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Chapter 7

Building the Workforce Analytics Function

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Introduction

Over the past several years, workforce analytics (WFA) has seen significant growth in popularity, with organizations from around the world leveraging workforce data to aid in making strategic decisions (Angrave et al., 2016; Marler & Boudreau, 2017). Appropriately, we have seen numerous examples of organizations effectively implementing the ACAI Model (introduced in Chapter 1) to demonstrate the impact of WFA and how organizations can effectively utilize workforce data to make critical decisions in areas such as diversity and inclusion, recruitment and selection, and training and development (Buttner & Tullar, 2018; Falletta & Combs, 2020; Minbaeva, 2018; Peeters et al., 2020; van der Togt & Rasmussen, 2017). However, despite its popularity among practitioners and advances made in the field, what remains nascent are studies illustrating the dualistic nature of WFA maturity, how this shapes the development of WFA function, and its evolution among different organization types. Furthermore, a holistic view concerning the various elements required to achieve the desired level of WFA maturity and to build an effective WFA function in contemporary organizations is needed. Accordingly, in this chapter we aim to address these gaps by proposing a new WFA maturity matrix offering a much-needed shift in thinking toward WFA maturity. In addition, we propose an overview of the essential elements required for building WFA functions, including team composition, and their relative advantages and disadvantages.

In the following sections, we set the stage by first outlining the various perspectives concerning WFA maturity and addressing the need to expand our view on what constitutes WFA maturity. In doing so, we challenge the established view of WFA maturity as a linear process that evolves in a predictable manner from low-level operational reporting to highly sophisticated advanced analytics. Instead, we argue that the equilibrium between "push" and "pull" factors

(Cascio & Boudreau, 2017) defines the desired level of WFA maturity. Within the context of WFA, “pull” factors represent a level of demand from the broader organizational context for knowledge that the WFA projects generate, while “push” factors capture the WFA team’s capabilities to generate such knowledge (see Figure 1). Next, drawing on the ACAI Model, we outline each of the “push” and “pull” factors that help shape the development of the WFA function. It is important to note that, although we acknowledge the importance of “pull” factors and their importance in building WFA functions, our intention in this chapter is to focus more deeply on the “push” factors, that is, what is in the control of WFA functions. Finally, building on the logic of supply and demand and on the “push” and “pull” factors discussed, we apply these concepts within the context of progressing the WFA function and propose that its structure depends on the needs of the organization and is best situated at a point of equilibrium between “push” (supply) and “pull” (demand). In this way, we conclude the chapter by discussing various setups of the WFA function based on the desired level of capability in addition to their relative advantages and disadvantages.

- INSERT FIGURE 1 AROUND HERE -

Unique to this chapter, we have taken the insights into the development of WFA functions and maturity from interviews conducted with expert WFA professionals. We draw on these interviews, offering illustrative quotes to help provide a novel and in-depth perspective that supports and strengthens the claims we make throughout the chapter.

Setting the Stage: Workforce Analytics Maturity

From the early days of WFA popularity, the key question has been “what does good WFA look like?” Companies have been curious to see the best-in-class standards and best practices to get inspired and have a better understanding of where to go and what to aim for. Meanwhile, practitioners and scholars have also contentiously debated the concept of WFA maturity. For instance, according to various consulting firms and professional associations, WFA should be thought of as a continuum, with the function's maturity determining the extent of analytics that may be performed (Chartered Institute of Personnel and Development (CIPD), 2019; Deloitte, 2019). For example, Deloitte (2019) claimed that WFA can be classified into four distinct levels: operational reporting, advanced reporting, advanced analytics, and predictive analytics. Likewise, the CIPD (2019) built upon this premise, suggesting that WFA operates on five levels: operational, descriptive, diagnostic, predictive, and prescriptive. This perspective has spread to the academic literature on WFA, where scholars such as Margherita (2020), Sivathanu and Pillai (2020), and Marler and Martin (2021) address the various levels of WFA. For example, according to Margherita (2020), WFA follows a linear three-stage maturity model. At its lowest level, "descriptive," WFA focuses on using data to answer questions concerning what has happened. Next, the "predictive" stage focuses on what might happen in the future and why. Finally, the "prescriptive" stage determines the actions to take in response to the analysis.

More recently, McCartney and Fu (2022b) expressed their belief that WFA maturity plays an important role in conceptualizing and developing value-added WFA programs:

> [Workforce Analytics] should be seen as situational, falling along a spectrum where organizations at the low end of maturity report on descriptive statistics. In contrast, organizations at the highest and most mature level of people analytics can utilize descriptive statistics and more advanced forms of technology (i.e., Artificial Intelligence, Machine Learning and organizational network analysis tools) to analyze workforce data to perform predictive and prescriptive analytics. (p. 8)

As can be seen, many scholars have categorized WFA maturity based solely on the principals of Phase 3 of the ACAI Model, which relates to the degree of analytical and statistical capabilities of the individual or WFA team. Although this is an essential component of analytics maturity, we argue that to fully realize business value from WFA it is equally important that organizations have the demand for new knowledge that WFA projects create and the willingness to implement actionable solutions derived from them. For example, if a WFA team has the required analytical competencies to deliver sophisticated predictive analyses, but there is no appetite for actions from the organizational side (Phase 4), the business value of WFA would be close to none. Therefore, progressing with WFA for business value creation will require working with two axes. This sentiment aligns well with current thinking by influential WFA leaders. For instance, Heather Whiteman, former, VP, Global Head of People Strategy, Analytics, Digital Learning & HR Operations and current Assistant Teaching Professor at the University of Washington School of Information stated the following:

> There is a difference between analytics maturity, meaning what you're capable of doing with analytics, versus the organization's maturity to use analytics. I have seen instances where the data approach itself is very advanced, where they are using some machine learning, very technical stuff. However, I would still consider the organization to not be very mature from an analytics standpoint. . . . Plenty of organizations have a really high demand for workforce analytics, but they don't know how to use it.

