Digital technologies and emotions: spectrum of worker decision behavior analysis.

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Abstract. Digital technologies enables industries to transform their processes to gain competitive advantage. Industry 5.0 puts the operator at the center of a digital and connected industry, but what about workers' emotions? To what extent do Industry 4.0 technologies in the industrial domain allows for a better understanding of the impact of emotions on workers' decision-making behavior? The overall objective of this systematic literature review is to explore the literature to assess the breadth of possibilities for analyzing emotions to understand workers' decision-making behaviors, based on data collected in industrial settings. The analysis of 29 articles extracted from the Compendex and Web of Science search engines allowed us to define the emotional factors measured in the analysis of human decision-making behavior, the tools used, and the sectors of application. The subject is still in its infancy for the scientific community and is a source of excitement.
The results of the qualitative analysis of the articles show the predominance of text analysis (social networks and/or online reviews) for sentiment analysis. The tools used within the technology are very diverse (deep learning, machine learning, mathematical models). The same is true for the sectors of activity, although there is a particular interest in customer emotions for marketing purposes in the service industries. Finally, future research avenues are proposed, such as the analysis of the impact of emotions on the decision-making process in manufacturing is practically absent from the study.

Keywords: Industry 5.0 · Decision-making · Emotions · Human behavior · Industry

1 Introduction

To meet the challenges of increasing competition and globalization, manufacturing industries need to find competitive advantages that will lead them towards the digitalization of their processes, leading to the 4th Industrial Revolution [1]. Industry 4.0's emphasis on digital technologies, is its main purpose but also its biggest criticism. In doing so, it omits the impact of this transformation on organizations and workers [2], but the operator is at the heart of the production process. That's why Industry 5.0 is putting the operator at the center of the digital transformation. Since emotions play an important role in human decision-making behavior [3], the question is whether and to what extent digital technologies allow us to better understand the impact of emotions of workers' on the decision-making behavior.

To this end, this paper proposes a synthesis of the literature related to the analysis of the impact of emotions on human decision-making behavior based on digital technologies in industry. The general objective is to explore the literature in order to assess the extent of the possibilities of emotion analysis for the understanding of the decision-making behavior of workers, based on data collected in an industrial context.

In the following, the methodology used to carry out the study is presented in section **2**, while the results obtained are proposed in section **3**. These results will be discussed in the section **4**, which will lead to the conclusion, in section **5**, on the impact of emotions on the understanding of human decision-making behavior in industry through digital technologies as well as on possible research directions to be explored.

2 Methodology

2.1 Extraction method

We followed the systematic literature review methodology developed by [4]. First, the subject and limitations of the study must be defined in order to limit its scope. This study aims to determine the extent to which Industry 4.0 technologies can be used to analyze the impact of emotions on human decision-making behavior in industry. Then, the following research questions are posed:

Whether and to what extent digital technologies allow us to better understand the impact of emotions of workers' on the decision-making behavior ?

- **RC1:** What do we measure when analyzing emotions to understand human decision-making behavior?
- **RC2:** What are the tools used for the analysis of emotions impacting human decision-making behavior?
- **RC3:** What are the sectors of activity in which the analysis of emotions for the understanding of human decision-making behavior is used?

A set of keywords were iteratively defined to conduct this literature review and answer the proposed research questions.

The identification of the research need was developed from the addressed problem, namely the use of Industry 4.0 technologies for the analysis of the impact of emotions on the decision-making behavior of human in the industrial environment. Thus the expression of the research need was translated by the sentence *"analysis of emotional impact on the decision-making behavior of human in industry using industry 4.0 technologies"*.

In each iteration, the most relevant articles were analyzed to extract the relevant keywords and add them to the initial query. Each iteration targets articles similar to the articles found previously.

The final query used consists of 6 subsets of words that represent the 6 topics of the research need, as shown in Figure 1.

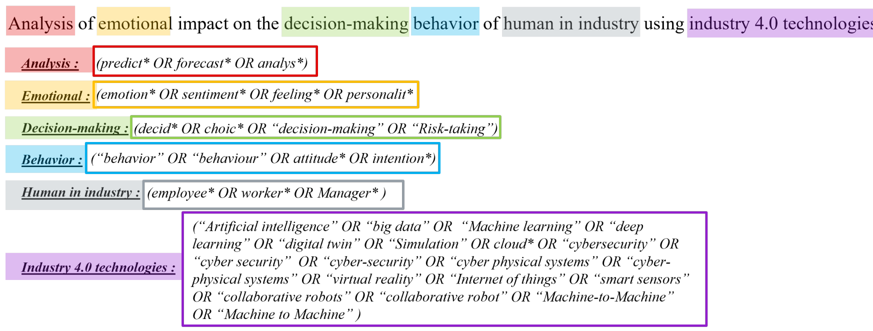

Fig. 1. Research needs analysis

The first two subsets of keywords in Figure 1 are used to target the area of emotion analysis while the next two subsets narrow the scope of the research results to studies dealing with decision-making behavior. Finally, the last two subsets of keywords focus the study on humans in an industrial context and Industry 4.0 technologies as defined by [5].

