DATAJUSTICE

ERC-funded project 'Data Justice: Understanding datafication in relation to social justice' (DATAJUSTICE) starting grant (2018-2023)

Working Paper

The datafication of the workplace

Javier Sánchez-Monedero and Lina Dencik

Sanchez-MonederoJ,DencikL at cardiff.ac.uk

Cardiff University

9th May, 2019

datajusticeproject.net

Contents

1. Introduction: The datafication of work and workers 1
2. Hiring 1
    2.1. Sourcing 3
        Advertising 3
        CV parsing and indexing 8
        Jobs and resumés matching 8
    2.2. Ranking and Screening 9
    2.3. Interviewing 10
        Automated interview via chatbot 10
        Video interview, skill tests and personality profiling 11
    2.4. Selection and rejection 15
        Offer 15
        Rejection 15
3. Employee monitoring and surveillance 15
    3.1. Data integration and intelligent data analysis 15
    3.2. Presence control 18
    3.3. Computer and mobile phone 19
        Meta-data monitoring 19
        Content monitoring 20
    3.4. Monitoring multimedia data 21
    3.5. Chips, Wearables and IoT 23
4. Management 27
    4.1. Workforce scheduling and activity forecasting 27
    4.2. Attrition, engagement and turnover prediction 28
    4.3. Profiling, performance evaluation, optimization and forecasting 31
        Metrics and Key Performance Indicators 32
        People Analytics 35
5. Conclusions and discussion 41
6. References 44

1. Introduction: The datafication of work and workers

With the increased datafication of the workplace and novel and heterogeneous data sources, a range of new tools and predictive models have come to the fore that are reshaping relations between capital and labour. In this working paper we outline new data-driven tools that are transforming the workplace, particularly in relation to standard employment, such as the rise of automated hiring, 'smart' warehouses and algorithmic management structures. Whilst a lot of recent discussion on the future of work in relation to technology has focused on the growing gig economy and platform labour, less focus has been on how more traditional forms of work and labour relations are being transformed with the implementation of data systems, particularly within Europe.[1]

Technological changes in the workplace has a long history, but the recent onus on the generation of data as a central part of the digital economy brings about particular transformations that deserve further attention. Communications tools such as phones, email and computers are monitored in many companies, at the same time as new data sources such as social networks, shared calendars or collaborative working tools are being integrated to increase knowledge not only about the professional activities of workers but also about who they are, or what they might be likely to do in the future. In addition, chips, wearables and sensor networks are increasingly integrated within the broader trend of the Internet of Things (IoT)[2] to facilitate emotional as well as physical states. The development of machine learning (ML) facilitates the automated processing of information, whilst multimedia databases are being labelled with semantic information to identify and measure activities, and natural language processing (NLP) can extract knowledge from non-structured texts, such as emails and social networking content to perform sentiment and tone analysis.

In this report we provide an overview of these trends within the context of Europe, and focus particularly on tools used for hiring, employee surveillance, performance assessment and management. The overview presented here is not intended to be comprehensive, but is intended to identify key trends with concrete examples of prominent companies and tools in this space, as a way to advance further research agendas on the datafication of the workplace.

2. Hiring

A key area of digital transformation is in Human Resources, and particularly in hiring practices. We can think of this in several steps, such as those outlined by Bogen's and Aaron's (2018) 'hiring funnel', which consists of sourcing, screening, interviewing, and selection (see Figure 1).

[1] The work by Phoebe Moore is a notable exception. See for example Moore, P. (2017) *Humans and Machines at Work: Monitoring, Surveillance and Automation in Contemporary Capitalism,* Palgrave.

[2] When sensors are integrated with industrial environment the term 'Industrial Internet of Things' (IIoT) is often used.

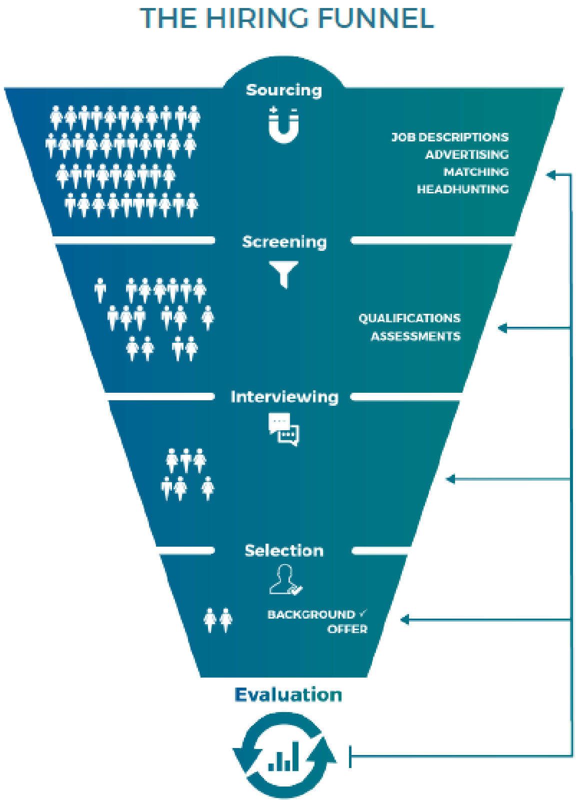

Figure 1 The hiring funnel. Source (Bogen and Aaron 2018).

Hiring technology has been developed to cover one or several stages of this process. In the early 1990s some online platforms (e.g. Monster.com, Indeed.com, etc.) offered classified job ads while at the same time some commercial tools allowed employers to track their recruitment candidates (Bogen and Aaron 2018). Later, professional networks such LinkedIn appeared to connect active and non-active workers, including HR professionals and managers, and recruiters began to use digital tools to look for and screen potential candidates. Also, specialised professional (social) networks such as Research Gate, an academic social network, were created[3]. These social networks are mainly monetised through feeds that allow companies to create job ads or to access specific data or features.

Hiring tools have evolved to include predictive features during all stages of the hiring process, targeting different activities. Most of the predictive tools rely on machine learning (ML) models built with past training data. These models perform tasks such as classification, scoring, ranking or recommendations, which are popular ML tasks also in other domains. The underlying logic of this adoption is to improve efficiency of candidate selection, for instance by improving the chances of hiring a successful candidate or by reducing the hiring time with candidate pool filtering and automated screening. As we will detail further below, the quality of candidates can be evaluated with data-driven tools to avoid hiring 'toxic' workers, and detecting which employees are more prone to quit, with some companies offering an entire 'end-to-end' cycle of automated hiring from sourcing to career advancement (see for example the illustration of the chatbot Mya outlined in Figure 2).

[3] Research Gate is a network of researchers that was created in 2008 https://www.researchgate.net/about

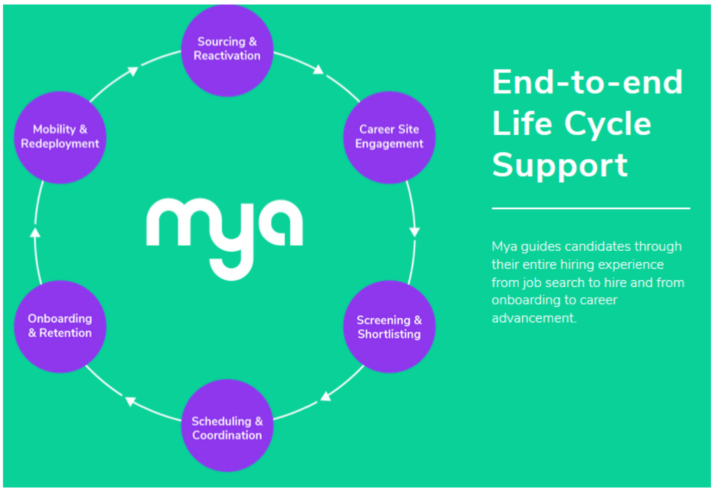

Figure 2 End-to-end hiring cycle support by chatbot Mya. Source https://hiremya.com/meetmya.

2.1. Sourcing

Sourcing refers to the activity concerned with looking for candidates to apply for job opportunities. Automated tools place and personalise advertisements and notify potential candidates that may or may not be looking for a job.

Advertising

General purpose search engines and social networks can place job ads to potential candidates. Social media networks provide demographic data, personal and professional interests and other type of information, including browsing habits, to inform ad placements. In 2017, Facebook included jobs bookmarks for clients which allow Facebook pages to include job posts[4] to advertise positions and interact with candidates (see Figure 3). By using generic marketing targeting techniques, companies can use the profiles to select or exclude who will view an announcement based on age (Angwin 2017), ethnicity, gender (Ariana Tobin 2018), job seniority or connections to other companies among others. To illustrate these features Figure 4 shows the Facebook dashboard with demographics of the target audience for an ad, which provides a filtering service for sourcing candidates. For example, ProPublica has documented how Facebook allows companies to create ads that explicitly exclude older persons from their target audience. In the report, they show that Verizon targeted people ages 25 to 36 who live or were recently near Washington and that the Boston Consulting Groups sought to reach people interested in Business, based on their activity on Facebook, and that they were only interested in women from 26 to 34 living near New York (Larson et al. 2017).

[4] https://www.facebook.com/business/news/take-the-work-out-of-hiring

Figure 3 Screenshot of job ads on Facebook. Source [https://www.facebook.com/business/news/take-the-work-out-of-hiring.](https://www.facebook.com/business/news/take-the-work-out-of-hiring)

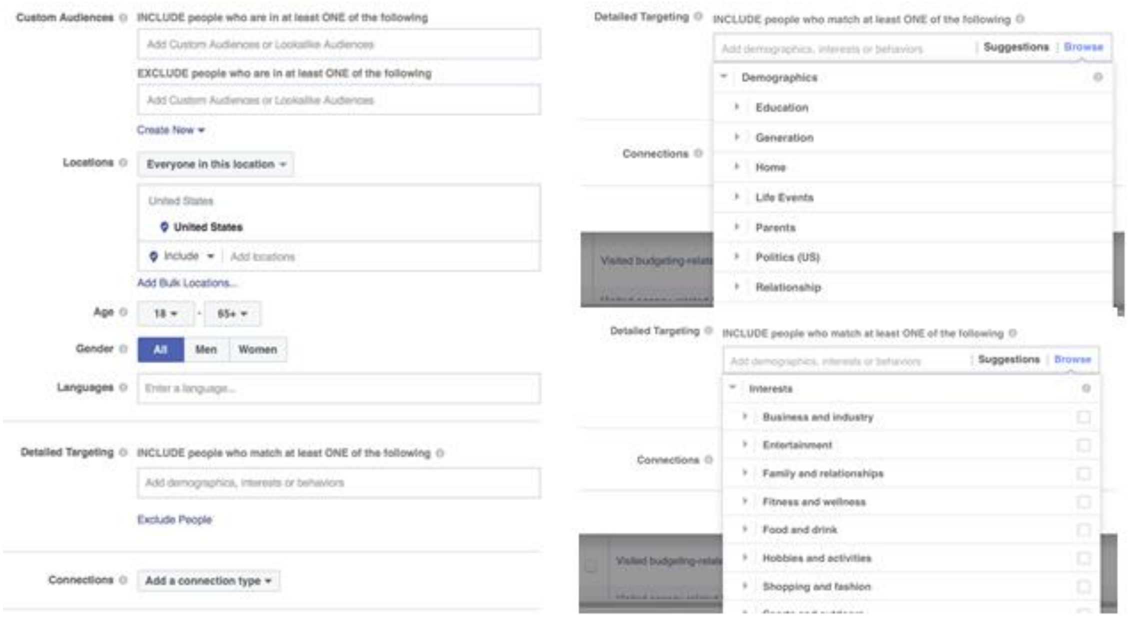

Figure 4 Demographics and interest based targeting options on Facebook. Source (AdEspresso 2017).

Professional social networks also perform job advertising to very specific profiles. LinkedIn provides many features for targeting specific profiles (see Figure 5). Research Gate encourages users to continually update their academic activity such as publications and projects, but also their positions, skills and expertise or even to endorse the skills of others, so it can place and advertise research job ads based on accurate candidate matching.

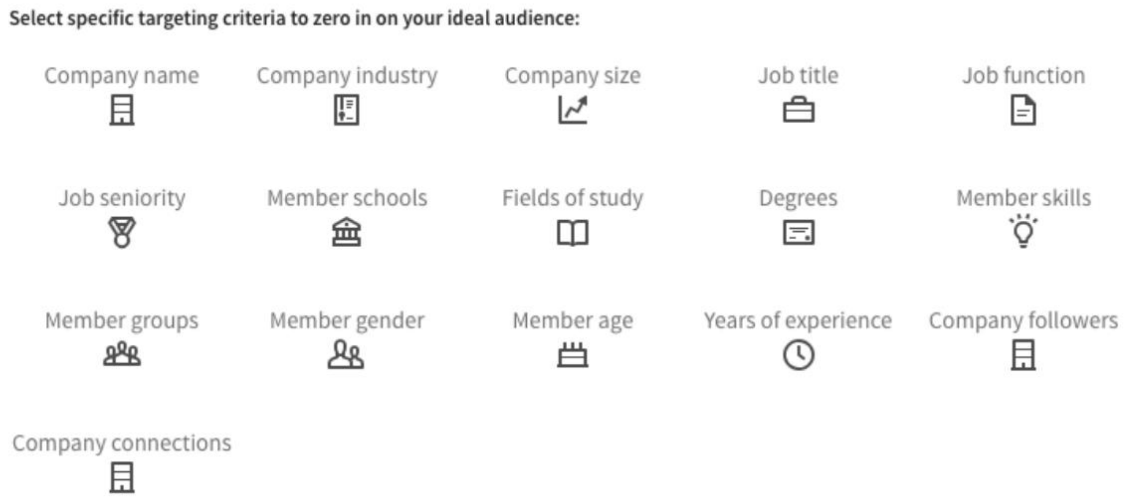

Figure 5 LinkedIn's targeting options. Source (Bogen and Aaron 2018).

Applicant Tracking System (ATS) such as TribePad[5] integrates job advertising in general and professional social networks. Networks are used to perform profiling-based advertising of vacancies as well as to find candidates that match a position so that the employer can contact them. For instance, BroadBean can be integrated with Research Gate to post vacancies that will be shown to a specific audience, e.g. filtering by education or skills, and to track candidates that have applied for a position through that professional network[6]. Moreover, social networks can be used to gather data from candidates. For instance, when a person applies for a position in TribePad, they can provide their social network ID and TribePad automatically completes most of the necessary fields such as experience or qualifications and ask the candidate for missing data for that specific job[7]. TribePad offers marketing analytics for vacancies posts as well and other tools for later stages of the hiring process (see Figure 6). Any applicant in TribePad is incorporated to the database so they can be contacted for future positions.

TribePad is used by several UK companies and organizations such as Tesco, BBC, Serco, Sodexo or The Church of England, but also other international companies[8]. For example, the BBC uses TribePad to manage its job search and career hub so candidates apply for the positions through the system[9]. Registered users, if desired, will continuously be matched to the latest BBC jobs based on their profile and will receive alerts on possible opportunities, including existing employees for redeployment. The system anonymises applications to reduce unconscious bias during the hiring. Tesco, meanwhile, moved to TribePad in 2014 to centralize all the hiring tasks[10]. The motivation for the adoption was to deal with the '*relatively high turnover of staff*' and to allow the applicants to easily apply for multiple positions. The company reported that these improvements gave the workers a much better experience and saved Tesco a considerable amount of time and money. TribePad adaptation to Tesco includes automatic parsing of CV and LinkedIn accounts, actively searching for candidates in job platforms, automatic filtering of

[5] https://www.tribepad.com/
[6] https://www.researchgate.net/blog/post/insights-into-international-research-collaboration-2
[7] https://www.tribepad.com/applicant-tracking-system/new-ATS/
[8] https://www.tribepad.com/case-studies/
[9] https://www.tribepad.com/wp-content/uploads/2018/12/TribePad-BBC-Case-Study.pdf
[10] https://www.tribepad.com/the-blog/how-tribepad-transformed-recruitment-for-two-retail-giants/

candidates not qualified for a role, multi-lingual and customization for roles, departments and countries, and data reports[11].

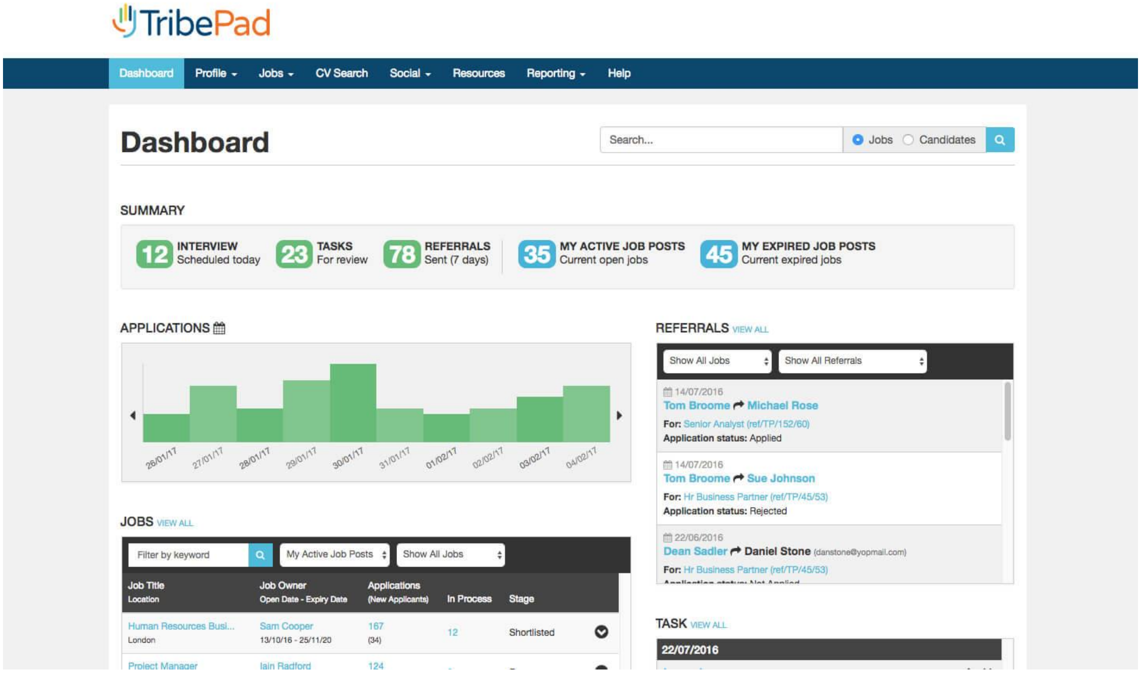

Figure 6 TribePad marketing analytics dashboard for job posts. Source TribePad https://www.tribepad.com/applicant-tracking-system/new-ATS/

Another popular tool is Workable[12], which incorporates a set of AI-powered tools for hiring management, including sourcing. It features careers pages, job advertising in general and professional networks, social recruiting, employee referrals, people search and resumé parsing. Workable performs filtering of people in the network[13] but also adds external candidates to the pool, for instance while browsing source code repositories such as Github[14]. Workable is used by many international companies operating in Europe such as Decathlon, Ryanair and M&S among many others[15].

