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DATA & ANALYTICS

FOR INSTRUCTIONAL DESIGNERS

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Introduction

I've been working in L&D since 2002, when I helped a large healthcare organization implement their first learning management system (LMS). It was the software company's first LMS, and mine too. These were the early days of SCORM (sharable content object reference model). The e-learning industry was about to take off as the advent of rapid authoring tools and LMSs began to democratize access to scale.

In 2012, I learned about Project Tin Can, which would create the Experience API, or xAPI. Our team at TorranceLearning had been seeking a learning and performance environment that offered a richer and more varied learning experience, and a correspondingly interesting data set. We were stretching our technical muscles. Our instructional designers were grappling with the new grammar of reporting data in a repeatable but not-yet-standardized environment. We were asking our LMS team: Shouldn't this do xAPI, too? (The answer: Why, yes, yes it should.)

In 2014, we launched the Ann Arbor Hands-On Museum's Digitally Enhanced Exhibit Program (DEEP). Student groups on field trips would use beacons to identify themselves to the networked tablets placed around the museum. They engaged seamlessly with interactions and questions that would be recorded by exhibit and curriculum standard. At the end of the visit, teachers would receive a stack of reports about their students' activities and engagement, and each student received a personalized one-page report detailing their field trip to the museum. This was exciting stuff. We often kept coming back to the question: What can we do with all this data? How can we take advantage of it? What insights might lie in there?

In 2015, our team took on the duty of hosting the Advanced Distributed Learning (ADL) group's cohort model for introducing innovators to xAPI. We started our first 12-week xAPI Learning Cohort with a group of 35 invited designers and developers in the fall of 2015, and ran two a year for the next seven years. Cohorts routinely exceeded 600 members each semester and the projects that teams took on ranged from e-learning to gaming to chat bots to virtual classroom to Alexa and everything in between. As of this writing, more than 5,000 L&D professionals have participated in the xAPI Learning Cohort.

As cohort members and organizations adopted xAPI and other data-rich learning experiences, we kept coming back to the question, "What can we do with all of this data?" That's what this book sets out to help you answer.

How L&D Can Use Data

In the early days of the COVID-19 pandemic, the L&D team the UK arm of PriceWaterhouseCoopers used their analysis of search requests on the organization's learning experience platform to identify the needs being faced by their staff and managers. This allowed the L&D team to respond very quickly, almost at a week-by-week pace, to these emerging needs.

At LeMoyne Institute in upstate New York, the learning design team used detailed data from a learning experience to fine-tune the screen design for an adaptive e-learning curriculum. By simply changing the layout of the screen, they could improve relevant performance in measurable ways.

QuantHub, a learning experience platform focused on data science, uses data to personalize learning across a competency map used by major organizations to upskill their professionals.

At Trane technologies, learner and manager feedback are combined with employee engagement survey results to prove the positive impact of their leadership courses. This data is used to obtain additional budget to continue running the program, as well as to attract new learners to the experience.

And as interesting as these quick case studies are, there are countless organizations using data and analytics in similar ways to identify learning needs, hone the design of their learning experiences, personalize learning in new ways, support decisions, and evaluate the impact of learning. We'll hear from several of them in this book, at the end of each chapter.

Why an L&D Book on Data and Analytics?

This book tackles an unaddressed need in the market for workplace learning and talent development.

First, there are lots of books, articles, courses, and academic degrees in data and analytics. However, I find they tend to be focused on the marketing, sales, or operational aspects of a business, where the data is rich and the metrics are commonplace. It's not very often that I see an analytics case study that addresses the kinds of data we are using in L&D.

Second, with K–12 and higher education maturing in their use of learning management systems, and the popularity of the MOOC (massive open online course), the academic field is investing in student analytics. There is much to be learned from our academic colleagues for sure, but their analytics work doesn't fully account for the workplace setting.

Third, there are handfuls of books about learning measurement in the corporate space, going into the familiar evaluation levels developed by Donald Kirkpatrick, Raymond Katzell, and Jack Phillips, and beyond them to address the culture and practice of regular data gathering, analysis, and reporting. In fact, if this is your interest, I strongly recommend *Measurement Demystified* by David Vance and Peggy Parskey (2021) and *Learning Analytics* by John Mattox, Peggy Parskey, and Cristina Hall (2020).