Each subset is linked by the operator *"AND"* while the terms within the same subset are linked by the operator *"OR"*. And, finally, the query is completed by defining exclusion criteria to refine the search.

2.2 Articles selected

Due to the important evolution observed in data analysis and artificial intelligence since the 2010s, only articles published in English between 2010 and 2023 are selected. Journal and conference papers are considered in the search engine **Engineering Village** (with databases *Compendex, Inspec, GEOBASE, GeoRef et Knovel*) while the journal articles, the proceedings papers and the reviews will be considered in the search engine **Web of Science**.

The search with the current query was performed on January 18, 2023. Figure 2 represents the evolution of the number of articles obtained using the initial query, with the exclusion criteria defined.

A total of 44 different articles were retrieved from the two search engines. A reading of the abstracts allowed us to define 3 exclusion criteria aimed at refining the search results obtained:

1. Inadequacy with the industry topic: Two articles were excerpts from medical conferences. A third medical article was on the assessment of mental illness.

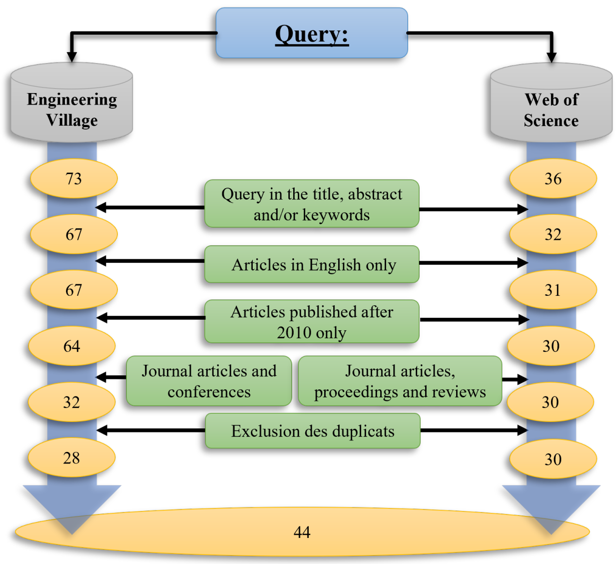

Fig. 2. Conduct of the literature review

Another was on the design of hypertext applications. These papers did not fit the purpose of supporting decision-making in an industrial context and were removed from the selected dataset.

2. Lack of decision making: One paper dealt with sentiment analysis on a social media such as Twitter, but no decision making was explored. Two articles dealing with dashboards in the education sector, with a macroscopic view of the perception of data use, did not fit the needs.One article studied the awareness of the digital footprint and the public perception of Big Data. Again, this article did not fit the research needs. All 4 articles were removed from the analysis set.

3. Misuse of terms describing Industry 4.0 technologies: Some articles do not deal with simulation technology as described by [5], but rather with serious games described by the term "simulation game" or the use of the keyword "mental simulation". Other articles deal with psychological models of technology acceptance (TAM), especially applied to "big data" technology, but not to Industry 4.0 technologies. One article uses the term "cloud" to represent the disruption of the model by the phenomenon of regret, while another uses the term "cloud model" to define the model widely used in security risk assessment. In both of these articles, the term "cloud" did not represent cloud technology. Finally, one article was misclassified with the automatic keyword "simulation" by the search engine **Web of Science** despite using a theoretical architectural model. Therefore, the term "simulation" was misused. There were 7 articles removed.

Thus, after the exclusion criteria detailed above, a total of 29 articles remain. This limited number of articles already allows us to conclude that the research theme is still underdeveloped.

3 Results

First, a brief descriptive analysis will present the general characteristics of the selected articles, followed by a more detailed content analysis to answer the research questions.

3.1 Descriptive analysis

Although the total number of articles is still low, the annual evolution of the number of relevant articles published up to January 18, 2023 shows the growing interest of the scientific community in this still nascent topic, although the year 2020 was heavily influenced by the COVID-19 pandemic. From a thematic point of view, the overwhelming majority of the selected articles are related to **Big Data & Analytics**, mainly using machine learning tools.

