6], such as: (tidyverse, RPostgreSQL, ggplot2, dplyr, caret, ...). And All our experiments were conducted on an Intel(R) Core(TM) i5- 540M2.53GHz. All data have been anonymized.

Experimental results for K-means:

As we have seen before, to determine the value of K, which represents the number of clusters, we have used the Elbow method (see Fig. 7).

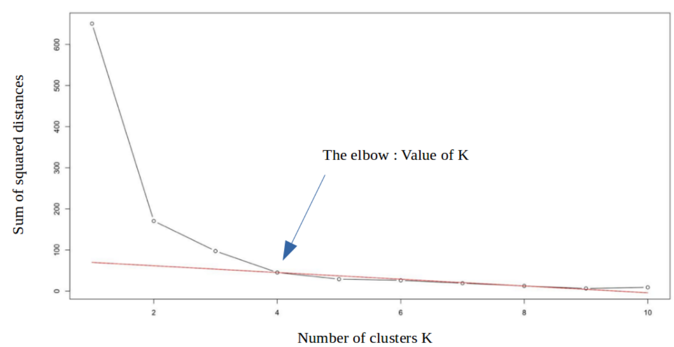

Fig. 7. Elbow Method - Sum of Squared Distances.

The plot represents the variation of the sum of squares with the number of classes. We notice that the most adequate number of clusters would be 4, since this point corresponds to an inflection point and the sum of squares seems to stabilize from this point on.

As we can see in Fig. 8, patients used in this clustering are divided into 4 clusters: patients with fewer than 8 falls (the blue cluster), 9 to 12 (the green cluster), 13 to 18 (the red cluster) and more than 24 falls (the black cluster). These latter represent the most critical cases. As we have seen before, The clustering algorithm helps us to categorize our event sources. In the following we will present some experimental results that proves the interest of integrating CEP into the IoDEP architecture, in order to manage the event that will trigger the process instances.

Experimental results for CEP integration:

The purpose of this series of experiments is to show the interest of integrating CEP in the IoT-BPM architecture. So we will compare two solutions. *Solution 1* represents incident management in our architecture without the integration of CEP, and *Solution 2* represents the integration of CEP in the architecture.

[5]https://fr.bonitasoft.com/

[6]https://www.tidyverse.org/

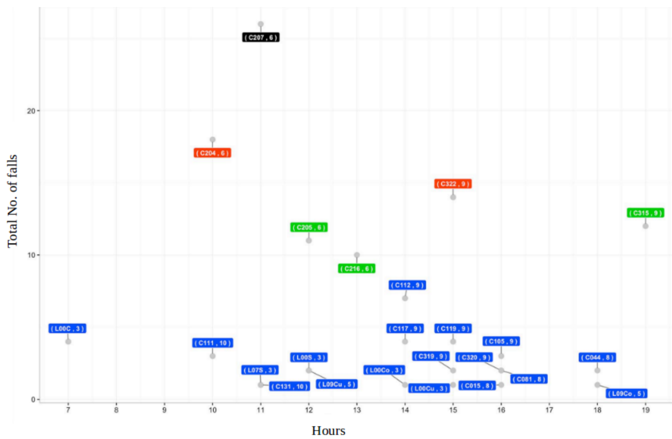

Fig. 8. Clustering with K-means.

CEP Rules:

Based on the context of our case study, we have defined some rules that help us to estimate the priority level of the incoming event. To define those rules we take into consideration the available information about the patient, his/her past incidents (falls) and the cluster to which this patient (event source) belongs. Taking into consideration the results of our clustering (detailed in the beginning of this section), we tried to manually define some rules. So basically we come up with the following rules:

- **IF** the event source belongs to cluster 4 (the critical cluster) **THEN** the new event generated by this source might be serious.
- **IF** The patient has some particular needs (Wheelchair, walker, etc.) **THEN** the new event generated by this source might be serious.
- **IF** The last event generated by this patient within one month was a serious or very serious alert **THEN** the new event generated by this source might be serious.

CEP Message broker:

As we have seen before, in order to manage the different incoming events within a CEP solution, we need a message broker. In this experiment, we have chosen RabbitMQ[7]. It is an open source message broker, lightweight and easy to deploy.