Missing across these resources is a focus on the unique data that is attainable in the corporate learning space at a granular level, as well as specific direction for instructional design teams about how to generate this data to feed the downstream uses.

Why? I'm sure there are several reasons for this. Chief among them is that in L&D we tend not to have as much data at our fingertips as other functions in the business, and therefore tend not to use data to drive our decisions. In most organizations, finance, sales, and operations all have very granular data available within a few clicks to drive their decision making. In L&D we have training completion data: Did learners complete the training? When? How long did it take? What are the test scores? Did they like it? Are they motivated to apply it?

We tend not to have good insight into the learning experience itself. For example, what did they click on? What did they do in class? How many times did they practice? Who gave them feedback along the way? Nor do we have good insight into what happens after the learning event: What outside sources did they use to fill in any remaining gaps in their knowledge? Did they use the job aids we gave them, and did that make any difference? How did they perform on the job after training? Did their manager support them?

As an industry, what we gained as we adopted SCORM and LMSs was a globally standardized, interoperable, interchangeable way of managing the learning function. This allowed for the rapid rise of formalized and yet distributed training delivery and the growth of this industry. With the technologies available at the turn of the 21st century, the institutionalization and globalization of business, and the interoperability offered by SCORM and LMSs came a shallow data set focused on the completion of event-based training. That was fine for its time, but didn't evolve as fast as other organizational functions, creating a sort of vicious cycle: We can't make data-driven decisions because we don't have rich data.

Don't Be Afraid of the Math!

Before we get deep into the weeds of data and analytics, I want to bring your attention to the fact that we're about to encounter something that looks a bit like math. I have found that the L&D profession is not rife with mathematicians, so this might start to trigger what's commonly known as “math anxiety” for you. Let’s pause for a moment and see if we can alleviate some of that.

Sarah Sparks, senior research and data reporter for *EdWeek*, wrote:

> *Emerging cognitive and neuroscience research finds that math anxiety is not just a response to poor math performance—in fact, four out of five students with math anxiety are average-to-high math performers. Rather, math anxiety is linked to higher activity in areas of the brain that relate to fear of failure before a math task, not during it. This fear takes up mental bandwidth during a math task. . . . In turn, that discomfort tends to make those with math anxiety more reluctant to practice math, which then erodes confidence and skill. In part for that reason, anxiety has been linked to worse long-term performance in math than in other academic subjects like reading.*

Here most of us are, having accumulated years and perhaps decades of avoidance of math. And as we saw in the prior section, L&D’s historical tools, platforms, and analysis do not require or even afford us the opportunity to do much math beyond the occasional averaging of some course evaluation data. It’s OK if you’re feeling anxious.

And don’t worry, we’re not going to spend a lot of time doing a lot of math. L&D data analytics isn’t about trying to multiply three-digit numbers without a calculator. In fact, a lot of the actual calculations are automated, and, even when they’re not, you have a computer to assist.

What we are going to do is provide the tools and some awareness of the concepts that you’ll be working with, perhaps in partnership with fellow professionals who are more experienced in these spaces.

Do you need to become a statistician to do data and analytics? No, I don’t believe so. However I do believe that having a working knowledge of the concepts will help you get started on your own, make you a better partner to team members who have these skill sets, and tip you off when you would be better served to consult someone else with this expertise.

This is very similar to the conversation our industry had a decade ago about whether or not instructional designers needed to be able to code. In my opinion, they do not; however, they do need to have a functional appreciation for computer science to collaborate effectively.

So, in the first part of the book, we'll cover the basics of why you should care (chapter 1), level setting with definitions (chapter 2), data specifications (chapter 3), L&D-specific data metrics (chapter 4), and a little bit of statistics terminology (chapter 5).

And if, as Sparks points out, this anxiety stems from a fear of failure that occurs before you even get started, I'm going to ask you to live with that discomfort just long enough to learn through the experience and perhaps get over a little bit of that trepidation about using analytics.

What Does It Mean to Design for Data?

> *We all know that data is knowledge, and knowledge is power, but once we have access to it and realize that it is, indeed, oceans of data, how do we not "drown" in it, and, perhaps more importantly, how do we make sense of it?*
>
> —Marina Fox, GSA's DotGov Domain Services,
> Office of Government-Wide Policy (OGP)

After we lay down the foundations of learning data and analytics, we will start to take a look at the process for actually getting and using data in part 2. First, we'll talk about making a plan for what kinds of data you will gather, including aligning with organizational metrics and many of the common learning and development frameworks that we use for analysis (chapters 6 and 7).