3.2 Qualitative analysis

The results extraction phase is guided by the previously defined research questions. Data extraction and statistical follow-up are performed after reading the abstracts of each of the selected articles. The results obtained will be synthesized in order to identify possible research areas by answering the three previously defined research questions.

In the field of construction, [6] analyze the relationship between personality and safety behavior based on a personality taxonomy. [22] determine the relationship between social factors and individuals' perception of danger. [31] explains the mechanisms of occurrence of dangerous behaviors in construction by the theory of the double attitude. In this field, [6] uses data analysis technologies (machine learning) with the comparison of different tools. The performance of the linear regression model is compared to that of a feed-forward neural network using back-propagation and Levenberg-Marquardt optimization. We also find two studies using **simulation**. Indeed, [22] uses a dynamic system simulation model just like [31]. However, the data source differs. [31] parameters the simulation model by combining the correlation coefficients observed in the literature. [22] adds to the use of the literature, the data obtained by survey.

In the field of transport, [11] determine the role of driver characteristics in modeling driving behavior. Here, the authors use the technologies of the **Big Data & Analytics** with machine learning tools such as Hierarchical Clustering, linear regression and Principal Component Analysis (PCA).

In the field of organizations and HR, [25] propose to understand the reactions of workers to procedural and interactional distributive (in)justice. [15] predict the performance of individuals and work teams based on the analysis of individual values and personalities. [17] evaluate the characteristics of a person on the basis of a digital trace. This research can be linked to [21] which proposes a literature review on the prediction of personality traits relevant to the human resources department based on the use of social media. [8] use adaptive interfaces based on language and social network analysis to help managers make decisions. Finally, [13] identifies research trends for sentiment analysis and opinion extraction through a knowledge management approach in organizations. In this area the most represented technology is again **Big Data & Analytics**. [15] use machine learning with tools such as SVM, XGBoost, SDG and linear regression while [25] use deep learning with a prediction model based on an artificial neural network. [17] proposes to build an onthology to be used in machine learning models. The articles [21, 8, 13] do not specify particular tools since they are literature reviews.

The service industries are strongly represented. In the field of e-commerce, [9] proposes a classification model of products based on their characteristics and the feelings of consumers. [20] evaluate which elements have the greatest impact on a consumer's purchase decision based on community feedback. [28] Examine how consumers' emotional and thematic preferences for products affect their purchase decision from the perspective of psychological perception and linguistic analysis. In the field of hotelling, [18] identifies key indicators perceived by travelers related to environmental management and sustainability of hotels, while [23] explains the decision-making process of travelers for the organization of their trips by analyzing feelings. In the field of tourism, [27] analyzes the impact of virtual reality during the COVID-19 pandemic on consumers' travel intentions. [26] Determine the factors that influence (positively or negatively) the opinions left by tourists about a destination. Finally, in the field of retail, there is a significant amount of literature review. [10] propose a literature review on the attitudes of retail managers towards new tools for capturing customer emotions for decision making. [14] Synthesize research on sensing consumer emotions from social media data to tailor firms' marketing strategies. [29] Address the influence of individual factors on perceptions of store type (online or offline) and consumer shopping behavior. [32] Address merchandising trends and key related issues such as virtual and augmented reality and shopper behavior. Finally, [33] compares the explanatory and predictive power of sentiment extraction methods (marketing) over several years for daily measures of customer sentiment obtained from survey data. The tools used vary widely. Some studies use commercial analysis models [9, 18, 33], while others are based on mathematical analysis. For example, [23] proposes to compare the performance of tools such as Choquet integrals, weighted arithmetic mean, ordered weighted averaging, and a linear model. [27] proposes to use a partial least squares structural equation model for his analysis. It is interesting to note that [27] discusses the use and application of **virtual reality** technology in data analysis. [20] proposes an alegbric SVD decomposition, then an exploratory factor analysis (EFA) and a Tobit regression. [26] uses logistic and linear regression tools. [28] uses tools closer to machine learning such as Bayesian networks, Support Vector Machines (SVM), Latent Dirichlet Allocation (LDA) and Importance Performance Analysis (IPA). The SVM algorithm is also used in the study [33] where it is compared with Sentiment Extraction Tool (SET) or commercial software solutions such as Linguistic Inquiry and Word Count (LIWC). [9] proposes its own segmentation algorithm that allows to group the comments with the closest sentiments. The article [10] does not specify the tools used, but states that it is a machine learning analysis, and the articles [14, 29, 32] do not specify particular tools as they are literature reviews.

