ANALYSIS MODEL OF THE VALUE OF INFORMATION FLOW FOR DECISION MAKING AND PERFORMANCE IMPROVEMENT IN SHOP FLOOR OF DEVELOPING COUNTRIES USING MACHINE LEARNING ALGORITHMS

Abstract
Performance improvement is a daily activity for Small and Medium Size companies in the manufacturing sector, which always depends on the good management of information flow for a better decision making to facilitate shop floor operations that will have a major impact on quality and timely product delivery to customers. The management of information flow is also conditioned by the characterization of the information flow. In this paper we used the characteristics of information flow to determine and predict an analysis model of the value of information flow that will facilitate decision making in shop floor operations by operators (machine, humans and computers) through the means of machine learning. The outcome of our work proposes the Decision Trees Model as the better one to predict the value of information flow as long as the characteristics are binary data or scale data, it shows that a digital information can always has a good value of information flow if there is no disruptions and finally we can still have a good value of information flow if using papers, visual, electronic real-time information which are accessible, timely, none volatile, and that has a major concern which the shop floor operations.

Keywords: Decision making. Developing countries. Information flow Characteristics. Machine Learning. Management of information flow. Shop floor.

Introduction
Customers satisfaction in terms of product quality and timeliness delivery has always facilitate the improvement of the development of Small and Medium Size Enterprises (SMEs), which also has always been at the center of scientific research, this development is function of the relationship existing between workers of companies explicitly known as information sharing and decision making. The management of information flow (MIF) moves towards digitalize information known as information of things and it is a key for performance improvement (Kim et al. 2017), but in some developing countries the concept of internet of things applied to the MIF is still not yet a mare event due to the lack of technology transfer and the random economic situation (Agu and Mbah 2013; Saymeh and Sabha 2014; Unido 2021). It is then an opportunity to work over a progressive transition from the traditional MIF in shop floor operations to the digital MIF. A proper MIF renders manufacturing companies continuously efficient when stochastics and none stochastics event related to machines and operators behaviors occur (Sushil 2017; Dey et al. 2019; Shukla et al. 2019; Singh et al. 2019; Contador et al. 2020; Evans and Bahrami 2020; Ojstersek et al. 2020). This paper focus on shop floor of manufacturing companies in developing countries where we have a poor management of information flow that result to a wrong decision making from the tactic to the operational level and later cause a
decrease performance of the company. The MIF refers to have an upper hand on the shared information by characterizing the information flow \textbf{(Mbakop et.al 2021)}, the MIF also consist of giving to information flow a value in order to facilitate decision making in shop floor operations for performance improvement of companies \textbf{(Tomanek and Schroder 2020)}. Many research works were done in the determination of the value of information flow (VIF) by integrating one of the characteristics of information flow (CIF) namely quality and later dimension. But they haven’t considered the influence of at list two CIF in their analysis of the VIF to facilitate decision making in manufacturing companies. Some tried to determine the VIF with the quality of information flow by using methods of technical audit, process information integration and recently, dimension of information by using the Value Added Heat Map (VAHM) method which leads to the degree of digitalization of processes in shop floor. Nevertheless, all these methods become limited when facing a poor MIF in an environment where all the CIF has an influence on the shop floor operation which is a particular case of some SMEs of developing countries. This paper aims to integrate the CIF in the determination of the VIF to facilitate decision making by operators or machines in the shop floor process using the approach of machine learning and the hypothesis that all the CIF can be binary data firstly and secondly that only dimension of information flow can be scale according to \textbf{Tomanek and Schroder (2016)}. The accomplishment of this gold will lead us to bring out a general presentation of decision making and the CIF, then illustrate the previous works on the VIF and finally propose an analysis model to determine or predict the VIF, followed by a results comparison.

1. Overview on Decision making and Information flow

Information flow can have several definitions depending on the context in which it is used, we will present three contexts depending on the definition of information flow related to our research.

