Work datafication and digital work behavior analysis as a source of social good

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***Abstract*—The digital transformation of organizations is boosting workplace networking and collaboration while making it "observable" with unprecedented timeliness and detail. However, the informational and managerial potential of work datafication is still largely unutilized in Human Resource Management (HRM) and its social benefits, both at the individual and the organizational level, remain largely unexplored. Our research focuses on the relationship between digitally tracked work behaviors and employee attitudes and, in so doing, it explores work datafication as a source of social good. As part of a wider research program, this paper presents some data analysis we performed on a collection of Enterprise Collaboration Software (ECS) data, in search for promising correlations between behavioral and relational (digital) work patterns and employee attitudes.**

To this end, we transformed the digital actions performed by 106 employees during a one year period into a graph representation to analyze data under two different points of view: the individual (behavioral) perspective, according to the user who performed the action and the action undertaken, and the social (relational) perspective, making explicit the interactions between users and the objects of their actions. Different employees' rankings are thus derived and correlated with their attitudes. We discuss the obtained results and their benefits in terms of perspective social good for both the company and the employee.

***Index Terms*—work datafication, social good, exploratory data analysis, Enterprise Collaboration (EC) graph, Human Resource Management (HRM)**

I. Introduction

The digital transformation of organizations, that is the embedding of ICTs, networking and web technologies in particular, into work processes [1], has at least two relevant consequences on the management of organizations. First, it is making workplace collaboration more and more powerful, in line with [2] statement that "[W]here media are primitive, coordination system is primitive" [. . .] and "[T]he more the efficiency of the communication in the organization, the higher the "tolerance for interdependence". Second, and along with the progressive adoption of enterprise collaborative software (ECS), either as stand-alone solutions (for example Jive) or as part of fully-fledged "digital workplaces" (for example Microsoft 365), it is making work – both execution and collaboration behaviors - "observable" in the digital traces it leaves. In other words, as work processes become increasingly digitalized, work behaviors produce an asset of digital traces that provides unprecedented information that can potentially inform HR theory and research and also transform HRM into an evidence-based, data-driven practice ([3], [4]). However, the informational and managerial potential of data point "exhausts" generated by digital workplaces still lack a theoretical framework, therefore data are still largely unutilized and consequently the potential social good deriving from work datafication remains unexplored. To the best of our knowledge, the few existing studies in HRM limit their scope to the social network behavior (see e.g. [5]) and only few large companies are now starting to address the issue with the help of some newly hired HR data scientist. In this respect, we envision two modes of social value extraction from "digital work behaviors", defined as those acts performed on company's digital platforms (e.g. digital workplaces, ECSs, intranets. . .) in the execution of employees' job that are traced and stored in digital formats. The first mode consists in correlating (digital) behavioral (individual level) and relational (organizational level) patterns with performance (for an example on sales representatives see [6]). The second mode consists in correlating the same patterns with employee attitudes (satisfaction, engagement, commitment, embeddedness and the like), given that, according to well-established research in organization and HRM, attitudes are deemed relevant predictors of work behaviors: the more satisfied employees are, the better they perform; the more organizationally embedded, the more they adopt behaviors that exceed task prescriptions and the less they leave the organization. If such a relationship exists, employee attitudes could be efficiently monitored and better analyzed on an on-going basis (film-like), out of digital work behaviors, instead of relying on traditional periodical expensive surveys (picture-like). In addition, digital work behaviors expressive of specific employee attitudes could be fruitfully exploited to predict other workers' decisions and behaviors (retention, attrition. . .) and to better investigate the predictive potential of employee attitudes on performance dimensions both at the individual and organizational level.

