Incentive Research Foundation

The Impact and Potential of Artificial Intelligence in Incentives, Rewards, and Recognition

By: Allan Schweyer, Chief Academic Advisor,
Incentive Research Foundation

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The exploration of the current uses of artificial intelligence (AI) in people management in the IRF's study, *Predictive Analytics and Artificial Intelligence in People Management*, demonstrates that AI already helps organizations find, attract, hire, and onboard talent by predicting what individuals want and need and whether their skills and attributes match the firm's needs. Moreover, AI currently helps organizations retain people by comparing employees' unique behaviors against past patterns of attrition observed by the algorithms and then assessing flight risk. It vastly improves learning outcomes by delivering training just in time and tailored to each learner's needs. AI boosts engagement and performance by leveraging what it knows about individuals and then delivering the precise information or interventions needed to aid their performance in the moment. AI tools can predict employee engagement six months into the future using social listening, sentiment analysis, and other algorithmic techniques. This gives leaders time to intervene, including using incentive and rewards to boost morale.

It is important to note that in virtually every example in *Predictive Analytics and Artificial Intelligence in People Management*, HR uses licensed, off-the-shelf software to achieve the results described. Vendors may configure their platforms for each customer, but the point is that (aside from notable exceptions such as Google, IBM, and select others) where HR is using AI today, it is mainly doing so through capabilities embedded in licensed, third-party software.

AI in Incentives, Rewards, and Recognition

"If you want to scale the individual talent in your company, embrace the idea that you'll need to reward that talent in new and customized ways," (Charan, Barton, and Carey 2018).

An obvious pattern emerges from the examples above, which applies equally to AI in incentives, rewards, and recognition (IRR). The greatest immediate impact today of AI and its best uses lies in helping organizations change the dynamic from one-to-many rewards to highly personal, individualized rewards.

Google, for example, rewards employees by connecting them to their passions and by giving them the autonomy they need to engage at work. According VP of people analytics Prasad Setty, people decisions are made with the same attention to the data as engineering decisions, and they are made at the individual level (Lohr 2013). Microsoft uses analytics in the same manner to engage and reward critical employees who are in danger of leaving, by fitting assignments to employees' areas of greatest interest (Klinghoffer 2014).

Neil Morrison, longtime UK group HR director for Penguin Random House, reports that the organization uses big data with predictive analytics to examine how rewards should be shaped and benefits structured, and to assess the balance between fixed and variable pay: *"That's [involved] everything from understanding people with different backgrounds but the same job titles, to the take-up of benefits and the specific value of certain ones," he says. "Whether they [the rewards] have the value you think they do and whether that has links with turnover and retention and whether, therefore, the investment is adding value,"* (Beagrie 2015).

Future reward program owners—individuals who design incentive and reward programs for their own organizations—will use predictive analytics and machine learning to help them understand who is drawn to which types of rewards. A VP of marketing for a major incentive house notes that they already use predictive analytics in sales prospecting tools, to provide intelligence concerning when to post blogs and, depending on when a person responds to an email, insights into ideal response strategies. As she puts it: *"We're starting to use AI tools to maximize our time, and to give us insights that make us smarter,"* (Chatfield 2018).

Professor Charles Scherbaum points out that a vast body of literature exists around the effectiveness of incentives, but big data and AI provide the tools needed to put the right reward in the hands of the right person at the right time. *"These better decision models mean higher personalization and better timing and what's nice about that is, as we get more information about people's preferences we can personalize incentives and rewards even more,"* (Scherbaum 2018).

Some IRR providers—individuals who design incentive and rewards programs for other companies and organizations—have taken steps in this direction with their clients already. One of the world's largest incentive and motivation houses, for example, uses machine learning algorithms to predict the rewards a loyalty program member is likely to redeem over the coming year. By analyzing past patterns, the AI suggests a redemption category to promote to each member. With a large banking client, for example, they recently sent 75,000 emails to credit card rewards members based on AI recommendations. Most members received tailored messages suggesting rewards in one of four categories: travel, merchandise, gift cards, or cash. A control group received an email suggesting a random category. Those that received targeted messages opened them 40 percent more often than the control group and redeemed in the AI-recommended categories 70 percent of the time. Those in the control group were three to four times less likely to use their points than those who received targeted emails (Wolfersberger 2018). These abilities come at a time when 71% of consumers claim that loyalty incentive programs don't make them loyal at all, making it clear that something better is needed (Zealley 2018).

