INSTITUTE FOR ADULT LEARNING SINGAPORE

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Exploratory study of analytics-based technologies used for corporate learning and development

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Executive Summary

This report focuses on the analytics-based technologies used in the corporate sector for learning and development, outlining the landscape for the types of technologies available through a summary of selected grey and academic literature. We give a descriptive summary of 80 analytics-based technologies selected through convenience sampling from grey literature on trends and developments in the sector. We describe the tools in relation to their function at the enterprise, the types of analytics they deploy, their intended users and types of feedback they envision for stakeholders. A few critical observations are drawn on the use of technology for learning and knowledge processes in the corporate sector. We observe that:

- Tools are undergoing a shift to support individual micro-processes of learning at work;
- Responsibility and autonomy to learn are increasingly placed on the employee who is expected to have the competence and available time to engage in learning in a digital environment;
- Systems provide performative metrics rather than learning analytics that can support learner progress;
- Evidence for the choice of analytics is weak;
- Tools with the highest frequency in our dataset are Human Resource (HR) analytics, followed by learning experience platforms (LXP) and learning management systems (LMS).
- Descriptive analytics (i.e., metrics for reflection) are present in almost all tools; both predictive and prescriptive analytics (i.e. analytics for decisions) were found in about a quarter of tools.
- Compared with other tools, HR Analytics are the most likely to be equipped with analytics for decision making. LXP also feature prominently for generating prescriptive solutions (i.e. personalised content).
- Dashboards represent the most common way of displaying analytics; many HR Analytics and LMS also display analytics through personalised reports.
- Analytics are presented most of the time to managers, then to employees and higher-level executives.
- The highest number of HR analytics are geared for the executives, and the highest number of LXP tools present insights for employees.

We also posit a few critiques, including:

- Vendor-driven learning technologies embed controversial assumptions about learning.
- Learning solutions are limited in what they presume on learning, placing burden on employees and managers to enhance learning effectiveness.
- Competence to learn, as well as levels of numeric literacy, critical thinking, and feedback recipiency are presumed, but not scaffolded.
- Whether SMEs eagerly adopt these tools for lifelong learning remains to be answered.

1. Introduction

The corporate learning industry is booming with a vast array of digital learning tools for developing the future workforce. The industry is valued at $14.23 billion as of 2017 and expected to reach $49.87 billion by 2026 (Corporate E-Learning – Global Market Outlook (2017 – 2026), 2019). Educational technology solutions are also booming; with this industry growing at 16.3%, it expects to double in the next five years and reach 404 billion in total global expenditure (“Global EdTech Market”, 2020).

Companies are increasingly aware of the need to learn and develop their employees. According to the latest Deloitte survey, 75% of companies believe they need to focus on employee learning, upskilling and knowledge creation but only 9% perceive themselves as ready for this challenge (Deloitte Human Capital Trends, 2020). The use of technologies for learning and development requires more than the availability of tools. Workplace learning is tightly linked to social practices and individual capabilities; so are the adoption and use of technology.

This report examines the analytics-based technologies available for learning and development in the corporate sector. The report briefly outlines the landscape for the types of technologies through a historical overview of the academic literature. We provide a descriptive summary of 80 analytics-based technologies sampled using convenience method from grey literature on trends and developments in the sector. The tools are described in relation to their function at the enterprise, the types of analytics they deploy, their intended users, and types of feedback they envision for stakeholders. This exploratory work enables to formulate critical observations about the assumptions of learning embedded within the tools, and the capabilities required from employees and managers to use them adequately. We discuss the implications of these critical observations on the industry, employee well-being, and training and development sector.

1.1 Analysis of Literature

This section presents selected grey and academic literature. The review is not exhaustive and is intended to provide some context to understanding of empirical findings. We highlight several focal points that surface in the empirical analysis:

- The shift in technological affordances towards micro-processes of learning at work;
- Responsibility and autonomy to learn are increasingly placed on the employee who is expected to have the requisite competence and available time to engage in learning in a digital environment;
- Systems provide performative metrics rather than learning analytics that are essential in supporting learner progress;
- Practically non-existent evidence-based practices of analytics-based technologies.

1.1.1 Evolution of Learning and Development Tools in the Corporate Sector

Based on consultancy reports and presentations on the state of the field taken from the grey literature search, the discourse about learning and development tools created for the enterprise shift from formal to more informal approaches to learning. Tools available for employees are shifting away from e-learning and talent management systems that have evolved into learning management systems (LMS) used for training and development. They become less formal with greater emphasis placed on the design of experience with technology.

This can be exemplified through 1) micro-learning tools which periodically expose users to learning content that is more easily understood (e.g., videos of brief durations, infographics); and 2) Learning Experience Platform (LXP) which grants autonomy to direct users (organizational employees) and predefined algorithms in defining the learning scope, determining the learning content and designing their training paths. These stand in stark contrast to LMS which positions learning as primarily organization-centric with emphasis placed on employees' compliance with completing assigned courses.

Although these technologies are generally aligned with employee work practices, they embed assumptions about learning as a "knowledge acquisition" process. New technologies at workplace are designed so that learning can occur through daily activities i.e., learning being self-initiated or socially situated, ground-up and micro-sized. Though micro-sized and available in diverse formats, these technologies still largely dictate that employees acquire knowledge via the medium which delivers it. Micro-learning presumes acquiring nuggets of information when the employee needs immediate help. This can be acquired by searching, asking questions, obtaining a recommendation from AI-driven curation of content created by other employees, or by watching a short compelling video that gets added to staff profile or path. Macro-learning then refers to knowledge acquisition in larger chunks, when platforms resembling an LMS (e.g. edX) have add-on bells and whistles to help learners stack courses, be reminded, collect assessments - as performativity metrics showcased to managers. These indicate a change from formal and instructor-driven upskilling to a more autonomous and self-directed one. However, these technologies hardly not support learning processes for the employees, they are more likely to offer opportunities to acquire knowledge and report it to their managers. In that, the responsibility on how to learn and self-direct fully appears to rest within the individual employees.