1.1 Collaborative and decision-making context

We can define information flow as the different types of flows that require a synergy between modern organizations and computer systems \textbf{(Mentzas et al. 2001)}. Information flow can be considered as production order, customers’ demands in a supply chain \textbf{(Mbhele, 2014)}. According to \textbf{Mbakop et.al. (2021)} information flow is a set of dynamic and static data in shop floor that can be characterized. From these previous definitions it makes sense to introduce collaboration in the enterprise, this collaboration in the enterprise leads to decision making which is a major aspect in performance improvement \textbf{Susilawati 2021}. A decision is the result of a personal or multi-personal brainstorm in the face of a given concern or problem containing multiple possibilities, an interval of which seems to optimally satisfy the company. Decision-making is therefore a permanent activity of managers and workers. information sharing in the company takes place in the levels of decision-making, and according to \textbf{Joseph and Gaba (2019), Partanen, et al. (2019), Hall et al.(2021)} decision-making is influenced by information flow. There are therefore 3 levels of decision making in companies that are influenced by the flow of information to facilitate better collaboration, we can therefore present them as follows:

1.1.1 The strategic level

Conditioned by strategic management, strategic decisions are generally taken by a company’s board of directors. These decisions focus on the company’s vision, on improving its performance and on perpetual customer satisfaction in the long term \textbf{(Julie Stal-Le Cardinal,2009)}. A strategic decision can be illustrated by modifying a product's packaging to attract more customers, multiply the company's performance, and renew the equipment available for manufacturing according to our local resources. Existential information at this level will converge to the tactical level.

1.1.2 The tactical level
The tactical level is an intermediate level between the strategic and operational levels. The decisions taken at this level are a direct consequence of those taken at the strategic level and sometimes they can result from an influence of the operational level, this type of decision generally applies in the medium term (Biard et al. 2017; Dumetz, 2018). This type of decision is taken by both management and planning staff in all types of departments. The tactical level, according to the previous decision of the strategic level, will be responsible for, for example, designing the packaging model, gathering the finances for the realization of the new packaging, ordering the new machines for the production of the packaging, gathering the resources for the realization of the new packaging.

1.1.3 The operational level

The operational level is a level of execution of the resolutions, it is the level of materialization of the ideas of the strategic management, the operational management therefore manages the implementation of the related operations with their resources (Biard 2017). Decision-making at this level is directly linked to the tactical level. Information flows most often in both directions, meaning from the tactical level to the operational level and from the operational level to the tactical level. In comparison to the example of changing the packaging of the company's product, the operational level will for example take care of the production of the packaging, assigning the tasks to the qualified human resource for the production of the packaging, the reception and installation of the machines, the marketing policy for the promotion of marketing.

![Diagram of the decision-making levels](image)

**Fig1.** Presentation of the information flow in the decision-making levels.

According to the figure presented, we note some cases of circulation of information flow, namely IOS and ISO which is a particularity of the companies in developing countries, the circulation of information flow in these countries does not respect the hierarchy of decision-making levels.

1.2 Information flow characteristics
The characterization of information flow in a shop floor can contribute to the amelioration of information sharing among operators or workers of the shop floor supply chain. Information flow that arrives in a shop floor or in the operational level can be characterized according to Berente and Vandenbosch (2004), Mbakop et al. (2021) by:

1.2.1 **Dimension of information flow:** it defines the means by which information flow can be transferred, namely

- Written information on paper, *(Thomas 1993 ; Durugbo et al. 2013)*
- Vocal information, *(Durugbo et al. 2013)*
- Visual information, *(Baudet et al. 2011 ; Müller et al. 2017)*
- Electronic non-real time information (ENRT), *(Tomanek and Schröder 2016;Tomanek and Schroder 2017).*
- Electronic real time information (ERT), *(Tomanek and Schröder 2016 ; Tomanek and Schroder 2017; Schmidtke et al. 2018 ; Skender et al. 2020)*
- Digital information, *(Demiris et al. 2008 ; Durugbo et al. 2013 ; Tomanek and Schroder 2017).*

1.2.2 **Direction of information flow:** related to the hierarchy of every company an information flow can take several directions according to where the message is being sent, it can be from the tactical level to the operational level, according to Forza and Salvador (2001), Global (2019) we have the following directions of information flow:

- The upward information, it can be easily described by IOS, ITS, IOT.
- The downward information refers to IST, ITO, ISO.
- The horizontal information concerns the information flow that can be shared in the same level of decision-marking.
- The diagonal information concerns the information flow than can be shared with different organization.