Our present research adopts this second mode and it builds on some previous exploratory analysis and evidence [7]. Our research question is to study whether a correlation exists between digital work behaviors and employee attitudes. The research relies on data collected in a sample of 106 employees working in an Italian business unit of a large-sized global retail company which supports employees' collaboration by means of the ECS networking platform Jive[1]. In addition to the raw data exported from Jive in CSV format over a period of time

[1]http://www.jivesoftware.com

of one year (2016), we collected data on relevant attitudes through two rounds of survey handed out at one-year distance (beginning 2016 and beginning 2017). To answer our research question, we:

- transformed data into a graph representation in order to make explicit the actions the employees perform and their effects;
- introduced the notions of *behavioral pattern* and *relational pattern*, leveraging the structural characteristics of the graph;
- computed different employees' rankings based on the behavioral patterns counts;
- derived a graph from *relation pattern views* and applied Social Network Analysis (SNA) centrality techniques to derive employees' centrality rankings;
- studied the correlations between the above rankings and rankings based on employees' attitudes;
- discussed the obtained results and their benefits in terms of perspective social good for both the company and the employee.

The rest of the paper is organized as follows: Section II reviews existing research on the topic, Section III introduces the data we collected and worked on, Section IV illustrates the analyses we performed and presents the results, Section V discusses the implications of our approach and results in terms of potential of work datafication for social good.

II. Related Work

Enterprise Collaboration Software (ECS), also known as Enterprise Social Software (ESS), represents an emerging kind of software systems that has been attracting a growing number of researchers, leading to a steadily growing number of publications in a variety of outlets, especially in the Information System research field. An exhaustive literature review on this topic is provided in [8]. The paper identifies areas of future research on the basis of the current publications and trending topics. One of the arising research questions that testifies the relevance of the topic addressed in this paper is "Which insights can be observed from a graphical analysis of relationships in ESSs?".

Nevertheless, few works propose an ECS data analytics approach and, as to our knowledge, none of them exploits Social Network Analytics to address the research challenge of framing employees' attitudes. For instance, the paper [9] proposes the analysis of log files and content data, to gain a better understanding of the actual usage of ESS. Authors state that Social Analytics could be particularly useful for their purpose, however they complain the lack of tools to this end and limit themselves to tabular analysis.

Behrendt et al. [10] identify four data dimensions for the analysis of ESSs: (1) Activities (usage data), (2) Content (user-generated data), (3) Relations (structural data), (4) Experiences (reported data). Authors propose to exploit such dimensions investigating an empirical ESS case through a mixed-method for data analytics that tries to derive insights from the different data dimensions and then to combine them. Our approach is a mixed-method that properly tunes usage data with structural data. They instead perform a quantitative data analysis through web analytics and a quantitative social network analysis. Finally, they postulate that structural data can be exported easily from the systems, however, they note that the analysis is challenging.

A mixed-method is proposed also in [11] with the aim of discovering latent relationships in ESSs. The proposed methodology makes use of user-generated content and incorporates multiple dimensions, such as social distance, semantic distance, geographic distance, temporal distance, and quantity, to determine the strength of latent social relationships.

[7], [12] are preliminary works of the current paper. [13] studies the correlation between digital activities and organizational embeddedness over the collection of ECS data used in this paper. [12] lays the foundation of our work by describing the graph representation of ECS data and by introducing some basic SNA concepts.

Our approach founds on Social Network Analysis that offers a wide range of well-established techniques that can be exploited for our purposes, mainly centrality analysis. For instance, different approaches for the identification of central users have been proposed, such as degree centrality, closeness centrality, and pagerank centrality. Each approach relies on different principles and gives rise to its own measures that could find compelling interpretations in the HRM application context. The survey [14] provides a comprehensive overview of the available solutions.

III. Preliminaries

In this section we will briefly discuss the data that will be the target of our analysis (Section IV):

- *activity data* from a sample of 106 employees working in an Italian business unit of a large-sized global retail company exploiting the ECS platform Jive. Starting from this data, we built an EC graph describing the activities performed by the employees during the year 2016 [12]. In Section III-A, we present the ECS platform and graph;
- *survey data* on relevant employees' attitudes through two rounds of survey handed out at one-year distance (beginning 2016, beginning 2017). See Section III-B for a brief description.