Global Schema of Event-pattern detection with CEP solution:

Fig. 9 illustrates our first attempt to integrate CEP engine in our IoT-BPM architecture.

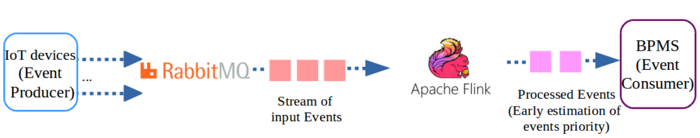

Fig. 9. Priority-based Event Management with CEP.

[7]https://www.rabbitmq.com/

The different modules of this architecture operate as follows:

- **Event Producer:** Events in this approach are mostly generated by some sensors or some IoT devices by sensing their environment (Smart cameras).
- **Lightweight Message Broker:** To manage the amounts of events received and that need to be processed by the CEP engine, we use a message broker that ensure the communication between the source and the target based on a publish/subscribe mechanism. This asynchronous mechanism implemented by message brokers allows source and target messages to be completely decoupled. Besides the message brokers can as well store the messages locally until they can be processed by the target element. That is why we have chosen RabbitMQ.
- **CEP engine:** Flink CEP is used in this case to filter and process incoming events based on the predefined rules, in order to detect the events with highest priority among the incoming stream of events.
- **Event consumer:** It represents in this approach a business process management system (BPMS) where the processes are managed, executed and monitored.

In our experiment for both solutions, we have simulated several event streams with different total number of events (100, 200, 300, 400, 500) (generated from the historical events in our data set). Our objective is to compare the evolution of the computation time of both solutions (as described in the following tables) as a response to increasing the number of input events (non-concurrent access (see Table III and Table IV) and concurrent access (see Table V and Table VI)). Besides, in both solutions we have used the results of the clustering step.

Non-Concurrent Access (NCA):

TABLE III. Computation Time (sec) for Solution 1 - NCA

Total event number	Computation time (sec) - Solution 1
100	19.0
200	19.45
300	25.48
400	31.3
500	37.4

TABLE IV. Computation Time (sec) for Solution 2 - NCA

Total event number	Computation time (sec) - Solution 2
100	22.07
200	32.14
300	44.25
400	55.6
500	70.62

Concurrent Access (CA) :

As we can see in Fig. 10, solution 1 presents better results comparing to solution 2 when we have a non-concurrent access of the incoming events. However, when we have a concurrent access, the CEP-based approach (solution 2) presents better results, especially when we increase the number of incoming events (see Fig. 11).

TABLE V. COMPUTATION TIME (SEC) FOR SOLUTION 1 - CA

Total event number	Computation time (sec) - Solution 1
200	48
400	72.1
600	108

TABLE VI. COMPUTATION TIME (SEC) FOR SOLUTION 2 - CA

Total event number	Computation time (sec) - Solution 2
200	27
400	34
600	60.3

Although solution 1 seems to be more efficient at low input events volumes, the CEP solution can performs better especially if implemented in an effective IoT architecture with 'Big' Data requirements.

For incident management systems providing a balance between (near) real-time event processing and scalability, it is very important to achieve an efficient and optimized business process instances scheduling and event management in BPM. Moreover, in real cases, we deal in most of the time with concurrent access of incoming events. So this confirm the efficiency of our assumptions that CEP can provide better results when integrated to an IoT-BPM architecture, and it can also provide better results comparing to traditional approaches for business process instances scheduling. Those initial results are encouraging to implement the entire end-to-end IoDEP architecture.

Interested readers can check the complete solution that we have implemented from GitHub[8].

IX. CONCLUSIONS AND PERSPECTIVES

Integrating IoT and BPM as a step towards an improved process management that benefits from data and event power, is possible via an integrated architecture (IoDEP). The idea behind this architecture is to manage data and events at the same time via an integration approach that includes four concepts: IoT (to sense the environment), CEP (to detect situations of interest since it is considered as the standard course for real-time analysis and situation detection), Machine Learning (to analyse our data, find patterns in it and then make predictions, to facilitate decision making), and BPM (to manage our business processes instances.