Personalization efforts using AI can seem disconcerting to some but according to the same incentive house's chief data officer, *"People will give you their information if they feel you are using it to help them, if they get a good deal on the exchange. As long as it's not invasive, as long as you're transparent about its uses, and as long as it augments the experience, it works,"* (Wolfersberger 2018). A GPS service, for example, might use algorithms to personalize and improve users' commute times. Over time, the algorithms know that when a user leaves a certain location at a certain time, it can predict where they're headed and plot the best, fastest course—a reasonable trade-off for enabling location services in a GPS app. And for goods that people need and don't want to run out of, such as cat food, detergent, or printer ink, algorithms can predict when supplies are running low and send replacements under a subscription model. Similarly, AI can predict reward preferences, letting reward program owners act on that knowledge to improve the user experience. The large banking client's experiments represent just the first step toward increasing personalization in the incentives industry.

Klick Health, a company introduced in *Predictive Analytics and Artificial Intelligence in People Management*, created Genome, a machine learning (ML) platform that connects employees to each other for purposes of recognition and yields relevant data. Klick knows who is recognizing whom and for what reason. It built its platform around the self-determination theory (SDT) of human motivation so that algorithms produce insights into whether an individual's needs for autonomy, purpose, mastery, connection/inclusion, and appreciation are being met, and to what degree. The platform analyzes the work employees are doing and their contributions, rewarding them accordingly with "Klick Dollars" they can use to support charities of their choice (purpose). Genome also connects employees to personalized learning in real time, as the need arises (mastery). Genome's AI also manages autonomy. By analyzing every project at every stage in the firm, it rewards more responsibility to people who have demonstrated consistent competency and success. The AI tracks every decision made in the firm and the context in which it was made. The more a person proves their judgment, the more flexibility the system grants in making bigger decisions. These factors take human bias and politics out of the equation and rewards people based on evidence and merit alone (Goldman 2018).

Jay Goldman, who now heads Klick spin-off Sensei Labs (which licenses Genome) says: *"Despite our best intentions, a lot of reward and recognition programs heavily weigh the most recent things that have happened and forget the contributions an employee may have made early in the performance cycle. We use ambient and self-reported data together to create a much better picture of what's been done—like getting tasks done on time throughout the year—and it's not subjective,"* (Goldman 2018).

Using AI to Find the Ideal Reward

Taking an analytical approach based on the scientific method[1], an IRR program owner and their team would make an educated guess about what reward(s) might work best. Next, they would roll out a corresponding incentive or recognition program to a sample of the population whose behavior the organization seeks to change. After an appropriate time, the team would analyze multiple factors to see whether or which rewards drive the desired behavior change and how those behaviors impact performance. Generally, behavior must change before outcomes occur. Organizations need to perform predictive analyses to know what behaviors lead to the outcomes they want, and then experiment with a variety of incentives to know which do the best job of encouraging those behaviors (Waber 2018).

For example, an IRR team might be tasked with using rewards to aid other efforts in building a high-performance culture. The first step is likely to identify the firm's high performers. This requires collecting and analyzing data from varied sources such as workforce planning, engagement surveys, email analysis, organizational network analysis, reward and incentive programs, and employee performance by hard and soft measures (i.e., performance reviews and peer recognition systems). The data, especially that drawn from email and organizational network analysis (ONA)[2] might also reveal who displays the citizenship behaviors needed to build a high-performance culture.

Knowing the high performers and their behaviors, in some organizations—with good, historical, and up-to-date rewards and performance data in place—it might be possible to run algorithms to find patterns and correlations between past rewards and incentives and the desired behaviors and outcomes that define a high performer. For most organizations, however, these models will have to be built. To do so, reward program owners must rely on their instincts and experience to form an opinion as to which incentives (broadly speaking) will work best for which employees to drive desired behaviors. Then, through a series of small experiments, test the hypotheses to discover which hold true and which don't. The resulting predictive models will also recommend who to recognize and reward outside the obvious measures of sales and other quantifiable

1 "A method of procedure that has characterized natural science since the 17th century, consisting in systematic observation, measurement, and experiment, and the formulation, testing, and modification of hypotheses." Dictionary.com

2 For a brief explanation and relevant example of ONA, please see Appendix A

performance measures. And, as above, the models will flag those at risk of attrition (e.g., through ONA, emails analysis, social media analysis, etc.). Ultimately, over time and with more data, these sorts of analyses can advise managers in how to drive retention and optimal performance at an individual employee level using a broadly imagined range of incentives, rewards, and recognition.