Further details can be found in [12].

A. The JIVE Platform and the EC Graph

Jive is an ECS platform offering many functionalities including online communities, microblogging, social networking, discussion forums, blogs, wikis, and instant messaging.

The heart of the Jive data model is a star schema: a central fact table represents occurred *events* (i.e., *actions*, also known as *activities*), while corresponding dimension tables include *actors* (i.e., *users*) and *objects* that took part in them. Each record of the fact table conveys the following information: **`at <TIME>, <USER> performed <ACTION> on <OBJECT> in <CONTAINER>`**. Jive objects can be either a *content* (e.g., document, discussion message, blog post,

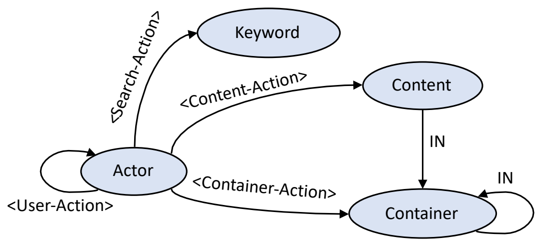

Fig. 1. Schema of the EC network graph

comment, and so on) or a *container* (e.g., a social group, project, community, ...) of other objects.

By means of the Jive Data Export Service we extracted the data corresponding to employee actions. Then, with such data we modeled and populated an *EC network graph* [12] having the schema shown in Figure 1. The graph is managed in the Neo4j graph database management software[2] and adheres to its property graph data model: it is constituted by *nodes* and *relationships*, each having a series of *properties* modeling the details (e.g., the ID of an employee, the title of a document, and so on).

The node types of our graph are the following: *Actor* nodes, i.e., the users of the ECS; *Content* nodes, i.e., content objects (sub-types are documents, videos, etc.); *Container* nodes, i.e., container objects (sub-types are social groups, communities, projects, etc.); *Keyword* nodes, i.e., keyword strings searched by users (e.g., ”Launch event”).

Graph relationships include both *action* and *containment* relationships. Action relationships connect users (Actor nodes) with the targets of their action (Content, Container, Keyword nodes). Containment relationships connect content to their containers. In particular, the graph models four “groups” of actions (depicted between angled braces in Figure 1): *content actions*, i.e., actions performed on a content object (e.g., view or create); *container actions*, i.e., actions performed on a container object; *user actions*, i.e., actions performed on a user (e.g., view or update user profile); *search actions*, i.e., actions looking for specific keywords. The actual relationship label denotes the specific action involved (e.g., CREATE, VIEW).

The final graph contains a total of 31711 nodes (11996 content nodes, 1549 container nodes, 106 user nodes and 18060 keyword nodes) and 324121 relationships (306463 action relationships and 17658 containment relationships).

As an example, Figure 2 shows a (very small) portion of the complete graph: user 40000654 created the “New launch event” project, which was viewed by user 40000615. Moreover, user 40000615 viewed document DOC-129572 and user 40500001 downloaded document DOC-132111, both related to the project.

B. Employees’ Attitudes Survey Data

The employees’ answers to the questions constituting the surveys were elaborated to obtain, for each employee, measures of their work attitudes [12]. The measures that we will