1.2.3 **Parameters of information flow:** it defines the static and the dynamism of information when it is shared *(krovi et al.2003),* it can be shown as:

- Velocity of information, which describe the speed at which an information flow.
- Viscosity of information, which describe the level of contradiction or resistance to the flowing of information.
- Volatilit of informaion flow, it can describe the loss of information while it is sent.
- Complexity of information flow, with describe the inability of a personnel to decode multiples informations that were sent.

1.2.4 **Quality of information flow:** Information flow as to be of a good quality and quality of information is vital for information sharing and decision-making. According to *(Berente et al. 2009), Berente and Vandenbosch (2004)* information flow qualities can be described as:

- Transparency denotes the ability of workers to understand the information delivered to them *(Barki and Pinsonneault 2005; Carlile 2004).*
- Accessibility defines the level of which an information is accessible, *( Berente et al. 2009).*
- Timeliness refers to the availability of information when it is needed it is neither too late, nor too early *(Berente et al. 2009; Durugbo et al. 2010 ; Tomanek et Schroder 2017).*
• Granularity can be seen as the level of details that an information flow can have (Volkoff et al., 2005).
• Cost of information can be considered as added or the reduced cost on an output product and also on product delivery to customers (Ballou et al. 1998).

1.2.5 Type of information flow: Information flow can be of two types according to Chibba and Rundquist (2004).

• Direct information, when the information flow is directly related to the manufacturing of a product and if it is not available the production process cannot start or if it has started it can be stopped, that information can be qualified as direct.
• Indirect information, an information flow is said to be indirect when its absence doesn’t stop the manufacturing of a product.

2. The value of information

In industrial and job processes, materials and information flow are always on motion except that their motions can be described by contrary direction. An information can then stop the flow of materials in process, cause the materials not to be in process, from this we can then be focused on the value of information that are in the process or that may trigger the process. According to the literature, there are many ways to define or to consider the value of information:

• In the job operations sequences, the value of information can be linked with the benefit that and information adds to a process or service, (Porter and Millar 1985).
• The value of information flow can be considered as a measure for the avoidance or minimization of the bullwhip effect (Lee et al. 1997).
• Considering the integration of information flow in a process be it shop floor or not, to Berente and Vandenbosch (2004), Berente et al. (2009), the value of information is based on the quality of information that is characterized by accessibility, transparency, timeliness and granularity.
• The value of information can be created by information, which are transmitted correctly, complete and in a timely manner (Reese 2016, wang et al. 2012), by avoiding disturbances and media disruptions.
• Considering the works of (Tomanek and Schröder 2016), the value of information flow is function of scale of the dimension of information flow as presented in Table 1.
### Table 1: Value added heat map—evaluation scale for information flow (Tomanek and Schröder 2016)

| Categorization               | Value Added Level | Dimension of Information Flow                                    | Scale |
|------------------------------|-------------------|-----------------------------------------------------------------|-------|
| No Added Value               | 0                 | Insufficient, incorrect or unnecessary exchange of information  |       |
| Limited Added Value          | 1                 | Written exchange of information (e.g. paper document, fax, e-mail, etc.) |       |
|                              | 2                 | Verbal or visual exchange of information                         |       |
|                              | 3                 | Electronical exchange of information not real-time (e.g. by spreadsheet application) |       |
|                              | 4                 | Electronical exchange of information realtime (e.g. by system-application) |       |
| Maximum Added Value          | 5                 | Digital exchange of information real-time (e.g. by Internet of Things and Services) |       |

- Considering the presence of materials on a production line in shop floor, the value of information can be deducted from the impact that materials undergo on shop floor, and also the value of information flow can be determined by knowing the digitalization degree in a context of industry 4.0 using the method of Value Added Heat Map (VAHM) (Tomanek et al. 2020).

### 3. Method used for to determine the value of information

The information flow is set of data that can be static or dynamics (mbakop et al. 2021), and according to the context of developing countries the information flow has different value due to the non-complete digitalization of processes, the value of information (VI) can decrease because of the information medium, the disruptions and redundancy. It is then very important to identify media disruptions and any others every bottleneck that can occurs (Tomanek et Schroder 2017). The determination of the VI according to the literature depends on the used methods. The determination of the value of information in a process or a service has been a long target for researchers.