Accordingly, we argue that WFA maturity evolves through the interaction between two dimensions: (a) WFA teams' capabilities and (b) the organizational demand for actionable insights that WFA projects create (see Figure 1). In Tables 1 and 2, we suggest that each of the two dimensions comprises three levels, and we offer examples to illustrate their differences.

- INSERT TABLES 1 AND 2 AROUND HERE -

For organizations and human resources (HR) departments to begin building capabilities in WFA, it is first important to be aware of the equilibrium required between “pull” (i.e., organizational demand for WFA) and “push” (i.e., WFA capabilities). This is particularly important in the context of the ACAI Model because the manner in which data can be collected (Phase 2), analyzed (Phase 3), and presented (Phase 4), is predicated on the box of the WFA maturity matrix in which the organization or department finds itself at that moment (Margherita, 2022; Marler & Martin, 2021). Likewise, the organizational demand for data and insights from stakeholders and the ability to implement actionable solutions directly relate to the required level of a WFA team’s capabilities.

In the following sections, we outline and provide in-depth insight into the “push” and “pull” factors that impact WFA functions and play a pivotal role in their paths within the WFA maturity matrix.

What Are the Push Factors?

Once organizations and HR departments have determined their level of analytics maturity, it is then critical to begin building upon the “push factors” that enable building and strengthening WFA capabilities. We refer to “push factors” as circumstances that must be met for WFA to be available within the HR department. These factors provide the “supply” for building effective and sustainable WFA capabilities. In terms of WFA, we identify three overarching push factors critical to establishing long-term WFA. In other words, to build organizational capabilities in WFA and provide actionable insights through workforce data, the following conditions must be met: (a) the workforce analyst or members of the WFA team must have the proper knowledge, skills, abilities, and other characteristics (KSAOs); (b) the department must have data quality procedures and processes in place; and (c) the workforce analyst or members of the WFA team must have the ability to partner with the business. We discuss each push factor in detail in the subsequent sections.

Skills and Competencies Required for Building Workforce Analytics Capabilities

Given the expanding number of HR functions embracing WFA to make more informed and data-driven decisions, many HR departments are now employing workforce analysts (McCartney et al., 2020; van den Heuvel & Bondarouk, 2017). This newly emerging role has become a unique addition to the HR function that focuses on collecting, analyzing, and implementing workforce data to generate actionable solutions to various HR and organizational challenges. Moreover, this role differs from traditional HR professions, such as HR business partners or HR generalists, given the technical nature of the tasks involved (McIver et al., 2018; van den Heuvel & Bondarouk, 2017).

As discussed earlier, the maturity level of the WFA capability will impact the sophistication of analytics that can be generated. If we look at the aspiring level of WFA maturity, a single analyst may be responsible for all aspects of the ACAI process. Therefore, this role requires a broad set of KSAOs to manage the entire ACAI process (Andersen, 2017; McIver et al., 2018). Several scholars and professional associations worldwide have made suggestions regarding the KSAOs that workforce analysts require to generate value-added WFA. For example, many scholars have suggested the need for robust data management skills (Andersen, 2017), storytelling and visualization (Andersen, 2017; McCartney et al., 2020; McIver et al., 2018), strong business acumen (Andersen, 2017; Ellmer & Reichel, 2021; McCartney et al., 2020; van der Togt & Rasmussen, 2017), and the ability to work with technology including human capital management (HCM) systems such as Workday, SAP SuccessFactors, and Visier, in addition to open-source statistical platforms such as R and Python (Ellmer & Reichel, 2021; Falletta & Combs, 2020; McCartney et al., 2020; McIver et al., 2018; Pessach et al., 2020). Comparatively, HR professional associations share a similar view concerning the KSAOs required for analysts to generate insight through workforce data. For example, according to the Society for Human Resource Management (SHRM), workforce analysts require a degree of understanding in using data to predict and suggest improvements to workforce challenges through analytical skills and statistical knowledge (SHRM, 2016).

Although a wide range of KSAOs are theorized among scholars and practitioner associations, it is also important to consider the perspective of WFA leaders tasked with the recruitment and overall strategic direction of the WFA program. One WFA leader, Thomas Rasmussen, former Senior Vice President, Digital and Automation, People and Culture at Vestas stated the following:

> You need a deep understanding of scientific methods, right? ’cause you know workforce analytics is an applied science. You need to know how to do a regression. You typically need to code, so knowing how to code is important. You also need to know about and research design all of that stuff, right? And then in addition to that, having a deep statistical skill set, and you need to be really, really, really good at telling the story on the results, so translating it from something that you would put in a journal to something that you can present in front of executives.

Another WFA leader, Pete Jaworski, Head of People Data and Analytics at A.P. Moller - Maersk stated the following:

> The core capability in essence of the workforce analysts is being able to understand what the problem is defined, what the potential solution is, and then

> feedback a recommendation based on insights so that that's the consulting capability that's really core to the role.

The views expressed in each of the three perspectives (i.e., scholars, practitioner associations, leaders) are similar, and WFA leaders' views align well with current assumptions that scholars and professional associations make on the KSAOs WFA professionals require to enact the ACAI Model and offer insight through workforce data. Recently, in an attempt to consolidate the three perspectives concerning the desired KSAOs for workforce analysts, McCartney et al. (2020) developed a comprehensive competency model through an extensive literature review and interviews with WFA professionals. In this review they uncovered six competency buckets that HR analysts require to perform value-adding WFA: storytelling and communication, consulting, research and discovery, technical knowledge, HR and business acumen, and data fluency and data analysis. Accordingly, workforce analysts who operate in functions at the aspiring level of WFA maturity require a blend of these six competencies to offer insights through workforce data.