[2]http://neo4j.com

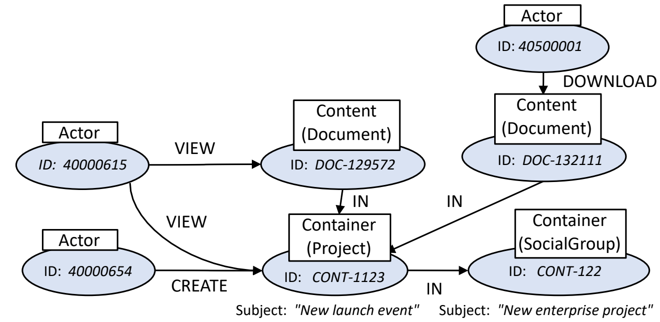

Fig. 2. A portion of the resulting final graph

	mean	std	min	25%	50%	75%	max
				2016			
Job Embeddedness: Fit	5.679	0.907	2.625	5.25	5.75	6.25	7
Job Embeddedness: Sacrifice	5.458	0.998	2.714	4.857	5.714	6.286	7
				2017			
Job Embeddedness: Fit	5.718	0.867	1.75	5.375	5.875	6.25	7
Job Embeddedness: Sacrifice	5.438	1.016	2	4.857	5.571	6.143	7

TABLE I
STATISTICS ABOUT SURVEY DATA OVER ALL EMPLOYEES

consider in this paper’s analyses are related to the construct of *Job embeddedness* [15] (web of connections “in which an individual can become stuck” [16]):

- *Fit*: measures (range [1,7]) the extent to which an individual perceives that his/her abilities and values match organizational requirements and culture. The scale consists of eight items, e.g. ‘I feel like I am a good match for this company’ and ‘My company utilizes my skills and talent well’;
- *Sacrifice*: measures (range [1,7]) the perceived economic and psychological costs associated with leaving the organization. The scale consists of seven items, e.g. ‘I feel that people at work respect me a great deal’, ‘My promotional opportunities are excellent here’.

Table I shows some descriptive statistics about the above discussed measures over all the 106 employees for both the 2016 (upper part) and 2017 (lower part) surveys.

IV. Analysis and Results

For our analysis, we followed a domain-expert driven approach that leverages on the knowledge of business engineers and economists. In particular, we propose a mixed-method that exploits both the usage data and structural data available in our EC graph. In our analysis, we will define and look for specific *patterns* characterizing the employee digital actions from different points of view:

- *behavioral patterns* (Section IV-A) - expressing what digital actions each employee performs;
- *relational patterns* (Section IV-B) - expressing what kind of impact/reaction is generated by the digital actions of a employee.

By means of different techniques, ranging from the simple counting of the patterns to well-established SNA centrality algorithms applied on ad-hoc views of the graph, we aim to

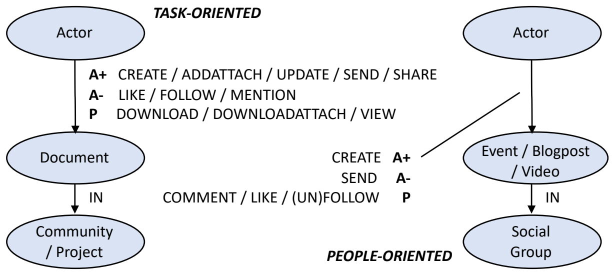

Fig. 3. A summary of behavioral patterns

discover if and how employees' attitudes are correlated to their digital actions.

A. Behavioral patterns analysis

Behavioral patterns focus on the *isolated behavioral component* of employee actions, i.e. they represent the action of a specific employee, independently from the context/reactions of other employees. The patterns can be expressed in Neo4J Cypher-like syntax in the following form:

```
(a:Actor)-[<Content Action>]->(o:Object),
    (o:Object)-[IN]->(c:Container).
```

Based on the target (content and container types) of the action, we introduce two types of behavioral patterns, as depicted in Figure 3:

- *task-oriented behavioral patterns*, describing actions performed on documents inside communities and projects;
- *people-oriented behavioral patterns*, describing actions performed on events, blogposts and videos inside social groups.

Both types include *very active (A+)*, *active (A-)* and *passive (P)* patterns, depending on the extent to which the performed action is related to the creation or addition of new contents as opposed to a simple view or download. In practice, the different `<Content Actions>` are grouped in three classes, *A+*, *A-* and *P*.