#### 3.1 The Value of the information process integration

The efficiency of a process depend on the quality of how a process is made, that process quality depends also of the information flow, that is why Aubert et al. (2003) have integrate the value of information in the Value of the process, they have consider the quality of information namely accessibility, transparency, timeliness, and granularity. Their value of information was considered as the sum of the
cost of accessibility, transparency, timeliness, and granularity. More the information quality cost is low, more the value of information is high and more the information process integration is high also according to the following equation:

\[
P_I = \frac{(VA-\sum_{j=1}^{n} C(a_j) + C(tr_j) + C(ti_j) + C(g_j))}{VA}
\]  

(1)

Where \( VA \): Value added by the process, 
\( C(x_j) \): Cost of providing property \( x \) for activity \( j \)
\( a_j \): Accessibility for activity \( j \), 
\( tr \): transparency for activity \( j \)
\( ti \): timeliness for activity \( j \), 
\( gi \): granularity for activity \( j \)

We can then extract from equation (1) the equation of the value of information based on cost.

\[
Q_I = \sum_{j=1}^{n} C(a_j) + C(tr_j) + C(ti_j) + C(g_j)
\]  

(2)

\( Q_I \): Value of the quality of information flow

**Berente and Vandenbosch (2004)**, have proposed another form of computation of the value of the process integration depending on the quality of information, instead of considering the cost of information quality, they have tried to attribute to every quality of information the factor of time. They carried out an audit and they determine the different time referring to information quality characteristics. The obtained formula of the process integration value is given by equation (3) and the value of information that can be considered from it is given by equation (4).

\[
P_{IT} = 1 - \frac{(\sum_{j=1}^{n} T(a_j) + T(tr_j) + T(ti_j) + T(g_j))}{TT}
\]  

(3)

Where \( TT \): Total time taken by the process, 
\( T(x_j) \): Time of providing property \( x \) for activity \( j \)
\( a_j \): Accessibility for activity \( j \), 
\( tr \): transparency for activity \( j \)
\( ti \): timeliness for activity \( j \), 
\( gi \): granularity for activity \( j \)

We can then extract from equation (3) the equation of the value of information based on time.

\[
Q_I = \frac{\sum_{j=1}^{n} C(a_j) + C(tr_j) + C(ti_j) + C(g_j)}{TT}
\]  

(4)

\( Q_I \): Value of the quality of information flow

The works of **Aubert et al. (2003), Berente and Vandenbosch (2004)**, were only based on the quality of information flow to influence the value of information in the process integration, it is not easy neither to quantify a cost nor the time related to accessibility, timeliness, transparency and granularity according to the authors, to quantify the time where and information may be accessible for each operations in a shop floor process is a difficult task and doing that will take much more time. That is why it is very important to look for an other way round.

### 3.2 The Value Added Heat Map
Proposed by Tomanek et Schroder (2017), the value Added Heat Map (VAHM) is an innovative visualization tool that indicates the level value creation concerning production relevant factors. It is following the methodically of a thermal heat map camera. The VAHM enables to have a view on the added value level of production relevant factors by using colors scaling and it by developing key performance indicators it finds also its application in determine relevant factors like the internal circulation of information flow. To analyze the VIF, they have done an audit in the company in with they have mapped the flow of information and the results of the audit lead them to scale the information that were given a more added value to the process. Table 1 and Table 2 illustrate the information flow in circulation in the shop floor and the VAHM respectively.