In the field of finance, [16] evaluates asset prices in the stock market based on sentiment analysis and [19] presents a model that measures and analyzes the intangible assets related to the reputation of digital ecosystems and their impact on tangible assets. **Big Data & Analytics** is presented. Deep learning is used in the article [16] with a model based on LSTM (RNN). The article [19] does not detail the tools used, but mentions the use of data mining.

In the area of risk management, [30] defines a new framework for cyber risk assessment and mitigation based on exploration and sentiment analysis of text in hacker forums. [34] propose a model for predicting the risk of an attack by a particular individual based on various personality traits and contexts. In this field, the technologies of **Big Data & Analysis** and **Simulation** are represented. Thus, [30] uses the multiclass classification algorithms CART, k-Nearest Neighbor (k-NN), Ensemble Boosted Tree, Multinomial Logit and Hierarchical Logit. [34] uses dynamic system simulation (Monte Carlo simulation and sensitivity analysis) to build the Bayesian Belief Network (BBN) prediction model for attack prediction.

In the field of crisis management, [24] Although this article does not mention any of the tools used in its abstract, the analysis of the keywords allows highlighting the notion of sentiment analysis. This term is defined in the abstract of [13] and can be classified in the technology **Big Data & Analytics** as it mainly uses the artificial algorithm on textual data.

In the field of logistics, there are only manufacturing case studies with very similar research topics on reverse logistics through social media analysis. [7] Analyze positive and negative customer feedback to make strategic reverse logistics decisions, while [12] develop reverse logistics strategies based on analysis of positive/negative consumer reactions. These two articles are interesting because they deal with similar issues but use different tools. In fact, both articles propose sentiment analysis based on social networks (Twitter). [7] uses a deep learning approach with the development of a hybrid CNN-LSTM model. [12], uses a machine learning approach with the combination of Naïve Bayes, Support Vector Machine (SVM) and Maximum Entropy algorithms, combined with a voting mechanism.

We note that sentiment analysis based on social network analysis [14, 7, 12] and online reviews [9, 18, 20, 23] is particularly used.

This research highlights the importance of open access databases and APIs for the advancement of research in a particular sector. Indeed, three of the four studies related to tourism and hospitality use data from the API *TripAdvisor* [18, 23, 26]. The APIs of e-commerce platforms like Amazon [9, 20] or their Chinese equivalent [28] are also used. The API of Twitter is also widely present in the selected articles. But, contrary to the others, this database is transversal to several domains [7, 12, 17, 24].

Synthesis :

As a synthesis, Figure 3 represents the distribution of the selected articles according to the research topic addressed and the field of application studied.

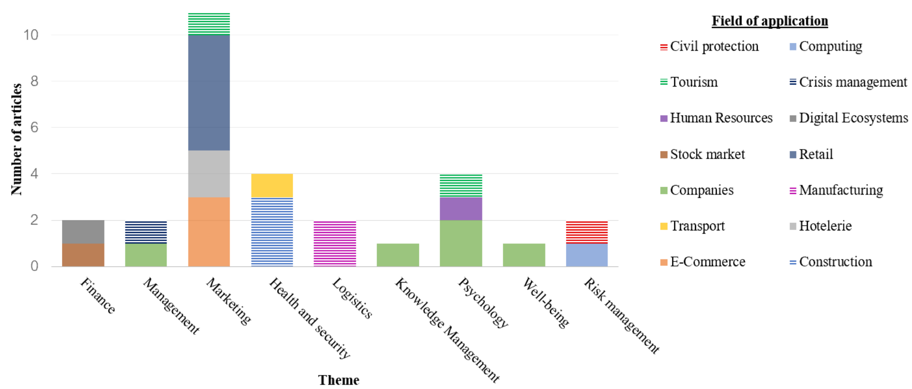

Fig. 3. Distribution of the selected articles by theme and field of application

The notions of Health and Safety are observed in the articles dealing with the construction industry but also in the transport sector. The notion of "wellness" is more related to organizations. However, [25] can be considered as a study relating to the **psychology** of the workers. This research theme is moreover the most widely represented in the application sector of organizations [15, 17]. We also find the psychological theme applied to human resources [21] and to tourism [26]. Finally, the thematic of **knowledge management** and **management** are also studied in the organizations with the articles [13] and [8] respectively. In the thematic of **management** we also find a study applied to the management of crisis [24].

The theme of **risk management** is applied to the sector of the civil protection [34] but also to the data-processing sector with the concept of cybersecurity [30].