We introduced in this article the reason behind using machine learning algorithms and CEP techniques in our IoT-BPM communication approach. In fact, this bi-directional communication is established through event in one direction and data in another direction. That is why conducting a data analysis approach with event management can facilitate this communication/integration. Moreover, we have presented the different functionalities proposed by this architecture and also the different requirements that should be addressed. Throughout the different overviews of our proposed architecture, we argue that our approach is generic and can be used in multivariate settings, and most importantly in normal and strict environments where time and priority matter.

[8]https://github.com/Abir-IA/CEPFlink_EventManagement

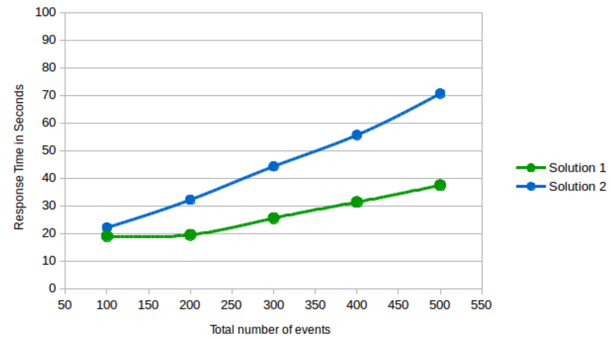

Fig. 10. Input Events with Non-concurrent Access.

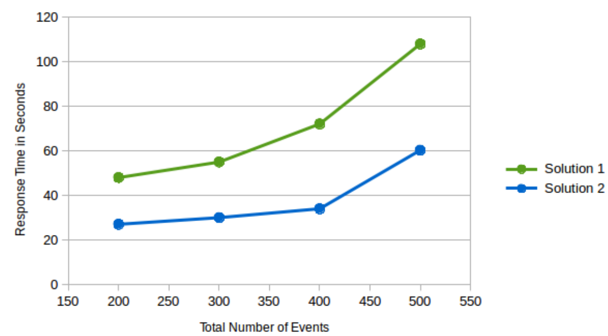

Fig. 11. Input Events with Concurrent Access.

Fully implementing this architecture, extending to test more machine learning algorithms, and exploring the automatic CEP rules learning in order to enrich the business rules engine for proactive event processing and process instances execution, are all plans to realize on our future schedule.

REFERENCES

[1] R. Mousheimish, *Combining the Internet of things, complex event processing, and time series classification for a proactive business process management.* PhD thesis, Université Paris-Saclay, 2017.

[2] W. M. Van der Aalst, "Business process management: a comprehensive survey," *International Scholarly Research Notices*, vol. 2013, 2013.

[3] R. Poll, A. Polyvyanyy, M. Rosemann, M. Röglinger, and L. Rupprecht, "Process forecasting: Towards proactive business process management," in *International Conference on Business Process Management*, pp. 496–512, Springer, 2018.

[4] A. Ismaili-Alaoui, K. Benali, K. Baïna, and J. Baïna, "Business process instances scheduling with human resources based on event priority determination," in *International Conference on Big Data, Cloud and Applications*, pp. 118–130, Springer, 2018.

[5] M. Anastassiu, F. M. Santoro, J. Recker, and M. Rosemann, "The quest for organizational flexibility: driving changes in business processes through the identification of relevant context," *Business Process Management Journal*, vol. 22, no. 4, pp. 763–790, 2016.

[6] F. Bergenti, G. Caire, and D. Gotta, "Interactive workflows with wade," in *2012 IEEE 21st International Workshop on Enabling Technologies: Infrastructure for Collaborative Enterprises*, pp. 10–15, IEEE, 2012.

[7] I. Barba, B. Weber, C. Del Valle, and A. Jiménez-Ramírez, "User recommendations for the optimized execution of business processes," *Data & knowledge engineering*, vol. 86, pp. 61–84, 2013.

[8] M. A. Setiawan, S. Sadiq, and R. Kirkman, "Facilitating business process improvement through personalized recommendation," in *Inter-*

national Conference on Business Information Systems, pp. 136–147, Springer, 2011.