Data Quality and Processes

The second "push" factor critical to the successful development of WFA capabilities is related to Phase 2 of the ACAI Model which is high-quality data that are error-free and easily accessible. According to McCartney and Fu (2022b), "If teams cannot trust HR data given the likelihood of missing values and wrong entries, having the analytical understanding and capabilities will only aid in running inaccurate analysis, thus generating little to no value" (p. 28). Furthermore, making decisions based on inaccurate data may result in implementing solutions that are not targeted at the underlying or root problem, causing more harm than good (McCartney & Fu, 2022a).

Despite HR departments' heavy investments in data infrastructure and efforts to centralize workforce data over the past years, several issues remain regarding data quality and effective data processes (Boudreau & Cascio, 2017; Minbaeva, 2018). For instance, according to Boudreau and Cascio (2017), although advances have been made concerning technology, systems are still unable to "talk" to each other and are designed with legacy WFA structures in place. Likewise, Minbaeva (2018) argued that most organizations still remain unsure of the types of data available to them, where they are stored, and how multiple datasets can be integrated. Equally important is the emerging concept of data governance, which further enhances the policies and procedures undertaken to ensure the accuracy and completeness of organizational data (Green, 2017; Peeters et al., 2020; Shet et al., 2021). Therefore, building capabilities to ensure data are of high quality and establishing processes to ensure data are complete and accurate are critical step in the ACAI Model and building WFA capabilities overall. Accordingly, in this section we will outline how to build organizational capabilities in WFA by illustrating how organizations leverage HR technology platforms to aid in collecting and storing workforce data. In addition, we will detail the types of data collected to help make strategic workforce decisions. Finally, we will present information concerning how HR is implementing data governance policies to ensure the accuracy and completeness of data.

HR Technology and Data Management. Over the past 60 years, HR technology such as human resource information systems (HRISs) or HCM systems have significantly influenced how employee data are collected, stored, and managed (Kim et al., 2021). For instance, according to Kavanagh et al. (2015), an HRIS is "a system used to acquire, store, manipulate, analyze, retrieve, and distribute information regarding an organization's human resources" (p. 17). Likewise, it has offered organizations the opportunity to effectively enhance the delivery of

HR services and support decision-making through various types of data (Kim et al., 2021). As such, HRISs and HCM systems are a key element of the ACAI Model as they form the foundation for *"Collecting the right data"* and building sustainable WFA as seen in Chapter 3. In other words, they enable the storage storing of data required for conducting analysis and generating actionable insights. For instance, one WFA professional, Tim Haynes, VP Organizational Development and People Analytics at Jazz Pharmaceuticals, stressed the importance of HR technology:

> [HR technology] is very, very important by definition, whether it is Workday or any of the other global HCMs. I think the principle is having a single system that has your core workforce data, especially if you are a global multinational company. . . . Having a single HCM makes life a lot easier from an analytics perspective.

Technological advances in cloud software platforms have made HRIS platforms more affordable and commonplace within organizations (Johnson et al., 2016; Plessis & Fourie, 2016). For example, according to Johnson et al. (2016), increased technology capabilities at lower costs have allowed smaller organizations that previously could not afford to purchase HRISs to invest in more cost-effective cloud-based technologies. However, despite this advancement, organizations operating at the aspiring level of WFA maturity may not have the resources to spend on these platforms nor the managerial buy-in. For example, according to Minbaeva (2018), a paradox exists where "the team responsible for HCA [human capital analytics] needs data to prove its point, but top management needs proof before it will invest" (p. 703). As a result, data collection may be rudimentary using basic forms of technology. Moreover, workforce data at this level are commonly fragmented and collected across several different systems. For instance, organizations at the aspiring level of WFA may be collecting data from forms and will manually transfer data into different Excel documents or databases. As mentioned earlier, this causes several issues, including a lack of understanding or awareness of where specific data are stored, how to access them, or if they are even available. Several WFA professionals discussed this. Tim Haynes stated the following:

> A lot of organizations still do not have a single HCM [system]. They then need to connect lots of different data from different systems, and when you are facing that situation, there is always a risk of data not getting connected in the right way, and it is just complex and creates a lot of work.

Likewise, another WFA professional, Maura Stevenson, Chief Human Resources Officer, MedVet, said the following:

> When I started at my organization, with the data we had, we could not even calculate turnover accurately. . . . With my other organization, I could not tell how many people worked for us across the globe because we only had the United States data in our system. So, I think sometimes analytics get this shininess, but the reality is that in the trenches it is not so shiny.

Given the manual aspect of this process, along with fragmented data stored in various databases and Excel files, data duplication errors and wrong entries are common, which perpetuates the need for HR technology and investment into ensuring data are accurate and reliable.

In contrast, organizations operating at the established to advanced levels of WFA capabilities will have implemented a sophisticated HRIS or HCM system such as Workday, SAP SuccessFactors, or Oracle PeopleSoft as their primary source of storing workforce data. These systems allow for mass data storage and retrieval of structured data, or data that are well defined and easily categorized, and unstructured data that are not defined and typically comprise long strings of text (Leonardi & Contractor, 2019). For example, when a new employee is onboarded, HCM systems such as Workday, SAP SuccessFactors, and Oracle PeopleSoft collect structured employee data and generate an employee profile, including key information such as age, gender, reporting structure, skills, and direct reports. Together, employers can easily access these structured data points and use them for reporting and analytics. In contrast, some even more advanced HCM systems allow for the collection of unstructured data. For example, the Workday Peakon Employee Voice module enables HR departments to collect unstructured data through intelligent listening and employee sentiment, feedback, and other forms of text or string data (Workday, 2021).