Next, we'll dive into forming your hypothesis from the questions you need to answer with data (chapter 8). We'll then take a look at actually identifying the data needs that will serve those purposes (chapter 9), building the data capture into our learning experiences so we actually get the data we need (chapter 10), and collecting and storing it (chapter 11).

At this point many people will arrive at what I have in my own projects referred to as the moment of "Oh my gosh my baby is ugly!" This is where you have collected some data, made some analysis, and realized that what you really wanted to answer was something other than what you just did. Here's where the fun begins as you iterate on the learning and data experience by looking at what you have gathered, and then fine-tuning it (chapter 12).

Many people conflate the visualization of data with the analysis of data. And up until this point, we haven't talked about visualizing data at all! We'll spend a little bit of time talking about how we communicate and visualize data in chapter 13. This is another one of those places for which dozens upon dozens of wonderful resources exist, so this book will cover it on just a very high level.

Finally, we'll take a look at what it means to scale up your analytics efforts, moving from one or two pilot projects to a future enterprise-wide state. There are few organizations at this stage as of the writing of this book, so the future is full of opportunity for you to define it.

How This Book Will Help You

This book takes an "If I can see it, I can be it" approach to learning data and analytics. In my work helping organizations adopt xAPI, I am frequently asked for case studies. The questions sound like "Who's really doing it?" "How does that actually work?" and "That sounds great, but can you share an example so I really know I'm getting it?"

My emphasis in this book will be not only on practical what-is and how-to content, but also real-world examples and longer case studies from practitioners. In some cases, I'm telling the story. In other cases, the people who have built it and lived with it share their story in their own words.

Each chapter will conclude with opportunities for you to put these techniques to work right away, whether you are in a data-rich environment already, or are just getting started and working on hypotheticals. These opportunities to give the concepts a try are a valuable part of extending your learning beyond the pages of this book and into the real world all around you. If you are learning with your team, these activities can be done in pairs or in small groups for shared learning impact.

As much as I would love to offer you a book with immediate practical value to your own work, it's entirely possible that you don't yet have the data necessary to apply these concepts right away. As such, the "give it a try" ideas at the end of most chapters include reflections and hypotheticals to let you dig in right away, even though they might not reach your loftiest aspirations just yet.

And while I aim to be definitive whenever possible, remember there are very few hard and fast rules. Simply, a lot of it depends. So, at the risk of sounding like I'm unable to make a firm decision in offering advice, I find that the very interesting questions in life often have multiple right answers. The "rightness" depends on your situation, your needs and capabilities, what you have access to right now, and what your leaders deem makes sense. And, some of the most complex "right" answers change over time.

Let me also note that this isn't a book about xAPI. While I believe that the widespread adoption of a rich and interoperable data specification is good for the industry, individual professionals, and organizations buying products and services, I also realize that xAPI is not the only way to work with learning and performance data.

Whether you're using xAPI that far extends the capabilities of SCORM to track learning, practice, and performance activity or another data model, we have the ability to get our hands on far more plentiful, granular, and interesting types of data. That's what this book is about: what data to get, how to get it, and what to do with it once you have it.

So, let's get some data!

PART 1 THE FOUNDATIONS

Chapter 1

Why Should Instructional Designers Care?

It's hard to pick up a business or organizational effectiveness publication these days without seeing multiple articles that refer to the use of data in the process of improving results. You may have heard these and other variations of these phrases:

- What gets measured gets done.
- What gets measured improves.
- What gets measured gets managed.

In other words, the ways that we prove that we have accomplished our goals is by measuring them. In turn, in the data-driven organization, the departments that are able to gather, process, analyze, and use data will be the ones that will gain influence.

At the same time, I can argue that a singular focus on data-driven results may lead to gaps in understanding and result in errors in judgment. Consider Chris Anderson's words, "There is no guarantee that a decision based on data will be a good decision." And this from Simon Caulkin, summarizing a 1956 VF Ridgeway article in *Administrative Science Quarterly*: "What gets measured gets managed—even when it's pointless to measure and manage it, and even if it harms the purpose of the organization to do so."