It is interesting to note that the manufacturing industries are particularly interested in **logistics** [7, 12] while the service companies are more interested in **marketing**. Moreover, it is this topic that is the most represented in the whole of the extracted articles. The researches on marketing are mainly related to concepts applied to e-commerce, retailing, hotels and tourism. The main objective of these studies is to increase the sales by redefining the commercial and marketing strategies according to the feedbacks of the customers in order to meet their requirements. The feedbacks are collected on social networks, but also and especially on the online reviews of the different sites of service providers (TripAdvisor or Amazon). The notion of **feeling analysis** is also very present in the studies related to marketing.

Some articles determine the tendency of individuals to take risks in order to be used as input for models for the prediction of individual and team performance or of the safety behaviour of construction workers. Only [11] considers the decision-making process in its model.

4 Discussions

Previous analyses allow for answering the various research questions proposed in section 2.

RC1: What do we measure when analyzing emotions for understanding human decision-making behavior? Language is the most analyzed element in the proposed studies. Sentiment analysis of online reviews or social media makes it possible to classify consumers' emotions. This information is then used for managerial decision-making in the definition of marketing strategies, human resource management policies or reverse logistics management strategies. However, although decision-makers use emotions to make decisions, the user decision process itself remains unexplained. Thus, the true value of language analysis for understanding the decision process remains to be determined.

RC2: What tools are used for the analysis of emotions impacting human decision-making behavior? As previously mentioned, the decision-making process is still poorly explored in the literature. However, the systematic literature review allowed us to highlight the predominance and variety of tools used in **big data and analytics** technology. We find mainly segmentation tools such as SVM, CART, k-Nearest Neighbor (k-NN), Ensemble Boosted Tree, Multinomial Logit, Hierarchical Logit or Hierarchical Clustering. These tools are especially associated with sentiment analysis. Mathematical and regression tools are also well represented. We compare the performance of tools such as Choquet integrals, weighted arithmetic mean, ordered weighted averaging, and linear models. We also find the use of structural equation of partial least squares model, but also algebraic models of SVD decomposition and factor analysis (EFA). different regressions are also used, such as logistic and linear regression and Tobit. Deep learning is also represented, but to a lesser extent. Feedforward neural networks (FNN), convolutional neural networks (CNN), and recurrent neural networks (RNN and LSTM) are used. These networks can also be combined to form hybrid models (CNN-LSTM).

On the contrary, the **Simulation** technology is characterized by the uniqueness of the tool used. In fact, the only studies dealing with simulation use the simulation of dynamic systems (SD).

RC3: What are the industries in which emotion analysis for understanding human decision-making behavior is used? The sectors of activity are varied: Construction, e-commerce, hotelerie, transportation, manufacturing, business, retail, stock market, digital ecosystems, human resources, crisis management, tourism, computing, and civil protection. However, the service industries are the most represented and are mainly associated with marketing research. Health and safety research is also well represented, but is largely dominated by studies in the construction sector. Finally, it is worth noting that the only two studies in the manufacturing sector deal exclusively with reverse logistics.

It is important to note the wide variety of results obtained. The literature review initially focused on the study of human behavior in industry. However, fields such as Marketing or Well-Being have emerged within the corpus of articles analyzed. This variety of topics and their distance from the initial industrial theme suggests a possible area for improvement. A refinement of the query to circumscribe the study and to be more efficient in reaching the set objective should be considered in the future.

5 Conclusion

Industry 5.0 puts the operator at the center of a digital and connected industry. Taking emotions into account is essential for understanding human decision-making behavior. Therefore, a systematic literature review was conducted to evaluate the impact of emotions on human decision-making behavior in Industry 4.0 technologies.

Language is by far the most analyzed element in the literature. Especially through sentiment analysis in social networks and online reviews. Marketing in service industries such as tourism, hospitality or e-commerce is the main user. But the digital technology of big data analytics is strongly represented in a variety of sectors such as psychology, construction or risk management. The variety of tools used is also interesting. Data analysis can be performed using purely mathematical tools, machine learning approaches or even deep learning.

The answers to the research questions show that emotions are still very little used to explain the human decision-making process. However, various tools allow us to use emotions to understand behaviors and guide users towards choices. Thus, the measurement of emotions does exist in the literature but it is still difficult to clearly make the link between emotions and the human decision making process.

However, it is interesting to note that none of the studies use manufacturing data. This is surprising given the high volume of decisions made in this environment. Understanding the impact on the decision-making process of operators in manufacturing remains an open area of research.

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