By means of a simple counting query, we can easily extract a ranking of the EC graph's employees based on how many activities of each type each of them performed. For instance, the following query returns the task-oriented A+ pattern counts (in Neo4J Cypher syntax):

```
MATCH (a:Actor)-[:CREATE|...]->(d:Document)-[:IN]->(c)
WHERE c:Community OR c:Project
RETURN DISTINCT a.actorId, COUNT(*)
ORDER BY COUNT(*) DESC
```

Correlation results. We computed the correlation between the rankings induced by the behavioral patterns counts and the ones based on the employee attitude measures through the Spearman rank-order correlation coefficient. The obtained results, together with the corresponding p-values, are shown in Table II. The significant values (shown in boldface) assess that a correlation exists between the number of actions performed and the fit and sacrifice measures of the surveys preceding (2016) and following (2017) the monitored activity period.

More specifically, results show that the higher the perceived level of fit and sacrifice at the beginning of 2016, the higher

	Fit			Sacrifice		
	rho	p-value	significant (α=0.05)	rho	p-value	significant (α=0.05)
2016						
count task oriented A+	0.107	0.276		0.132	0.177	
count task oriented A-	**0.198**	**0.042**	*	**0.255**	**0.008**	*
count task oriented P	**0.203**	**0.037**	*	**0.293**	**0.002**	*
count people oriented A+	0.04	0.68		0.07	0.479	
count people oriented A-	0.152	0.119		0.083	0.396	
count people oriented P	0.037	0.709		0.027	0.784	
count any action	**0.216**	**0.026**	*	**0.286**	**0.003**	*
2017						
count task oriented A+	**0.241**	**0.013**	*	**0.198**	**0.042**	*
count task oriented A-	**0.196**	**0.044**	*	0.155	0.113	
count task oriented P	0.179	0.066		0.081	0.408	
count people oriented A+	**0.237**	**0.014**	*	**0.238**	**0.014**	*
count people oriented A-	**0.251**	**0.009**	*	**0.211**	**0.03**	*
count people oriented P	**0.235**	**0.015**	*	**0.308**	**0.001**	*
count any action	**0.221**	**0.023**	*	0.171	0.079	

TABLE II
SPEARMAN RANK-ORDER CORRELATION COEFFICIENTS AND P-VALUES FOR BEHAVIORAL PATTERNS

the level of active and passive task-oriented actions on the Jive platform during the year 2016. Then our results show that those employees who performed during 2016 a higher number of very active or active task-oriented digital actions experienced higher fit and sacrifice at the beginning of the following year (2017) compared to coworkers. The same happens for those employees who performed a higher number of people-oriented digital actions (very active, active or passive) on the ECS platform.

B. Relational patterns analysis

Behavioral pattern analysis is strictly limited to how/how much the ECS is used by each employee. Above and beyond this aspect, another insightful question is "what is the impact of each employee's actions?". The answer requires going beyond simple activity counting, analyzing the EC structural graph data with appropriate SNA techniques. Considering again, for instance, the graph example shown in Figure 2, we might want to understand which users have created projects that have generated a lot of interest (i.e., actions) around them. Even if the creation of a project is certainly not a very frequent activity, all the activities that are performed around it can give us a measure of "importance" of the user who created it, (as in the case of user 40000654 which created a seemingly popular project).

To capture these aspects, we introduce the concept of relational pattern, focusing on the *relational component* of employee actions. A relational pattern has the form:

```
(a1:Actor)-[<A+ Action>]->(o:Object),
    (a2:Actor)-[<(P,A-) Action>]->(o),
    (o)-[IN]->(c:Container),
```

i.e. it represents the very active (A+) action (e.g., **`CREATE`**) performed by an employee **`a1`** on an object on which another employee **`a2`** worked on through an active (A-, e.g., **`LIKE`**) or passive (P, e.g., **`VIEW`**) action; as such, it represents the indirect relation between the two employees, the action of a user and the reaction of other users to it. From a practical point of view, relational patterns can be easily created by joining two behavioral patterns on the same object. For instance, we might be interested in analyzing the reactions to the documents that users create in projects (i.e., task oriented pattern A+) in terms of views and likes by other users (i.e., task-oriented patterns A- and P).