Advertising can also be done to 'passive' candidates, meaning job seekers who are not actively looking for new jobs. This is sometimes referred to as 'headhunting', and here predictive models aim to detect job seeking actions. For instance, Entelo[16] is a tool that builds smart profiles that, apart from the processing the typical information included in a resumé, calculates a score on how likely the person is to leave his/her current job and how well he/she fits in the company (see Figure 7). LinkedIn also offers employers headhunting tools that predict if an employee is open to be hired based on their member profile, connections, interactions and reads[17].

---

[11] https://www.tribepad.com/wp-content/uploads/2018/12/Tesco-Case-Study.pdf
[12] https://www.workable.com/
[13] *'Our Campaigns tool targets 1000+ qualified candidates per job to deliver on average 10-20 applicants to your pipeline. Perfect for hard-to-fill roles.'* https://www.workable.com/candidate-sourcing
[14] https://www.workable.com/candidate-sourcing
[15] https://www.workable.com/testimonials
[16] https://entelo.zendesk.com/hc/en-us/articles/360003166832-Entelo-Smart-Profiles-with-Candidate-Insights
[17] https://talenttechlabs.com/trends/trends-report-comprehensive-look-on-matching-technology/

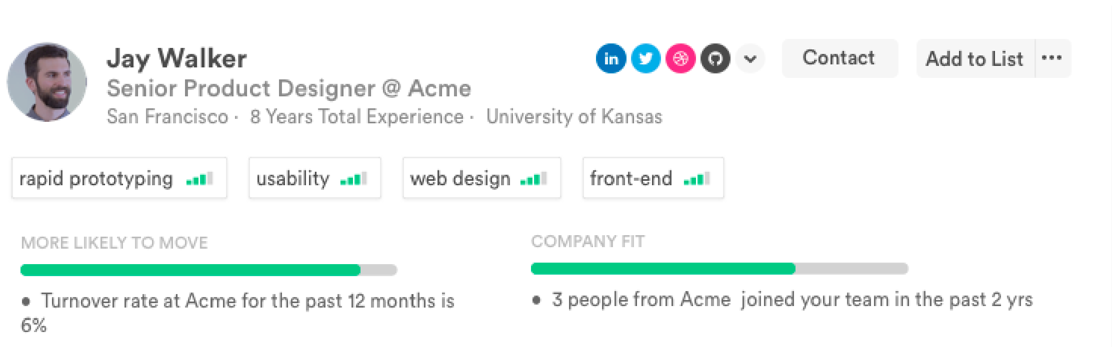

Figure 7 Example of candidate summary by Entelo. Source https://entelo.zendesk.com/hc/en-us/articles/360003166832-Entelo-Smart-Profiles-with-Candidate-Insights

Finally, some tools automate job descriptions and search filters. For instance, Research Gate can generate automatic audience selection[18] (search filters), based on the job title and description, to later perform data-driven jobs notification to potential candidates. Textio Hire performs text analysis to provide what they call *text augmentation*, which is said to predict how people can react to the text. The tool is intended to improve the chances that a person will be attracted to a job post or a recruitment email[19], including considerations for 'gender tone' that could potentially discourage certain genders from applying for a position[20] (see example in Figure 8). Textio is used by several global companies operating in Europe such as Nestlé, Atos or McDonald's.

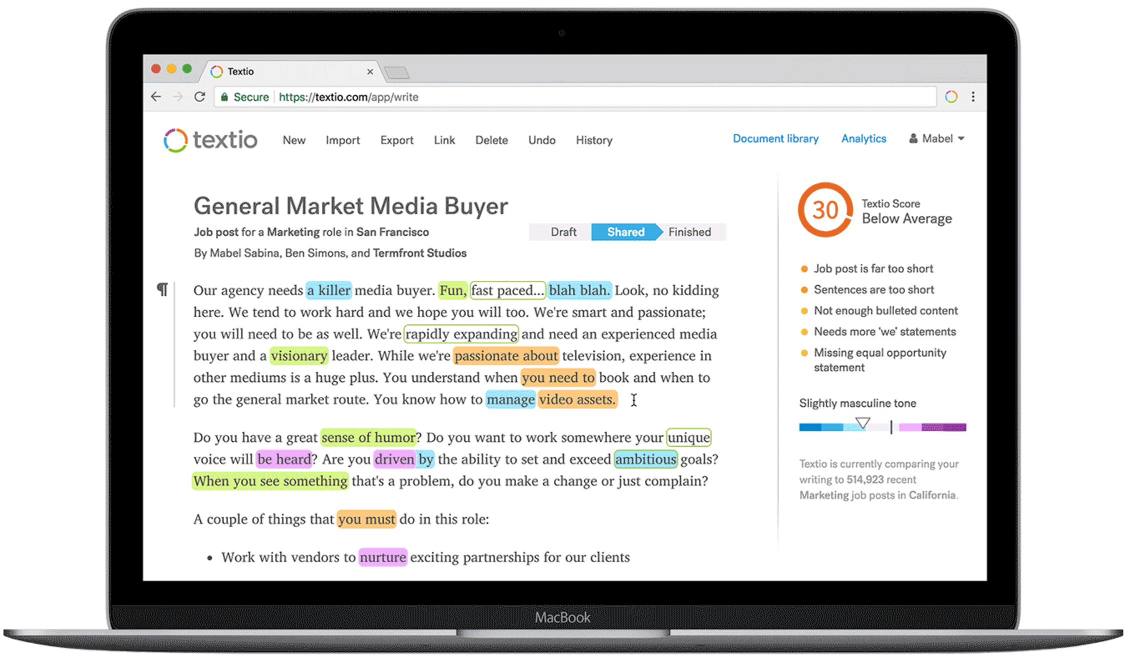

Figure 8 Screenshot of text augmentation and gender tone analyser features by Textio. Source https://textio.com

---

[18] ResearchGate's automatic targeting https://www.researchgate.net/blog/post/researchgate-rolls-out-automatic-audience-selection
[19] https://textio.com/products/
[20] https://textio.ai/watch-your-gender-tone-2728016066ec

CV parsing and indexing

CV or resumés are non-standardized text documents. To facilitate hiring tasks, many tools feature automatic parsing and indexing of CVs. For instance, BroadBean, another ATS, can perform information fusion from several platforms as well as non-structured CVs to allow the companies to visualize or filter specific features of the candidate pool[21]. Worktable can augment candidate profiles by adding links to their social and professional networks such as Wordpress, Twitter, Quora, Facebook, Github and more[22]. Other tools such as Ideal can enrich CVs by automatically inferring qualifications or skills: '*For example, a typical keyword search, such as "retail," will only return candidates with "retail" on their applications. Ideal's technology adds additional intelligent dimensions as it understands that job experience at "Walmart" or "Macy's" can also represent retail experience.*'[23].

Jobs and resumés matching

Candidate and job matching refer to the task of pairing job descriptions with CVs and/or profiles. From the candidate's point of view, the task is to deliver a list of jobs they would be interested in. From the recruiter's perspective, the system should provide a ranked list of suitable candidates for a position. Matching and ranking can be implemented in several ways, but the most popular is by creating a recommender system. Recommender systems were first popularized as tools to suggest items to users of a platform, for instance as Netflix does with films and series. Recommender engines can be approached by content-based filtering, collaborative filtering or hybrid approaches. The most popular solution to tackle job matching is hybrid collaborative filtering systems (Bogen and Aaron 2018). This is the case of *Browsemaps*, the recommendation engine of LinkedIn (Wu et al. 2014), Xing[24] or Infojobs[25]

Content-based filtering aims to match the content of CVs and/or network profiles with descriptions of job vacancies. One key component here is the Natural Language Processing (NLP) method that will transform unstructured text into information, so as to create structured features describing the candidates and jobs. For example, Named Entity Recognizer (NER) allows for the label sequences of words such as 'person', 'organization', 'time', etc. (Finkel, Grenager, and Manning 2005) that can be used later to infer the experience of a candidate or their education. To perform the matching and ranking, a score can be calculated by weighting each feature, e.g. the candidate has a specific skill, or group of features such as 'Experience' (Lin et al. 2016).

The problem of content-based filtering it that it requires the algorithms to 'understand' the items, which can be a complex task. Collaborative filtering, meanwhile, does not focus on content but on user preferences and behaviour so that the system can use the behaviour of all the network to predict the preference of every user about new items. The underlying assumption is that users will prefer items selected by similar users. In the case of jobs, the assumption is that similar candidates will apply for similar vacancies but also that recruiters/managers are specialised in finding candidates with profiles that match past candidate selection practices. How to measure this similarity is key in each particular network. A simple and common way of considering that two candidates are similar is if they have clicked or applied for the same position, but often real platforms incorporate more information.

[21] https://www.broadbean.com/uk/products/features/search-cv-databases/
[22] https://www.workable.com/candidate-profiles
[23] https://ideal.com/wp-content/uploads/2017/01/Ideal-AI-For-Retail-Recruiting-eBook-2.3.pdf
[24] https://www.elastic.co/use-cases/xing
[25] https://orientacion-laboral.infojobs.net/ofertas-para-ti-infojobs

More ‘successful’ recommender systems are context-aware collaborative filtering systems that add more dimensions to the candidate-job matrix. The recommended list can be refined by looking for shared characteristics between the vacancy description and the candidate profile, e.g. education, positions, etc. However, comparing content is not straightforward. For instance, the work of Schmitt, Caillou, and Sebag (2016) analysed data of the French employment website Qata[26] to study particular issues of matching temporary and low-wage jobs. One of the conclusions was that CVs and job ads ‘*tend to use different vocabularies, and same words might be used with different meanings*’. Other tools such as Ziprecruiter[27] are specifically intended to learn from recruiter preferences so they can rank candidates similar to previous candidates for each type of vacancy (Bogen and Aaron 2018).

Automatic candidate matching and ranking is also implemented in the public sector. The public employment service of Flanders in Belgium (VDAB) monitors how people search for jobs on their website to provide the job seeker with a list of recommended jobs and analogously to match them with potential employers. The system not only performs the role of a job platform site where job seekers register to apply for positions, but it also analyses the behaviour of the job seekers in the platform. The VDAB reports that this information is very relevant for predicting long-term unemployment and can allow for early and more efficient intervention (AlgorithmWatch 2019).

2.2. Ranking and Screening

Screening refers to the filtering of the preliminary pool of candidates that match a position to later perform an interview. Reducing the number of candidates is a repetitive task for which many companies are relying on algorithmic solutions. In this case, the ML tools perform a ranking of candidates based on their experience and skills, but also on other estimated characteristics such as performance or the likelihood of them staying in the job.

For instance, one of the features of the chatbot Mya is to engage with applicants, ask for additional information, answer questions the candidate has about the role, but also to assess eligibility and to deliver a ranked selection of candidates[28]. Workable incorporates an ATS to manage the database of candidates and organize and store interviews, messages and other information that can be used to filter and rank applicants[29]. Ideal includes AI predictive models to determine who will stay longer and perform better using multiple data sources[30]. Also, its AI tool can learn from feedback to update the model for improving the accuracy of predictions. TribePad can perform automatic shortlist selection and reject candidates based on predefined criteria[31]. For instance, Tesco uses TribePad to parse CVs and LinkedIn accounts and automatically reject candidates not qualified for a position applied for[32]. TribePad is also used by Exclusive Hotels & Venues to manage a pool of non-selected candidates that can be searched, filtered and screened for future vacancies[33]. Many professional networks privilege premium users that pay money to

[26] https://www.qapa.fr/
[27] https://www.ziprecruiter.com/
[28] https://hiremya.com/meetmya
[29] https://www.workable.com/hiring-dashboard
[30] https://ideal.com/product/screening/
[31] https://www.tribepad.com/applicant-tracking-system/candidate-selection/
[32] https://www.tribepad.com/wp-content/uploads/2018/12/Tesco-Case-Study.pdf
[33] https://www.tribepad.com/wp-content/uploads/2018/12/Exclusive-Case-Study.pdf

influence the screening process. For example, XING modifies the ranking results to highlight users with premium accounts so that they have a higher chance of being discovered by recruiters[34].

2.3. Interviewing

Interviewing is also being transformed by datafication and predictive models by extracting more information from the candidate or by automating parts of the interview.

Automated interview via chatbot

Some companies are using chatbots to arrange interviews, perform preliminary interviews, get additional data from selected persons or answer questions from candidates. Figure 9 shows some conversation examples of the Mya chatbot while Figure 10 shows an example of a decision tree to semi-automate responses. This chatbot can interact with employees via many popular platforms such as WhatsApp, Facebook, Skype or LinkedIn[35] to ask and answer the typical questions in early job interviews such as starting date, salary, required qualifications, etc. The creators of Mya claim that they recognise that there is no guarantee that the best candidate will avoid rejection, as also happens with human recruiters (Prior 2017). To improve the system and minimize errors, Mya collects data of the interviews to look for behavioural patterns in the interview that can be related to future behaviour in the position. For instance, Mya found that people who insists on 'compensation questions' during an interview are more prone to leave jobs more quickly (Prior 2017). Because of its features, Mya is used in high volume hiring organizations such as L'Oreal, Pepsico and Adecco[36]. For example, in 2017 the Adecco Group announced they would use Mya '*to enhance the quality, speed and efficiency of its recruitment service experience for both clients and candidates*'[37]. Mya integrates their current ATS and calendar of the company's light industrial, call centre, and administrative-clerical recruiting sectors.

---

[34] https://www.xing.com/upsell/pro_jobs_offers?reagent=uplt_205

[35] https://hiremya.com/blog/mya-adds-whatsapp-and-facebook-messenger-to-bolster-omni-channel-approach-to-candidate-engagement

[36] Many of the customer testimonials in the product website are anonymous so that the rest of their customers are unknown.

[37] https://www.businesswire.com/news/home/20170810005371/en/AI-Recruiting-Company-Mya-Systems-Inks-3-Year-Global

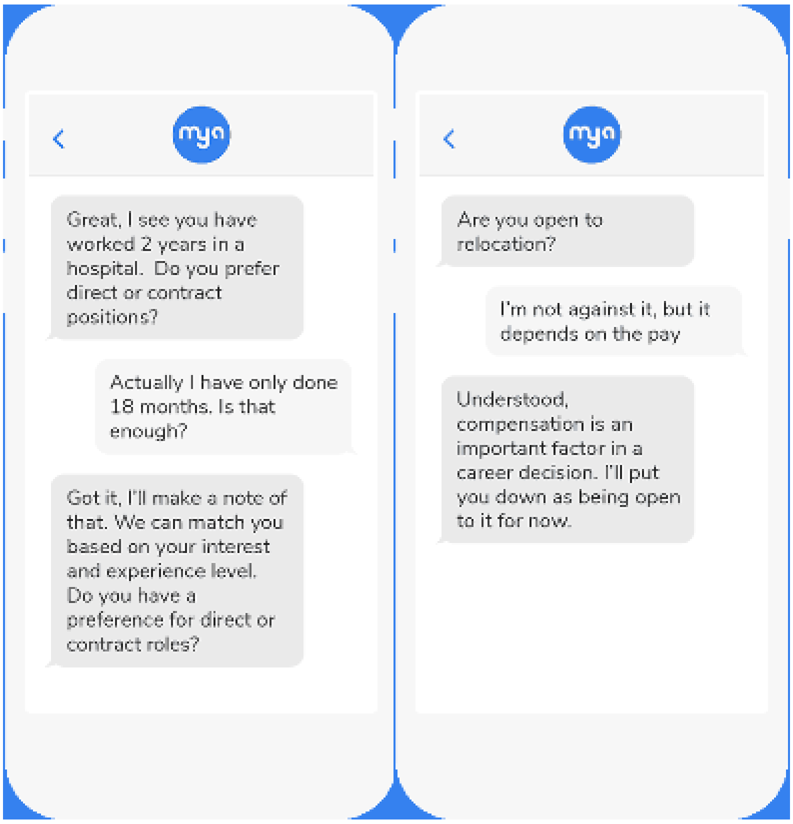

Figure 9 Mya Chatbot conversation example. Source https://hiremya.com/our-clients/refreshing-passive-databases.

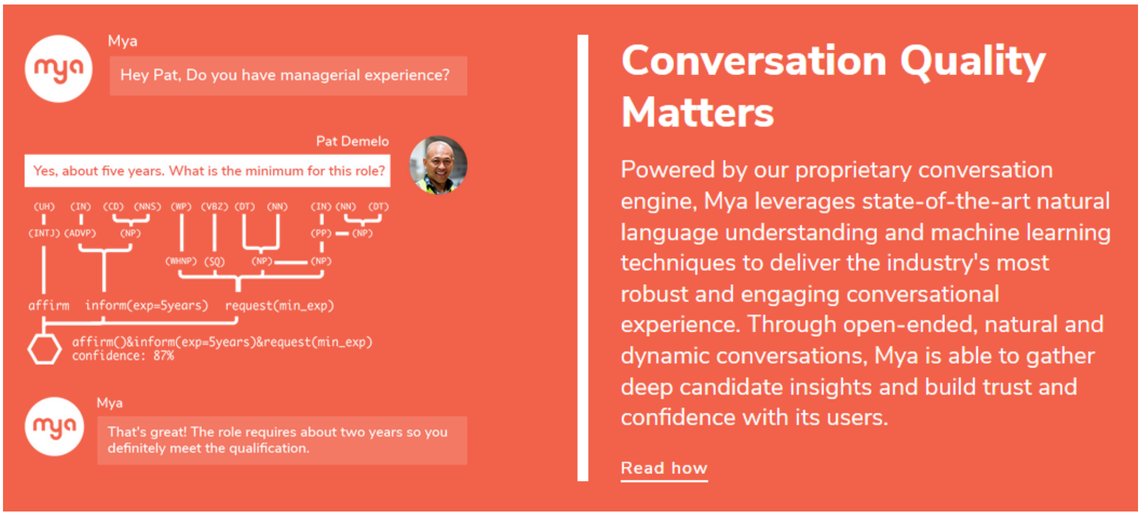

Figure 10 Mya Chatbot example of semi-automated dynamic answers. Source https://hiremya.com/meetmya.

Video interview, skill tests and personality profiling

Interviews have often included tests and games to validate some specific aspects of candidates. This is being amplified with the rise of psychometrics in data-driven technologies with companies trying to extract (predict) the most insights as possible about people. For example, Pymetrics have designed neuroscience games whose results are analysed to look for trends that can be used to identify success[38] but also to discover bias in the hiring process[39]. HireVue includes

[38] https://www.pymetrics.com/employers/

[39] Pymetrics has released their toolbox to identify statistical bias in machine learning models https://github.com/pymetrics/audit-ai

assessments based on games and AI[40] to provide scores on leadership, memory, problem solving, attention, etc. (Mondragon, Aichholzer, and Leutner 2018). According to the company, their 'scientific approach' produces an assessment score that is correlated to the job performance. An example is shown in Figure 11. Moreover, some tendencies in the predictive performance of employees aim to estimate the 'learning quotient'; that is, candidates more willing to learn new skills[41].