Shortcuts to some of these insights already exist. For example, as discussed in detail in *Predictive Analytics and Artificial Intelligence in People Management*, Joberate helps firms use the J-Score to flag employees at risk of leaving and then, especially if they are high performers, develop individualized rewards to keep them. Joberate's CEO, Michael Beygelman cites a large insurance client who used this approach with their sales team and reduced job seeking behavior by more than 50% percent, using tailored rewards for those people (Beygelman 2018). Beygelman also recommends that organizations reward and recognize people who are *not* looking for work. He reasons that if people—other than high performers—are on their way out, employers might waste money rewarding them. He recommends using predictive analytics to identify core, committed employees and then focus reward programs on good people who want to stay (Beygelman 2018).

Beygelman hits on another key theme in IRR, imagining how AI might help organizations avoid the unintended consequences of reward programs. Using correlations from big data and predictive analytics, designers can more readily see the effects as a reward program's impact ripples its way across an organization. Recognition of one person could potentially cause negative J-Scores in others, which the system would reveal. An organization might announce the members of the annual Presidents Club, for example, and then watch the derivative consequences of that announcement on other people's job seeking activity.

Resulting insights from such analyses might drive changes and improvements to incentive programs. Beygelman points out that AI might help firms experiment their way to optimal incentives and rewards. For example, the money invested in spot gift card rewards might be diverted for three months to extend family leave, or vice versa. Reward program owners could observe the impact on J-Scores in real time and over the course of the experiment, then compare the returns against each option tested. Much smaller experiments might be performed as well, such as a gift certificate for a spa treatment versus a spot cash reward of $100, and, of course, they can be operated right down to the individual level (Beygelman 2018). In these ways, AI will bring much greater use of evidence into decisions about which rewards to use for groups, teams, and individuals, validating some "best practices" but inevitably disrupting long held beliefs elsewhere.

Where travel rewards are concerned, AI is likely to help hotels understand and manage guest and attendee preferences at scale, for example, personalizing each traveler's experience right down to the flavors of coffee available and the way the furniture is organized in their room (Wolfersberger 2018). For instance, WayBlazer is an AI-enabled travel search company that uses algorithms to crawl the web, classify, compare, and find patterns in descriptions, fares, and reviews for flights and hotels, so that it can automatically match individuals to options they're likely interested in.

Carnival Cruise Line provides every guest with an "Ocean Medallion" to wear onboard. It serves not only as a room key and charge card, the medallion is also a sensor and internet-connected transmitter that keeps passengers connected wherever they go on the ship. The data streams into Carnival's servers. Analysis occurs in real time revealing each guest's preferences. AI informs crew members so that guests enjoy a personalized experience tailored to their preferences in activities, dining, and so on (Wilson and Daugherty 2018).

Hertz uses analytics based on past behavior to predict which offers will appeal most to which customers. This allows the company to deliver targeted deals, resulting in significantly greater uptake. Targeting based on past behavior extends to other industries as well; CVS pharmacy uses predictive analytics and machine learning to improve its service to customers by sending reminders to take medicines and to predict when they might need additional care. CVS expects these initiatives to drive greater loyalty as its brand becomes associated with broader care and well-being, beyond just providing drugs (Zealley 2018). Like similar systems used in matching people for relationships or in providing financial advice, these tools get dramatically better with use (Faji 2018).

Implications for Reward Program Owners

Efforts at CVS, Hertz, Klick Health, and elsewhere showcase the ability of advanced analytics and AI to micro-segment a workforce or customers based on the characteristics of individuals, and then use that knowledge to personalize services, products, or rewards. This will fundamentally change the way organizations compete. Those that continue to serve employees and customers generically will likely be eliminated from the competition first (McKinsey Global Institute, 2016).