The goal of this book is not to encourage you to focus solely on data and analytics as a source of insight for decision making, but rather to use it as one of several sources of insight.

But this gets us to the question of why instructional designers and L&D professionals should care about data and analytics in the first place. We should care because our organizations care. We should care because . . .

Digital Transformation Is Everywhere

CIO magazine offers a commonsense definition of *digital transformation*: "A catchall term for describing the implementation of new technologies, talent, and processes to improve business operations and satisfy customers" (Boulton 2021).

And while you may be thinking, "We've been digitizing work for half a century" (and you would be right), organizations are still reimagining the use of technology, the skills of their people, and their business processes. Digital transformation includes both delivering value to customers and channel partners through new software and processes (such as e-commerce, mobile, social, and cloud-based solutions) and gathering data from those interactions to form insights and improve results.

L&D is ripe for digital transformation. Gathering analytics on the incoming data will be a key component of this shift.

Consumer-Focused Software Is So Good at What It Does

One of the results of digital transformation is that as consumers we all use digital tools that have far more sophistication than ever before. Our learners, or employees, are used to interacting with software that is highly personalized to their needs, makes useful recommendations, and adapts overtime. All of this is possible because of the data that is gathered at every interaction.

In their personal lives, our learners interact with very smart apps that are designed and informed by software designers using analytics. But when people get to work, the learning and performance tools they interact with seem far less mature.

We Will Need to Improve in How We Use Data

As a result, data literacy is an emerging skill. In ATD's Talent Development Capability Model, under the Impacting Organizational Capability domain, lies the data and analytics capability. According to the model, "Discerning meaningful insights from data and analytics about talent, including performance, retention, engagement, and learning, enables the talent development function to be leveraged as a strategic partner in achieving organizational goals" (ATD 2019). Skills for this capability include developing a plan for data analysis, gathering and organizing data, analyzing and interpreting analysis results, and selecting data visualization techniques.

Gartner Group defines *data literacy* as "the ability to read, write, and communicate data in context, including an understanding of data sources and constructs, analytical methods, and techniques applied; and the ability to describe the use case, application, and resulting value. Further, data literacy is an underlying component of digital dexterity—an employee's ability and desire to use existing and emerging technology to drive better business outcomes" (Panetta 2021).

Whereas in the past instructional designers have focused on performance outcomes and the delivery experience, we will now need to also attend to the data and how that informs our work. We have the opportunity to explore how well the learning experiences we design perform in the field, how people interact and engage with them, and whether or not they lead to improved performance on the job. The insights we gather from this exploration will absolutely inform our design work.

We Need the Insights for Continuous Improvement of the Learning Function

In *Measurement Demystified,* David Vance and Peggy Parskey (2021) offer this list of reasons why we measure in L&D:

- Improve programs.
- Establish benchmarks.
- Communicate findings.
- Monitor results.

- Manage operations.
- Discover insights.
- Analyze results.
- Ensure goal accomplishment.
- Demonstrate process.
- Inform stakeholders.
- Evaluate programs.
- Assess value.
- Plot trends.
- Identify success rates.
- Assess gaps.

This is quite a list! As professionals, we are constantly curious about how we are performing in our work, how we compare to the past and to our peers, how can we make changes in the future to better serve our learners and our organizations, and how to communicate our value to the rest of the organization. All of this can be done with data.

It's no longer sufficient to simply create a learning experience and put it out into the world for people to consume without gathering data about its effectiveness, efficiency, or outcomes. In small L&D teams or "team of one" situations, instructional designers must include some aspect of learning data and analysis in their work. On larger teams, a dedicated measurement and analytics team may complete this task. Without some degree of rigor in our data collection and analysis, we risk having only anecdotal evidence of impact, missing out on opportunities to improve and becoming irrelevant.

We Will Need to Design Experiences to Collect Data

While we will be using data to inform our work, we will also need to design our learning experiences in ways that enable the effective and efficient capture of that data. It is one thing to want to know how a learner interacts with a particular piece of content, and an entirely different thing to be able to design for the capture of that interaction with the content. We will explore this aspect of designing for data in chapter 10, "Build in Data Capture."

Where Do We Stand in L&D?