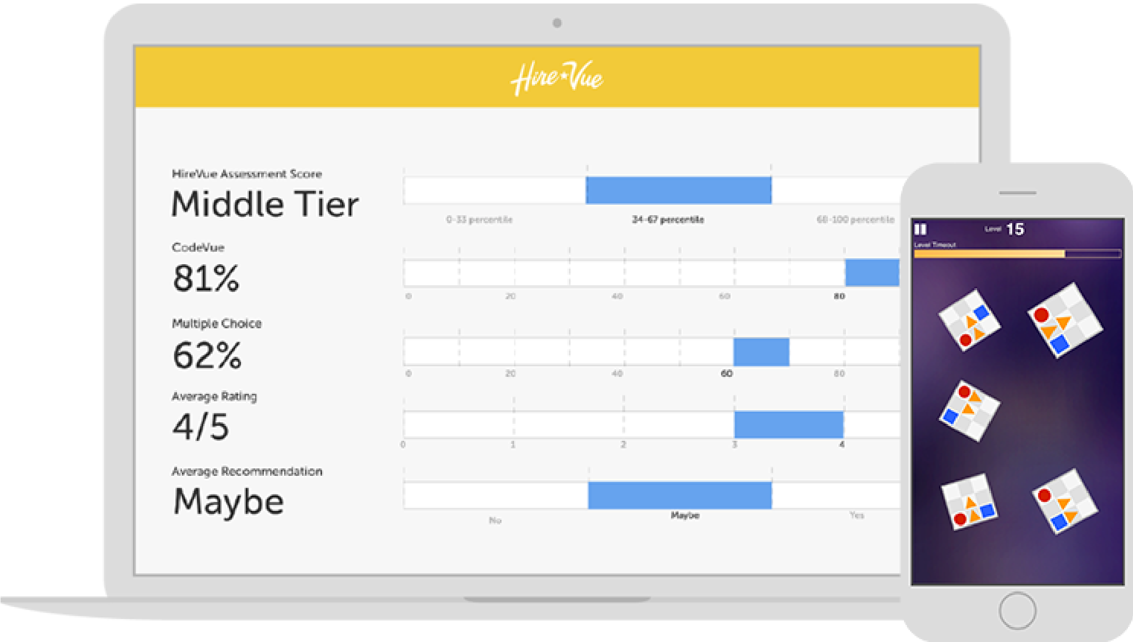

Figure 11 HireVue game-based assessments. Source https://www.hirevue.com/products/assessments.

Some tools provide video interviewing that include features that extend traditional videoconference or video recording. For instance, TribePad ATS includes automatic video transcription that can be used for several purposes. For instance candidates can be indexed and filtered based on their answers during the video interview. Additionally, the interviewer can define a set of priority keywords related to a profile that the ideal candidate is expected to say in an answer to a given question. The ATS can look for these words in the transcriptions and score a candidate's responses automatically[42]. According to TribePad, video transcription can also be used to perform anonymous video interviewing to mitigate unconscious bias[43].

Personality insights, or what we might think of as personality profiling or personality tests, are not new in the field of hiring and it is an active area in ML to build marketing and recommendation systems. With new (indirect) data sources, and the increase of datafication and monitoring during interviews, many tools are labelling and scoring workers in new ways. For instance, HireVue, in addition to the game-based scoring, performs video-based assessments to create a personality profile (see Figure 12) by comparing 'candidates' tone of voice, word clusters and micro facial expressions with people who have previously been identified as high performers on the job' (Schellmann and Bellini 2018). This includes, according to the company, a way to

[40] https://www.hirevue.com/video/reimagining-pre-hire-assessments
[41] https://business.linkedin.com/talent-solutions/blog/future-of-recruiting/2018/future-of-recruiting-predictions

[42] https://www.tribepad.com/the-blog/video-interviewing/
[43] https://www.hirevue.com/blog/bias-in-interviewing

‘understand the emotional intelligence of your candidates’, ‘Find candidates with the perfect cultural fit’ and ‘Make use of Neuro-Linguistic Programming’[44]. The software provides insights into the ability to work in a team, problem solving, adaptability, communication, conscientiousness, responsibility, driving for results, personal stability or stress tolerance[45]. In both game and video-based gathered data the candidate’s scores are ‘statistically linked’ to previous profiles to predict the job performance of the person. Similarly, the tool Catalyte[46] seeks to estimate cognitive agility, problem solving skills and stress tolerance of candidates by analysing the data they generate during problems resolution. In this case, the goal is specifically to find computer programming skills in people without technical background as it is dedicated to advancing coding skills (Giang 2018).

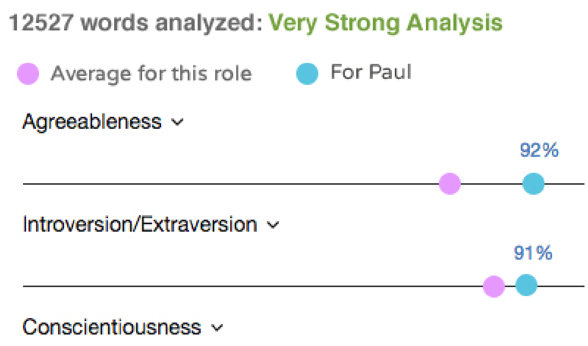

Figure 12 Example of personality profiling by HireVue. Source https://www.tribepad.com/video-interviewing/.

All the previous examples are based on data gathered during the interview. However, other companies claim to obtain insights about people exclusively based on their social network and internet activity. DeepSense scan applicants’ social media profiles, without their knowledge, to infer personality features (Schellmann and Bellini 2018). Predictim, another tool for personality profiling based on social media, recently gained significant media attention (Harwell 2018). The company uses AI to score the personality of workers, in this case babysitters, to predict risk degrees for bullying, harassment, being ‘disrespectful’ or having a ‘bad attitude’ (see Figure 13). The profiling was done based on user activity analysed from Facebook, Twitter and Instagram posts. However, soon after the tool appeared in the news Facebook and Twitter banned this tool saying it strides against their policy on data use for eligibility decisions (Lee 2018). In Finland, the company Digital-Minds[47] performs personality profiling of candidates by using AI-based text processing of emails and social networks public data. The company has between 10 and 20 Finnish companies as customers (AlgorithmWatch 2019). The aim of the product is to replace traditional personality profiling tests and is in line with other general purpose personality insight tools such as that provided by IBM Watson (see Figure 14). IBM Watson Personality Insights is based on linguistic analytics from digital communications to infer individuals' intrinsic personality characteristics. IBM developed models to calculate scores for the *Big Five* dimensions (Agreeableness, Conscientiousness, Extraversion, Emotional range and Openness), Needs, and Values from textual information. The models are based on research in the fields of psychology, psycholinguistics, and marketing (IBM Corp. 2019). Personality Insights scoring relies on machine

[44] Neuro-Linguistic Programming has been accused of pseudoscience by several authors https://en.wikipedia.org/wiki/Neuro-linguistic_programming#Scientific_criticism
[45] https://www.hirevue.com/products/video-interviewing
[46] https://learn.catalyte.io/
[47] https://www.digitalminds.fi/

learning models that are trained using Twitter feeds together with scores from personality surveys that were conducted among thousands of users to serve as ground-truth. The general assumption in all these systems is that characteristics that are inferred from text are reliable predictors of real-world behaviour (IBM Corp. 2019).

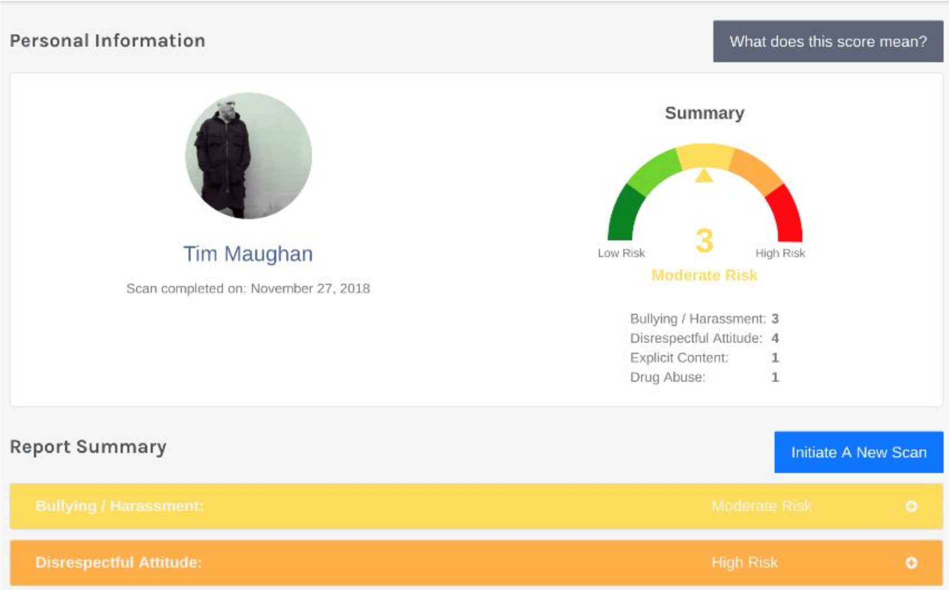

Figure 13 Predictim example report. Source (Merchant 2018).

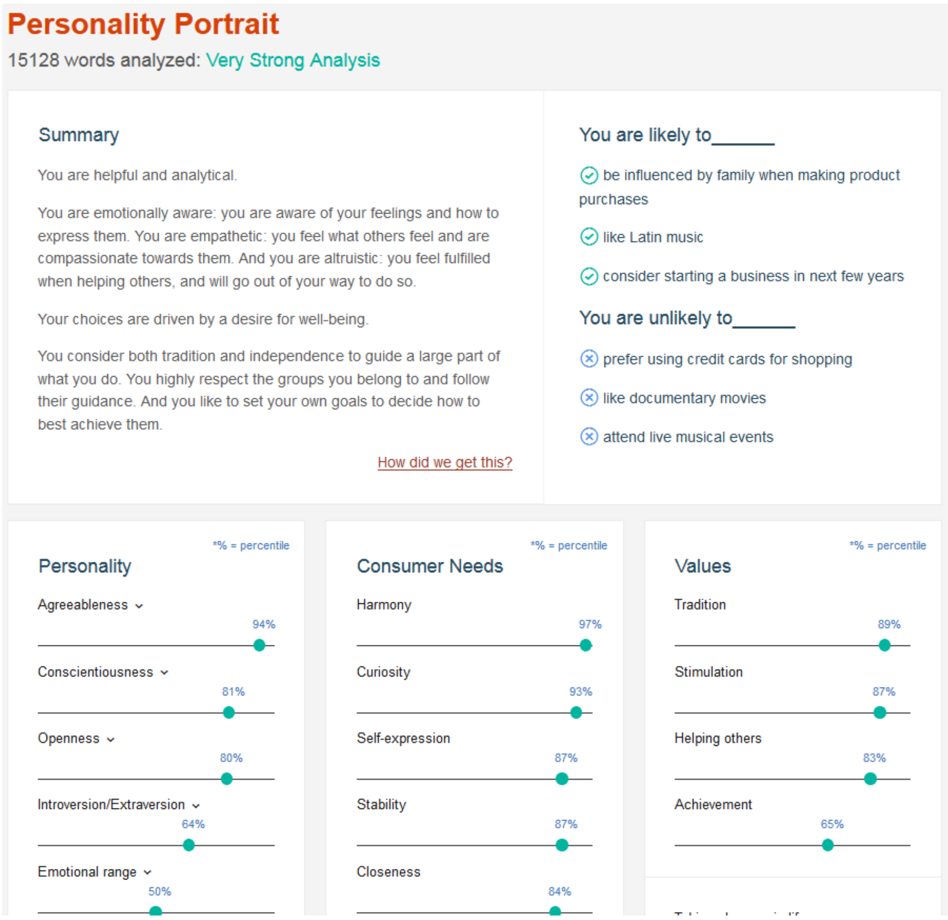

Figure 14 Personality insights generated by IBM Watson. Source https://personality-insights-demo.ng.bluemix.net/.

2.4. Selection and rejection

The last stage of the hiring process is the selection of candidates. Personality profiling can also be performed here to complete the decision.

Offer

By the offer stage, we are referring to the process by which an employer seeks to negotiate salary, benefits, starting date, duration of the contract, etc. Some tools allow for the personalisation of offers and predicts if the applicant is likely to accept the offer (Bogen and Aaron 2018). As an example, Oracle's Recruiting Cloud[48] promises they can estimate, based on previous data (although the details of what kind of data is not specified), the likelihood of a candidate accepting a job and how different changes in the offer will increase or decrease this probability offer (Bogen and Aaron 2018). Another example is the PeopleStrong HR platform, which is based on an ML model trained with historical recruitment data in order to assist in salary negotiation. In case the HR recruiter salary offer is higher than the suggested one the software can block the decision subject senior leadership approval[49].

Rejection

Some companies are using hiring tools such as TribePad to keep communication with candidates by generating email templates, calendar alerts for calls or emails, but also by using chatbots to inform the candidate about the status of the process. In the case of rejection, some tools such as Pymetrics can make suggestions for ways the candidate can improve skills for future positions, or can recommend they apply for different positions or different types of jobs[50]. Mya chatbot is also designed to answer questions and provide feedback to all the candidates and maintain contact from the moment they apply for a position. For example, the chatbot integrates with the calendar of the ATS to schedule messages and meetings and it can interact with passive or rejected candidates when new vacancies appear[51]. Workable includes a feature to pause the hiring process and 'snooze' candidates that will be contacted in the future[52].

3. Employee monitoring and surveillance

In this section we focus particularly on the ways in which the long-standing history of worker surveillance and employee monitoring is evolving with the development of data-driven technologies.

3.1. Data integration and intelligent data analysis

The last years has seen a significant transformation in the nature of employee monitoring with the possibility of building multi-source datasets, the processing of unstructured data (text, audio and video), the deployment of predictive models, the popularization of wearables technologies, the omnipresence of smart phones and the use of social networking platforms. Monitoring can be performed at the workplace computer and phone or by tracking the movement and activity of employees by CCTV, wearables, access cards, etc. Figure 15 from Trades Union Congress (2018) shows the most common practices perceived by employees in the UK. The same report identified that surveillance practices grows with the size of the company.

[48] https://cloud.oracle.com/en_US/adaptive-intelligent-apps
[49] https://www.peoplestrong.com/this-hr-firm-is-using-ai-to-hire-without-bias-negotiate-salary/
[50] https://www.pymetrics.com/candidates/
[51] https://mya.com/meetmya
[52] https://www.workable.com/snooze-job-candidates

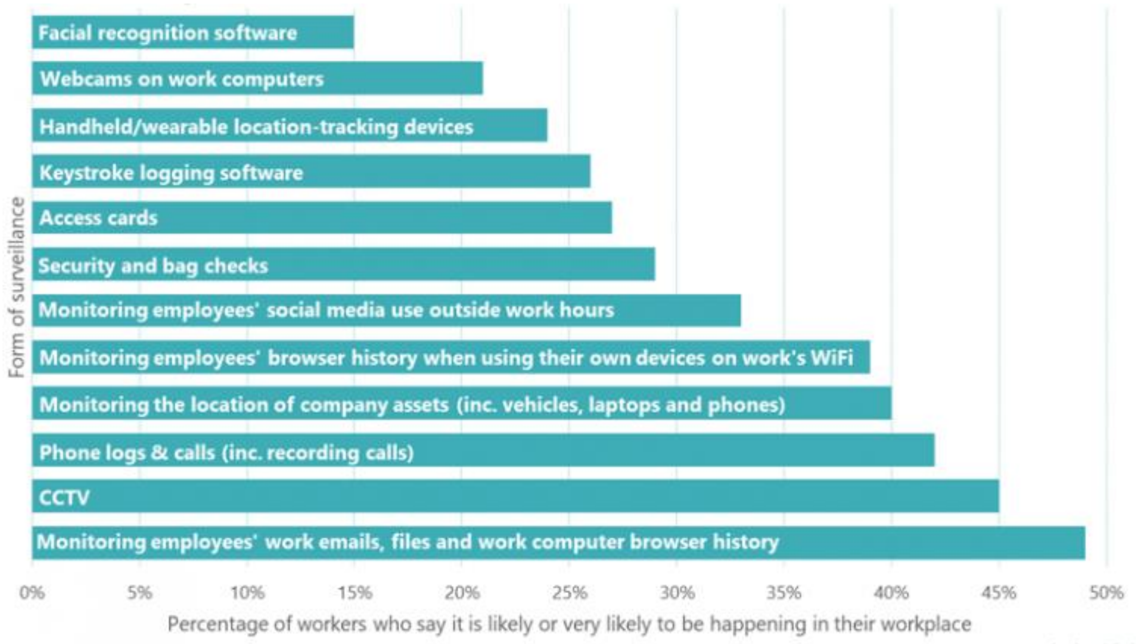

Figure 15 Most extended practices in surveillance in the UK. Source (Trades Union Congress 2018).

For instance, CCTV monitoring is not new, but in recent years it is possible to track individuals based not only on facial recognition but also on gait recognition from features extracted, at a relatively far distance, from the silhouette or the shadow of the individual[53]. Moreover, automatic scene semantic labelling (see Figure 16) and understanding of video can create activity reports on how much time a person has used to expend in different activities (Deng et al. 2015) as well as emotion analysis (see example in Figure 17).

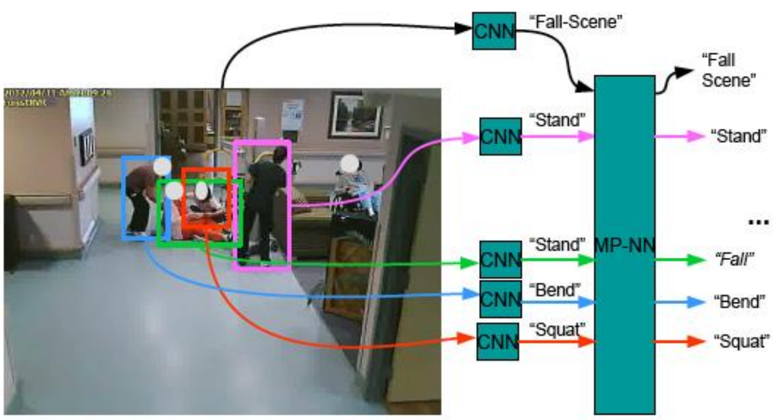

Figure 16 Example of scene automatic semantic understanding with Deep Learning. Source (Deng et al. 2015).

[53] http://www.watrix.ai/en/gait-recognition/

Figure 17 Example of emotion analysis with computer vision. Source https://nordicapis.com/20-emotion-recognition-apis-that-will-leave-you-impressed-and-concerned/.

Amongst the rise of new surveillance practices, perhaps the most significant issue is the information fusion tendency to allow further processes of profiling and predictive management of employees. For example, the RetailNext system shown in Figure 18 can integrate internal and external data sources to create reports, generate alerts, perform predictive analytics among others.