Table 2: Value Stream Analysis - symbols for the visualization of an information flow (Tomanek et Schroder 2016),

| Symbols for the information flow | Meaning                                      |
|---------------------------------|----------------------------------------------|
| Image of a manual information   | Manual information flow                       |
| Image of an electronic information | Electronic information flow                   |
| Image of a production planning  | Levelled production planning                 |
| Image of a kanban card          | Route of a kanban card                        |

The value of information was then the estimate function of the digitalization degree, The layout-specific digitalization degree indicates, which percentage the degree of information flow promotes added value and it is computed from the ratio of the sum of each information transfer multiplied with the corresponding value added level and the amount of transferred information per time unit multiplied with the highest possible value added level according to Equation (5) developed by Tomanek and Schroder 2017.

\[
DIGITALISATION\ DEGREE = \frac{\sum_{i=1}^{N} (Information\ Transfer \times Value\ Added\ Level)}{N \times Max(Value\ Added\ Level)} \times 100 \quad (5)
\]

\[Information\ Transfer \equiv I = 1,\ldots,N;\]

\[N = \text{Amount of transferred information per time unit}\]

\[Value\ Added\ Level = 0,\ldots,5;\]

Though the Value Added Heat Map analyses the information flow, it shows a possibility on how deficient information or defective information can be cause to the losses of time, in their work they have only considered that the medium of information with is the dimension of information can be scale, they haven’t integrated the scaling of direction of information flow, of the parameters, of the types and of the quality of information flow. The considerations of all these characteristics of the information will give a real knowledge on information flow management in the context of developing countries because it is not all the SMEs manufacturing company with are high industrialized. It is important to consider
that a digital information (dimension) of information can face disruption according to the network of the environment such digital information will cause losses and will no more have “5” has added value.

It is therefore important to bring out a new method to determine or to analyze the value of information flow in shop floor of developing countries considering the decision making and the characteristics of information. Having many characteristics of information flow, the method of Value-Added Heat Map will not be helpful unless we consider a reduction of variables, we have then focused our analysis on machine learning methods.

4. Machine Learning Methods review

The analysis of the VIF in shop floor of developing using a machine learning algorithm approach has not yet been a studies focus according to article that we have read in the literature, because the development of information characteristics has been updated by Mbakop et al (2021). Machine Learning Methods have been used in many applications in industries, we will the present a briefly view of machine learning techniques and their different roles. Researchers have characterized machine learning in trees groups, namely: Supervised Learning, Unsupervised Learning, Reinforcement Learning. In this paper we will be concerned by supervised learning, among supervised learning algorithms we can list:

![Fig 2. classification of algorithms of supervised learning](image)
There are many algorithms of supervised learning but we have just listed some as noted in fig 2.

**Support Vector Machine (SVM)** is an algorithm of ML technique use for classification and prediction analysis due to its high accuracy which is based on statistical analysis, it has been developed for pattern recognition, classification, it uses a great number of data (Parikh et al. 2010; Kankar et al. 2011; Ahmad et al. 2019; Dataflair 2020), it objective relies on is the individualization of hyperplanes parallel to error minimization.

**Decision Tree (DT)** is an algorithm of ML with is also used for classification and prediction analysis. The main purpose are to expose the structural information contained in data, his network is formed of nodes which represents features (inputs) and the leaf nodes which represent the output (Lingitz et al. 2018; Cinar et al. 2020).

**Logistic regression (LR)**: this is a classification function that uses class for building and uses a single multinomial logistic regression model with a single estimator, it is also used for prediction and it is usually states where boundary are between 0 and 1 (Bhavsar and Ganatra 2012; Osisanwo et al. 2017).

**Bayesian Networks (BN)**: it is a statistical classifiers that predict the class of probability, Bayesian networks are graphical models, showing the relationship between the subset of attributes and BN have exhibited high accuracy and speed when applied to large databases (Jensen 1996; Friedman et al. 1997; Bhavsar and Ganatra 2012; Osisanwo et al. 2017).

**Random Forest (RF)**: this classification algorithm contains a set of trees, in which similar independent vector vectors are distributed, and every tree issues a voting unit for the most common category in input, (Breiman 2001; Jhonnerie et al. 2017; Goel et al. 2017).

**KNearest-Neighbour (K-NN)**: k-NN is an algorithm mostly used for classification problems and pattern recognition, This method classifies cases based on the relationship between variables and can be used for both classification and regression (Mishra and Sahu 2011; Alam 2019; Abdulqader et al. 2020).