Other functions in most organizations operate with far more data than the L&D function is accustomed to using. This an interesting phenomenon. Whereas the L&D industry has had a common interoperable data specification for more than 20 years (SCORM), and most other functions do not have such a vendor-agnostic specification, we tend not to have the richness of data that these other functions have. SCORM has enabled the e-learning and LMS segments of our field to grow in volume and number of vendors. It has enabled both great fragmentation as well as ease of consolidation, creating an environment in which the market is very fluid for buyers and has very few barriers to entry for suppliers.

However, the shallowness of the data available from SCORM, and the fact that it is only available for e-learning content that is launched from an LMS, has left our industry with a lot of surface-level data, leading to our current predicament. Three solutions are emerging in this space:

- Elegant all-in-one learning platform solutions offer rich learning experiences and deep analytics on the data they generate. These software platforms expose us to the power and promise of data and analytics in our space. However, since most organizations have multiple platforms and environments in which learning takes place, the full picture of learning and performance data may be invisible to these systems.
- A new free, shared, global specification for learning and performance data interoperability, the Experience API (xAPI) offers the richness that SCORM lacks. With xAPI, we can track nearly any learning or performance experience at very granular levels of detail and still retain the data's marketplace fluidity and vendor-agnostic nature. xAPI Learning Record Stores (LRSs) provide the analysis and visualization tools to pull this data together.
- Some organizations are pulling all their data from multiple learning experiences regardless of format or data standard and exporting it to business intelligence tools for analysis.

There is no one right approach, and the three listed here are an oversimplification of the current and future possibilities. What is clear is that as a function and an industry, we are relatively new to the data and analytics space. As a group, we're a bit behind, but we can catch up quickly using the tools and skills that have been developed in other functional areas.

What Kinds of Data Drive Decision Making?

Data is used in nearly every industry and every function to improve performance. These lists are examples of the kinds of measures and metrics used. (The difference between *measures* and *metrics* is defined in chapter 2.)

Sales Metrics

- Annual recurring revenue
- Average revenue per user
- Quota attainment
- Win rate
- Market penetration
- Percentage of revenue from new versus existing customers
- Lifetime value (LTV) of a customer
- Average profit margin
- Conversion rate
- Sales cycle length
- Average deal size
- Year-over-year growth
- Deal slippage

Finance Metrics

- Earnings before interest and taxes (EBIT)
- Economic value added (EVA)
- Current ratio
- Working capital
- Debt-to-equity ratio

- Contribution margin
- Customer satisfaction
- Liquidity ratio
- Return on equity
- Days in accounts receivables
- Net cash flow
- Gross profit margin
- Transactions error rate

Human Resources Metrics

- Time to hire
- Cost per hire
- Employee turnover
- Revenue per employee
- Billable hours per employee
- Absenteeism
- Cost of HR per employee
- Employee engagement
- Cost of training per employee
- Diversity and EEOC numbers

Customer Service Metrics

- Average issue count (daily/weekly/monthly)
- First response time
- Average resolution time
- Number of interactions per case
- Issue resolution rate
- Preferred communication channel
- Average handle time
- Self-service usage
- Backlog
- Average reply time
- Customer satisfaction score

Healthcare Metrics

- Number of medication errors
- Complication rate percentage
- Leaving against medical advice
- Post-procedure death rate
- Readmission rate: hospital acquired conditions (HACs)
- Average minutes per surgery
- Average length of stay
- Patient wait times by process step
- Doctor–patient communication frequency
- Overall patient satisfaction
- Patient-to-staff ratio
- Occupancy rate

Hospitality Metrics

- Energy management
- Labor costs as percent of sales
- Employee performance
- Gross operating profit
- Occupancy rate
- Average daily rate (ADR)
- Average room rate (ARR)
- Revenue per available room (RevPAR)
- Net revenue per available room (NRevPAR)
- Revenue per occupied room (RevPOR)
- Gross operating profit per available room
- Marketing ROI
- Online rating
- Customer satisfaction
- Loyalty programs

Manufacturing Metrics

- On-time delivery
- Production schedule attainment
- Total cycle time
- Throughput
- Capacity utilization
- Changeover time
- Yield
- Scrap
- Planned maintenance percentage (PMP)
- Uptime/uptime + downtime
- Customer return rate
- Overall equipment effectiveness (OEE)

Childcare Metrics

- Child abuse indicator
- Immunization indicator
- Staff–child ratio and group size indicator
- Staff training indicator
- Supervision or discipline indicator
- Fire drills indicator
- Medication indicator
- Emergency plan or contact indicator
- Outdoor playground indicator
- Toxic substances indicator
- Handwashing or diapering indicator

Technology Metrics

- Defect density
- First response time
- Function points
- Incidents

- Information security scores
- IT overhead
- IT risk score
- IT security training rates
- Noncompliance events
- Patch rate
- Planned downtime rate
- Project cycle time
- Security overhead

What Could Possibly Go Wrong?