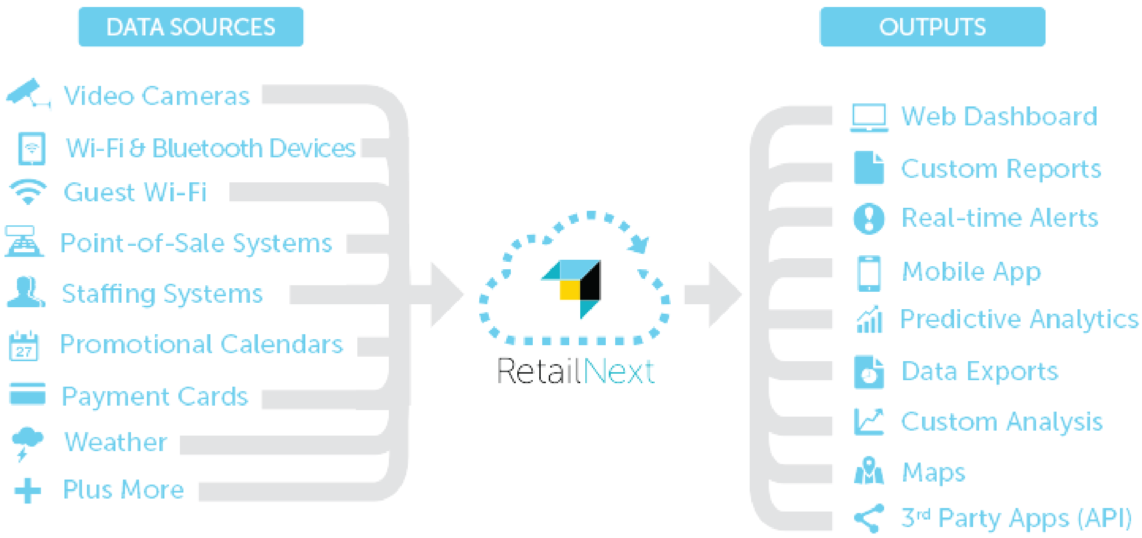

Figure 18 RetailNext integration of different data sources. Source https://retailnext.net/en/how-it-works.

Worker surveillance can be also run in an indirect manner. The research of Levy and Barocas (2018) suggests that data gathered on one group often impacts on another group not directly surveilled. Levy and Barrocas call this *refractive surveillance* to describe the dynamic of collecting information about one group to ease control over a different group. For instance, customer tracking with surveys, facial recognition or behaviour analysis in retail can typically be used to automatically schedule the workforce. Refractive surveillance is very relevant since many customer datafication techniques are being deployed rapidly in stores. According to research by CSC in 2015, 25% of UK retailers were using facial recognition technology, and near 60% in the case of fashion retailers[54]. Refractive surveillance can happen in other contexts. For instance, teachers and academics are frequently evaluated by monitoring students' behaviour, outcomes and surveys, as documented elsewhere (see for example Mardikyan and Badur 2011; O'Neil 2016).

3.2. Presence control

The most basic form of monitoring is presence control which is deployed to sign in at work or to implement security policies. To prove their presence in the workplace, employees must use codes, ID cards, RFID chips or biometrics. Biometric authentication for identification is also integrated with data analytics tools to register worker activity. Kronos InTouch uses employee fingerprint and passcodes to perform employee-tracking[55] inside retail stores, e.g. employee's activity in cash queues. In addition to presence registering, some organizations use these identity systems to track employees along facilities. For instance, some companies monitor the toilet use via these presence control systems (Trades Union Congress 2018; Van Oort 2018). Extreme cases of activity registering can occur, such as the Spanish company Abengoa which subtract toilet time from the overall working hours. This policy is implemented by placing barriers that the workers have to open with their ID cards so that every in-out event is registered in the system. This company also demands that workers use their ID cards as electronic wallets to buy food in the company's vending machines and restaurant. External food is not allowed and if the workers do not use their cards during several consecutive days the HR department demands an explanation (González Paulino Ramos 2013).

Other presence control systems designed to monitor the whereabouts of workers can be subtler and do not depend necessarily on intended actions. For instance, OccupEye sells a monitoring solution based on heat and movement sensors that tracks the presence of employees in specific places such as desks or meeting rooms. The sensors send all the collected information to a data repository to create presence reports that can be used, for instance, to optimise office space (see Figure 19 and Figure 20).

Figure 19 OccupEye monitoring device. Source https://www.occupeye.com/how-it-works/.

[54] https://www.biometricupdate.com/201509/csc-report-finds-that-25-of-u-k-retailers-use-facial-recognition-in-store
[55] https://www.kronos.co.uk/products/kronos-intouch

Figure 20 OccupEye report example. Source https://www.occupeye.com/how-it-works/.

3.3. Computer and mobile phone

Meta-data monitoring

The monitoring of computer activity accompanied the introduction of the computer into the workplace. For instance, Wavecrest, an employee monitoring system, dates back to 1996[56]. The reasons provided for computer monitoring are related to security, intellectual property protection, health and safety or performance among others. Common computer surveillance includes screen records, tracking of the changes in the local or network drives, keystroke monitoring, idle time, printer records and video/audio obtained from peripherals[57].

However, certain prominent trends have emerged in recent years that highlight the current form of employee monitoring. The extension of computer surveillance to mobile phones increases the variety of available data, e.g. multiple sensors information. For instance, VeriClock allows workers to clock in and out with their smart phones. The app can include location and IP details in the register. Mtoag builds employee tracking apps as customer requirements. It includes employee status monitoring, such as whether the staff are available, engaged, on-route, busy, reached or completed a task or not; assignment information related to order progress; and client feedback after work completion[58]. Monitoring software such as RescueTime is also focused on improving personal and enterprise productivity and is available both for computer and mobile phones. It monitors and categorises the activity of the user such as time spent in each app/software or time dedicated to each website and calculates screen time and warns when employees are working excessively[59].

---

[56] https://www.wavecrest.net/products/monitoring/employee_monitoring.php?utm_adgroup=employee_monitoring
[57] As an illustrative example of popular features, a review of employee monitoring software is provided here: https://uk.pcmag.com/cloud-services/92098/the-best-employee-monitoring-software
[58] https://www.mtoag.com/employee-tracking-app-solution.htm
[59] https://www.rescuetime.com/features

Furthermore, computer surveillance has extended to data from systems such as professional email, personal social networks or mobile phones to the creation of databases for augmenting so-called 'people analytics'. 'People analytics' mainly refers to the use of data collection and analysis methods to understand and optimize the employees of a business and will be covered in more detail in Section 4 on Management. For instance, Humanyze anonymizes and integrates data from several data sources such as the Sociometric Badge (see Section 3.4), Skype, Slash, Office 365, shared calendars and email[60]. The integrated data is then analysed with data science techniques, organizational network analysis and behavioural science to 'discover' patterns such as informal communication networks or to measure and test the effect of interventions such as moving office or employee engagement programs.

Content monitoring

The previous monitoring tools register and analyse meta-data or anonymised data of worker communications. However, the analysis of communications content is a growing trend due to the popularization of tools for unstructured data analysis. For instance, the field of sentiment, emotion and tone analysis based on digital data, initially motivated by marketing research, is being incorporated into worker surveillance for different purposes. Emotion recognition application programming interfaces (APIs) can be used to develop surveillance and monitoring tools on unstructured information such as text. Figure 21 shows an example of text analysis with Tone Analyzer by IBM Watson.

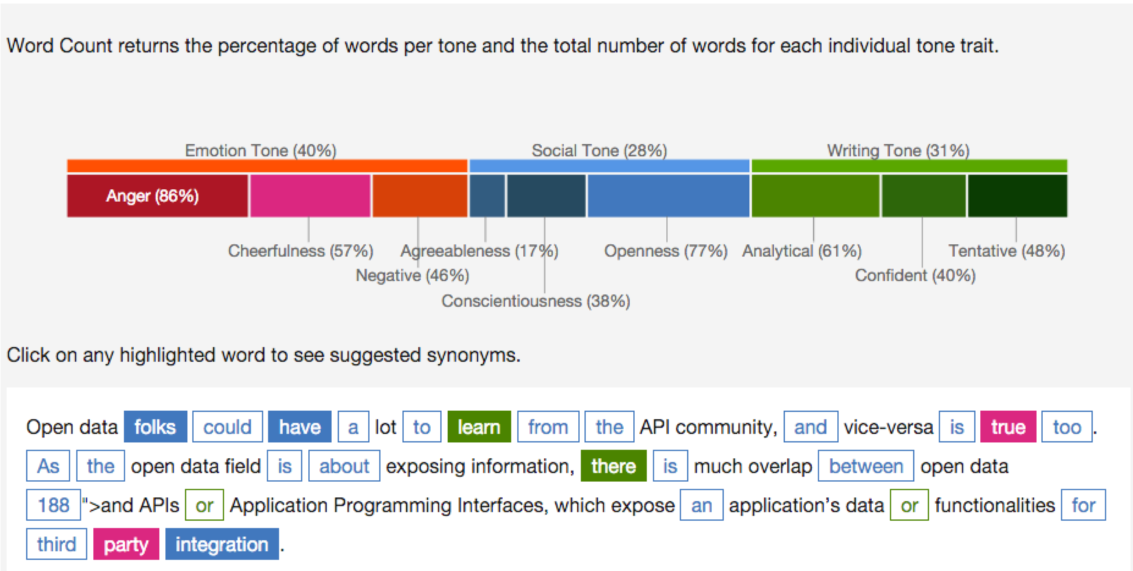

Figure 21 Example of tone evaluation of unstructured text with IBM Watson Tone Analyzer. Source https://nordicapis.com/20-emotion-recognition-apis-that-will-leave-you-impressed-and-concerned/.

By scanning corporate communications or surveys, sentiment-analysis tools can tell managers how employees are feeling, i.e., what they like and dislike about the company or specific managing decisions. For example, Twitter hired Perception, former Kanjoya, to analyse the open questions of the twice-yearly survey the company send to its employees to evaluate workplace experiences. Later, Twitter decided to add more open questions to the survey and started sending the survey every month (Waddell 2016). The sentiment-analysis tools analysed the narrative answers to extract patterns that are then shared with managers. According to Ultimate Software, the company behind Perception, the philosophy is that '*building a great workplace and*

60 https://www.humanyze.com/solutions/

culture that engages, motivates, and retains employees is understanding what they care about'[61].

Tools such as Perception can be integrated with corporate social networks such as Yammer (Microsoft) or Workplace (Facebook) to perform a continuous sentiment-analysis of employee communications. IBM's corporate social network Connections is available to all their employees in 170 countries and is also sold to other companies. The network features the functionality of Facebook, Dropbox and Wikipedia at once. To analyse Connections data, IBM developed an analytics tool called Social Pulse to monitor employee data in Connections.[62] It provides insights using topic extraction and sentiment analysis of unstructured text in combination with structured demographic information from staff information systems (Shami et al. 2014). Social Pulse can track specific themes '*such as eight core emotions, and workplace concepts such as social relations, financial transactions, respect, use of power (e.g., cooperation as contrasted with conflict), and some recently identified factors that indicate collaboration-health (e.g., use of first person *plural* pronouns)*'. In addition to this, IBM has also developed an unsupervised learning tool called Avalanche to look for trends or alerts on internal and external social media[63].

3.4. Monitoring multimedia data

In addition to the monitoring of content such as text, a number of tools have been developed to monitor multimedia data. In mid-2018 Walmart patented an audio surveillance technology called 'Listening to the Frontend' to record customers and employees sounds in the shopping facility to '*determine performance of employees based on those sounds*' (Jones, Vasgaard, and Jones 2018). Other research projects propose to scan employees' faces every time they access the building to determine if they are happy, sad, depressed or angry, with the purpose of using that data to optimize productivity (Waddell 2016).

Smart video surveillance allows companies to perform people analytics in video and audio data. For instance, Faceter[64] deploys office workforce attendance reports and analytics based on computer vision to identify time card fraud, monitor employee attendance, compare work hours and overtime and report time allocation breakdown. Computer vision is also used by Eyetech DS[65] to offer monitoring solutions based on eye tracking and observe visual search processes, for instance in security staff training for baggage screening (see Figure 22).

[61] https://www.ultimateperception.com/employee-engagement-survey-software

[62] https://www.forbes.com/sites/jeannemeister/2016/10/05/the-future-of-work-companies-use-marketing-tools-to-create-a-compelling-employee-experience/#549b0ea4227e

[63] https://researcher.watson.ibm.com/researcher/view_group.php?id=5965

[64] https://faceter.io/

[65] https://www.eyetechds.com/trainingandsecurity.html

Figure 22 Eyetech DS example of eye tracking for baggage screener training. Source Eyetech DS.

Customer analytics based on video and sensors are relevant as refractive surveillance methods. Intel's AIM Suite delivers real-time anonymous audience measurement and analytics, e.g. shoppers' movements and reactions to visual cues, but also number of viewers, gender and age range or how much time they spent viewing content.[66]. The suite includes a web API to ease the integration with other systems such as POS to allow richer data gathering[67]. Others such as 3VR by Identiv converts raw video data into a searchable database that includes demographics, mood of the persons, etc. but also recognises and measures activities such as dwell time and loitering[68]. The semantically labelled video database allows fast investigations of crime and other events, but also the measurement of employee performance by creating analytics of specific tasks such as customer lines processing.

Voice analysis is also monitored. Cogito[69] is a system for call centres used by Zurich Financia and others. It can monitor callers and agents and suggest workers to change their behaviour if some events are detected. For instance, it analyses customer dissatisfaction levels and suggests actions, warns about fast speech, notifies about missed legal requirements or suggests calling a supervisor. Figure 23 shows an example of information displayed by Cognito.

[66] https://aimsuite.intel.com/inside-aim-suite
[67] https://aimsuite.intel.com/inside-aim-suite/core-components
[68] https://www.identiv.com/products/video-data-analytics/video-analytics/
[69] https://www.cogitocorp.com/

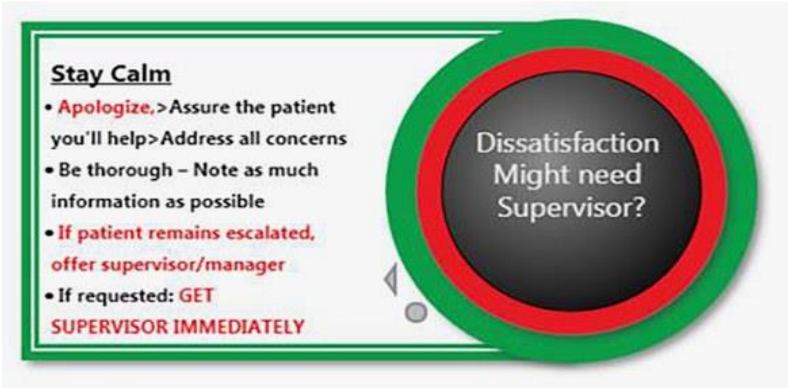

Figure 23 Screenshot of Cogito tool for conversational guidance. Source (Simonite 2018).

3.5. Chips, Wearables and IoT

As RFID chips and wearables spread, and in general the Internet of Things (IoT) is deployed, new means of tracking appear that go beyond those focused on content or desk-based devices. The purposes can vary from implementing health and safety to a continuation of surveillance and control. Wearables and the IoT are key components of the 'smart warehouse' and the 'smart employee'. In addition, some type of monitoring does not need any additional hardware since they rely on information collected by standard WiFi access points to collect motion information[70]. In general, radio signals can be used for several purposes including pose estimation or sentiment detection[71].

For instance, RetailNext generates data from Bluetooth low energy beacons (BLE)[72] to register the paths of both shoppers and staff members to get performance indicators such as when and where interactions occur. Also, by tracking sales associates, their movement can be excluded from traffic counts and shoppers' in-store buying paths[73].

Radio-frequency identification (RFID) can be used to track workers with different purposes. By adding RFID tags to uniforms, boots, helmets, etc. and associating a unique code with the item of each operator. This, together with a sensor network is used to monitor worker location and presence. For instance, the Spanish company Tagingenieros implements safety against dangerous machines or moving vehicles through RFID tags[74]. It can also detect if the worker is wearing all the necessary protection before accessing dangerous zones. The product registers the access of each operator.

Wearables in the workplace has become a prominent trend with hundreds of new devices launched every year[75]. For instance, Amazon has patented a wristband to track and conduct workers. The device uses ultrasonic signals to precisely identify workers' hand movements and it utilizes haptic feedback to nudge them in different directions by vibrating against the wearer's skin (Solon 2018). Amazon's gadget is aimed at increasing productivity in their smart warehouse but other gadgets such as ViSafe watch workers' safety habits. ViSafe collects movement and muscle activity information from multiple body locations, and then analyses and reports on how

[70] https://www.datumize.com/warehousing-industries
[71] http://rfpose.csail.mit.edu/
[72] https://en.wikipedia.org/wiki/Bluetooth_low_energy_beacon
[73] https://retailnext.net/en/download/employee-exclusion-measurement/
[74] http://www.tagingenieros.com/ENGLISH/?r=es/node/33
[75] https://www.wearable-technologies.com/?s=employee

employees move through their work time daily[76]. The data analytics of ViSafe is intended to improve workplace safety, manual handling, office ergonomics, workplace design and employee productivity. It has been used in the Transport of London to study the emergency response workers movement and muscle activity information from multiple body locations simultaneously[77]. Kinetic's REFLEX[78] is another smart device that uses sensors and biomechanical analysis to determine worker postures and warn them with vibrations if a dangerous posture is detected, for instance excessive bending (see Figure 24). REFLEX sends in-device collected data to a dashboard analytics to provide managers with a centralised data repository that includes analytics of individual workers (see Figure 25) and the whole company (Figure 26). The system allows for the creation of personal goals and competitions to reduce unsafe postures or improve work habits.

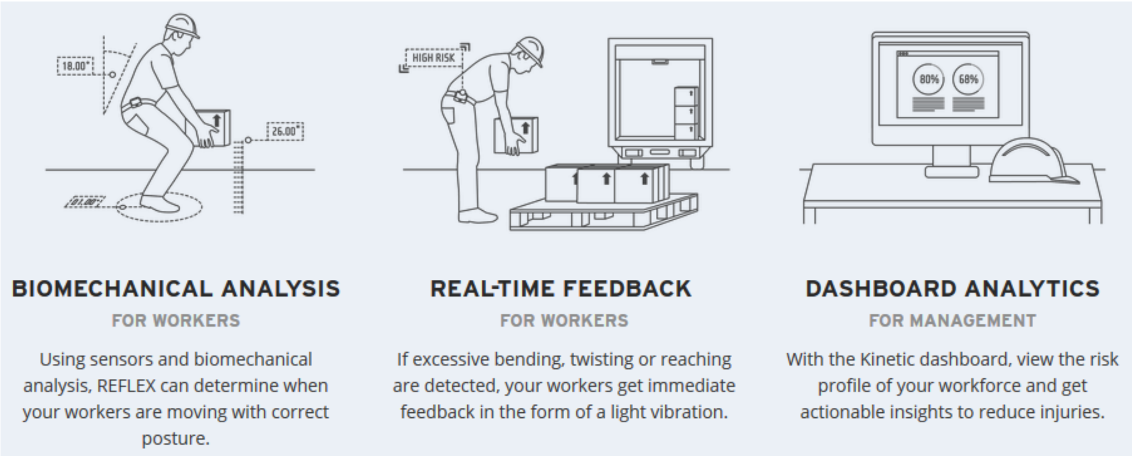

Figure 24 Illustration of the features of REFLEX. Source Kinetics https://wearkinetic.com/product.

[76] https://www.dorsavi.com/uk/en/visafe/
[77] https://get.dorsavi.com/tfl-visafe/
[78] https://wearkinetic.com/product

Figure 25 Screenshot of Kinetic Dashboard. Source https://www.wearkinetic.com/kinetic-dashboard.