**Neural Network (NN)**: NN are machine learning tools that can perform classification or /and regression task at once. Artificial Neural Network (ANN) depends upon three fundamental aspects, input and activation functions of the unit, network architecture and the weight of each input connection (Kankar et al. 2011; Osisanwo et al. 2017; Lingitz et al. 2018; Cinar et al. 2020).

A comparative studies has been done and presented by (Bhavsar and Ganatra 2012; Osisanwo et al. 2017) in Table 3, we present an extract of that comparative study.

**Table 3: Comparative study of commonly used Classification Techniques**

|                      | Decision Trees (DT) | Neural Network (NN) | Bayesian Network (BN) | K-Nearest Neighbor (K-NN) | Support Vector Machine (SVM) |
|----------------------|---------------------|---------------------|-----------------------|---------------------------|-----------------------------|
| **Accuracy in general** | Good                | Very Good            | Average               | Good                      | Excellent                   |
| **Speed of learning**         | Very Good           | Average              | Excellent             | Excellent                 | Average                     |
| **Speed of classification**    | Excellent           | Excellent            | Excellent             | Average                   | Excellent                   |
| **Tolerance to missing values** | Very Good           | Average              | Excellent             | Average                   | Good                        |
### Tolerance to redundant attributes

|                | Good     | Very Good | Average | Good     | Very Good |
|----------------|----------|-----------|---------|----------|-----------|
| Dealing with discrete/binary/continuous attributes | All      | Not discrete | Not continuous | All      | Not discrete |

### Support Multiclassification

|                | Excellent | Naturally extended | Naturally extended | Excellent | Binary classifier |
|----------------|-----------|--------------------|--------------------|-----------|--------------------|

## 5. Methodology

To bring out a new approach that will be lightly based on the previous one techniques (VAHM) and for the characteristics of information flow to be integrated in the analysis, we will be using the different steps to predict the VIF using the classification algorithms of ML. In shop floor of developing countries, IFC can have an impact on the production or manufacturing based on decision making by operators. In this analysis we will consider the following hypotheses(H1,H2).

**H1:** The IF is a row matrix $M_{IF}$ of 5 rows Matrix $(X_k, 1 \leq k \leq 5 )$ representing all the 5 matrix of the IFC and all the IFC are not dependent each other. Each of $X_k$ row matrix has a $x_i$ component that is totally binary for one case and for an order one only the dimension information value will not be binary data but they will derive from the scale of information dimension as presented in Table 2.

For each $X_k = (x_i)$, $x_i = \begin{cases} 1, & \text{for Type, } 1 \leq i \leq 2 \\ 1, & \text{for Dimension, } 1 \leq i \leq 6 \\ 1, & \text{for Direction, } 1 \leq i \leq 4 \\ 1, & \text{for Parameters, } 1 \leq i \leq 4 \\ 1, & \text{for Quality, } 1 \leq i \leq 4 \end{cases}$ (6)

For quality, we will not consider the fifth sub characteristics which is the cost of information flow in this paper, that is why quality contain 4 components.

**H2. First case:** In this case the characteristics of information flow will be taken as binary data and each characteristic we will present some considerations.

- **Types of information flow:** An information flow arriving in the shop flow can directly influence the process of manufacturing of a product then the “direct value” will be consider as 1, if we don’t have any indirect information flow (that doesn't influence the process) it will be consider as 0, we can also have a direct information flow and then an indirect information flow at the same time in the process.
- **Dimension of information flow:** We consider here that an information flow can only be sent in the shop floor on one dimension, then if it is documented it takes the value of 1 and the rest of information dimension is 0.
- **Direction of information flow:** if one direction like the upward is at 1 the rest will be at 0.
- **Parameters of information flow:** here all the parameters can exist at the same time and can have the same or different binary values.
- **Quality of information flow:** it carries the same assumption like the parameters of IF.
H2. **Second case** : In this case only the dimension characteristics of information flow won’t be a binary data, but the rest will be considered as binary data and the previous considerations of the first case will be the same.

The upward hypothesis will be the backbone to carry on this methodology steps of our work as presented in fig. 3.