Data Governance in HR. Although HRISs and HCM systems allow for the quick and easy collection of data, ensuring processes are in place to consistently maintain the integrity of the data is critical (Green, 2017). As such, HR departments at all levels of the WFA maturity matrix are introducing data governance structures to help guarantee that the data fed into the system are reliable, accurate, and credible (Peeters et al., 2020; Shet et al., 2021). For example, according to Green (2017), developing and implementing policies and practices surrounding how data will be maintained and stored along with privacy and security are "basics" for all organizations embarking on their WFA journey. Echoing this sentiment, Shet et al. (2021) stated that setting up data governance systems and establishing data workflows are critical in maintaining and enhancing data quality. Many WFA professionals share this perspective. Tim Haynes stated the following:

> I think [data governance] is essential. There is an element around the structure and organizing the data in the first place, but there is also the more data

> management or data engineering way to structure your data to ensure you have the best data that is consistent and of good quality.

Alexis Fink, Vice President, People Analytics and Workforce Strategy offered the following example:

> One thing that will drive people crazy is a data governance problem. Reflecting back on a previous organization, we had seven different fields across our systems labeled start date and they all meant different things. So, your start date at the organization, start date with a company we acquired, calculated start date for a break in service, your calculated start date for a particular acquisition, a start date for training, a start date for a particular job, and all of them meant different things, and if you didn't know what you were doing you would just look for start date, pick the first one you found, and have a completely inaccurate analysis.

Altogether, all HR functions must get data governance right at the outset to have high-quality, reliable, accurate, and credible data.

Business Partnering Ability

Finally, the third "push" factor in building sustainable WFA which closely relates to Phases 3 and 4 of the ACAI Model is the ability for the workforce analyst or WFA team to partner with various business units (BUs) across the organization. Accordingly, this will allow the analyst or team to provide insights through analytical capabilities that aid in strategic decision-making and influence change management activities as discussed in Chapter 5. As with the two previously mentioned "push" factors, this factor is too impacted by the level of analytics maturity, whereby organizations operating across the WFA maturity matrix will have different capabilities. These capabilities determine the insights workforce analysts and teams can generate along with their influence and impact on decision-making.

Looking at the aspiring level of WFA maturity, analysts or functions that operate at this level can offer basic reporting capabilities, including descriptive statistics on demographic information, turnover, and head count. Although important, these types of descriptive statistics, often referred to as HR metrics (van den Heuvel & Bondarouk, 2017), do not lead to high levels of influence concerning decision-making and change management. For example, according to Boudreau and Cascio (2017),

> At best these kinds of data represent operational or advanced reporting, and not strategic or predictive analytics that incorporate analyses segmented by employee population and that are tightly integrated with strategic planning. While these data can be informative, they can also lead to a focus on the operations of the HR function, rather than on the effects of human capital decisions and investments on organizational outcomes. (p. 122)

One WFA professional, Pete Jaworski mentioned the following:

> HR metrics have been a starting point [at my organization]. I've had to make the rounds and do a bit of work with the different functional heads asking which metrics do you want to use? And once we know that, then we can plan for what's going to get into a dashboard or plan. . . . [HR metrics] is all about connecting the dots for HR partners.

At the established level of WFA capability maturity, WFA teams have more breadth and depth concerning the insights they can provide. This is partly because of their access to technology, including HCM systems coupled with business intelligence (BI) tools. For instance, according to McCartney and Fu (2022b), BI tools are being integrated with modern HCM systems to allow for greater functionality and, as a result, the ability to generate more advanced insights. Consequently, access to HR technology and collaboration with senior leaders and HR business partners offer insights that can help shape and guide operational and tactical decision-making. When discussing how COVID-19 has positively benefited the impact of WFA, Thomas Rasmussen stated the following:

> COVID has led us to look at a lot of different things that we probably normally wouldn't look at. So, for example, there is a lot of focus on the employee. In particular, well-being more so than usual where it's looking at how are our employees coping? . . . We've also done some research, for instance, around hybrid work in terms of our diversity agenda and how this may affect different demographic groups in the organization.

As can be seen, organizations operating at the established level of WFA have significantly more influence with the insights they can provide. They can go beyond operational reporting and simple descriptive statistics and offer recommendations to help drive evidence-based decision-making.

Finally, at the advanced level of WFA capability maturity, and illustrated in Chapter 3, HR departments can leverage existing technology platforms coupled with automation to influence workforce planning and HR strategy. For example, HR departments may implement artificial intelligence (AI) and machine learning (ML) algorithms to apply predictive and prescriptive analytics to future HR or business challenges. Heather Whiteman offered this example:

> We implemented a full talent management system built on capabilities and skills data connections where individuals could rate their own skills, and capabilities

> get feedback from their managers and from peers. We could then validate those skills through an objective criterion. It allowed us to offer employees an assessment of what skills they most need to work on and directly linked them to those learning assets in our learning catalog. It would prompt employees based on how they rated themselves. For example, it would say, hey, you know you indicated that you're only a three on this skill, but did you know people in your role are typically a four? Here are a couple of courses aimed specifically at getting someone from level three to four. . . . We also built in some predictive algorithms and other machine learning to say, did you know you're actually an 85% fit for this other role in a different department? And oh, by the way, there's a job posting.

Similarly, Alexis offered the following example concerning how automation and ML can help generate prescriptive analytics:

> Automation can be an analytical tool if you are looking for areas of risk. If I am going out and doing analysis manually, I can probably do interactions between two or three variables, and I will probably be doing them in large chunks. But a machine can go out and do many, many, many more permutations. . . . So, for example, as companies right now transition to remote work, we can start to figure out what teams are vulnerable or struggling or what are the indicators I should be looking at? And the ability of a machine is it can go out and find whatever those indicators may be which could be manager feedback, or attrition, or missed objectives, or whatever else, and then take that data and say here are

> your ten most struggling combinations and notify management to go look there and this can be done at a much finer level of granularity if we use a machine.