Relational patterns views. The interesting aspect about relational patterns is that they enable us to define *relational patterns views* of the data graph, through which we can deeply analyze the inter-employee connections by means of SNA techniques.

Definition 1: Given an EC network graph, a relational pattern view is a sequence of rules $H_1 \leftarrow B_1, \ldots, H_n \leftarrow B_n$ where each body B_i, for $i = 1 \ldots n$, is a relational pattern that introduces a pair of Actors (`a1`, `a2`) related by the target of their actions, and the corresponding head H_i is a graph fragment in the form `a1-[]->a2`.

Please note that the graph generated by such views only include employees as nodes. For instance, the relational pattern view definition query when all the task-oriented A+, A- and P actions are considered ("..." stands for all the other actions of the corresponding group) is:

```
(a2)-[]->(a1) ←
   MATCH (a1:Actor)-[:CREATE|...]->(o),
    (o)<-[:LIKE|...|:DOWNLOAD|...]-(a2:Actor),
    (o)-[:IN]->(c)
   WHERE (o:Document)
   AND ((c:Project) OR (c:Community))
```

In this case, the graph view produces a graph where an arc goes from a node `a2` to a node `a1` if employee `a1` created (/updated/...) a document which employee `a2` downloaded (/liked/...). In the following, we will adopt the brief notation "(P)->A+ task-oriented" to denote the relational pattern view above.

During our work, we tested different views for our analysis by considering possible variations of relational patterns. In this paper, we will focus on the following views:

- (P,A-)->A+ task-oriented (composed by 106 nodes and 54128369 links);
- (P,A-)->A+ people-oriented (composed by 106 nodes and 4064 links);

which are among the most representatives (also because they include all the behavioral patterns we defined).

SNA centrality analysis. In order to rank employees according to their "impact", we applied a selection of well known node SNA centrality measures on the obtained views. In this paper we will focus on two well-established centrality measures in the SNA field [14] that seem particularly relevant for the considered application scenario: *degree centrality* and *eigenvector centrality*.

Degree centrality is the most straightforward one, as it measures the number of incoming relationships for a node; it has been found useful in many application scenarios (e.g. [17]). For example, in the case of our task-oriented views, employees performing very active actions (e.g. creation) on objects (e.g. documents) on which a large number of other employees work will be "rewarded" with a high centrality score.

	Fit 2017			Sacrifice 2017		
	rho	p-value	significant (α=0.05)	rho	p-value	significant (α=0.05)
degree task oriented (P,A-) -> A+	**0.253**	**0.009**	*	0.134	0.172	
degree people oriented (P,A-) -> A-	**0.206**	**0.034**	*	**0.201**	**0.039**	*
eigen task oriented (P,A-) -> A+	**0.322**	**0.001**	*	**0.244**	**0.012**	*
eigen people oriented (P,A-) -> A+	0.166	0.088		**0.225**	**0.02**	*

TABLE III
SPEARMAN RANK-ORDER CORRELATION COEFFICIENTS AND P-VALUES FOR RELATIONAL PATTERNS (2017 SURVEY)

Eigenvector centrality is an algorithm that measures the transitive connectivity of nodes; in our case it can be used to capture further aspects in the web of relations constituting our views. In particular, relationships to high-scoring nodes will contribute more to the score of a node than connections to low-scoring nodes. This means that employees who created, for instance, many "popular" documents will contribute more to the centrality of coworkers when working, in turn, on the latter's contents. This is especially true if they worked exclusively on documents created by few other employees (the ones they possibly consider more "reliable").