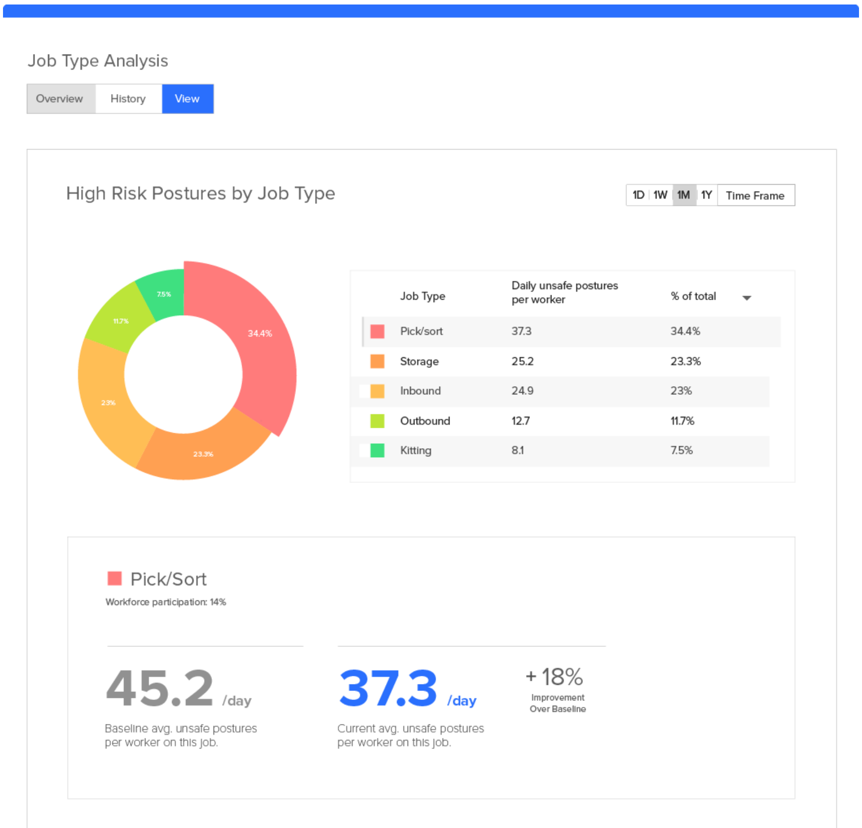

Figure 26 Analytics panel generated with REFLEX data. Source Kinetics https://wearkinetic.com/kinetic-dashboard.

In other cases, smart phones and general wearables are repurposed for employee monitoring. Fitbit, a popular smartwatch company, offers health and wellness programs to companies based on data gathering to promote physical activity between employees[79]. This includes 'best practice' recommendations such as positioning managers as role models for physical activity or organizing competitions for teamwork[80]. In other cases, the life style of employees is tracked by installing specific apps in their mobile phones. For instance, Ciclogreen aims to promote sustainable commuting by working with employers and organizations to encourage employees to cycle to work. To do so, they organise competitions and prices to reward employees by measuring their mobility patterns with an app, and then it produces a shared score of employees related to the competition, e.g. number of cycling kilometres in the last two weeks[81]. Also related to the tracking outside of working hours, productivity tools such as the BetterWorks management software '*blends aspects of social media, fitness tracking and video games*' into a shared dashboard to encourage productivity among workers (Ajunwa, Crawford, and Schultz 2016).

In 2015 the Sweden start-up Epicenter attracted significant attention after they started to offer microchip hand implants to office staff (The Guardian News 2015). The chip implant played the role of other chip-based technologies such as traditional pass cards allowing employees to open doors or use the photocopier. To engage with workers, the company held parties for those willing to be implanted. In the case of Epicenter, the chips were built by Biohax[82], and they are based on NFC (Near-field communication) to interact with the smart building. Chip implants are still a marginal practice, but they have generated an extensive debate in the media about the changing nature of the workplace (Solon 2017; Zolfagharifard 2018). The European Parliament has recently published an extensive report on several issues related to chip implants including legal aspects, workers privacy, devices security, ethics and health and safety risks (Graveling, Winski, and Dixon 2018).

In opposition to some of the previous systems mentioned, other projects claim to provide team analytics whilst upholding individual privacy. Humanyze is a company that offers organization level analytics without storing names and content of communications[83]. They have commercialised a former MIT research project named The Sociometric Badge[84]. The 'sociometer' (see Figure 27) is an electronic wearable that instead of gathering data automatically measures '*the amount of face-to-face interaction, conversational time, physical proximity to other people, and physical activity levels using social signals derived from vocal features, body motion, and relative location*'. These measures are based on movement, audio volume and Bluetooth and infrared pings from other sociometers. The features extracted by the device are later analysed to estimate '*individual and collective patterns of behavior, predict human behavior from unconscious social signals, identify social affinity among individuals working in the same team, and enhance social interactions by providing feedback to the users of our system.*'. The purpose of the system is to enhance social interactions by providing feedback to the users on an individual and private

[79] https://healthsolutions.fitbit.com/employers/
[80] https://healthsolutions.fitbit.com/corporatewellness/
[81] https://www.ciclogreen.com/
[82] https://www.biohax.tech/
[83] https://www.humanyze.com/
[84] http://hd.media.mit.edu/badges/ and https://www.humanyze.com/product/order-sociometric-badges/

dashboard. The private dashboard shows participants '*how they spend their time and what contributes the most to creativity, collaboration, productivity*'[85].

Figure 27 A Sociometer badge prototype. Source http://hd.media.mit.edu/badges/index.html.

4. Management

Management has a tradition of finding ways to measure, evaluate and optimize the workforce. Numerical methods such as operational research, games theory or econometrics among many others are well known techniques used by management science to model and optimize workforces as well as other resources. The increasing datafication of work and spaces, as well as the availability of a variety of tools to process and use new types of data, presents some pertinent further developments in how management is carried out.

4.1. Workforce scheduling and activity forecasting

HR scheduling and customer traffic forecasting is based on more and more integrated data. Kronos, which is widely used in retail and restaurant chains, collects information from a variety of sources such as shoppers and customers' traffic or weather (Van Oort 2018). The information is continuously gathered, so that a company can break down the analysis in segments of time, for instance 15 minutes segments. From this, it can analyse the human resources needs for each time slot, so that the software comes out with the optimal -- in salary cost terms-- assignment of staff. Moreover, by fitting predictive models of historical data, the system can forecast customer traffic to dynamically change the labour hours of employees and then reduce costs. For example, Jamba Juice used this software to reduce 5% of labour costs (Greenhouse 2012).

The platform RetailNext also implements future predictions of retail in-store behaviour based on historical data and statistical modelling. The tool simulates different scenarios such as interior remodels or larger footprint stores to assess the impact of decisions and investments[86]. TARA[87] is another tool to automatically create development tasks and timelines for software projects based on millions of previous software projects data. In addition, it automatically matches these tasks with pre-screened external contractors or with internal developers.

Predictive modelling can also be used to identify the resources needed to perform certain tasks. For instance, Amazon launched a data science competition to predict an employee's access

[85] https://www.humanyze.com/resources/data-privacy/
[86] https://retailnext.net/en/press-release/retailnext-in-store-retail-analytics/
[87] https://tara.ai/

needs, given their job role[88]. The purpose is to use historical data of staff roles to automatically grant or revoke employee access to resources (e.g. being able to log into a reporting portal). Tasks scheduling are also shaped by employees and clients profiling. For instance, Afiniti develops an AI based solution for call centres to pair callers and agents based on behavioural characteristics[89]. The objective is to improve the chances of successful caller-agent interaction so that previous patterns of successful pairing are used to schedule the connection. These types of approaches need constant monitoring to produce behaviour analytics in combination with metrics such as conversion rate, customer satisfaction score, average handling time, etc. According to the company, this approach outperforms previous 'performance-based routing' (PBR) solutions for call centres.

Automatic Call Distributors (ACD) based on skills are systems that match callers and agents based on predefined skills of the available staff, e.g. language knowledge or training on loans, and typically it is assumed that all the agents with a specific skill are equally capable of handling a customer's enquiry[90]. The caller provides some information that is used to direct the call to the first available target agent that can handle the type of call. In some contexts, the traditional skills routing is not suitable since categories are static and must be carefully defined. An emerging option is to automatically derive skills of agents by looking at the records of previous successful agent-customer interactions to extract patterns of successful interactions and then use these patterns to perform ACD based on automatic skills detection (McGann et al. 2017). Moreover, labelling of staff capabilities can be used to schedule turnover to ensure that all the areas are permanently covered[91].

4.2. Attrition, engagement and turnover prediction

Many studies demonstrate that engaged companies improve indicators such as sick days, productivity, employee retention or customer satisfaction. Therefore, companies are using profiling and predictive tools to measure employee engagement or reactions to changes in a company. For example, Peakon[92] is an engagement platform used by many UK companies that are moving from annual surveys to a continuous data gathering and evaluation approach. Peakson includes performance benchmarks to produce an engagement score that is connected to targets of the business (see Figure 28). It uses machine learning to identify how demographics such as age, tenure, gender, department, job level and office location are related to employee engagement scores. Peakson also provides employee segmentation to evaluate the alignment of different segments with the company values as shown in Figure 29. My Happy Force[93] is a mobile app to gather data on how employees feel and analyse their opinions, worries and motivations. The tool claims that it aims to create an environment to make employees feel that their opinions are considered. Every day, the app asks the workers how they feel, and the company dashboard presents information of the staff's app use during the current day, last week and last month. Understanding employee opinion about the employer is also done by opinion mining in general social networks and employer rating sites such as Glassdor. For example, Starbucks used sentiment analysis to perform a study of workforce engagement by collecting 5000 reviews from Glassdor (Meister 2016). The opinion mining results revealed that many of the workers felt 'pride' working for the company and they had a '*deep emotional connection*' towards the

[88] https://www.kaggle.com/c/amazon-employee-access-challenge
[89] https://www.afiniti.com/what-we-do/how-it-works
[90] https://www.rostrvm.com/pdf/Call_centre_skills_based_routing_in_practice.pdf
[91] https://www.genesys.com/capabilities/workforce-optimization
[92] https://peakon.com
[93] https://www.myhappyforce.com/en

company's mission. However, it is worth noting that the reviews did not pay attention to health benefits or other compensation schemes.

Social networking sites have emerged as key sites for management, as they have become integrated platforms in the workplace. These platforms serve different purposes such as alternative communication channels (messages, chats, videoconferences…), team coordination, documents repository, knowledge base, etc. but also as a means to improve worker engagement by allowing managers and employees to communicate and provide feedback, discuss or value organizational changes, recognise the work of others, etc. We already mentioned Yammer (from Microsoft), *Workplace* (software as a service by Facebook) or Connection (IBM) that all engage in this kind of analysis. For instance, *Workplace* features polls to get a quick pulse on issues by analysing Facebook-like reactions to news and content, and features chatbots to perform HR tasks such as making payroll or speeding up and facilitating so-called 'onboarding processes'[94], which refers to the process by which new employees adapt to the social and performance culture of an organization. *Workplace's* functionality can be extended with existing tools such as Kronos to submit, for instance, time-off requests directly from within the application to the managers[95]. Other extensions such as Recognize[96] aims to implement role-based employee recognition, employee nomination, staff rewards like gift cards or paid time-off, work anniversaries and more. *Workplace* is used in Domino's, Heineken, Danone, Volkswagen, WWF amongst many companies[97].

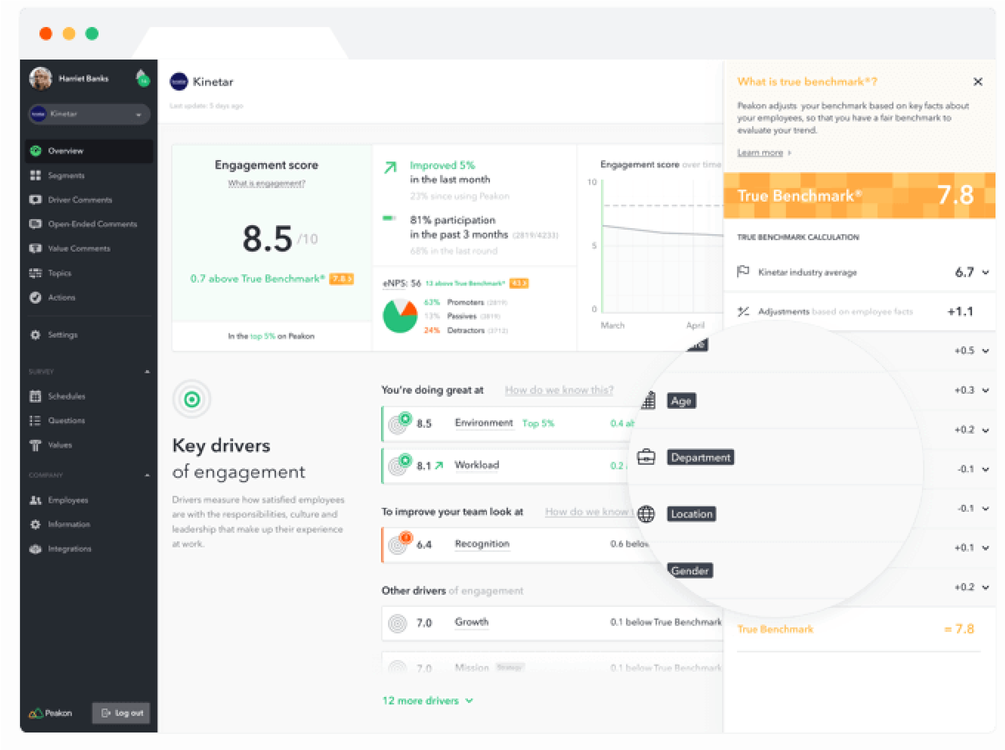

Figure 28 Peakson's dashboard showing employee engagement report. Source https://peakon.com/products/engage/bespoke-benchmarking/.

94 https://www.workplace.com/workplace/about
95 https://www.workplace.com/workplace/integration?app_id=168596273947060
96 https://www.workplace.com/workplace/integration?app_id=349213015502973
97 https://www.workplace.com/workplace/case-studies/wwf

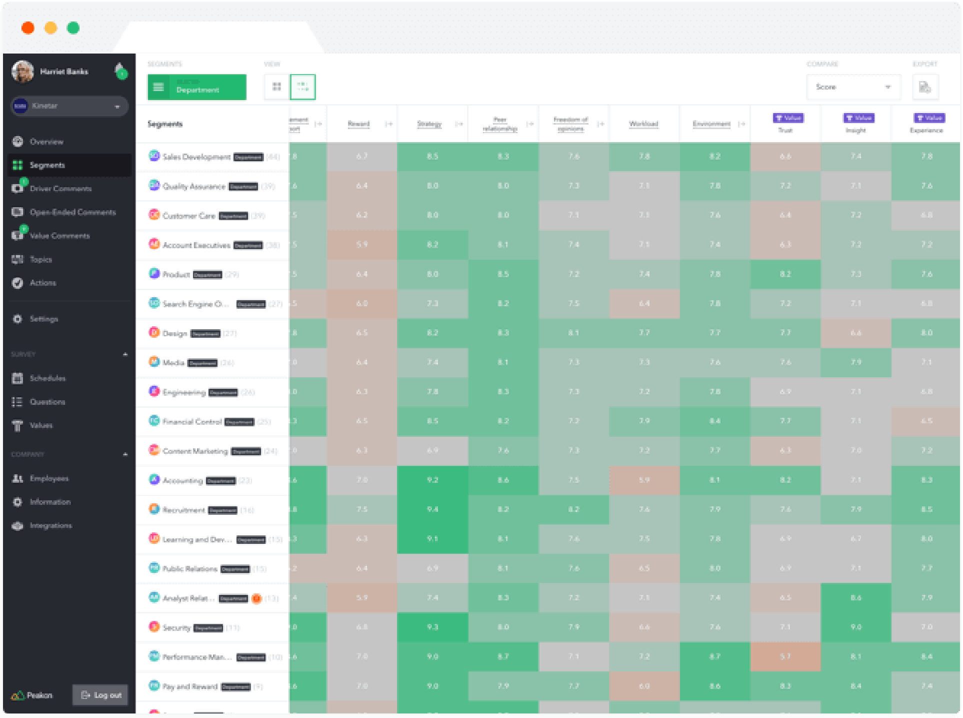

Figure 29 Peakson's values overview pane.. Source https://peakon.com/products/engage/values/.

A prominent activity making use of predictive analytics in the context of workplace management is employee turnover prediction. For instance, IBM released a dataset with fictional data to motivate research on attrition prediction and models to calculate the risk of an employee quitting. By analysing the models, it is said that managers can identify causes and act consequently[98]. The dataset includes variables such as overtime hours, distance from home, age, marital status, number of companies worked at, years in current role, income, etc. In addition, predicting a person's willingness to leave an organization goes beyond talent retention or improving working conditions. For instance, these tools can be used to take actions related to information security and information leaks, e.g. revoking access to confidential information or resources. For example, IT security practitioners interviewed by Korolov (2018) claimed that it is easy to spot a person that is leaving the company by detecting more sent emails with attachments to their personal address than usual. However, even this simple heuristic needs the constant processing of email logs for the purposes of monitoring and analytics. Other data competition, based on Happy Force records, tries to study the feasibility of predicting turnover, no matter if the worker quit or was fired, based on data of mood, comments and interactions of workers using the app[99]. The goal is to clarify indicators of employees that will churn (quit the job), or that are at risk of churning, to contribute to the understanding of causes and attempt to reduce the turnover rate. HR systems such as UltiPro by Ultimate Software have modules to 'measure' employee engagement through surveys and non-structured questions that allow organizations to uncover not only what employees say '*but also how they truly feel about the workplace and leadership*'[100]. The analysis can be turned into a score metric of each employee, team or company to allow engagement comparison as shown in Figure 30.

---

[98] https://www.kaggle.com/pavansubhasht/ibm-hr-analytics-attrition-dataset
[99] https://www.kaggle.com/harriken/employeeturnover
[100] https://www.ultimatesoftware.com/UltiPro-Solution-Features-Employee-Surveys

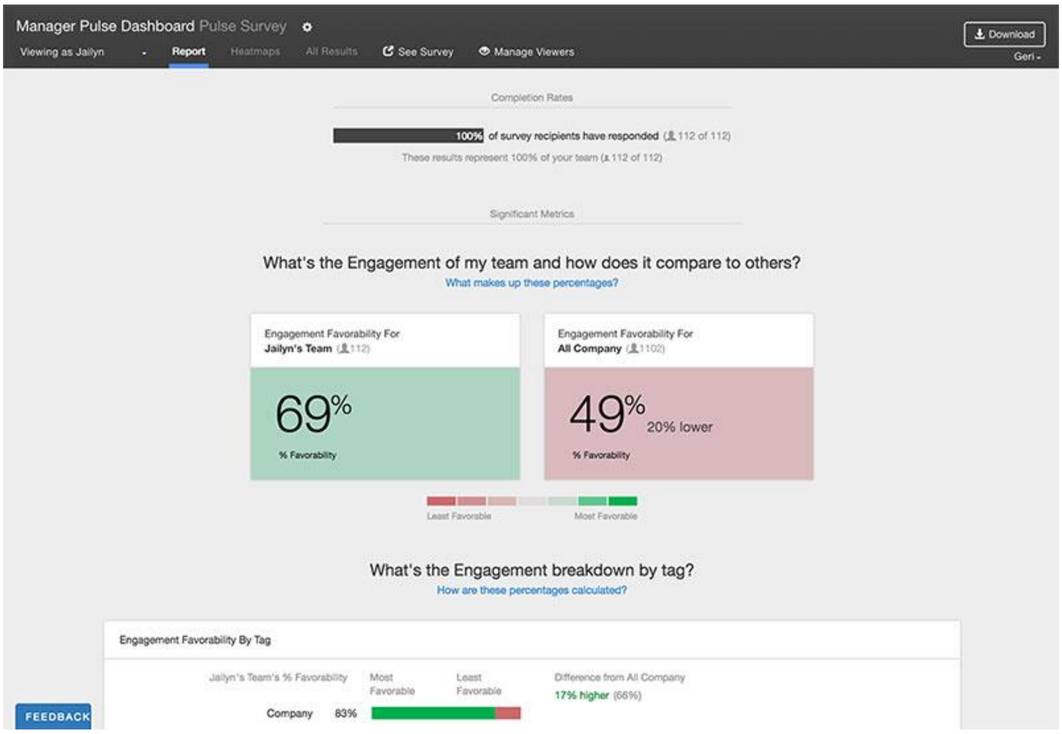

Figure 30 Example of engagement comparison tool UltiPro Perception. Source [https://www.ultimatesoft-ware.com/UltiPro-Solution-Features-Employee-Surveys](https://www.ultimatesoftware.com/UltiPro-Solution-Features-Employee-Surveys).