Under the pressure of COVID19 pandemic with increasing digitization, a parallel trend in learning and development is also emerging. Enterprises of different sizes adopt digital adoption and workflow tools that support coordination, task management, communication, and collaboration processes for employees during remote work Several prominent solutions that are available including Slack, Microsoft Teams, Trello, and Jira. Newer solutions (e.g., Microsoft Cortex) helping employees to search and interact with databases and virtual work spaces (e.g., Facebook for Workplace) that merge elements and functions of various tools are also surfacing. These technologies digitally transform their underlying work practices and are projected to play a larger role in how learning and development will unfold in the future.

Josh Bersin, a renowned industry analyst on topics related to human capital, L&D, and workforce management describes this transition as a move from formal to self-directed learning. Future development of L&D in the corporate sector, according to Bersin, is on the trajectory towards capability development. Capability academies are envisioned here as enterprise-initiated and funded *spaces* to learn – where the development of business capabilities is sponsored by business leaders and taught by in-house experts (Bersin, 2019).

1.1.2 Academic Literature on Analytics for Human Capability Development and Learning

In addition to consultancy reports, we reviewed several academic reviews of analytics-based technologies for human capability development and learning at the workplace. Besides unpacking the trajectory of HR related technologies, reviews on human capability development question the notion of HR analytics and its meaning within the literature and ongoing practices. Reviews on learning analytics at the workplace also question the assumptions about learning and functions offered by technology for workplace capability development. Both strands of research would interrogate the quality of the knowledge on which learning and development technologies are based.

1.1.2.1 HR analytics

In the academic discourse, terms commonly used to refer to talent management and capability development based on analytics and embedded within enterprise technologies include “HR analytics”, “human resource analytics”, “talent analytics”, “workforce analytics” and “people analytics”. Van den Heuvel and Bondarouk (2017) sketched out the historical developments for analytics systems in the workplace. Starting from the 1980s, HR processes were largely centralized within payroll and data administration, and technologies were developed to help support these processes digitally with the aim to automate some of them. The Internet shifted communication in the enterprise from 1% in the 1990s to more than 97% by 2007, which prompted the development of a number of HR systems. According to CedarCrestone (2006), the most common applications in 2000s were eHRM (62%), followed by talent acquisition services (61%), performance management (52%), and compensation management (49%). In the last decade, however, the shift has been on datafication – with HR professionals using data generated by technologies to support HRM and business solutions towards “HR decision science” (Van den Heuvel & Bondarouk, 2017; p.129). Three related terms capture the similar meanings but emerged in other contexts: *workforce analytics* introduced as early as 1999; *talent management* applications were around since 2006 as popularized by consultants, and *people analytics* stemmed from Google’s data-driven approach to HRM.

We highlight three critical points from the academic literature: 1) the definition of HR analytics; 2) the lack of evidence HR analytic usage is based on; and 3) the tension between metrics and analytics brought to the fore in HR literature.

First, divergence in the functions of HR analytics in the academic literature suggests analytics to be understood as means to very different ends by different stakeholders. Marler & Boudreau (2017) defined HR Analytics as a “HR practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and data-driven decision-making” (p. 15). They conceptualized HR analytics as Human Resource Management (HRM) innovation. However, Van den Heuvel and Bondarouk (2017) defined HR analytics as the “systematic identification and quantification of the people-drivers of business outcomes, with the purpose of making better decisions” (p. 130). The disagreement between the two definitions regarding the core of HR decision science stems from the distinction between innovation processes geared towards development and exploration (March, 1991) and efficiency processes geared towards performance and exploitation.

Second, Marler and Boudreau (2017) reviewed 14 academic papers on HR analytics, out of which four are empirical-based. The scarcity of empirical research can be attributed to the small number of organizations (16%) which reported using HR analytics (CedarCrestone, 2015). Van den Heuvel and Bondarouk (2017) consulted Deloitte’s (2015) industry trend report and thereafter concluded that “most organizations, even large multinationals, lack a clear vision of the future HR analytics within their company”, and “empirical research on HR analytics is virtually non-existent” (p.131).

Third, both academic reviews differentiated between metrics and analytics. Metrics encompass numerical insights into what is happening as reflective of behaviour, whereas analytics produce more sophisticated insights on a data, such as explaining causes of event and projecting future event occurrence, thus aiding decision making. Academic work suggests that as of 2017, HR analytics was focusing on metrics. This observation is interesting in light of our empirical findings – reported further in the paper – the contrast between the emphasis on descriptive analytics (i.e. metrics) and the narrative concerning technology use as aiding decisions (i.e. claiming to be analytics).

1.1.2.2 Learning Analytics

Ruiz-Calleja et al. (2017) conducted a systematic literature review of workplace technologies related to learning analytics, comprising 30 peer-reviewed publications to describe and evaluate technological affordances. The authors concluded that this research area was under-developed compared with the other fields in learning analytics. Their analysis discussed the role of different conceptions of learning present in technological solutions, and how that might impact product design. They found 11 tools to fall within the “knowledge acquisition” metaphor which assumes that learners acquire knowledge from a source of information independent of the context they are working within. The tools used within this paradigm can relate to assessment, self-regulation, learning by doing, and cognitive apprenticeship. They identified 11 papers that examined tools within the “participation” metaphor proposing that learning takes place through accepting membership as organizational member and participation in social practices. Finally, they identified five papers where the tools were examined from the perspective of the “knowledge creation” metaphor: learning involves collaborative and systematic development of knowledge artefacts and objects of activity to be shared among all.