Correlation results. We computed the Spearman correlations between the obtained centrality scores, for each of the considered views and centrality measures, and the employee attitude measures (Table III). We show in particular the correlations with the 2017 surveys; in this case, we have several significant values, assessing that a correlation exists between the digital relational patterns and the employees' attitudes (Fit and Sacrifice measures) measured after the period in which the digital actions were monitored. More specifically, results show that the degree centrality in task-oriented relational patterns correlates to fit, while the degree centrality in people-oriented relational patterns (perfomed during the 2016) correlates to both fit and sacrifice (surveyed at the beginning of 2017). The eigenvector centrality in task-oriented relational patterns (performed during the 2016) correlates to both fit and sacrifice (surveyed at the beginning of 2017), while the eigenvector centrality in people-oriented relational patterns correlates to sacrifice only.

These findings suggest that the impact generated by employees' digital actions on ESS platform affect employees' attitudes so that the more the employee is central in digital relational patterns the more he/she will perceive fit and sacrifice. This relationship between centrality in relational patterns and HR attitudes seems to be stronger between, respectively:

- degree centrality in relational pattern and fit;
- eigenvector centrality in relational pattern and sacrifice.

Moreover, the higher the employee's degree centrality in relational patterns is, the more he/she will perceive fit to the organization. This suggests that performing digital behaviors that generate impact in terms of many reactions by others, affects positively the perception of match between those employees and their work groups and the company. Similarly, the more the employee's eigenvector centrality in relational patterns is, the more he/she will perceive sacrifice associated with leaving the organization. This suggests that when influential and powerful actors react to digital behaviors, thus increasing the transitive centrality of employees who performed these behaviors, these latter will feel highly respected at work will perceive to have excellent opportunities for promotion. Indeed, in many organizations such opportunities depend on links to influential people and on decisions made by central actors.

V. Discussion

As part of a process of digital transformation, organizations adopt more and more Enterprise Collaboration Software that have the potential to change what firms do, the way firms organize what they do, and the way employees work, coordinate and cross boundaries to accomplish their tasks, with likely consequences on the way they perceived the overall work experience. However, many theories and methodologies currently adopted in Organization and HRM studies may not be able to exploit the potentialities offered by work datafication, enhancing the so-called theory-practice divide [18]. In this paper, we argue that to capture the social impact of these changes at multiple levels (individuals and their performance, teamwork and organizations) it may be necessary to leverage on different knowledge fields. In particular, we proposed a novel pattern analysis and SNA approach to "digital work behaviors" and showed how it can improve individual and organizational information processing and decision-making. The revealed existence of correlations between employees' attitudes and digital work behaviors (that are currently detectable on a continuous basis) suggest that algorithmic models could be developed and implemented to represent employee attitudes from digital work behaviors on an on-going basis, in a film-like mode. For instance, the counting of (active) behavioral patterns seems suitable to model employees' job embeddedness (i.e. fit and sacrifice). Moreover, data on centrality in task-oriented relational patterns might be used for deriving insights on employees' fit, and centrality in people-oriented relational patterns could help to predict employees' sacrifice. Similarly, data on the degree centrality in digital relational patterns might provide information on employees' fit to their job, work group and organization and data on the eigenvector centrality (transitory influence) may offer useful insights on the sense of sacrifice experienced by employees. Such information, insights, models can be exploited by companies to improve decisions and policies about human resources in terms of efficiency (for example, avoiding expensive employee surveys) and accuracy (for example, timely spotting employees' discomfort). Also, such information, insights and models might be used to improve employees' working experience, leveraging on appropriate HR practices which may increase employees' positive attitudes. Indeed and moreover, since employee attitudes (and specifically job embeddedness) are identified as predictors of employees role performance (e.g. [7], [8]), in-role and extra-role performance, including innovative behaviors, they could be much better understood, managed and predicted relying on the digital work behaviors data extracted from digital workplaces. Similarly, drawing on extant research which suggests that individual creativity is affected by social relationships, data on employees' centrality derived by the graph analysis on relational patterns might help to better understand, predict and manage creative and innovation processes inside organizations.

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