In the chapters to come, I'll highlight some of the common missteps in each area (or some glaring ones with big consequences, even if they're not common). I'll also offer two or three opportunities to try out the concepts, with both hypothetical and real-world challenges. This way you'll have a chance to practice or reflect, even if your current job role doesn't offer much opportunity to work with data (yet!).

What could possibly go wrong? You skip over the activities and don't give yourself the benefit of these experiences to support your learning with this book. It's your choice!

Give It a Try

Here's a Hypothetical

Leverage the consumerization of data-driven apps to examine the use of data in your daily life. Choose a piece of software or an application that you're familiar with and see how many of these questions you can answer:

- What data is being gathered?
- How is the data gathered and stored?
- What kinds of insights might the company being making from the data?
- What kind of data is not being gathered but might also be useful?
- What do I, as a user, get from this data?

Do It for Real

It's entirely likely that if you are reading this book, you are also on the lookout for experts, articles, podcasts, and conference sessions on data analytics in L&D. As you do so, take a structured approach to your learning. Here are some questions you can ask about the case studies you discover on your hunt (including the ones in this book):

- What data is being gathered?
- How is the data gathered and stored?
- What kinds of insights were derived from the data?
- What kind of data was not gathered but might also have informed this decision?
- What do the learners get out of this?
- What is the next iteration of this work?

Bonus Points

Reach out to someone in your organization (outside the L&D function) and ask them how data is used in their work. Use as many of the questions from the two lists here as are relevant to your conversation.

Using Analytics to Improve Video Design

By Josh Cavalier, Owner, JoshCavalier.com

Some years ago, I released a series of training videos on YouTube. The learning objective was to transfer knowledge about specific functions within e-learning authoring tools. This was the first time I had used YouTube, so I had no idea if the format would be successful, the content was appropriate, or the audience was even interested in watching the entire video. I also wanted to leverage YouTube's analytics to make format adjustments and other improvements to future videos.

YouTube's platform provides rich data points, including audience retention over time, the geographic distribution of views, and total view count. All of this is available when viewing your video in YouTube Studio and navigating to the Analytics tab. You can immediately see the number of views and audience retention.

For me, the most insightful data point from YouTube is audience retention over time, which measures if a viewer stays or leaves the video at that moment in time. Interestingly, this specific piece of data will also track when an audience member scrubs to a different part of the video. Retention will drop as they scrub the playback head, and retention will gain when they stop at a point in the video that piques their interest. You can also check relative retention, which will compare your video to all the other videos on YouTube with a similar length.

I use this data to design better videos. For example, I learned not to list learning objectives as animated bullet points at the beginning of a training video. Our audience retention would drop 45–65 percent during the first 30 seconds when we displayed the learning objectives in this format. Viewers would constantly scrub to see the result of the steps we were describing, so it was easy to adjust to visually show the results while describing the goal of the video at the beginning.

Using Analytics to Evaluate Program Performance

By Becky Goldberg, Learning Analyst, Travelers Insurance

Travelers hires experienced underwriters, but our focus on underwriting excellence and our extensive client base makes it challenging to source all our talent needs through the open market. We also value tenure and employee development, and providing upskilling opportunities is a priority for our organization. The Underwriting Professional Development Program (UPDP) is designed to teach professionals with little to no insurance background how to be independent underwriters in the business insurance segment. UPDP is a two-year course of study that learners can complete while working in their business units in supporting roles. Part of our evaluation and program modification analysis is to compare participants' performance with their peers who did not go through the program.

All underwriters' performance is evaluated, among other metrics and feedback, based on the performance of their book of business. This is reflected on a dashboard our managers use to provide coaching and performance feedback.