Ley (2019) suggested another dimension of conceptualizing workplace learning. Instead of focusing on mechanisms for learning, he focused on the types of knowledge structures that employees are expected to engage with. Ley differentiated between emergence and guidance approaches to learning through knowledge structures that are already in place versus are being negotiated. His review and analysis were based on 13 research projects conducted between 2006–2019, with the focus on workplace technologies. He argued that through the perspective of guidance, learning refers to the adaptation of knowledge and practices, and is achieved through instruction, scaffolding, and apprenticeships. Tools supporting emergent knowledge structures were described as technologies that enable collaborative creation of new knowledge and practices, where learning is directed by learner’s agency, and knowledge structures are emerging rather than already in place.

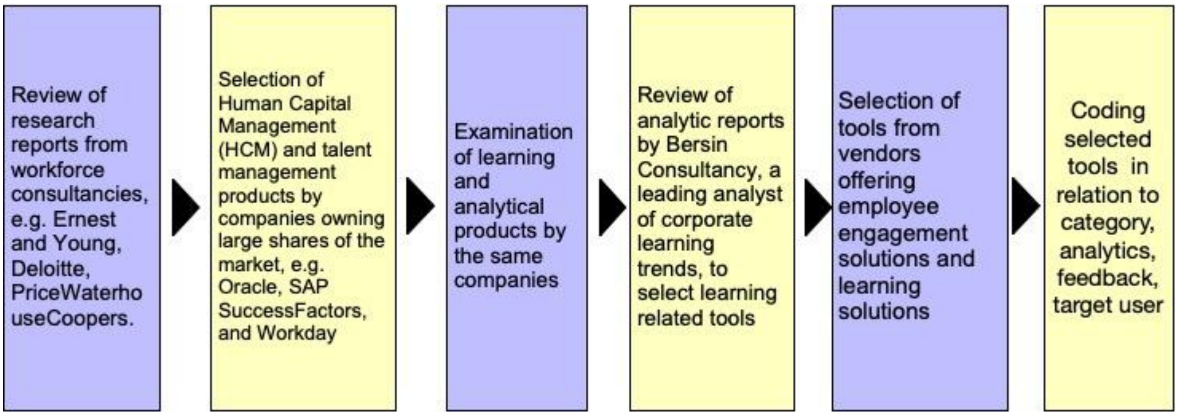
Through our empirical study, we observed a disconnect between the emphasis placed on objectives of learning analytics and workplace learning within this research strand, and the vendor-driven solutions we would review in our empirical section.

2. Methodology

2.1 Selecting digital learning solutions

An exploratory study was conducted using convenience sampling on digital learning solutions available in the market for the corporate learning industry. Selected tools might or might not be representative of the entire sample. We were interested in identifying types of technologies, and major features observed within them. The collation of these tools took place through an iterative review of grey literature followed by an examination of selected prominent or relevant tools. A total of 80 digital solutions were selected (See Appendix for a full list of tools). The processes taken to select the tools are captured in Figure 1.

Figure 1: Snowball selection workflow



For each of the products, we looked at the supporting documentation explaining and describing the tool and sought information about the tool through online presentations. Each tool was coded in relation to the following categories: 1) Types of categories the tool fell under; 2) Type of analytics in use; 3) Target users; 4) Type of feedback available.

2.2 Categories of tools

Each digital solution was labelled using Bersin's (2020) initial classifications of product categories, except for the four product categories of HR Analytics (i.e. Human Capital Management (HCM), Talent Management, Analytics tools) and Hybrid which were guided by our knowledge of each product's functions. These categories broadly capture the evolution and popularity of the types of technologies adopted in the corporate sector. HR Analytics encompasses a wide array of technologies related to HCM, whereas LMS represents more conventional systems of learning and training at workplaces. LXP represents a new generation of tools that consider employee-driven content creation and self-regulation, with micro- adaptive platforms, video-learning platforms and hybrid platforms being more noteworthy subsets within experience learning systems. Finally, digital adoption and workflow tools refer to a new generation of *learning in the flow* tools, whereas employee engagement systems assist in capturing and processing employee participation and their reflection of enterprise processes. Table 1 presents the operational definitions of each category of technologies.

Table 1: Categories of Technologies Used for Corporate Learning and Development

Category	Operational definition
HR Analytics	HCM solutions (e.g., Workday) primarily focus on executing human resource functions like recruitment, compensation and benefits. *Talent management solutions* (e.g., UltiPro) focus on the identification of good performers in the organization, and provide resources like coaching tools to develop their career growth and succession plans. *Analytics solutions* usually promoted as standalone products involve the integration of data from different platforms (e.g., SAP SuccessFactors), and their analytical capabilities may differ in levels of sophistication. These vary from simple metrics like retention and promotion rate (e.g., Workday) to advanced models like predicting likelihood of employees staying in organization in next 12 months (e.g., UltiPro).
LMS	LMS solutions are *employee learning platforms* which the knowledge content is dictated by the client organization and compliance in course completion is of great importance (e.g., SumTotal).
LXP	LXP solutions are employee learning platforms which the client organization leaves the jurisdiction of knowledge content to 1) algorithms embedded in the solutions for personalized recommendations tailored to employees' job roles and content preferences and to 2) employees themselves for manual content curation and regulating learning progress (e.g., Saba).
Hybrid	Hybrid solutions integrate elements from both LMS and LXP and are not easily classified as either (e.g., Adobe).
Video-learning solutions	Video learning solutions use audiovisual media as the primary mode of learning, and employees are both consumers and producers of video content (e.g., Rali). One noteworthy application of video learning is developing employees' sales capabilities through practicing their sales pitch on video and soliciting feedback from video audience such as peers and managers.
Micro- and adaptive learning platforms	Micro- and adaptive learning platforms as distinct forms of LXP further enhance learning and retention in memory by promoting bite-sized learning content periodically and repetitively (e.g., SwissVBS), or adapting learning content and assessments to employees' varying proficiency levels over time (e.g., Trivie).