Altogether, workforce analysts or members of WFA teams partner with organizational stakeholders to enable strategic decision-making and *"Influence the right decisions"*. As we have shown, this influence has different levels of sophistication. For instance, at the aspiring level, stakeholders will receive analytics in the form of descriptive statistics that highlight the current state of several key performance indicators (KPIs) and HR metrics. However, these offer little in the way of decision-making power. In contrast, different BUs more often consult those HR departments operating at the higher levels of maturity on specific challenges rather than general HR metrics, thus offering additional insights enabling more strategic decision-making.

What Are the Pull Factors?

As discussed earlier in this chapter, building sustainable WFA capabilities necessitates a level of demand to use analytics as inputs for business decisions across the broader organization. Following Cascio and Boudreau (2017), we refer to this demand as "pull" factors. These are factors that may be impeding holding back the maturity of the WFA function: "No matter how rigorously or completely the HCA are prepared and 'pushed' out to their audiences, the advancement and effectiveness of HCA still depends on the capability, opportunity, and motivation of analytics users" (Cascio and Boudreau, 2017, p. 123). These factors may represent requests from organizational stakeholders actively seeking workforce data to aid in making business decisions. Moreover, pull factors could also represent the organizational context that would enable organizational stakeholders to deploy and utilize the WFA for value creation. We suggest that two factors will manifest in various degrees of "pull," resulting in a low, medium, or high level of organizational demand for WA.

Analytical Requests Derived From the Digitalization of Business Processes

The first pull factor concerns stakeholder requests derived from data and analytics because of the digitalization of business processes. With the arrival of "big data," any (growing) organization is undergoing dramatic changes in its business model, centered on how it creates and delivers value to its customers. Organizations pursue data-orientated approaches across all their business processes (including HR) to create opportunities to gain new knowledge about how to deliver *information-enriched customer solutions* (Minbaeva, 2021). Although the HR function lags "behind other functional areas of management in the adoption of analytics technology and in the analysis of big data" (Angrave et al., 2016, p. 9), WFA could definitely "ride the wave" of greater use of data and analytics by other business functions within the organization.

Greater use of data-oriented approaches in business function spurs curiosity among organizational stakeholders, who begin to ask questions like "what do we know about our own people?" or "can we connect our people data with business data?" This curiosity is contingent on organizational stakeholders' buy-in and attitude toward analytical decision-making and will considerably influence how sustainable WFA programs are built. For instance, at the low level of stakeholder requests, departments are beginning to evaluate how digitalization may enable workforce data to inform decision-making relevant to their functional challenges. As a result, stakeholders will be mainly curious about questions on "what," "how many," "who," or "what happened" and will aim to evaluate or benchmark the current state of their workforce through descriptive statistics. For example, BUs or organizational stakeholders may send requests to the workforce analyst or WFA function asking for a snapshot of diversity and inclusion metrics, employee engagement, performance, and job satisfaction (Falletta & Combs, 2020; Levenson, 2018; Margherita, 2022; McCartney & Fu, 2022b; Peeters et al., 2020). Other common deliverables for stakeholders would be basic reports or visualizations highlighting key HR metrics, including head count, number of hires, number of promotions, and turnover (Angrave et al., 2016; Levenson, 2018; van den Heuvel & Bondarouk, 2017).

In contrast, the digitalization of business processes may elicit more modest demands for organizations, raising expectations from the WFA function. In particular, at this medium level of requests, stakeholders are interested in identifying the root cause of challenges exclusive to their function. To do so, stakeholders ask the analyst or WFA team for answers to questions such as "why did this happen? or "is this good or bad?" Levenson and Fink (2017) and Peeters et al. (2020) classified this collaborative process between WFA and stakeholders as "organizational research" where the workforce analyst or WFA team will carry out research on specific business issues in line with the demands from their stakeholders. In situations like these, BUs may come to the workforce analyst or WFA function to evaluate predictors of employee engagement, collaboration, team satisfaction, or performance (Peeters et al., 2020). One example of this is analytics departments' critically examining internal collaboration patterns through network analysis a technique outlined in Chapter 3. Michael Arena, Dean, Crowell School of Business and former Vice President Talent and Development an analytics expert, said the following:

> We do a ton of network analysis where we're looking at interaction patterns and then using that to anticipate how to get people better positioned for performance, and how to think about idea flow across an organization . . . [network analysis] is a much deeper science than doing the more traditional how do you look at performance management or how do you look at even the flow of talent in an organization? It just requires a different level of thinking.

Finally, building on the previous two levels, organizations intent on completely digitalizing their business processes and integrating data with BUs from across the organization will focus on making predictions and generate actionable solutions from data. As such, organizational stakeholders will begin to ask questions about "what might happen next." For instance, according to Margherita (2020), stakeholders operating at this level of digitalization would ask the WFA team to use statistics and advanced algorithms to examine various data points to create predictions and run alternative scenarios for their business problems. Then, stakeholders ask for prescriptive analytics to determine "what should be done about it" and select the best course of action in line with the organization's strategy. For instance, Thomas Rasmussen stated the following:

> In my team, our goal this year was to demonstrate five different instances where we have had a significant impact on discussions and the decisions made to improve business outcomes. . . . If we can bring analytics to the table five times and significantly change the discussion and the decisions that we make, that is our outcome.

Similarly, at these higher levels, stakeholders expect WFA to link to BU proprieties and KPIs such as costs and employee experience. Maura Stevenson said the following:

> In my previous organization, we had very advanced operational training, and we had ten to twelve thousand courses completed every single day . . . So, we could do things like look at how many training courses you took and link course completion to unit performance.

Altogether, the organizations' desire to digitalize business processes and the subsequent requests derived from this digitalization are primary drivers in building organizational demand for WA. As each stage shows, increased digitalization shifts the demands and types of requests from organizational stakeholders and influences the analysis that the WFA function provides.