![Flowchart](chart.png)

**Fig. 3** Analysis method of determination or prediction of the VIF with Machine learning algorithms

6. **Results and Discussion**

6.1 **Heat Map of information flow describe by the correlation matrix when having binary data**

When the CIF are totally binary or except the dimension which isn’t binary, from the data collected in a sharing of an information flow based of its characteristics in shop floor of developing countries, it happens that the correlation matrix is the same and its shows the relationship or the dependency between the CIF as presented by fig 4.
The correlation Matrix indicates the following observations

**Observation 1**

A perfect dependency (1.0) of every characteristics of information flow with each other, which mean technically that, the information flow sharing depends on the CIF and that none of the characteristics should be left out for they have the same weight.

**Observation 2**

A negative dependency (-0.5) between each of the sub characteristic of the type of information flow, namely direct and indirect, on shop floor process it can be seen as to have a look on the type of information that are sent or shared in the shop floor depending on their influence on the process, more the direct information is in the process, the indirect information has to be left out, more the indirect information are in the process the direct one has to be left out, there shouldn’t be both of them at the same time to avoid confusion.
**Observation 3**

A negative dependency (-0.2) between each of the sub characteristic of the dimension of information flow, which means that in the shop floor operations processes, the arrival of information flow in a shop floor for a process has to be only and only on one information dimension in order to avoid loss of time for in operations processes and facilitate decision making, the operator should not see two same information in two different dimension at the same time, this correlation matrix is the same even when the dimension of information flow changes. that is why the correlation matrix of the dimension of information is given by fig.6.

**Observation 4**

A negative dependency (-0.3) between each of the sub characteristic of the direction of information flow, which signify to avoid confusion in decision making by operators in shop floor an information flow should come only from one level and not two level at the same time.

**Observation 5**
From observation 2, 3, and 4, the influence of levels of decision making is more than the one of the dimension of information flow looking at the negative dependency, the types of information flow (direct or indirect) has a great negative influence more than an information that comes from the decision level and also the transmission support (dimension) of information. From all the above observation the dependency between the features or information characteristics does not exist, therefore we can’t use this dataset for regression only for classification.

2) Modeling of the Value of information flow (VIF)

The VIF that we want to obtain or predict for every information flow arriving in the system is described by equation, (7), is presented by fig. 8.

\[ VIF = f(X_k) \] (7)

\[ M_{IF} = (\text{Direct, Indirect, Document, Audio, Visual, E}_N\_R\_T, E\_R\_T, \text{Digital, Upward, Downward, Horizontal, Diagonal, Velocity, Viscosity, Complexity, Volatility, Transparency, Accessibility, Timeliness, Granularity}) \] (8)

Focusing on the specificity of developing countries which has not yet improve in the development of new technologies, based on the information disruptions and the work of (Aubert et al. 2003; Berente and Vandenbosch 2004; Tomanek and Schroder 2017) which considered that a VIF will be good or add a value to a process in terms of quality or time, if it respects the for both cases equation (9):

\[ VIF = 1 \text{ if } \begin{cases} 
\text{Velocity} = 1 \\
\text{Volatility} = 0 \\
\text{Accessibility} = 1 \\
\text{Timeliness} = 1
\end{cases} \] (9)
The determination of VIF in the shop floor process will be of a difficult task if we base ourselves just on the upward equations (7), (8) and (9). Therefore we will use classification algorithm to determine the correct model to be chosen to facilitate the determination or the prediction of the VIF as indicate by fig.8.

![Diagram](image)

**Fig.8** Analysis of VIF with machine learning model.

### 3) Analysis of the VIF with Classification algorithms

In this paper we will be focus on these various classifications algorithms: DT, KNN, RF, SVC, LR, GNB,GB. After splitting and train the dataset, the results obtained from our computation with python using the complete binary data and when it is only the dimension which is not binary (Tomanek and Schroder 2016) are presented in fig. 9 and fig.10 respectively.

#### 3.1) Models evaluation

From the results obtained from fig.9 and fig.10 respectively, we can observe that:

- The accuracy of all the chosen algorithms except from KNN is equal to one, it means that for this total binary dataset all the chosen algorithm can predict the value of an information flow arriving in the process.
- The accuracy of DT is higher among all when data are totally binary.
The chosen model for both type of data is DT because it has the highest accuracy and it has a good speed of classification and it is mostly fit for all type of data.