4.3. Profiling, performance evaluation, optimization and forecasting

Performance evaluation is perhaps the main objective that motivates workplace monitoring. From basic input/output indicators to sophisticated metrics and predictive scores each particular business tries to measure and predict what is happening or would happen. Beyond metrics and analytics, performance evaluation has evolved to obtain finer levels of measurement of worker activity and behaviour throughout, to include forecasting related to turnover prediction or risk assessment such as ‘loss prevention’ (the likelihood of internal theft, shoplifting, return fraud, etc.) based on data-feed models.

We categorise the measurement and evaluation of performance in three ways:

- *Reports* and *metrics* are direct observation of data, e.g. cost per hire.
- *Key Performance Indicators* (KPI) are measures of performance against business objectives and are typically used to reward employees if their performance is on target, e.g. customer retention rate.
- *Analytics* are intended to identify which factors impact on performance. They can be used to figure out how to improve the company but also to forecast performance in future scenarios. Examples are *People Analytics*, which refers to behavioural data that reveals how people work or that can drive changes in how companies are managed, or *HR Analytics*, which relates to HR administrative processes.

While metrics and KPI are focused on individual performance, analytics have a wider view that typically involves the whole company and pays attention to teams and collaboration amongst workers. Figure 31 shows a trending employee value framework that combines the worker individual, team and organization level contributions.

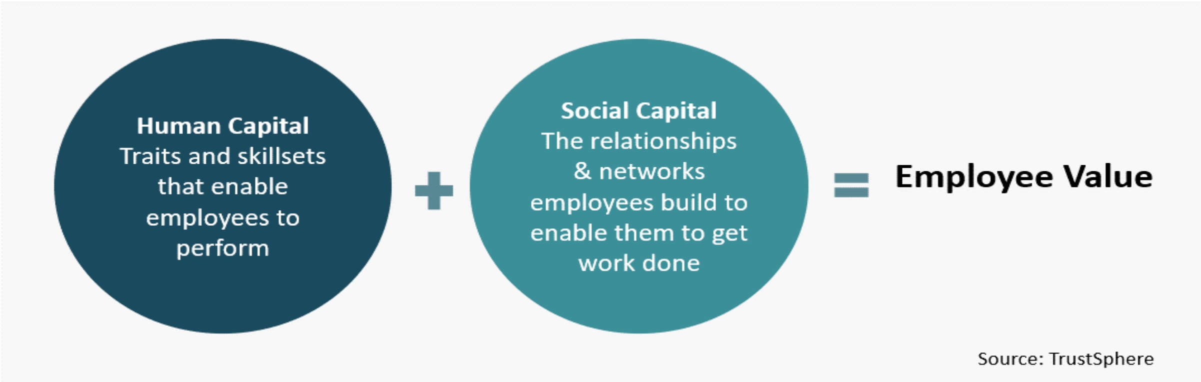

Figure 31 Social capital point of view of employee value by TrustSphere. Source https://www.trustsphere.com/why-social-capital-matters/.

Metrics and Key Performance Indicators

Relevant metrics and KPIs are defined differently across industries. The German company Data Pine features performance evaluation templates of metrics and KPIs for each industry[101]. For instance, for logistics and warehouses the list includes *shipping time*, *degree of incidents*, *delivery time*, *transportation costs*, *warehousing cost*, *inventory turnover* and others (see Figure 32). In this case, the metrics are a proxy for worker behaviour and performance. Direct performance metrics for warehouses are those related to the movement of workers within the facilities or the number of packets they process. In this case, data can be extracted from any or several of the means discussed earlier. Once metrics are collected, optimisation methods can be used to improve processes. For example, Datumize provides metrics related to the flow of workers and customers in a warehouse and determine the optimal path for each motion operation and can combine this information with other sources to measure workforce performance[102].

[101] https://www.datapine.co.uk/dashboard-examples-and-templates/management
[102] https://www.datumize.com/datumize-motion-intelligence

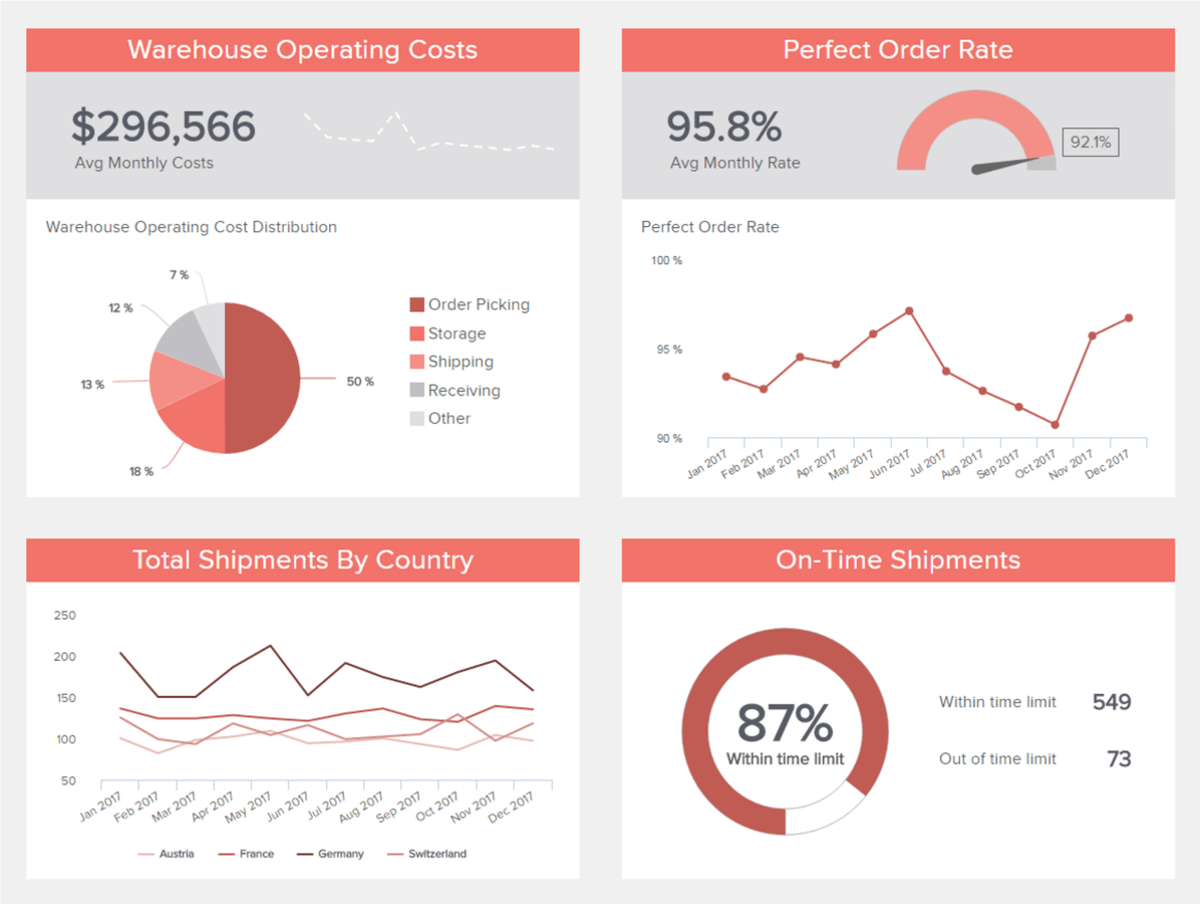

Figure 32 Dashboards of KPIs for a logistics warehouse. Source https://www.datapine.co.uk/dashboard-examples-and-templates/logistics.

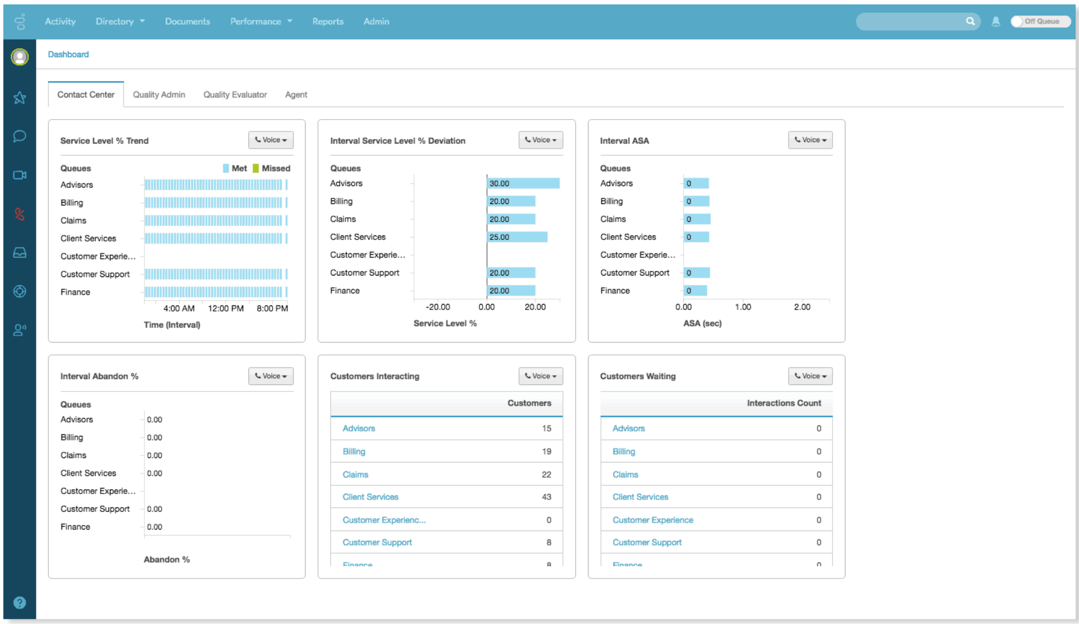

Figure 33 PureCloud analytics by Genesys. Source https://www.genesys.com/capabilities/analytics-and-reporting

Genesys is a worldwide company offering tools to deploy in call centres. Their system monitors many of de facto standard KPI metrics (International Finance Corporation 2007) to create analytics dashboards, but it can also produce automatic warnings if an individual or team activity deviates from established thresholds (see Figure 33). The Performance Management Advisor Suite by Genesys can display business metrics such as revenue, units, etc. in combination with the above call centre metrics[103]. Another example is Talk Desk, a company that deploys to contact or call centres affiliated with many global companies operating in the EU such as TaskRabbit, Scott (Monsanto) or Zenconnect. Talk Desk's dashboard presents KPIs together with the level of compliance with targets. The dashboard is available both for agents and managers (see Figure 34 and Figure 35).

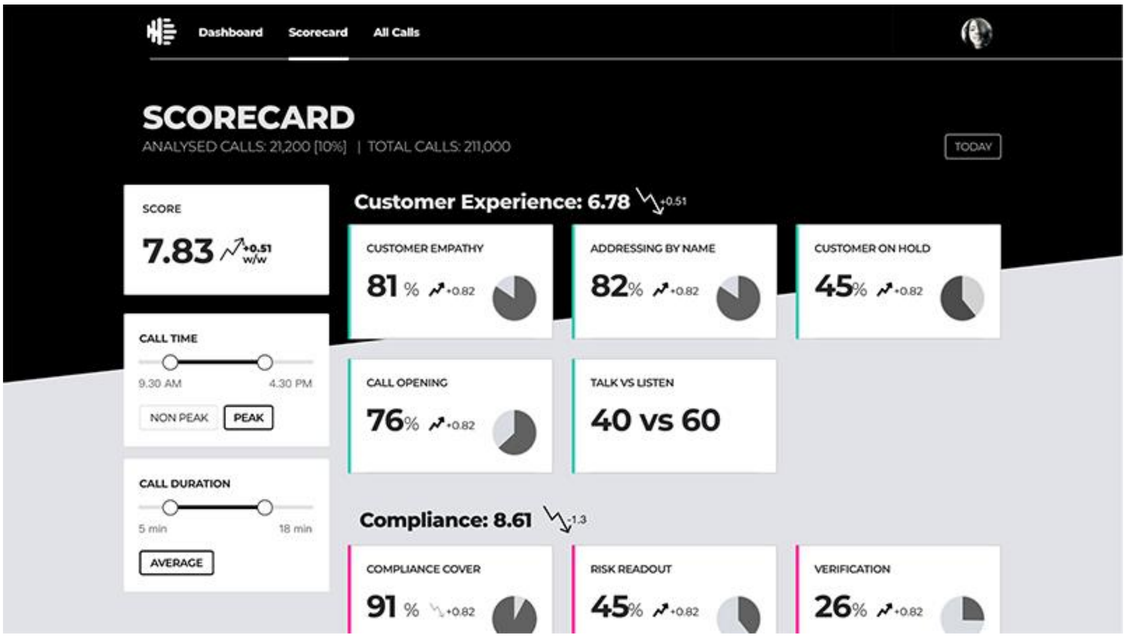

Figure 34 KPIs and performance targets produced by Talk Desk. Source https://appconnect.talkdesk.com/app/ob-serveai.html.

[103] https://genbin.genesys.com/media/Genesys-Performance-Management-Advisors-DS-EN.pdf

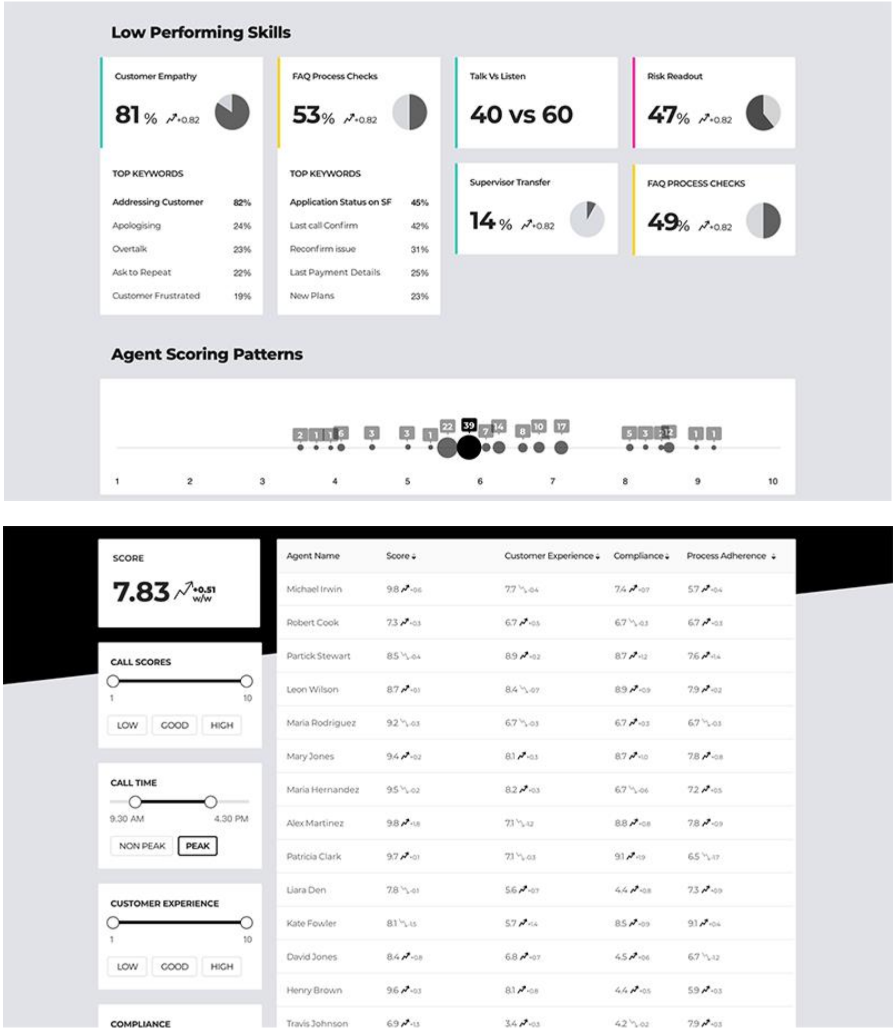

Figure 35 TalkDesk dashboard showing performance of skills that are correlated to business objectives. The dashboard is constantly updated and is available for agents and managers. The manager Dashboard ranks employees according to the skills scoring produced by AI models. Source [https://appconnect.talkdesk.com/app/observeai.html.](https://appconnect.talkdesk.com/app/observeai.html)

People Analytics

We have presented organization data systems that serve the purpose of measuring performance of workers by registering and reporting their activity. However, as we pointed out in other sections, predictive tools are creating new ways of evaluating workers trying to estimate how they would behave or perform in the future, as a way to identify which factors drive business improvements.

Skills and predictive analytics related to performance

The range of performance metrics and workplace surveillance we have outlined above, together allows for the creation of statistical and machine learning models that not only forecast events and performance of staff, but also analyse what characterizes individual and team performance profiles. For instance, Genesys combines KPI metrics reports, text and speech analysis and business metrics to identify critical agent skills that lead to successful interactions and then develop specific training for these skills in the context of call centres. Based on the continuous monitoring of all conversations the system can establish whether the key abilities that the 'good workers' must have are being used or if the training is really improving those key skills. Speech and text processing can be used to automatically categorize conversations, detect unexpected events and trends or to monitor compliance. Other products such as Talk Talk offers, through third party apps, speech transcription, automated quality assessment, compliance monitoring, sentiment and empathy analysis of agents and customers, caller churn prediction and others, as a means of creating quality assurance analytics (see Figure 36 and Figure 37).