Analytical and Data-Driven Culture

The second pull factor that affects the demand for analytics from the WFA function is the degree to which the organization has an analytical and data-driven culture. How an organization embeds data and evidence into its values and culture will set the tone for how it will use analytics. For instance, organizations that have little interest in using data to support decision-making will require little in the way of analysis from the WFA function. In cases such as this, although the WFA function may provide reactive analysis, this is not the organization's main priority. In contrast, organizations that have a strong analytically driven culture focus on answering business questions using advanced methodologies and tools discussed in Chapter 3 to influence strategic decision-making and change management activities covered in Chapter 5.

In growing a data-driven culture, the mindset of a senior management team is decisive. In one midsize manufacturing company, the strength of its data-driven culture differed significantly because the company had had three different CEOs during the previous 10 years. A WFA specialist explained that, "Culture implies a CEO focus. If he or she has a focus on data and repeatedly requests data and evidence from all business-domain experts, then the culture eventually shifts." In this company, with the arrival of a new CEO who continuously focused on using data for improving strategic decision-making, the attitudes toward evidence-based decisions shifted over time, creating a culture of inquiry and a habit of making evidence-based decisions in the whole company.

Notably, in established and successful firms, a strong organizational culture could be difficult to manage because it is often associated with a strongly conservative mindset regarding the power of managerial intuition. This often masks general managerial discomfort with analytics and a lack of understanding of how to interpret findings from analytics projects. In such companies, the challenge for WFA functions is to act as effective boundary spanners to gather, filter, and deliver a wide range of knowledge across the organizational boundaries, ultimately fostering the creation of trust and maximizing organizational buy-in.

Overall, although WFA functions may aspire to be higher in their maturity, it is important to stress that this alone may not warrant this investment in WFA capabilities. Rather, it is this equilibrium between push and pull that should determine the investment in furthering or remaining at the desired level of WFA capability. In other words, organizations that significantly invest in WFA maturity but have little organizational demand will see no benefit and vice versa. Taking this a step further, it is important to note that maturity levels of the WFA function are not idle; rather, organizations and HR departments can evolve and attain higher levels of WFA maturity at their own pace (Margherita, 2022) as long as the demand for such activity aligns with the overall WFA strategic goals and outcomes of the organization while maintaining WFA equilibrium.

Building the Workforce Analytics Function

So far in this chapter we have offered an overview of WFA maturity as it relates to the ACAI Model and have demonstrated how the two competing dimensions of level of WFA capabilities and organizational demand for WA, influence the formation of WFA capabilities. In addition, we have detailed the individual push and pull factors that make up each of these dimensions. In the final section of this chapter, we will integrate the application of the logic of demand and supply—the push and pull factors—discussed within the context of progressing the WFA function. We will also illustrate how a point of equilibrium between “push” (supply) and “pull” (demand) defines the structure of WFA functions.

Although limited research exists concerning WFA functions, researchers have begun to illustrate how they may be structured in industry (Kaur & Fink, 2017; Peeters et al., 2020). According to Peeters et al. (2020), the internal WFA team structure will stem from the WFA leader responsible for several specialists or experts. This WFA leader has the autonomy to divide the team into several subspecializations, including reporting, advanced analytics, and visualization, to meet the needs of their stakeholders effectively. For example, according to Kaur and Fink (2017), organizations may choose to structure their teams around three categories of work which closely align to the ACAI Model presented at the beginning of this book. First, infrastructure and reporting refers to the individual team members responsible for the administration and maintenance of the human capital system, including maintaining data quality and running specialized reports on business metrics and KPIs. Second, advanced data analysis refers to employing individuals who perform tasks greater than reporting on KPIs or basic statistics. Third, organizational research includes team members focused on designing studies or experiments to address particular business challenges.

During our interviews with WFA professionals, many expressed similar views on how they structured their teams based on the various required capabilities and skill profiles. For example, Thomas Rasmussen stated the following:

> We have a relatively small team of five people. We have a person leading it. Then we have a lead senior data scientist who does all the advanced analytics and can also code. So, very much on the data science side of things. There is also a role which is more somewhere in between data manipulation, reporting,

> and analytics, not on the advanced side, but focused on data extraction, data merging, all that stuff. And then there is a role supporting that role who is a bit more junior, and then there's a person essentially running all of our surveys and so exit surveys onboarding surveys, employees surveys.

Heather Whiteman suggested that, depending on the mindset of the team leader, teams can be divided into or thought of from two perspectives: (a) what team members' roles will offer the business, or (b) what tasks the team members will perform daily. She stated the following:

> The way I think of it is not how [team members] spend their days but what they do for the organization. Other workforce analytics leaders will structure their functions more based on how they spend their time. So, they'll tend to bucket them in more of a reporting-type role. More of an analyst-type role. More to a scientist-type role. Maybe even a researcher-type role, and it's just a slightly different mental approach to how we think about the roles.

As can be seen, configuring the WFA function in a way that aligns to the ACAI Model is a critical step for any organization looking to incorporate data and analytics into its decision-making process. However, contrary to existing logic and research outlining how to build effective WFA functions, we argue that each organization and WFA function is dynamic and fluid and, therefore, may have different configurations and numbers of members. As such, when deciding upon the right "mix" the strength of the "push" and "pull" factors will play a significant role in determining the makeup of the team, causing teams to vary considerably in size and roles. We argue that, although in some cases forming a team as the practitioners described may be the right "mix," this might not always be the case for other organizations facing different levels of push and pull factors.