3.2) Prediction analysis

An information flow sharing between shop floor operators (humans and or machines) during a operations processes can have a VIF that is to considered or not according to the characteristics of the information flow. Depending on the kind of operators some information characteristics differs it can be illustrated by this example: An information flow can be complex for man operator but not for an automated machine , a paper information is more for a human operator and not of the machine . It has to be noted that , operators will do their tasks or not according to VIF , as presented in fig.11.

Fig 9. Accuracy of selected classification models with binary data

Fig 10. Accuracy of selected classification models with binary data except dimension of information

Fig 11. Illustration of the analysis of VIF with the DT model.
The predicted value of the VIF will be shown for some cases of the information flow chosen randomly when it arrives in the shop floor.

### 3.2.1 Prediction analysis based on the dimension of information flow

- For an information flow having the following inputs:
  \[ M_{IF} = [1,0,0,0,0,1,0,0,1,0,0,0,1,1,0,1,1,0] \], meaning that the information circulating in the shop floor has a direct impact to the operation process, the information has been sent through an electronic application (computer aided manufacturing program), the process has been ordained in by an operator uniquely (horizontal) and that the information in the system is supposed to be communicated is speedily, but on there is a low signal of connection, the information is well transparency for the operator, the information is accessible, though it is not details, a such information flow will have a good added value to the process meaning the process will be realized without any delay as predicted by the model. So VIF=1.

\[ M_{IF} = [1,0,0,0,0,1,0,0,1,0,0,1,1,0,1,1,0] \], this information flow is digital but it volatility is at 1, and the timeliness is 0, so the information doesn’t arrived on time though it is digital, this is because of the poor availability of a continuous network in some developing countries, such information will not have an added value to the process, so it VIF=0.

The result obtained is proportional to the real one happening in the shop floor of developing countries, a documented information having all the manufacturing information will have the same added value as the digital information that is sent in a machine without any disruption as shown in fig.12. Do the world are moving towards paperless operations to digital one, the none digital information in this context has also their application in the added value of information.
For an information that the dimension of information is scale the results [1] Tomanek and Schroder 2016 the prediction examination where medium is the paper and the accessibility is good, the volatility do not exist, the timeliness of the information flow is good, the velocity is good, all this describe by: 
\[ M_{IF} = [1,0,0,0,0,0,0,0,1,0,1,1,0,1,1,1,1] \]
, the predicted VIF = 1 and facilitate a good decision making, stating that such information is good and can add a value to the system. So an information paper with is accessible, which has a velocity and if it arrive on time to the operator and if the operator is able to decode it, it will have the same added value with the digital information according to our prediction and hypothesis. The predicted VIF function of the dimension of information flow with is not binary, justifies our results according to fig.13.

**Fig.12** VIF function of the dimension of information flow with binary data.

**Fig.13** VIF function of the dimension of information flow with scale data of the dimension of information flow.
### 3.2.2 Prediction analysis based on the direction of information flow

The result obtained in the decision making in shop floor, based to whom to send the information according to the decision level is described here by the direction of information, the VIF (with binary data and scale data) is also function of the direction of the information as show in fig. 14. It present a real life situation of SMEs for decision making where has to come from a decision level for an action to be taken.

![Graphs showing VIF function of the direction of information flow](image)

**Fig.13 VIF function of the direction of information flow**

### Conclusion

Information management in shop floor operations is at the center of decision making, a well-organized MIF based on the CIF will increases the efficiency of the SMEs. This article aimed at analyzing a machine learning model to determinate and also predict the VIF in shop floor of SMSs in developing countries in order to improvement decision making by operators or machine on operations tasks. It emerges from this research works that previous methods as VAHM and Information process integration for the determination of VIF, but without integrating all the CIF. According to the specificity of developing countries where information flow disorderly, we went on the hypothesis of having binary data for the CIF firstly and secondly scale data for the dimension of information flow based on the results of [Tomanek and Schroder( 2016)](#), DT classifier was the best model that has been chosen for both cases and it results out that even a paper information in motion in the shop floor for production operation can have also an acceptable added value as digital information and finally we observe that that direction of information doesn’t has a mare difference influence on VIF when changing data.
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