Digital adoption and workflow learning tools	Digital adoption tools make gradual the curves of software learning for employees through automating certain aspects of the onboarding process and supporting employees in resolving technical difficulties (e.g., Walkme). Workflow learning tools also support employees' digital learning processes through facilitating online social collaborations and building knowledge communities, but they also have an automated assistance function which automates certain digital workflow processes (e.g., Kissflow). Noteworthily, workflow learning tools should not be perceived strictly as learning platforms as they concern "less learning than it is performance support or just-in-time assistance." (Hogle, 2019).
Employee engagement	Employee engagement solutions help organizations to solicit and track feedback from employees to understand employee sentiment and draw actionable insights from employee feedback with the primary aim of promoting positive organizational cultures (e.g., Glint).

2.3 Categories for Analytics, Feedback, and Target Users

Each of 80 digital solutions was coded according to 1) types of analytics; 2) format of feedback; 3) target users. These basic categories provide minimal descriptions of technology conceptualized as a socio-technical system for learning: capturing the domain of implementation, function of data collected by the tool, as well as assumptions about how feedback is to be given, and to whom.

During data collection, we did not seek licenses for the digital solutions; hence, we were not privy to the actual user interface and analytic information outlook interface. The websites for each digital solution and descriptions of product features were scrutinized alongside visual screenshots and video demonstrations of product interface. We assigned labels to describe different tools based on these observations. When the information could not be coded with sufficient accuracy for several digital solutions, labels were not assigned. Detailed information on the coding for each dimension is presented below.

2.3.1 Types of Analytics

Each tool was coded in relation to four types of analytics: descriptive, diagnostic, predictive and prescriptive (arranged in order of stage of workflow to be implemented; Hardoon & Shmueli, 2013). The categories were defined as followed:

- *Descriptive analytics* inspect the data to understand what phenomena had occurred, through arithmetic techniques like frequency counts, aggregation and obtaining descriptive statistics (e.g., mean, standard deviation).
- *Diagnostic analytics* inspect the data to explain why certain phenomena occurred, through analytical techniques including correlation and regression.
- *Predictive analytics* make forecasts on the likelihood of certain phenomena occurring, through machine learning algorithms such as clustering.
- *Prescriptive analytics* suggest specific courses of actions to arrive at favorable future outcomes, and these machine learning models continually refine themselves through feedback on real-world situations.

No strict requirement exists for the four types of analytics to be implemented in sequence. For instance, companies and data holders can conduct prescriptive analytics using raw data without tapping on descriptive, diagnostic and predictive analytics. All four types of analytics were hence coded independent of each other, and this generates four variables, each coded in a binary fashion to indicate the application versus non-application of analytical function in the digital solution.

2.3.2 Types of Feedback

The second domain concerns the ways that employee data in analytic form is presented to stakeholders. Three broad dimensions were used to record different ways to present analytics from learning, engagement, HR systems: analytical dashboards, personalized reports, and personalized recommendations (Wong & Li, 2020). Descriptions of each of the categories are presented below:

- *Analytical dashboards* are learning support tools which allow learners to "review their online learning behavior patterns intuitively through the provision of visual information" (Kim, Jo, & Park, 2016; p. 13). They present only the information deemed most important and useful to an audience for achieving his/her primary objectives in a simplistic and easy-to-understand form (Few, 2013). They can be effective in enhancing learning outcomes as they help learners to develop metacognitive skills in planning, monitoring, and regulation of knowledge acquisition (Chen, Lu, Goda, & Yamada, 2019; Kim et al., 2016). Dashboards are also increasingly used in managerial contexts to serve similar functions of monitoring, planning and communication (Noonpakdee, Khunkornsiri, Phothichai, & Danaisawat, 2018; Rahman, Adamu, & Harun, 2017).
- *Personalized reports* differ from dashboards as they are generally less graphical and illustrative, and they may also provide more elaborate and analytic information for recipients beyond click-level data which are typical of analytic dashboards. They are customized according to individual's learning data and analytical results (Wong & Li, 2020). Personalized reports typically lay out certain metrics of interest to stakeholders and elaborate in detail, their implications.
- *Personalized recommendations* (i.e., promoted via dashboards, reports, emails or social media notifications) often focus on suggesting courses of actions to stakeholders based on present analytic information to improve future outcome favorability. These were coded at the broadest level, and reflected whether the algorithmic rules selected and pushed feedback towards end-users and other stakeholders.

All dimensions were coded independently of each other as they are not mutually exclusive. This generated three variables, each coded in a binary fashion to indicate the presence versus absence of each system of presenting analytical information in each digital solution.