UPDP graduates are identified through an HR indicator, allowing us to compare their performance with their non-program peers. Tapping into the dashboard that's already being used to evaluate underwriter performance allows us to evaluate the program's overall success, and tracking individual UPDP performance correlated to their training participation performance helps us identify which learning experiences were the most impactful.

We track the following data for this program:

- Completion of learning activities
- Participation in graduate advanced learning offerings (such as a three-year graduate conference)
- Performance data: How well the individual's book of business does in comparison with their peers' books of business
- Retention data: How long do UPDP graduates stay with Travelers as compared to peers

After collecting the data for the UPDP program, we determined that graduates have a faster time to proficiency than non-program new hires. UPDP graduates also stay with Travelers longer than their non-program new hire peers. Those who are still with Travelers three years after graduating from the program are invited to a VIP graduates' conference, which is attended by senior leaders and offers advanced development opportunities. This conference has also boosted the length of time UPDP graduates stay with Travelers.

Even pre-pandemic, we had been transitioning more of the program to a virtual, self-study format. We're now evaluating if the move to on-demand training has an impact on the quality of the results. Currently, we're using extensive xAPI data to determine the length of time people spend in the self-study modules and the average length of time to complete segments of the program. This data will help us understand if there's time-saving potential over instructor-led training. We also expect to see cost savings in the reduction of travel expenses of bringing the cohorts together from all over the country.

UPDP provides an avenue toward career development for individuals who would otherwise have limited opportunity to establish an underwriting career. Many of our participants start with Travelers in a service partner role at an hourly rate. Others enter the program directly from school, and in two years' time are set up with a full book of business. UPDP is one of our strongest responses to the competitive hiring landscape and the need to upskill, grow, and retain top talent. We're able to demonstrate the value of the program by contemplating all aspects of our performance: If we only looked at assessments and consumption data, we'd miss the big picture that our development program produces better quality books, reduces turnover, and positions Travelers as a place people want to stay their whole career.

Acknowledgments

> *"We are uncovering better ways of developing software by doing it and helping others do it."*

The acknowledgments of my previous ATD Press book opens with this quote from the Agile Manifesto, and it seems fitting for this book as well. As practitioners, leaders, and members of the community of professionals, we are uncovering better ways of accomplishing our work by doing it and by helping others do it. In this case, we're uncovering and sharing better ways of using the data at our disposal to create better learning experiences, more capable and confident people, and more successful organizations.

The work this industry is doing now to come up to speed with a more data-centric world means we're all learning together, and the process of researching and writing this book has an iterative and collaborative experience.

> *"If you want to go fast, go alone. If you want to go far, go together."*

This proverb means so much to me on so many levels. Here, we are going far and we're doing it together. In my work with xAPI, I am often asked for examples of who's doing it "for real." Having case studies from a variety of sources, industries, and experiences was something that I knew was going to be very important for this book. I so appreciate the time and care that the contributors spent to share their stories so generously for this book: Josh Cavalier, Becky Goldberg, Emma Weber, Ben Betts, Tammy Rutherford, Andrew Corbett, Derek Mitchell, Tiffany Jarvis, Kimberly Crayton, Rodney Myers, Brent Smith, Wendy Morgan, Janet Laane Effron, Ulduz Berenjforoush Azar, Stella Lee, Matt Kliewer, John Polk, JD Dillon, and Alfonso Riley.

When I think about "going together" I think about the xAPI Learning Cohort. Picking up from the ADL's xAPI Design Cohorts run by Craig Wiggins, the TorranceLearning team led 14 cohorts over seven years, supporting 4,500 professionals as they learned about xAPI, getting data from their learning experiences, and ultimately doing something with it. Alison Hass, Peter Guenther, Jessica Jackson, Erin Steller, Jami Washington, Leanne Gee, and the utterly unflappable Matt Kliewer have been a huge part in growing a community of professionals learning together—and teaching one another—about data.

Jack Harlow and Hannah Sternberg, the editors I work with at ATD Press, have once again helped guide this work with gentle nudges, thoughtful research of their own, and their most delicate way of saying, "Megan, this makes no sense. Try again." Thank you.

"Skip to the good parts."