[9] M. Khanbabaei, F. M. Sobhani, M. Alborzi, and R. Radfar, "Developing an integrated framework for using data mining techniques and ontology concepts for process improvement," *Journal of Systems and Software*, vol. 137, pp. 78–95, 2018.

[10] W. Van Der Aalst, A. Adriansyah, A. K. A. De Medeiros, F. Arcieri, T. Baier, T. Blickle, J. C. Bose, P. Van Den Brand, R. Brandtjen, J. Buijs, *et al.*, "Process mining manifesto," in *International Conference on Business Process Management*, pp. 169–194, Springer, 2011.

[11] S. Aguirre, C. Parra, and J. Alvarado, "Combination of process mining and simulation techniques for business process redesign: a methodological approach," in *International Symposium on Data-Driven Process Discovery and Analysis*, pp. 24–43, Springer, 2012.

[12] D. Redlich and W. Gilani, "Event-driven process-centric performance prediction via simulation," in *International Conference on Business Process Management*, pp. 473–478, Springer, 2011.

[13] A. Yousfi, K. Batoulis, and M. Weske, "Achieving business process improvement via ubiquitous decision-aware business processes," *ACM Transactions on Internet Technology (TOIT)*, vol. 19, no. 1, pp. 1–19, 2019.

[14] C. Stoiber, "Exploiting internet of things for business process improvement," 2021.

[15] M. M. Queiroz, S. F. Wamba, M. C. Machado, and R. Telles, "Smart production systems drivers for business process management improvement: An integrative framework," *Business Process Management Journal*, 2020.

[16] S. Cherrier and V. Deshpande, "From bpm to iot," in *International conference on business process management*, pp. 310–318, Springer, 2017.

[17] R. Wehlitz, I. Rößner, and B. Franczyk, "Integrating smart devices as business process resources–concept and software prototype," in *International Conference on Service-Oriented Computing*, pp. 252–257, Springer, 2017.

[18] S. Meyer, A. Ruppen, and C. Magerkurth, "Internet of things-aware process modeling: integrating iot devices as business process resources," in *International conference on advanced information systems engineering*, pp. 84–98, Springer, 2013.

[19] C. Janiesch, A. Koschmider, M. Mecella, B. Weber, A. Burattin, C. Di Ciccio, G. Fortino, A. Gal, U. Kannengiesser, F. Leotta, *et al.*, "The internet of things meets business process management: a manifesto," *IEEE Systems, Man, and Cybernetics Magazine*, vol. 6, no. 4, pp. 34–44, 2020.

[20] S. Schönig, L. Ackermann, S. Jablonski, and A. Ermer, "An integrated architecture for iot-aware business process execution," in *Enterprise, business-process and information systems modeling*, pp. 19–34, Springer, 2018.

[21] P. A. Stalenhoef, J. P. Diederiks, L. P. de Witte, K. H. Schiricke, and H. F. Crebolder, "Impact of gait problems and falls on functioning in independent living persons of 55 years and over: a community survey," *Patient Education and Counseling*, vol. 36, no. 1, pp. 23–31, 1999.

[22] P. A. Stalenhoef, J. P. Diederiks, J. A. Knottnerus, L. P. de Witte, and H. F. Crebolder, "The construction of a patient record-based risk model for recurrent falls among elderly people living in the community," *Family Practice*, vol. 17, no. 6, pp. 490–496, 2000.

[23] P. Stalenhoef, J. Diederiks, J. Knottnerus, A. Kester, and H. Crebolder, "A risk model for the prediction of recurrent falls in community-dwelling elderly: a prospective cohort study," *Journal of clinical epidemiology*, vol. 55, no. 11, pp. 1088–1094, 2002.

[24] V. S. Stel, S. M. Pluijm, D. J. Deeg, J. H. Smit, L. M. Bouter, and P. Lips, "A classification tree for predicting recurrent falling in community-dwelling older persons," *Journal of the American Geriatrics Society*, vol. 51, no. 10, pp. 1356–1364, 2003.