2.3.3 Target Audience

Technologies were also interpreted in relation to who would receive the employee analytical information. The following stakeholders were chosen as potential recipients of feedback: *higher-level executives*, *managers*, and *employees.*

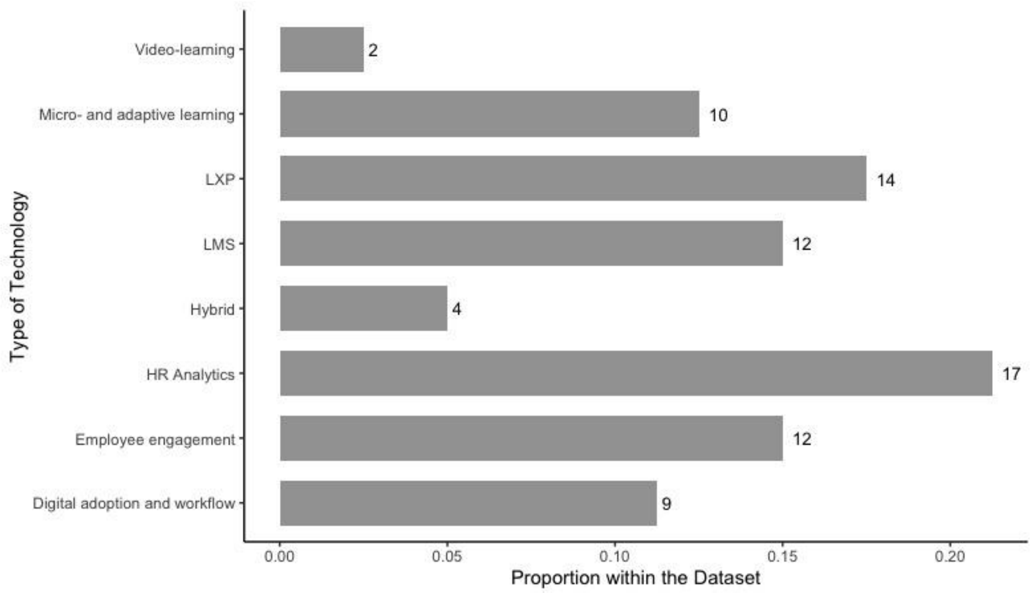
The typical use cases for these stakeholders differed. Executives are vested in maximizing the utility of the digital solutions and expect the products to generate useful and timely analytic information on the employees' learning behaviors as well as possible implications on organizational functioning. Managers would also be interested in employees' learning behaviors and outcomes, since their managerial role involves taking charge of supervising their job roles and appraising their work performance. Managers should hence be apprised of and be able to effortlessly access employees' learning analytic data. Employees as end users of digital solutions should also find great value in accessing their learning analytic information to help them keep track of their learning behaviors and look out for ways to improve their learning outcomes.

3. Results

In this section we present the summary of characteristics of selected technology. Please note that the trends are based on a non-random convenience-based sample in line with our aim to map the state of the field. Figures within the report provide a snapshot of the trends based on frequency counts. The major observations in empirical data were as followed:

- Tools with the highest frequency counts in our sample were HR analytics, followed by LXP and LMS.
- Tools were predominantly equipped with descriptive analytics (i.e. metrics for reflection); both predictive and prescriptive analytics (i.e. analytics for decisions) were found in about a quarter of the tools.
- Compared with other tools, HR Analytics tools were equipped with most analytical functions for decision making. LXP also featured prominently in a number of prescriptive solutions (i.e. personalised content) pushed unto the employee.
- Dashboards were the most prevalent way of displaying analytics; many HR Analytics and LMS also displayed analytics through personalised reports.
- Analytics information and feedback were the most likely to be presented to managers, followed by employees and then higher-level executives.
- The most important stakeholder for HR analytics appeared to be the executives, while the most important stakeholder for LXP tools appeared to be employees.

Figure 2: Frequency and Proportion of each Technological Tool Selected for Analysis



3.1 Types of Analytics

Across our sample of 80 digital solutions, 85% conducted descriptive analytics, 8.8% diagnostic analytics, 23.8% predictive analytics and 25% prescriptive analytics. Figure 2 demonstrates what tools used correspondent analytics types.

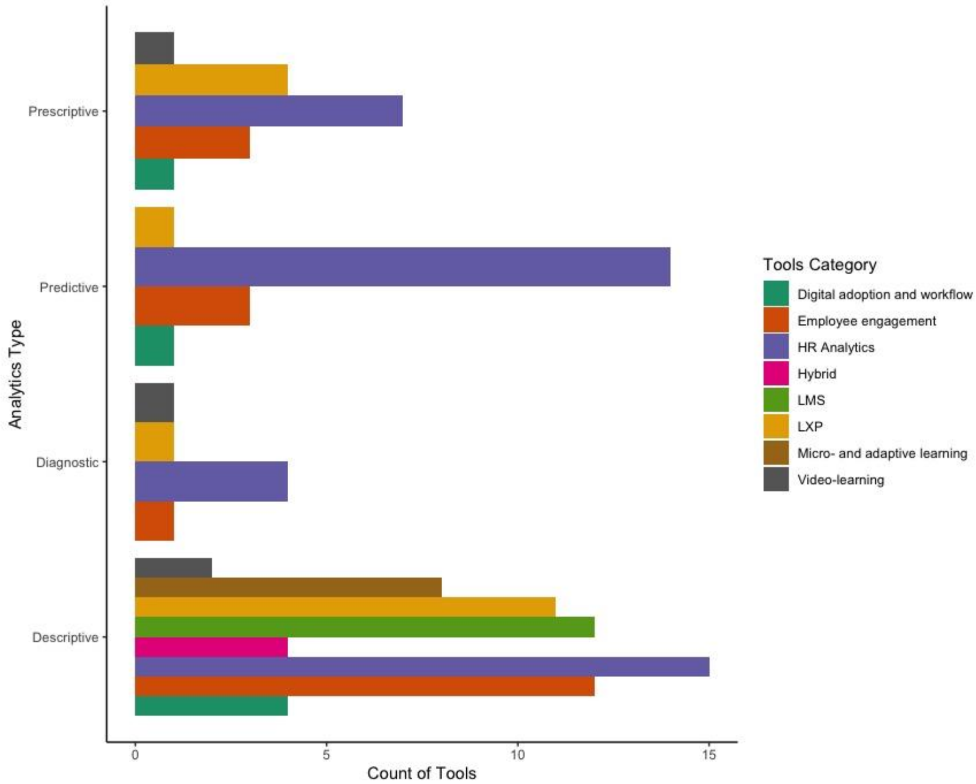
Descriptive analytics were the most commonly presented to end users and other stakeholders. They generally cover telemetry metrics like user activity frequency and time spent, course progress and completion status. They may also involve comparisons with analytic information of other single and grouped end users of software, which gives important benchmark information for all audiences.