About the time I kicked off the writing of this book in earnest (or should have kicked it off), I got some fantastic advice that has helped me push through some of the big blockers in life—including writers' block: "Just skip to the good parts." So many people—Michelle, Matt, Maria, the entire team at TorranceLearning—have helped me see the "good parts" of life along the way. And a well-placed "you've got this" goes a long way (I'm looking at you, Emmet). Thank you.

"You need a vacation."

The daily demands of my role at TorranceLearning make carving out time for writing very difficult. My parents have provided support, space, and places to write this book. And, at the same time, they've helped to manage my burnout. And now . . . now, I'm ready for a real vacation. Thanks, Mom and Dad. I love you.

Further Reading

Are you ready for more? I found these books interesting and useful along my own journey, some of which provided insight and direction for this book. Others were interesting beach reading.

The Data Detective: Ten Easy Rules to Make Sense of Statistics
Tim Harford (Riverhead Books, 2020)

Behind Every Good Decision: How Anyone Can Use Business Analytics to Turn Data into Profitable Insight
Piyanka Jain and Puneet Sharma (American Management Association, 2015)

The Art of Statistics: How to Learn From Data
David Spiegelhalter (Basic Books, 2019)

The Functional Art: An Introduction to Information Graphics
Alberto Cairo (New Riders, 2013)

The Big Book of Dashboards: Visualizing Your Data Using Real-World Business Scenarios
Steve Wexler, Jeffrey Shaffer, and Andy Cotgreave (Wiley, 2017)

Show Me the Numbers: Designing Tables and Graphs to Enlighten
Stephen Few (Analytics Press, 2012)

Learning Analytics: Using Talent Data to Improve Business Outcomes
John R. Mattox II, Peggy Parskey, and Cristina Hall (KoganPage, 2020)

Investigating Performance: Design and Outcomes With xAPI
Janet Laane Effron and Sean Putman (MakingBetter, 2017)

Measurement Demystified: Creating Your L&D Measurement, Analytics, and Reporting Strategy
David Vance and Peggy Parksey (ATD Press, 2021)

Making Sense of xAPI
Megan Torrance and Rob Houck (ATD Press, 2017)

Data Story: Explain Data and Inspire Action Through Story
Nancy Duarte (IdeaPress, 2019)

The Visual Display of Quantitative Information
Edward R. Tufte (Graphics Press, 2001)

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About the Author

Megan Torrance is CEO and founder of TorranceLearning, which helps organizations connect learning strategy to design, development, data, and ultimately performance. She has more than 25 years of experience in learning design, deployment, and consulting. Megan and the TorranceLearning team are passionate about sharing what works in learning, so they devote considerable time to teaching and sharing techniques for Agile project management for instructional design and the Experience API. TorranceLearning hosted the xAPI Learning Cohort, a free, virtual 12-week learning-by-doing opportunity where teams form on the fly and create proof-of-concept xAPI projects.

Megan is the author of *Agile for Instructional Designers, The Quick Guide to LLAMA,* and two *TD at Work* guides: "Agile and LLAMA for ISD Project Management" and "Making Sense of xAPI." She is a frequent speaker at conferences nationwide. TorranceLearning projects have won several Brandon Hall Group awards, the 2014 xAPI Hyperdrive contest at DevLearn, and back-to-back eLearning Guild DemoFest Best-In-Show awards in 2016 and 2017 with xAPI projects. TorranceLearning is a 2018 Michigan 50 Companies to Watch.

A graduate of Cornell University with a degree in communication and an MBA, Megan lives and works in Ann Arbor, Michigan.

About ATD

The Association for Talent Development (ATD) is the world's largest association dedicated to those who develop talent in organizations. Serving a global community of members, customers, and international business partners in more than 100 countries, ATD champions the importance of learning and training by setting standards for the talent development profession.

Our customers and members work in public and private organizations in every industry sector. Since ATD was founded in 1943, the talent development field has expanded significantly to meet the needs of global businesses and emerging industries. Through the Talent Development Capability Model, education courses, certifications and credentials, memberships, industry-leading events, research, and publications, we help talent development professionals build their personal, professional, and organizational capabilities to meet new business demands with maximum impact and effectiveness.

One of the cornerstones of ATD's intellectual foundation, ATD Press offers insightful and practical information on talent development, training, and professional growth. ATD Press publications are written by industry thought leaders and offer anyone who works with adult learners the best practices, academic theory, and guidance necessary to move the profession forward.

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