[25] K. A. Faulkner, M. S. Redfern, J. A. Cauley, D. P. Landsittel, S. A. Studenski, C. Rosano, E. M. Simonsick, T. B. Harris, R. I. Shorr, H. N. Ayonayon, *et al.*, "Multitasking: association between poorer performance and a history of recurrent falls," *Journal of the American Geriatrics Society*, vol. 55, no. 4, pp. 570–576, 2007.

[26] A. Furness, "A framework model for the internet of things," *GRIFS/CASAGRAS: Hong Kong, China*, 2008.

[27] J. Rifkin, *The zero marginal cost society: The internet of things, the collaborative commons, and the eclipse of capitalism*. St. Martin's Press, 2014.

[28] E. Natalizio, *Mobility as a Primitive to Improve Communications in Wireless Networks*. PhD thesis, UTC Compiègne, 2017.

[29] D. Grigori, *Eléments de flexibilité des systèmes de workflow pour la définition et l'exécution de procédés coopératifs*. PhD thesis, Université Henri Poincaré-Nancy 1, 2001.

[30] H. Harrington, "P. american society for quality control quality, business process improvement: the breakthrough strategy for total quality, productivity, and competitiveness," 1991.

[31] M. Dumas, M. La Rosa, J. Mendling, H. A. Reijers, *et al.*, *Fundamentals of business process management*, vol. 1. Springer, 2013.

[32] D. Grigori, F. Casati, M. Castellanos, U. Dayal, M. Sayal, and M.-C. Shan, "Business process intelligence," *Computers in industry*, vol. 53, no. 3, pp. 321–343, 2004.

[33] B. Schwegmann, M. Matzner, and C. Janiesch, "A method and tool for predictive event-driven process analytics.," in *Wirtschaftsinformatik*, p. 46, Citeseer, 2013.

[34] W. Schmidt, "Business activity monitoring (bam)," in *Business Intelligence and Performance Management*, pp. 229–242, Springer, 2013.

[35] O. Etzion and P. Niblett, "Event processing in action, manning publications," 2011.

[36] R. von Ammon, O. Etzion, H. Ludwig, A. Paschke, and N. Stojanovic, "Introduction to the second international workshop on event-driven business process management (edbpm09)," in *International Conference on Business Process Management*, pp. 345–346, Springer, 2009.

[37] C. Janiesch, M. Matzner, and O. Müller, "Beyond process monitoring: a proof-of-concept of event-driven business activity management," *Business Process Management Journal*, vol. 18, no. 4, pp. 625–643, 2012.

[38] D. Bo, D. Kun, and Z. Xiaoyi, "A high performance enterprise service bus platform for complex event processing," in *2008 Seventh International Conference on Grid and Cooperative Computing*, pp. 577–582, IEEE, 2008.

[39] D. Luckham, "Soa, eda, bpm and cep are all complementary," *Retrieved May*, vol. 20, p. 2011, 2007.

[40] A. Estruch and J. A. H. Álvaro, "Event-driven manufacturing process management approach," in *International Conference on Business Process Management*, pp. 120–133, Springer, 2012.

[41] R. v. Ammon, C. Emmersberger, F. Springer, and C. Wolff, "Event-driven business process management and its practical application taking the example of dhl," 2008.

[42] C. Costello, O. Molloy, and K. Hinkelmann, "Towards a semantic framework for business activity monitoring and management.," in *AAAI spring symposium: AI meets business rules and process management*, pp. 17–27, 2008.

[43] D. Luckham, *The power of events*, vol. 204. Addison-Wesley Reading, 2002.

[44] K. Danielsson and G. Trotta, "Key requirements for event-driven bpm and soa."

[45] W. Yao, C.-H. Chu, and Z. Li, "Leveraging complex event processing for smart hospitals using rfid," *Journal of Network and Computer Applications*, vol. 34, no. 3, pp. 799–810, 2011.

[46] R. Mousheimish, Y. Taher, K. Zeitouni, and M. Dubus, "Pact-art: Enrichment, data mining, and complex event processing in the internet of cultural things," in *2016 12th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS)*, pp. 476–483, IEEE.