Diagnostic analytics were the least common. The primary function of digital solutions in corporate learning industry lies in enhancing learning and work performance outcomes, but not in explaining learning behaviors. There were few digital solutions which measure and assess business performance outcomes, attempting to uncover a causal link between software use and important criterion outcomes.

Predictive analytics were present in approximately one-quarter of our sample, and are concerned with making forecasts on metrics and outcomes that matter to organizations such as individual employee turnover and performance growth rate, and more strategic metrics like future workforce projection.

Prescriptive analytics, present in one-quarter of our sample, were geared towards improving outcome favorability of employee learning and engagement processes. These products present recommendations and suggest action courses to executives and managers (e.g., holding appraisal meetings with direct reports), as well as employees themselves (e.g., suggesting mentors that they can connect with to boost their learning outcomes).

Figure 3: Frequency of Analytics Types by Tool Category



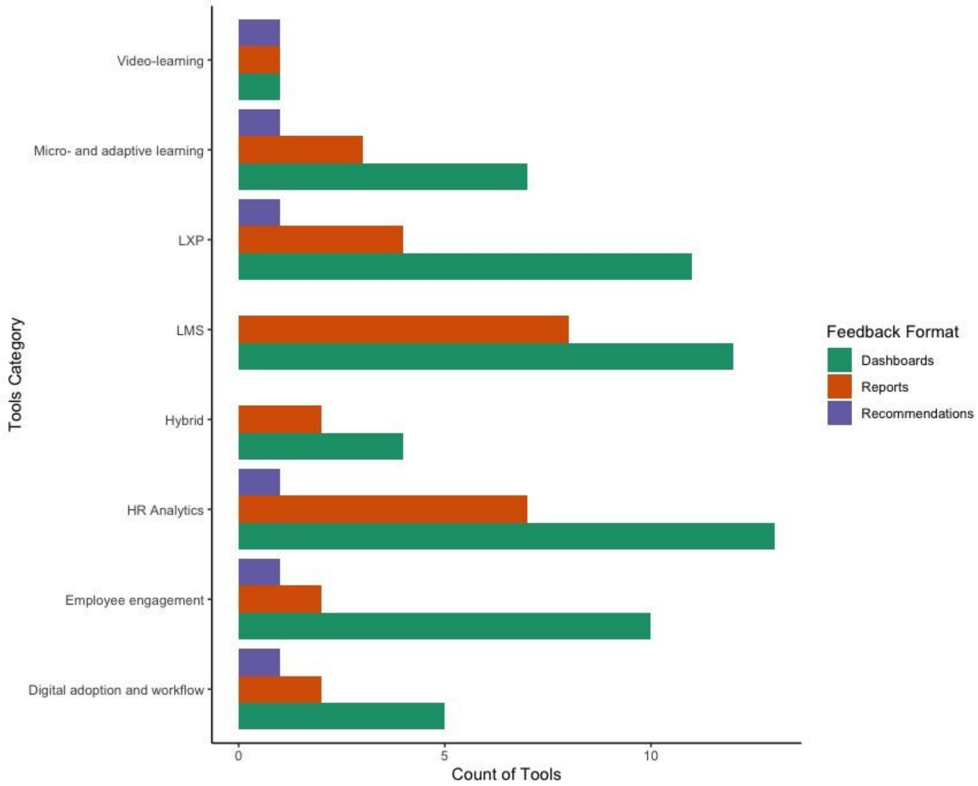
3.2 Types of Feedback

Across our sample of 80 digital solutions, 78.8% used dashboards to present analytic information, 36.3% used personalized reports and 23.8% made personalized recommendations to end users or other stakeholders. Dashboards are a ubiquitous feature of digital solutions as only 2.5% of our sample did not utilize dashboards.

About one-third of our sample seemed to present more elaborate forms of analytic information to stakeholders (e.g., explaining the implications of certain metrics), and personalized reports are useful in expanding on and discussing the insights gained from the analytic computations. However, likely due to limited functionality of some digital solutions to customize reports based on learning and engagement metrics, personalized reports were not as prevalent as analytic dashboards.

Personalized recommendations were the most infrequent format of presenting analytic information, as the digital solution would require advanced analytical capabilities to generate meaningful insights – not yet attainable in most digital solutions by present standards. This sub-dimension is similar to the coding of prescriptive analytics, and the difference of 1.2% in the frequency of both dimensions was due to one product which advertised itself as capable of prescriptive analytics but did not explicitly state or illustrate the feature of personalized recommendations.