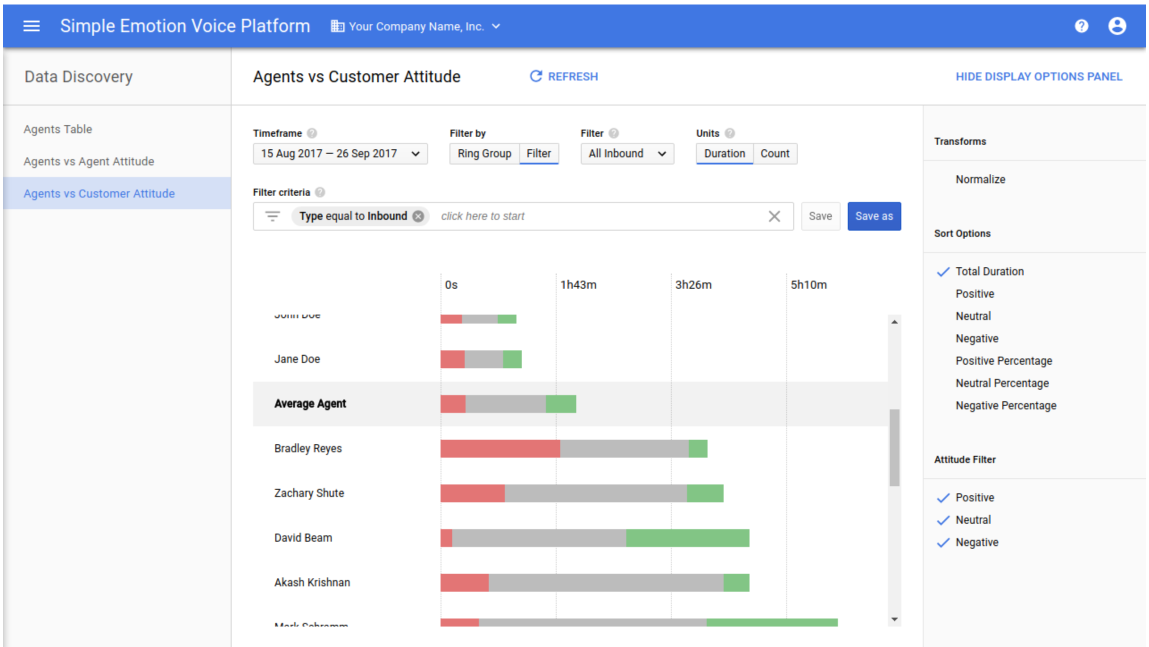

Figure 36 Example of agent's tone analysis by Simple Emotion. Source https://appconnect.talkdesk.com/app/simple-emotion.html.

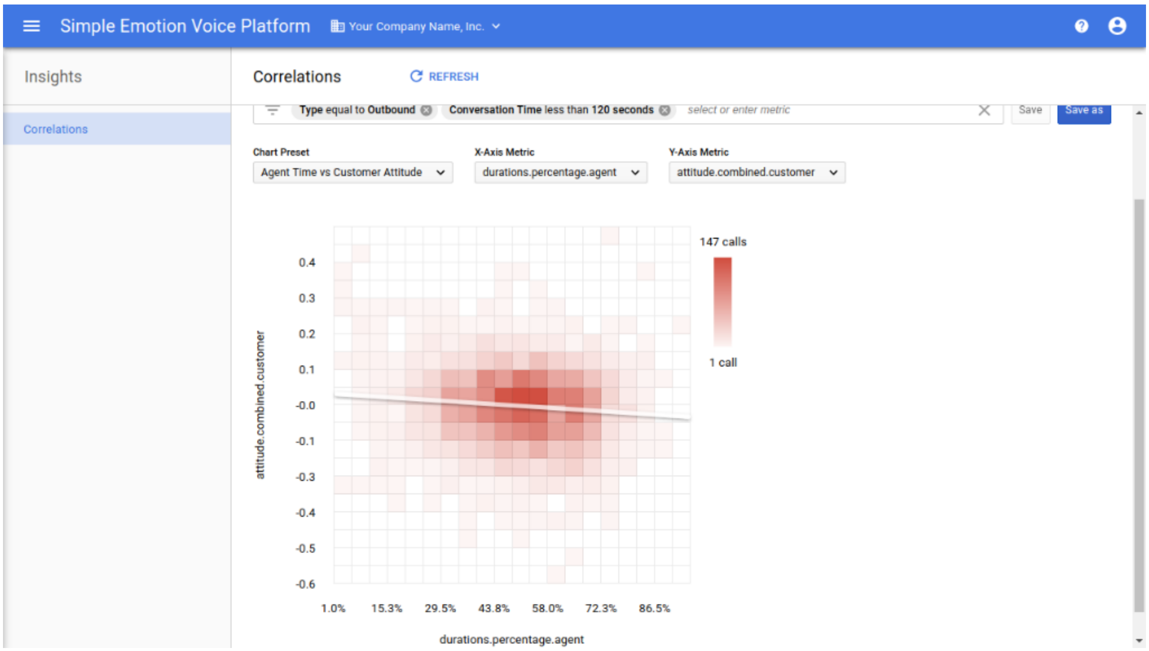

Figure 37 Agent attitude correlation analysis tool to evaluate the attitude of workers based on voice tone analysis. Source https://appconnect.talkdesk.com/app/simpleemotion.html.

Revisiting retail, RetailNext not only register, aggregate and centralise information of all transactions of every employee at the point of sale, but also creates profiles of stores and employees with labels of '*highest risk stores*' and '*highest risk cashiers*'. By combining POS data with CCTV, it can also perform exception reporting that automatically alerts if high-risk transactions like cash refunds and post-sale voids happen where customers are not present (Hartjen 2016).

Figure 38 shows the RetailNext panel showing scores and trends of stores and workers related to these predictions. However, research has shown that behaviour profiling and exception alerts can exert more pressure on already demanding tasks. According to the field work of Van Oort (2018), workers come out with strategies such as introducing ‘technically valid, but inaccurate’ information at the cash register to meet performance requirements or to avoid automatic alerts.

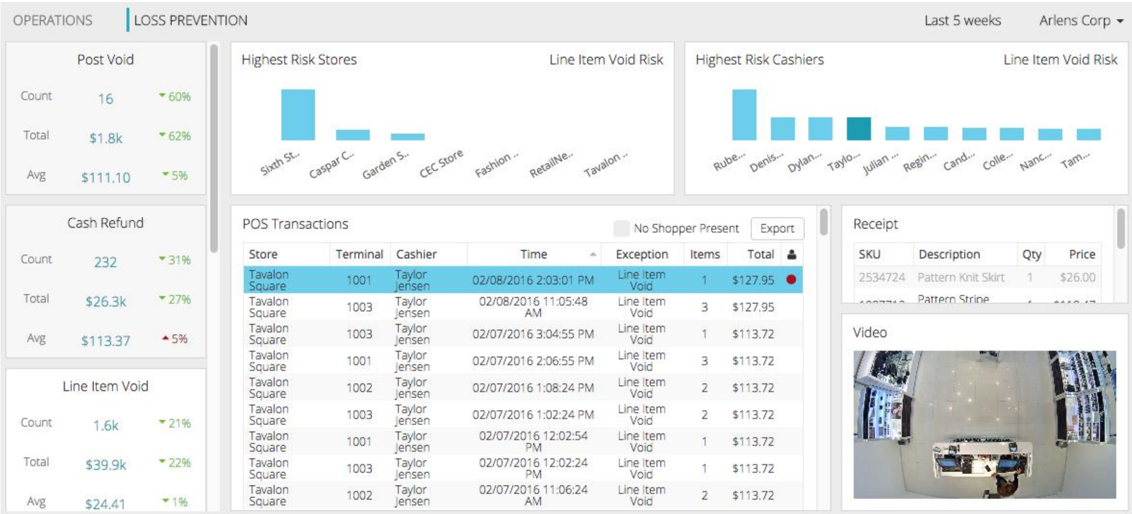

Figure 38 Loss prevention report panel of RetailNext. Source RetailNext.

Predictive profiling is also a trend in some HR tools. For instance, UltiPro incorporates a tool not only to create analytics to identify top performers in an organization, but also to estimate the likelihood of an employee being a high performer in the future. As other tools, it forecasts workers’ intent to stay or leave the organization within the following 12 months. Figure 39 shows a screenshot of predictive analytics by UltiPro.

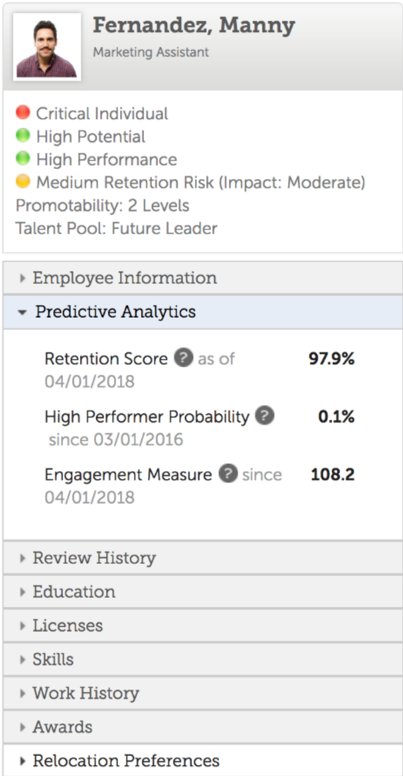

Figure 39 Example of UltiPro predictive profiling of employees. Source Ultimate Software https://www.ultimatesoftware.com/UltiPro-Solution-Features-Predictive-Analytics

Organizational Network Analysis

Organizational network analysis (ONA) refers to the discovery and optimization of the social network of a company. The social network of a company refers to the actual relations that drive the company in parallel to the formal organization and roles. The idea is to get insights on how people show up in an organization by revealing invisible patterns of information flow and collaboration (Green 2018). ONA aims to measure the social value at individual, team and organization levels by building or learning the social graph of an organization. In the social graph, people are nodes who serve as essential connections to exchange ideas and information. Figure 40 shows an illustrative example of the network structure that can reveal ONA.

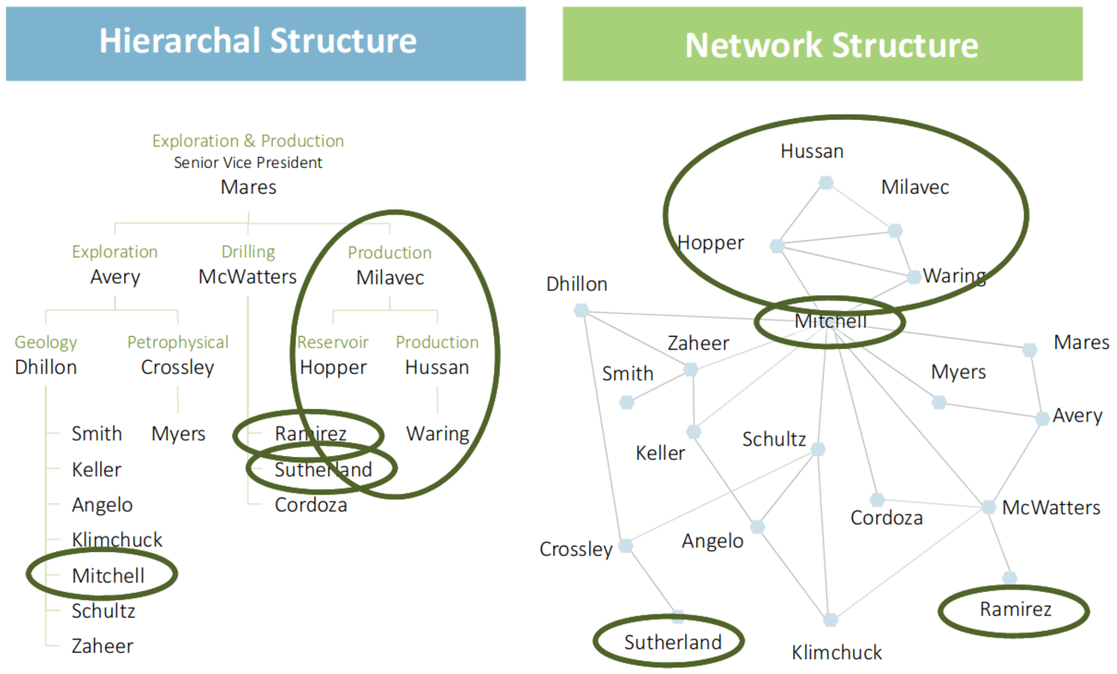

Figure 40 Fictional example of the formal structure of a company versus the social network structure. Source Rob Cross https://www.robcross.org/wp-content/uploads/2017/02/half-day-leadership-development-presentation-deck.pdf.

In a document that heavily influenced HR texts, Deloitte identifies three type of nodes (McDowell, Horn, and Witkowski 2016):

- *Central node* are people that seem to know every co-worker, share lots of information and influence groups. This role is not necessarily linked with a specific position in the formal hierarchy but they are highly engaged in the company.
- *Knowledge broker* are people who creates links between groups helping information to disseminate.
- *Peripheral* are workers overlooked and unconnected to the rest of the company.

The central node are core elements that must be identified and managed properly. Central nodes are essential, for instance to help the rest of the workforce to quickly adopt changes. On the other hand, peripheral people are labelled as '*risk of exit*' people that, especially if talented, can leave the company in any moment and can be hard to replace since the people with this profile are less likely to share their knowledge with others (McDowell, Horn, and Witkowski 2016). See Figure 41 for an example of an ONA based on this typology.

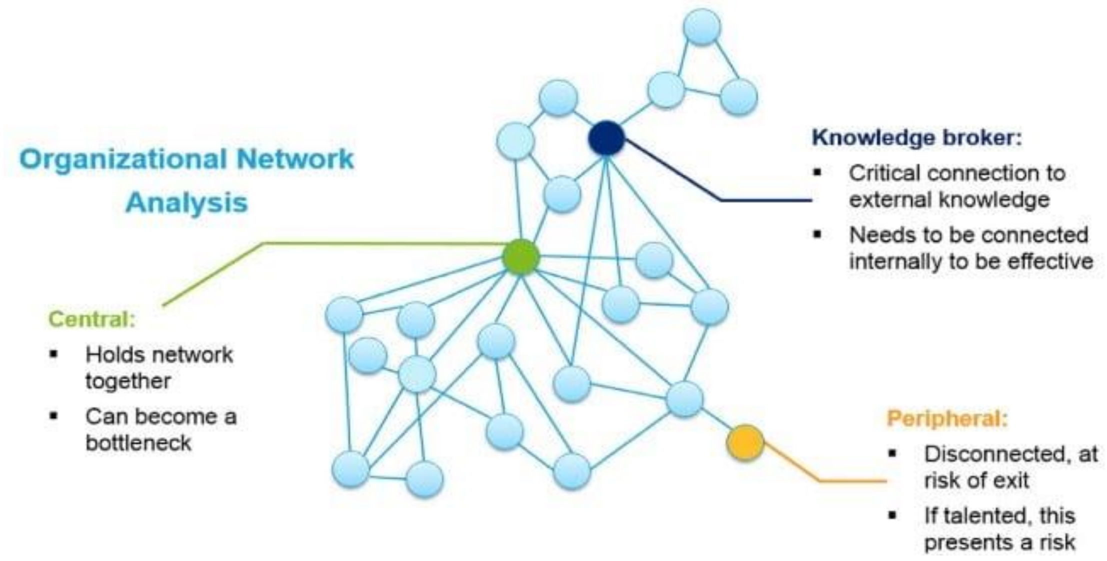

Figure 41 Example of ONA and roles identification. Source Deloitte (McDowell, Horn, and Witkowski 2016).

The purposes of ONA go beyond role identification. For instance, TrustSphere, a global company providing People Analytics tools[104], can analyse the network evolution to characterize a 'typical' set of communication patterns so that deviations from normal behaviour signal fraud events such as information leakage[105].

ONA is also used at organizational level to produce information that will help to reconfigure the organizational design or infrastructures so that they are closer to the real web of employees. This is the case of The Municipality of Odense in Denmark, that applied the *Organizational Network Diagnostic* by Innovisor to get insights into the collaboration networks among the employees and detected that the people in charge of services of one of the most important neighbourhoods had weak social cohesion, and then acted to improve the service in that neighbourhood[106]. According to Innovisor, as a result of the analysis, the public organization also moved work organization from a project-based approach to an operations-based approach.

The social graph is built by using several information sources such as IT communications, e.g. metadata of emails, shared calendars, file sharing systems, productivity tools, etc. Figure 42 shows different social graphs produced by Worklytics, a product used by Telefonica, WeWork and others, to analyse how employees interact through different IT communication tools. ONA can use information from the physical workplace for instance by gathering data from wearables such as the Sociometric Bagdet. For instance, Humanyze used these data sources and techniques to identify performance disparities between two branch locations of a large European Bank[107]. In this case, they measured virtual and physical corporate communication and then segmented this data by compensation and tenure. The analysis of the face-to-face interaction between employees revealed that the best performing branches typically have more interaction amongst all the employees. Figure 43 shows networks of interaction between employees of different branches of the bank.

[104] https://www.trustsphere.com/organizational-network-analytics/
[105] https://www.trustsphere.com/risk-analytics/
[106] https://www.innovisor.com/2019/02/18/case-municipality-of-odense/
[107] https://www.humanyze.com/case-studies-european-bank/

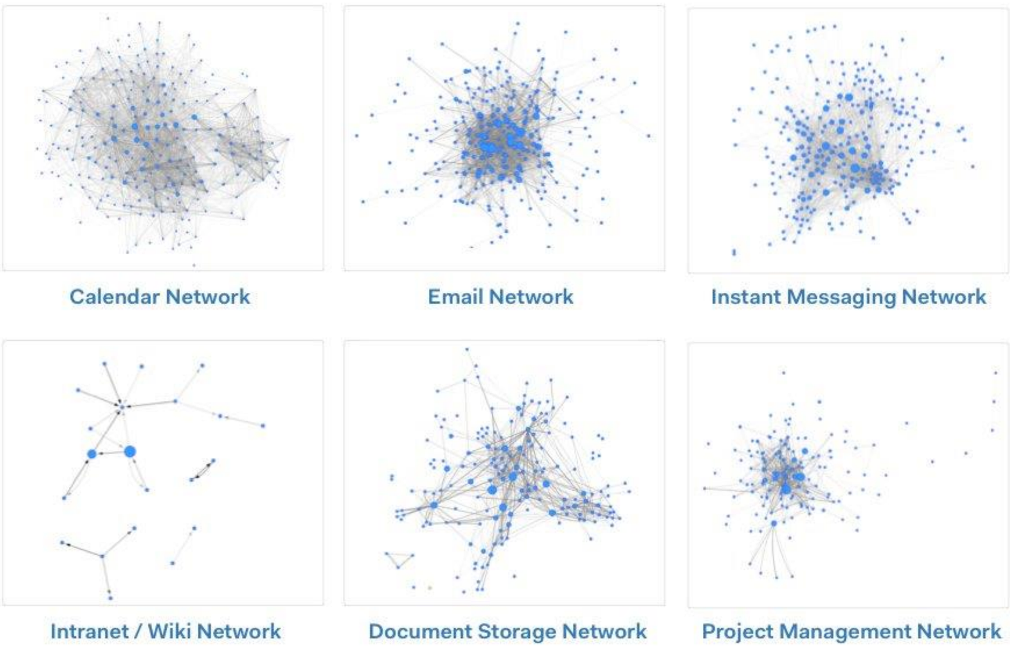

Figure 42 Social graphs of interactions of employees through different communication means. Source https://www.worklytics.co/blog/going-beyond-email-in-organizational-network-analysis/.