[47] Z. Maamar, E. Kajan, I. Guidara, L. Moctar-M'Baba, and M. Sellami, "Bridging the gap between business processes and iot," in *Proceedings of the 24th Symposium on International Database Engineering & Applications*, pp. 1–10, 2020.

[48] C. Friedow, M. Völker, and M. Hewelt, "Integrating iot devices into business processes," in *International conference on advanced information systems engineering*, pp. 265–277, Springer, 2018.

[49] R. Song, Y. Wang, W. Cui, J. Vanthienen, and L. Huang, "Towards improving context interpretation in the iot paradigm: a solution to integrate context information in process models," in *Proceedings of the 2018 2nd International Conference on Management Engineering, Software Engineering and Service Sciences*, pp. 223–228, 2018.

[50] S. Schönig, L. Ackermann, S. Jablonski, and A. Ermer, "Iot meets bpm: a bidirectional communication architecture for iot-aware process execution," *Software and Systems Modeling*, vol. 19, no. 6, pp. 1443–1459, 2020.

[51] S. Schönig, L. Ackermann, and S. Jablonski, "Internet of things meets bpm: A conceptual integration framework.," in *SIMULTECH*, pp. 307–314, 2018.

[52] C. Sturm, S. Schönig, and C. Di Ciccio, "Distributed multi-perspective declare discovery.," in *BPM (Demos)*, 2017.

[53] D. Evans, "The internet of things: How the next evolution of the internet is changing everything," *CISCO white paper*, vol. 1, no. 2011, pp. 1–11, 2011.

[54] Z. A. Almusaylim and N. Zaman, "A review on smart home present state and challenges: linked to context-awareness internet of things (iot)," *Wireless networks*, vol. 25, no. 6, pp. 3193–3204, 2019.

[55] A. Ismaili-Alaoui, K. Baïna, K. Benali, and J. Baïna, "Towards smart incident management under human resource constraints for an iot-bpm hybrid architecture," in *International Conference on Web Services*, pp. 457–471, Springer, 2018.

[56] C. Soto, "Bpm and iot: The signal of true disruption," *Redmond Media Group*, 2015.

[57] C. Chang, S. N. Srirama, and R. Buyya, "Mobile cloud business process management system for the internet of things: a survey," *ACM Computing Surveys (CSUR)*, vol. 49, no. 4, p. 70, 2017.

[58] J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of things (iot): A vision, architectural elements, and future directions," *Future generation computer systems*, vol. 29, no. 7, pp. 1645–1660, 2013.

[59] J. Pielmeier, S. Braunreuther, and G. Reinhart, "Approach for defining rules in the context of complex event processing," *Procedia CIRP*, vol. 67, pp. 8–12, 2018.

[60] D. C. Luckham, *Event processing for business: organizing the real-time enterprise*. John Wiley & Sons, 2011.

[61] D. Canty, "Architecting for dynamic analytics in iot.." https://dzone.com/articles/architecting-for-dynamic-analytics-in-iot, 2014. [Online; accessed July-2021].

[62] S. Tjoa, S. Jakoubi, G. Goluch, G. Kitzler, S. Goluch, and G. Quirchmayr, "A formal approach enabling risk-aware business process modeling and simulation," *IEEE Transactions on Services Computing*, vol. 4, no. 2, pp. 153–166, 2011.

[63] A. Ismaili-Alaoui, K. Baïna, and K. Benali, "Harnessing the power of data and event data for business process improvement," in *CAISAM 2019-Complexity Analysis of Industrial Systems and Advanced Modeling*, 2019.

[64] U. ITIL, "Introducing service operation.." https://www.ucisa.ac.uk. [Online; accessed January-2021].

[65] J.Kaplan, "When internet of things meets big data." https://www.informationweek.com/big-data/big-data-analytics/when-internet-of-things-meets-big-data/a/d-id/1298137?,. [Online; accessed July-2021].

[66] J. Gutiérrez, V. Rodríguez, and S. Martin, "Comprehensive review of vision-based fall detection systems," *Sensors*, vol. 21, no. 3, p. 947, 2021.

[67] Y. Chen, X. Kong, L. Meng, and H. Tomiyama, "An edge computing based fall detection system for elderly persons," *Procedia Computer Science*, vol. 174, pp. 9–14, 2020.