Figure 4: Frequency of Tool Category by Feedback Types

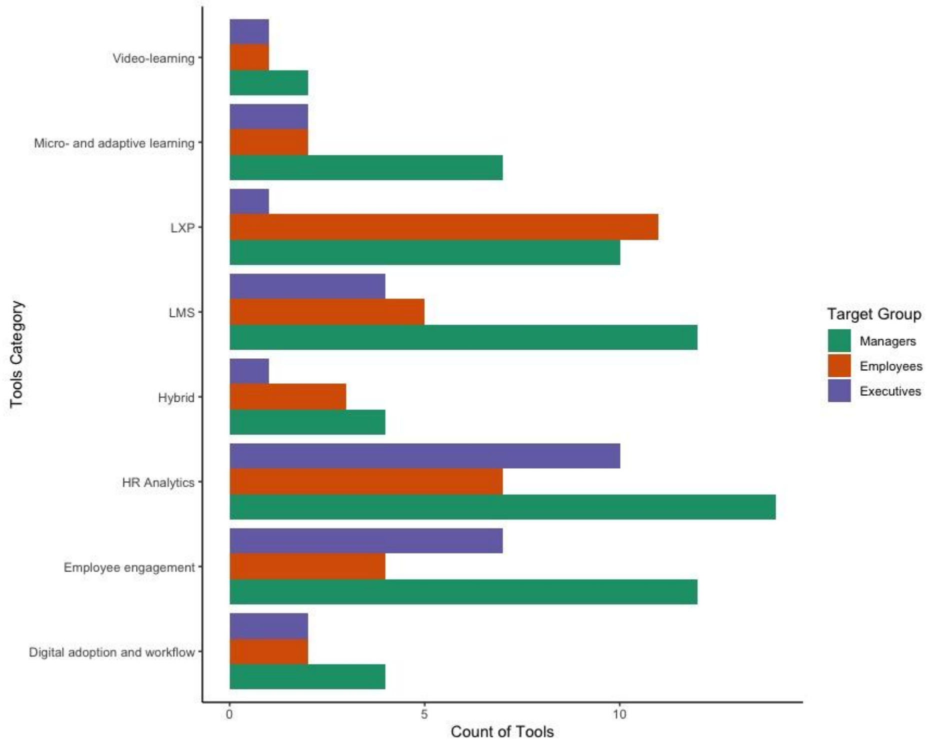


3.3 Target Audience

Across our sample of 80 digital solutions, 23.8% presented analytic information to higher-level executives, 81.3% to managers, and 43.8% to employees. Approximately one-quarter of our sample reported higher-level executives as recipients of analytic information from the product platform, but this may be an underestimation of the actual number of executives accessing this information. Executives are likely one of the key decision maker on whether to adopt a digital solution for an organization, and they should be authorized to access timely and accurate analytical information concerning the overall usage frequency and product efficacy. One possible reason why this was not commonly described as a product feature is because it could be considered a hygiene factor, and assumed to be an unspoken component of product usage.

Managers on the other hand were the most frequently mentioned in accessing their direct reports' analytic information. Most digital solutions market themselves in this manner to suggest that managers can effectively monitor and play an important role in regulating employees' learning and engagement behaviors. Slightly less than half of employees as direct end users could also access their usage and other analytic information. This allows them to monitor their learning activities and set realistic and achievable targets as they progress in their learning journeys. However, not all digital solutions (e.g., analytics softwares, digital adoption and video learning tools) made this function available to employees; possibly because these products do not involve self-regulatory behaviors on the part of employees to enhance learning outcomes.

Figure 5: Frequency of Tool Category by Target Audience



4. Discussion

Based on our review of a selected small pool of academic literature and convenience sampling of analytics-based technologies, we drew out several critical observations that require further investigation.

4.1 Critical observations

Vendor-driven learning technologies embed controversial assumptions about learning.

Although the affordances of technology are in line with facilitating learning as a social practice at the workplace, the types of analytics captured by these systems suggest that vendors assume learning to be a knowledge acquisition process, driven by curated content or collegial recommendations. Types of analytics in use, such as rate of courses taken, or levels of participation and engagement also suggest that development is conceived as motivated by performative metrics. Although Bersin claims that the new generation of learning and development is that of capability development, current analytics suggest very little support for learner agency or interest-driven skills development. Most analytics do not seem to capture the development of soft skills.

Many learning solutions are conservative in achieving their purpose, placing burden on employees and managers.

The affordances of existing technologies are in line with contemporary developments of tools, but the notion of what they are meant to achieve seems to be underpinned by technological determinism. Analytics or metrics used to reflect employee activity appear to be rudimentary, focuses on performativity, are manager-oriented and heavily reliant on self-regulation of skills and availability of time. These metrics might be a burden on employees, expecting them to be equipped with certain requisite skills and make themselves available for learning. The strong focus of metrics on performativity, decision making and their general orientation towards reporting to managers rather than employees signal their potential as a control mechanism, casting doubts on the intentionality and genuine uptake across all industries. This has negative implications for the nature of good work and satisfaction. The concept of decent work, in the ILO definition, describes such work as productive with fair pay, security in the workplace, satisfactory prospects for personal development and social integration, freedom for people to express their concerns, organize and participate in the decisions that affect their lives and equality of opportunity and treatment for all women and men (Bound, Sadik, Evans, & Karmel, 2019).

Types of learning embedded within the tools assume learner readiness to participate and require expertise in learning skills.

As noted previously, participation in digital learning requires a higher degree of self-regulation. Pacing oneself through LMS content, planning, and making choices about courses and trajectories require from the employee and manager an understanding of where and how they want their personal capabilities to unfold. In another scenario, LXP requires collective participation and feedback support from others as employees engage in content creation for the learning benefits of others, assuming the learning content is reliable and credible. These tools require the employees to be able to engage in self-regulation for effective learning and capabilities for developing content for others, but the means and ends of developing these competencies and attitudes remain unclear.

Numeric literacy, critical thinking and feedback recipiency competences are presumed.

To use information about the analytics presented on dashboards and to question if automated recommendations are relevant, target groups require certain levels of numeric literacy and critical thinking. Further, recent research emphasizes that feedback is a dialogic process which necessitates skills in managers and direct reports to engage in fruitful conversations. It is unclear how the tools could effectively aid in this process and the degree to which these analytics represent the interests of managers and employees.