Consider three different scenarios visualized in Figure 2. Scenario 1 is typical for an organization with a basic setup of WFA function: usually, there will be just one or two employees managing multiple data input, often in Excel. The development of WFA function is "pulled" by business functions other than HR, usually because of the established habits of using data for business decisions. For example, a telecommunication firm was heavily reliant on data analytics in understanding customer experience. Data analysts from the sales and marketing departments reached out to HR with a request for workforce data to test for correlations between employee engagement and customer net promoter score. The firm was not interested in developing its WFA capabilities, but the use of WFA grew with developments in other business areas. Such organizations find themselves at the aspiring level of WA, with some demand for WA, a nonexistent data culture, and small business operations. This would warrant a structure of a single analyst (see Scenario 1 in Figure 3).

-INSERT FIGURE 3 AROUND HERE -

A firm in scenario 2 has been regularly providing the insights generated by advanced operational reporting, has created multiple dashboards for different levels of management, and has been developing an understanding of WFA among human resources business partners (HRBPs). Through much closer integration with the business strategy, the WFA function is establishing an ongoing dialogue with the executive team regarding the strategic development of the workforce needed to enable strategy implementation. Strategic workforce planning becomes a must-have tool in the managerial portfolio of team leaders. In this context, WFA functions are usually structured around two main organizational pillars—reporting, including data management, and advanced analytics (see Scenario 2 in Figure 3).

Scenario 3 describes advanced development of the WFA function. Such moves are typical for firms going through strategic digital transformation. The insights WFA generates are considered as inputs for automation, and the WFA function plays a key role in augmentation processes toward producing an AI-based, structured ML algorithm.

Given well-established WFA capabilities and strong organizational demand, WFA leaders in such organizations will be required to assemble a WFA team with diverse skills (Fernandez & Gallardo-Gallardo, 2020; Huselid, 2018; Jörden et al., 2021; Peeters et al., 2020). In this scenario, as stakeholder requests increase, more advanced forms of insights linked to BU proprieties and KPIs to address short-term and long-term business needs are required. Consequently, this demand forces WFA functions to employ different configurations of team roles and capabilities and engage with external experts to bring in more advanced technical knowledge (see Scenario 3 in Figure 3). Low-level reporting tasks are usually outsourced as well.

Conclusion

Recent growth in WFA adoption and advancements in HR technology have enabled HR departments to leverage data to make evidence-based decisions. However, despite significant scholarly attention, it remains unclear what key ingredients are required to build organizational capabilities in WA. Accordingly, in this chapter we detailed the various “push” and “pull” factors as they relate to the ACAI Model to develop organizational capabilities in WFA at each stage of the WFA journey. Overall, to fully realize the potential of WA, these “push” and “pull” factors should be in equilibrium so that WFA capabilities reflect both the maturity of WFA function and the organizational demand and appetite for WA.

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Figure 1. *Workforce Analytics Maturity Matrix*