[68] Cisco, ""cisco fog computing solutions: Unleash the power of the internet of things", syst. inc., san jose, ca, usa, white paper, 2015." https://www.cisco.com/c/dam/en_us/solutions/trends/iot/docs/computing-solutions.pdf. [Online; accessed July-2021].

[69] D. Luckham, "A short history of complex event processing," *Part 1: Beginnings. 1-a-short-history-of-cep-part-1. pdf*, 2007.

[70] D. Robins, "Complex event processing," in *Second International Workshop on Education Technology and Computer Science. Wuhan*, pp. 1–10, Citeseer, 2010.

[71] G. Cugola and A. Margara, "Processing flows of information: From data stream to complex event processing," *ACM Computing Surveys (CSUR)*, vol. 44, no. 3, p. 15, 2012.

[72] D. S. Rosenblum and A. L. Wolf, *A design framework for Internet-scale event observation and notification*, vol. 22. ACM, 1997.

[73] M. Eckert and F. Bry, "Complex event processing (cep),"

[74] A. Margara, G. Cugola, and G. Tamburrelli, "Learning from the past: automated rule generation for complex event processing," in *Proceedings of the 8th ACM International Conference on Distributed Event-Based Systems*, pp. 47–58, ACM, 2014.

[75] M. von Rosing and S. Polovina, "Business process trends," 2015.

[76] M. Daum, M. Götz, and J. Domaschka, "Integrating cep and bpm: how cep realizes functional requirements of bpm applications (industry article)," in *Proceedings of the 6th ACM International Conference on Distributed Event-Based Systems*, pp. 157–166, ACM, 2012.

[77] M. Weidlich, H. Ziekow, J. Mendling, O. Günther, M. Weske, and N. Desai, "Event-based monitoring of process execution violations," in *International conference on business process management*, pp. 182–198, Springer, 2011.

[78] F. Koetter and M. Kochanowski, "A model-driven approach for event-based business process monitoring," *Information Systems and e-Business Management*, vol. 13, no. 1, pp. 5–36, 2015.

[79] P. Soffer, A. Hinze, A. Koschmider, H. Ziekow, C. Di Ciccio, B. Koldehofe, O. Kopp, A. Jacobsen, J. Sürmeli, and W. Song, "From event streams to process models and back: Challenges and opportunities," *Information Systems*, vol. 81, pp. 181–200, 2019.

[80] B. Mazon-Olivo, D. Hernández-Rojas, J. Maza-Salinas, and A. Pan, "Rules engine and complex event processor in the context of internet of things for precision agriculture," *Computers and electronics in agriculture*, vol. 154, pp. 347–360, 2018.

[81] N. Mehdiyev, J. Krumeich, D. Enke, D. Werth, and P. Loos, "Determination of rule patterns in complex event processing using machine learning techniques," *Procedia Computer Science*, vol. 61, pp. 395–401, 2015.

[82] Q. Zhang, L. Cheng, and R. Boutaba, "Cloud computing: state-of-the-art and research challenges," *Journal of internet services and applications*, vol. 1, no. 1, pp. 7–18, 2010.

[83] P. Mell, T. Grance, *et al.*, "The nist definition of cloud computing," 2011.

[84] J. Bell, *Machine learning: hands-on for developers and technical professionals*. John Wiley & Sons, 2020.

[85] J. A. Hartigan and M. A. Wong, "Algorithm as 136: A k-means clustering algorithm," *Journal of the royal statistical society. series c (applied statistics)*, vol. 28, no. 1, pp. 100–108, 1979.

[86] R. L. Thorndike, "Who belongs in the family," in *Psychometrika*, Citeseer, 1953.

[87] P. J. Rousseeuw, "Silhouettes: a graphical aid to the interpretation and validation of cluster analysis," *Journal of computational and applied mathematics*, vol. 20, pp. 53–65, 1987.

[88] R. Tibshirani, G. Walther, and T. Hastie, "Estimating the number of clusters in a data set via the gap statistic," *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, vol. 63, no. 2, pp. 411–423, 2001.