Present usage of analytics in corporate learning technologies appears to be tightly linked to performativity measures and business decisions. Empirical evidence on which the design of metrics and analytics is based is weak.

Our brief review of academic work suggests that empirical bases for HR analytics and workplace analytics are weak. Dashboards in learning analytics have also been found to build on little theoretical work, despite being extensively adopted (Matcha, Gasevic, & Pardo, 2019). Practitioners could be under the influence of vendors and consultants who present themselves, their systems and tools as credible, effective and indispensable in the course of making business decisions. Our review of different types of analytics suggests that they are more likely to measure shallow-level activity rather than quality of engagement, and are not well suited or adequate in reflecting learning and capability development. The misfit of these tools in facilitating business decisions may produce harm beyond profit loss into the erosion of trust and corroded reward systems at workplaces.

Adoption of the tools for lifelong learning is questionable for SMEs.

In principle, the range of tools we have evaluated is not limited to be used in large corporations, but can also be adopted by smaller agile companies. It appears that workflow tools are likely to be more aligned with the ways SMEs navigate their trajectory for learning and development. We hypothesize that tools like Facebook for Workplace can also become useful in supporting work processes, but the cost and value of investing into these tools for SMEs need greater understanding.

4.2 Limitations

We noted two major limitations of our research method. The first limitation pertains to the use of superficial information on digital solutions presented on their respective websites for coding purposes. There may be some features which were absent in the product descriptions yet actually present in actual product use (e.g., displaying analytic information for executives). Our coding processes were conservative. The second limitation refers to the underlying non-random nature of the sample. Since the aim of the research note was to map the field, generalizability of the sample was not central to our inquiry.

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Appendix

Company	Name of tool	Coded Category
Oracle	Learning Cloud	Hybrid
Accenture	Future Talent Platform	Hybrid
SAP Success Factors	Learning Management System	LMS
	Talent Management System	HR Analytics
	Workforce Analytics	HR Analytics
Workday	Human Capital Management	HR Analytics
	People Analytics	HR Analytics
	Talent Management	HR Analytics
	Learning Management System	LMS
Cornerstone	Learning Management System	LMS
	Analytics	HR Analytics
Sumtotal	LMS	LMS
Saba	Learning Management System	LMS
	Learning Experience	LXP
	Social Learning	LXP
	Video Learning	Micro- and adaptive learning
	Micro Learning	Micro- and adaptive learning

Company	Name of tool	Coded Category
Saba (continued)	Career Growth and Development	HR Analytics
	Extended Enterprise	LMS
	Extended Enterprise	LMS
Kallidus	Learn	Hybrid
Adobe	Captivate Prime	Hybrid
Degreed	No information	LXP
Edcast	LXP (Learning Experience Platform)	LXP
Fuse Universal	Learning	LXP
Fuel 50	Career Pathing Software	HR Analytics
Instructure	Bridge	LMS
Everwise	Learning Experience Platform	LXP
BetterUp	Talent Development	LMS
	Insights and analytics	HR Analytics
Glint	Employee Engagement	Employee engagement
	Employee Life Cycle	Employee engagement
	Manager Effectiveness	Employee engagement
	Team Effectiveness	Employee engagement

Company	Name of tool	Coded Category
Ultimate Software	Xander®	HR Analytics
	UltiPro Learning	LXP
	UltiPro Talent Management	HR Analytics
	UltiPro Workforce Intelligence	HR Analytics
TinyPulse	Employee Feedback	Employee engagement
Perceptyx	Employee Surveys	Employee engagement
	People Analytics	HR Analytics
Trust Sphere	People Analytics	HR Analytics
	Trustvault	Employee enagement
Hyphen	Surveys	Employee engagement
	Voice	Employee engagement
	Insights	HR Analytics
Culture Amp	People and Culture Platform	HR Analytics
	Engagement	Employee engagement
	Performance	HR Analytics
Officevibe	Employee engagement solution	Employee engagement
	Grow as a manager	Employee engagement
Skillsoft	Percipio	LXP

Company	Name of tool	Coded Category
Filtered	Magpie	LXP
360Learning	-	LXP
Valamis	Learning Experience Platform	LXP
Tribridge	Contentsphere	LXP
LinkedIn	Learning	LXP
Axonify	LMS	LMS
	LXP	LXP
	Micro Learning	Micro- and adaptive learning
Area9 Lyceum	Rhapsode™	Micro- and adaptive learning
Grovo	Micro Learning Solution	Micro- and adaptive learning
Qstream	Micro Learning	Micro- and adaptive learning
Rehearsal	-	Micro- and adaptive learning
Jubi	-	Video-learning
Wisetail	LMS	LMS
Mindtickle	Sales readiness and sales enablement	Video-learning

Company	Name of tool	Coded Category
Trivie	-	Micro- and adaptive learning
SwissVBS	Echo	Micro- and adaptive learning
EduMe	-	Micro- and adaptive learning
WalkMe	Digital Adoption Platform	Digital adoption and workflow
SAP	Enable Now	Digital adoption and workflow
Microsoft Teams & Vitalyst	Digital Adoption Solution	Digital adoption and workflow
ELearningForce	LMS365	LMS
Microsoft	Teams	Digital adoption and workflow
Slack	Workflow builder	Digital adoption and workflow
Orangescape	Kissflow	Digital adoption and workflow
Wizy.io	Form Workflow Plus	Digital adoption and workflow
Atlassian	Jira Software	Digital adoption and workflow
Atlassian (continued)	Confluence	Digital adoption and workflow