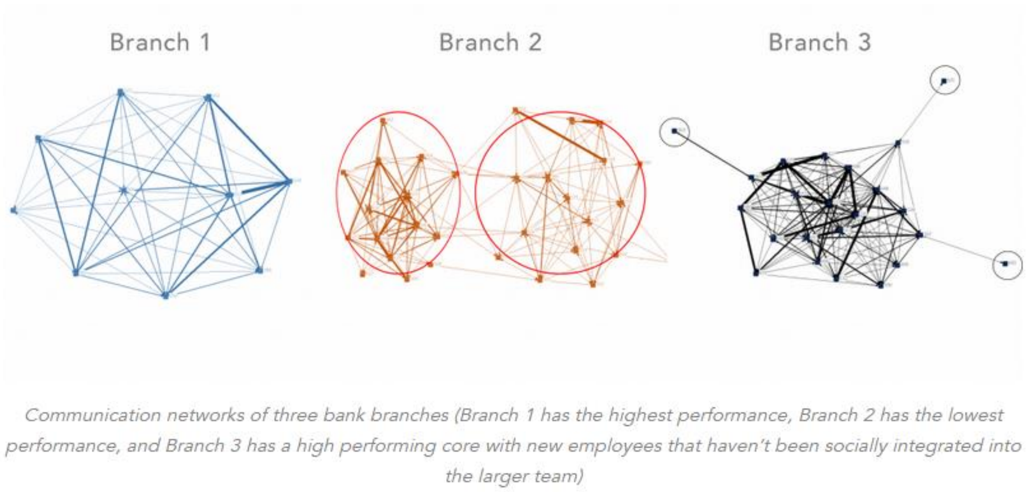

Figure 43 Networks of people interactions build by Humanyze. Source https://www.humanyze.com/case-studies-european-bank.

5. Conclusions and discussion

In this report we have sought to scope ways in which the workplace is being transformed by data-driven technologies, from hiring to firing and everything in-between. In particular, we have identified and categorised a set of tools and tried to illustrate how are they work and ways in which they are used based on industry material, previous research and media reports. Whilst our focus has been on tools that are used by European organisations or international companies operating in Europe, in several instances use cases are not publicly listed and so it is unclear who is using the tool and for what purpose. Therefore, it is difficult to identify trends in sectors out-side those using sector-specific tools such as retail stores or call centres. Nevertheless, a few prominent trends stand out that highlight some of the terms upon which the datafication of the workplace is happening. First, it is important to note that, in line with the analysis from the Trade Union Congress (2018), surveillance and control system adoption increases with the size of the company. Obvious examples are call centres, retail branches or the smart warehouses of Amazon (Arens 2017) that all seek to scale processes and have been prominent in our research into the use of such technologies. Moreover, according to a survey done by the Trade Union Congress (2018), the more common a form of surveillance is, the more accepted by the workforce it is. Second, many tools to automate the hiring funnel are used in companies with high-volume hiring and high turnover, particularly in low-wage employment. For instance, Unilever adopted HireVue to speed up the process of hiring 800 individuals from a pool of 250,000 applications and reduced 75% of the recruiting time[108]. Urban Outfitters, a global retail company, uses HireVue to evaluate emotion and personality profiles to select employees that will interact directly with customers[109]. Companies well known for offering low-wage salaries and high turnover positions such as KFC, Subway or Pizza Hut rely on TribePad to manage their candidate and worker pools[110].

In assessing the automation of the hiring process, the funnel metaphor helps to understand hiring as a set of stages that will filter candidates. Candidates will be discarded, matched and ranked based not only on the profile they explicitly create regarding their skills or experience, but also by considering inferred scores related to personality or speculative estimations of their future performance or how likely will they quit or not the job. That is, with automation we see an emphasis on not just what candidates are able to do, but who they are or are likely to be. Recommendation systems have become prominent along with the kinds of problems that are imbued in such systems. For example, Bogen and Aaron (2018) warn about the problem of reinforcing biases in hiring practices with the use of collaborative filtering since these tools are purposed to capture user preferences to select similar items. At the end of this process, the interviews are augmented to infer information not directly provided by candidates, but through inferences based on a range of data sources that then also inform predictive tools right down to salary estimation. Whilst these tools are often said to address issues of discrimination in hiring practices and can be used to highlight 'unconscious' bias against particular groups (or eliminate other factors that might influence decision-making), they are also seen to increase the information asymmetry that defines the employer-candidate relationship.

This increase in information asymmetry is also prevalent in the overview of employee monitoring and workplace surveillance. Digital data and meta-data monitoring is being pushed forward by text analysis tools that allow to perform opinion and emotion mining, video analysis systems able to perform semantic understanding, as well as mood and emotion evaluation, of CCTV, and audio analysis techniques, that create new performance metrics, implement automatic compliance of legal terms or perform tone classification to optimize the behaviour of the agents. Apart from prominent concerns related to privacy and data protection, there are some fundamental questions being asked about the 'scientific' basis of these technologies. The rise of emotional AI is playing an important role in measuring the mood of both the workforce and customers, that later directly or indirectly impact on the organisation of work. Many companies providing these tools claim that these emotion detection models are based on solid scientific principles, and that the detected emotions are valid predictors of how the person will behave in the workplace. However, the premise of the field of emotional AI is being challenged in recent years. For instance, most of the emotional detection tools assume that all humans feel the same six basic emotions and that they express these emotions in similar ways, a largely outdated scientific

108 https://www.hirevue.com/customers/global-talent-acquisition-unilever-case-study
109 https://www.hirevue.com/customers/urban-outfitters-hirevue
110 https://www.tribepad.com/clients/

premise (Firth-Godbehere 2018). In addition, misuse of ML models can happen if the model and training data is not property documented or understood by the development team. For instance, a computer vision model that detect smiles could be wrongly used for emotion detection or a NLP model aimed to predict the toxicity of a comment in content moderation could be misused to make judgments about a person (Mitchell et al. 2019). Therefore, although new monitoring tools can improve health and safety in the workplace, these systems often include a centralized repository of activity that can be accessed by managers and repurposed for control.

Such analyses of workers that rely on the constant monitoring of activities and behaviour have become an integrated part of management science and operational research, finding new ways to 'optimize' staff using different tools and forecasting models for organising workload, scheduling and engagement. Various forms of People Analytics and Organizational Network Analytics, using a range of tools and metrics, increasingly shape the management of workers and the workplace. These trends highlight the broader issue of interpreting identities and social relations based on data points, as a way to assess 'performance' both at individual and collective levels that raise fundamental questions about the design of data collection and the information used to 'measure' such identities and relations, and the kinds of anxiety and stress such mechanisms might induce (O'Neil 2016). Whilst companies seek to use such tools to enhance productivity and overall performance, analyses now also extend to predictive models seeking to estimate risk and likelihood of leaving a job. The basis upon which such predictions are made remains obscure as the nature of the training data or variables used is not readily available. Some research has found that the use of multiple source data incorporates biases that can worsen structural inequalities (Sam and Michelle 2018). For instance, Cornerstone found that applicants using newer versions of browsers on their computers will stay 15% longer than those using default browsers, thus penalising the score of people using public computers (e.g. at a library) that are likely to have less updated software. There are also growing concerns about the automation of firings that close down the possibility of explanation or ways to challenge decisions (Diallo 2018).

The discussion of the impact of these technologies is not straightforward and many grey areas exist. In several instances, systems are being deployed in contexts imbued with long-standing histories of discrimination and inequalities, and where ambiguity already exists with regards to worker autonomy and workers' rights. As we continue to research the rapid datafication of the workplace and explore case studies as part of the DATAJUSTICE project, we hope to shed further light on this debate.

6. References

AdEspresso. 2017. 'The Beginner's Guide to Facebook Audiences and Targeting'. *AdEspresso* (blog). 2017. https://adespresso.com/guides/facebook-ads-beginner/demographic-targeting/.

Ajunwa, Ifeoma, Kate Crawford, and Jason Schultz. 2016. 'Limitless Worker Surveillance'. SSRN Scholarly Paper ID 2746211. Rochester, NY: Social Science Research Network. https://papers.ssrn.com/abstract=2746211.

AlgorithmWatch. 2019. 'Automating Society. Taking Stock of Automated Decision-Making in the EU'. AlgorithmWatch in cooperation with Bertelsmann Stiftung. www.algorithmwatch.org/automating-society.

Arens, Marianne. 2017. 'Amazon Conducts Total Surveillance of Workers in New German Plant'. World Socialist Web Site. 16 December 2017. https://www.wsws.org/en/articles/2017/12/16/amaz-d16.html.

Ariana Tobin, Jeremy B. Merrill. 2018. 'Facebook Is Letting Job Advertisers Target Only Men'. Text/html. ProPublica. 18 September 2018. https://www.propublica.org/article/facebook-is-letting-job-advertisers-target-only-men.

Bogen, Miranda, and Rieke Aaron. 2018. 'Help Wanted: An Exploration of Hiring Algorithms, Equity and Bias.' Upturn.

Deng, Z., M. Zhai, L. Chen, Y. Liu, S. Muralidharan, M. Roshtkhari, and and G. Mori. 2015. 'Deep Structured Models For Group Activity Recognition'. In *British Machine Vision Conference (BMVC)*.

Diallo, Ibrahim. 2018. 'The Machine Fired Me'. Ibrahim Diallo Blog. 2018. https://idiallo.com/blog/when-a-machine-fired-me.

Finkel, Jenny Rose, Trond Grenager, and Christopher Manning. 2005. 'Incorporating Non-Local Information into Information Extraction Systems by Gibbs Sampling'. In *Proceedings of the 43nd Annual Meeting of the Association for Computational Linguistics (ACL 2005)*, 363–70. http://nlp.stanford.edu/~manning/papers/gibbscrf3.pdf.

Firth-Godbehere, Dr Rich. 2018. 'Silicon Valley Thinks Everyone Feels the Same Six Emotions'. How We Get To Next. 5 September 2018. https://howwegettonext.com/silicon-valley-thinks-everyone-feels-the-same-six-emotions-38354a0ef3d7.

Giang, Vivian. 2018. 'This Company Uses AI to Test Unlikely Engineers for Their Potential'. Fast Company. 30 November 2018. https://www.fastcompany.com/90269298/this-company-uses-ai-to-test-unlikely-engineers-for-their-potential.

González Paulino Ramos, Ana. 2013. 'Abengoa: la explotación del siglo XXI'. El Salto. Hemeroteca Diagonal. 26 April 2013. https://www.elsaltodiario.com/hemeroteca-diagonal/abengoa-la-explotacion-del-siglo-xxi.

Graveling, Richard, Thomas Winski, and Ken Dixon. 2018. 'The Use of Chip Implants for Workers'. European Parliament Think Tank. http://www.europarl.europa.eu/thinktank/en/document.html?reference=IPOL_STU(2018)614209.

Green, David. 2018. 'The Role of Organisational Network Analysis in People Analytics'. MyHRfuture. 23 May 2018. https://www.myhrfuture.com/blog/2018/5/23/the-role-of-organisational-network-analysis-in-people-analytics.

Greenhouse, Steven. 2012. 'A Part-Time Life, as Hours Shrink and Shift for American Workers'. *The New York Times*, 27 October 2012, sec. Business Day. https://www.nytimes.com/2012/10/28/business/a-part-time-life-as-hours-shrink-and-shift-for-american-workers.html.

Hartjen, Ray. 2016. 'LP Made Easy (-Ier): POS Exception Reporting with Integrated Video'. RetailNext. 9 February 2016. https://retailnext.net/en/blog/lp-made-easy-ier-pos-exception-reporting-with-integrated-video/.

Harwell, Drew. 2018. 'Wanted: The "Perfect Babysitter." Must Pass AI Scan for Respect and Attitude.' *Washington Post*, 23 November 2018. https://www.washingtonpost.com/technology/2018/11/16/wanted-perfect-babysitter-must-pass-ai-scan-respect-attitude/.

IBM Corp. 2019. 'Personality Insights. The Science behind the Service'. IBM Cloud Docs. 7 March 2019. undefined.

International Finance Corporation. 2007. 'Measuring Call Center PerformanceGlobal Best Practices'. International Finance Corporation. World Bank Group. https://www.ifc.org/wps/wcm/connect/75ce96004cf85d4f8752c7f81ee631cc/Tool+9.4.+Measuring+Call+Center+Performance.pdf?MOD=AJPERES.

Jones, Nicholaus A., Aaron J. Vasgaard, and Matthew A. Jones. 2018. Listening to the frontend. United States Patent US010020004B2, filed 20 April 2017, and issued 20 July 2018. https://pdfpiw.uspto.gov/.piw?PageNum=0&docid=10020004.

Julia Angwin, Noam Scheiber. 2017. 'Dozens of Companies Are Using Facebook to Exclude Older…'. Text/html. ProPublica. 20 December 2017. https://www.propublica.org/article/facebook-ads-age-discrimination-targeting.

Korolov, Maria. 2018. 'Corporate Pre-Crime: The Ethics of Using AI to Identify Future Insider Threats'. CSO Online. 20 August 2018. https://www.csoonline.com/article/3297930/corporate-pre-crime-the-ethics-of-using-ai-to-identify-future-insider-threats.html.

Larson, Jeff, Madeleine Varner, Ariana Tobin, Julia Angwin, and Noam Scheiber. 2017. 'These Are the Job Ads You Can't See on Facebook If You're Older'. ProPublica. 19 December 2017. https://projects.propublica.org/graphics/facebook-job-ads.

Levy, Karen, and Solon Barocas. 2018. 'Refractive Surveillance: Monitoring Customers to Manage Workers'. *International Journal of Communication* 12 (0): 23.

Lin, Yiou, Hang Lei, Prince Clement Addo, and Xiaoyu Li. 2016. 'Machine Learned Resume-Job Matching Solution'. *ArXiv:1607.07657 [Cs]*, July. http://arxiv.org/abs/1607.07657.

Mardikyan, Sona, and Bertain Badur. 2011. 'Analyzing Teaching Performance of Instructors Using Data Mining Techniques'. *Informatics in Education* 10 (2). https://eric.ed.gov/?id=EJ1064325.

McDowell, Tiffany, Hillary Horn, and Dave Witkowski. 2016. 'Organizational Network Analysis'. https://www2.deloitte.com/content/dam/Deloitte/us/Documents/human-capital/us-cons-organizational-network-analysis.pdf.

McGann, Conor, Bharath ARAVAMUDHAN, Petr Makagon, Herbert Willi Artur Ristock, Yochai Konig, Gregory Duclos, Vyacheslav Zhakov, and Damjan Pelemis. 2017. System and method for generating a network of contact center agents and customers for optimized routing of interactions. United States US9716792B2, filed 19 October 2015, and issued 25 July 2017. https://patents.google.com/patent/US9716792B2/en.

Meister, Jeanne. 2016. 'The Future Of Work: Companies Use Marketing Tools To Create A Compelling Employee Experience'. *Forbes*, 5 October 2016. https://www.forbes.com/sites/jeannemeister/2016/10/05/the-future-of-work-companies-use-marketing-tools-to-create-a-compelling-employee-experience/.

Merchant, Brian. 2018. 'I Tried Predictim's AI Scan for "Risky" Babysitters on People I Trust'. *Gizmodo*, 6 December 2018. https://gizmodo.com/predictim-claims-its-ai-can-flag-risky-babysitters-so-1830913997.

Mitchell, Margaret, Simone Wu, Andrew Zaldivar, Parker Barnes, Lucy Vasserman, Ben Hutchinson, Elena Spitzer, Inioluwa Deborah Raji, and Timnit Gebru. 2019. 'Model Cards for Model Reporting'. In *Proceedings of the Conference on Fairness, Accountability, and Transparency*, 220–229. FAT* '19. New York, NY, USA: ACM. https://doi.org/10.1145/3287560.3287596.

Mondragon, Nathan, Clemens Aichholzer, and Kiki Leutner. 2018. 'The next Generation of Assessments'. White Paper. HireVue. https://grow.hirevue.com/thank-you/the-next-generation-of-assessments.

O'Neil, Cathy. 2016. *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*. New York, NY, USA: Crown Publishing Group.

Prior, Ryan. 2017. 'Your next Job Interview Could Be with a Recruiter Bot'. *CNNMoney*, 16 May 2017. https://money.cnn.com/2017/05/16/technology/ai-recruiter-mya-systems/index.html.

Schellmann, Hilke, and Jason Bellini. 2018. 'Artificial Intelligence: The Robots Are Now Hiring'. *The Wall Street Journal*, 20 September 2018. https://www.wsj.com/articles/artificial-intelligence-the-robots-are-now-hiring-moving-upstream-1537435820.

Schmitt, Thomas, Philippe Caillou, and Michèle Sebag. 2016. 'Matching Jobs and Resumes: A Deep Collaborative Filtering Task'. In . Vol. 41. https://hal.inria.fr/hal-01378589/document.

Shami, N. Sadat, Jiang Yang, Laura Panc, Casey Dugan, Tristan Ratchford, Jamie C. Rasmussen, Yannick M. Assogba, et al. 2014. 'Understanding Employee Social Media Chatter with Enterprise Social Pulse'. In *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing*, 379–392. CSCW '14. New York, NY, USA: ACM. https://doi.org/10.1145/2531602.2531650.

Simonite, Tom. 2018. 'This Call May Be Monitored for Tone and Emotion'. *Wired*, 19 March 2018. https://www.wired.com/story/this-call-may-be-monitored-for-tone-and-emotion/.

Solon, Olivia. 2017. 'World's Lamest Cyborg? My Microchip Isn't Cool Now – but It Could Be the Future'. *The Guardian*, 2 August 2017. https://www.theguardian.com/technology/2017/aug/02/microchip-contactless-payment-three-square-market-biohax.

———. 2018. 'Amazon Patents Wristband That Tracks Warehouse Workers' Movements'. *The Guardian*, 1 February 2018, sec. Technology. https://www.theguardian.com/technology/2018/jan/31/amazon-warehouse-wristband-tracking.

The Guardian News. 2015. 'Microchip Hand Implants Offered to Swedish Office Staff - Video | World News | The Guardian'. The Guardian News. 27 February 2015. https://www.theguardian.com/world/video/2015/feb/27/microchip-hand-implants-offered-swedish-office-staff-video-report.

Trades Union Congress. 2018. 'I'll Be Watching You. A Report on Workplace Monitoring'. London: Trades Union Congress. https://www.tuc.org.uk/research-analysis/reports/i%E2%80%99ll-be-watching-you.

Van Oort, Madison. 2018. 'The Emotional Labor of Surveillance: Digital Control in Fast Fashion Retail'. *Critical Sociology*, July, 0896920518778087. https://doi.org/10.1177/0896920518778087.

Waddell, Kaveh. 2016. 'The Algorithms That Tell Bosses How Employees Are Feeling'. The Atlantic. 29 September 2016. https://www.theatlantic.com/technology/archive/2016/09/the-algorithms-that-tell-bosses-how-employees-feel/502064/.

Wu, Lili, Sam Shah, Sean Choi, Mitul Tiwari, and Christian Posse. 2014. 'The Browsemaps: Collaborative Filtering at LinkedIn'. In *6th Workshop on Recommender Systems and the Social Web (RSWeb 2014)*, 8. Foster City, CA, USA.

Zolfagharifard, Ellie. 2018. 'Major UK Companies Preparing to Microchip Employees'. *The Telegraph*, 10 November 2018. https://www.telegraph.co.uk/technology/2018/11/10/major-uk-companies-preparing-microchip-employees/.