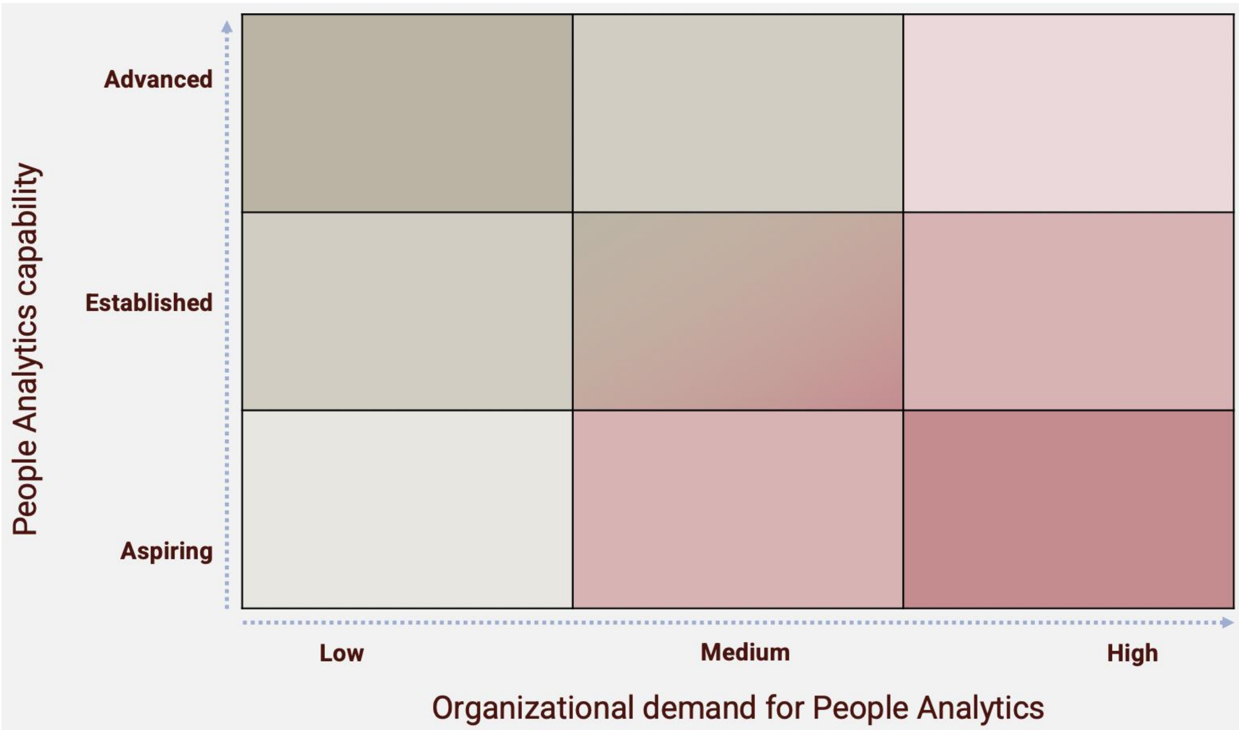

Figure 2 *Workforce Analytics Maturity Matrix: Three Scenarios*

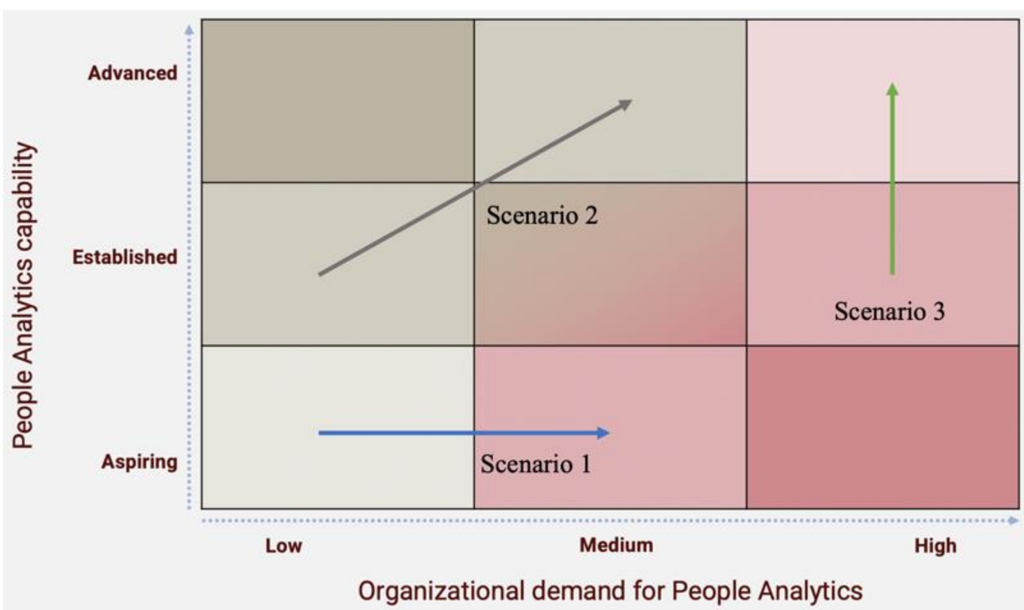

Figure 3
Examples of WFA Function Configuration

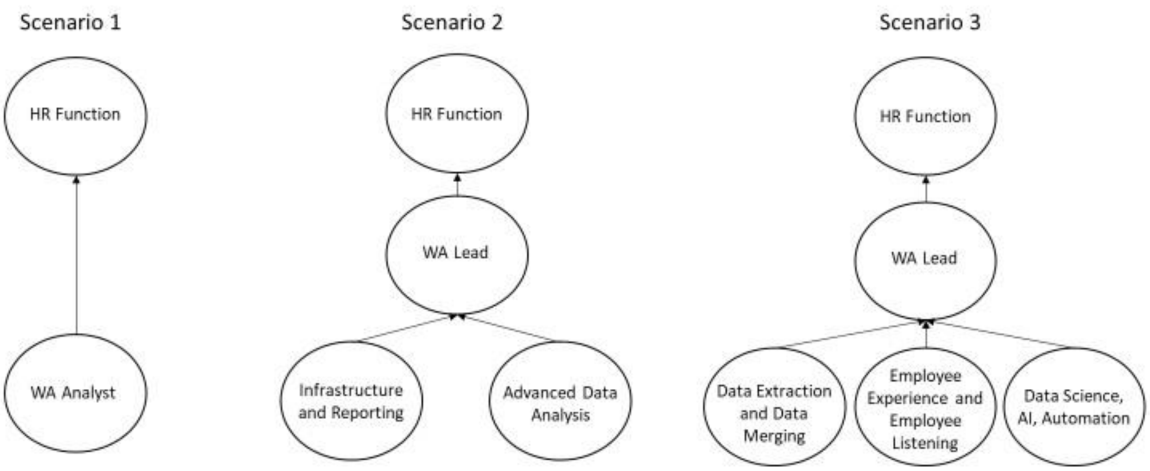

Table 1

Levels of WFA Capabilities

	Aspiring	**Established**	**Advanced**
Analytical Competencies:	Uses reporting tools via HCM interface, basic visualization skills. Is an Excel superuser.	Enables trusted diagnostic reporting and delivers insights via dynamic BI tools.	Bespoke predictive analytics, produced with SPSS, Stata, R, Python, or similar software; open to experimentation with AI and ML.
Data Quality and Processes:	At best, uses clean and reliable data, typically from just a single source (e.g., HCM system).	Uses data from multiple sources, which are organized and transformed within a single environment, e.g., DW/SQL.	Uses structured and unstructured data from across business functions, with high-volume data processing tools.
Business Partnering Ability:	Delivers basic HR reporting leading to increased understanding. Limited decision-making impact.	Offers advanced insights to leaders and HRBPs that may guide some operational and tactical decision-making.	Influences business planning or HR strategy. Offers tactical sparring and hypothesizing about foreseen HRM issues.

Table 2
Organizational Demand for WA

	Low	Medium	High
Analytical Requests Derived from the Digitalization of Business Processes:	Reporting figures (e.g., head count trends, hires, promotions, and exits), internal comparisons. Teams or functions review HR data	Linking HCM KPIs to organizational priorities (e.g., time to hire). Linking HCM practices to costs using external benchmarks, insights into employee experiences. Functions or BUs apply insights.	Knowledge about internal collaboration patterns and networks. Linking the root causes of HCM issues to business outcomes. Forecasting, simulating HCM impacts of business scenarios. BUs or enterprise adapt significant changes.
Analytical and Data-Driven Culture	Limited implementation of data and analytics for decision-making. Decisions based on personal experience rather than evidence. Reactional decision-making processes.	Functional or BU decisions based on data and analytics. Analytics focus on answering functional or unit challenges. Analytical and data-driven culture enacted by functional or BU leader.	Strategic business decisions encompass data from all facets of the organization. AI and ML outputs highly influence strategic decision-making and change management activities.