Imagine, for example, a breaking news item about an earthquake in Los Angeles. People may read similar headlines in whatever news source they prefer, but an ML-equipped news provider might alter the article body depending on the reader. For example, if the AI knows a subscriber has family in LA, it might conduct an information/social media sweep in the background and add a paragraph to the article telling them that their family is safe and where they can be reached. Imagine articles that adjust to match people's reading levels, or a new, more fashionable Google Glass[3] equipped with facial recognition that can tell the wearer the names of the people around them, where and when they last met, and other facts about each person. Similarly, rewards tailored to a person and their current emotional state might dramatically improve behavior change and desired results. The applications are endless—competing against those capabilities will be difficult for laggards.

Considerations and Concerns

Despite the potential, personalization comes with dangers and drawbacks that IRR professionals, like others who might use AI, must be aware of (Frick 2017). China's "social credit" system, for example, scores millions of citizens every day on nearly every facet of their online lives. Bill payments, comments on social media sites, purchases, and even the "quality" of friends and associates factor into a person's score, which is determined by machine learning algorithms. By 2020, every Chinese resident will participate, whether they like it or not. A person's score will determine their eligibility for and interest rates on loans, what jobs they can aspire to, even what schools their kids can attend (Botsman 2017; Rollet 2018).

Orwellian as China's system seems, AI systems often cross the line in the West as well (Botsman 2017). They have spied on people and run experiments using unwitting social media users as subjects. Systems that tailor news to people's "preferences" sometimes filter out alternative views, making people's natural confirmation biases much worse. Fake or provocative news is commonly delivered to people based on their past behaviors and predicted emotional states. Worse, some outlets have used predictive algorithms to send "fake" and/or provocative news at precise times designed to unduly influence or even inflame recipients (Rosenberg, Confessore, and Cadwalladr 2018).

As described in *Predictive Analytics and Artificial Intelligence in People Management*, AI tools are

3 Please see: Google Glass Could Make Comeback In AR Revolution: www.forbes.com/sites/paullamkin/2018/02/26/google-glass-could-make-comeback-in-ar-revolution/#6cbbe10923a6

now commonly used to screen applicants out of job selection processes. They can also be used later in the hiring process to reject a late stage candidate for a position, or even an employee for a promotion. AI might be used to deny people loans or favorable terms (Gershgorn 2018). And as machine learning employs deeper and deeper layers, growing ever more complex, it can be impossible to understand the reasons for the decisions and recommendations it makes (Datta 2017) (Daugherty and Wilson 2018; Gershgorn 2018).

"Deep neural networks may have hundreds of millions of connections, each of which contributes a small amount to the ultimate decision. As a result, these systems' predictions tend to resist simple, clear explanation. Unlike humans, machines are not (yet!) good storytellers. The machines may have hidden biases, when the ML system does make errors, as it almost inevitably will, diagnosing and correcting exactly what's going wrong can be difficult," (Brynjolfsson and McAfee 2017).

Organizations that collect and analyze data about employees run the risk of violating (or being perceived to violate) employees' privacy. Only organizations that have built sufficient trust with their employees will succeed in using employee data in reward programs (or people analytics generally). If trust doesn't exist, leaders must build it first through greater openness and transparency. Wise organizations fully disclose the data they are collecting and are clear about the purposes for said data collection. They use only public information about employees—such as their level of training, their performance reviews, emails, calendar entries, business-related phone calls, project budget information, etc., and the self-reported information they provide voluntarily through employee engagement surveys, for example. Unless explicitly authorized by the employee, ethical, smart leaders don't use data of a private nature.

Savvy leaders also know that although analytical and predictive capabilities are game changers, machines and AI should not be trusted to make final decisions in important matters. By combining data with human experience, wisdom, and instincts, organizations leverage the sixth sense that organizations like Klick, Google, W.L. Gore, and others enjoy. Data and algorithms enhance experience and instinct, they do not replace it (Brynjolfsson and McAfee 2017; Daugherty and Wilson 2018; Segal, Goldstein, Goldman, and Harfoush 2014).

"On its own, the AI doesn't make decisions. We are experimenting with AI and machine learning around decision support insights at Klick, but staying away from the software making decisions on its own. The algorithms are intelligent but not smart. They find patterns humans might miss but are not good at making decisions … yet. We use algorithms to help people make better decisions faster. We call that 'informed intuition,'" (Goldman 2018).

Though employers are free to collect and use data on every email, keystroke, or call—and even move—their employees make, only a few employers do so (Peck 2013). Most allow employees to opt in and out of programs and are transparent in their use of the data they collect. Tellingly, when employers act ethically and transparently, even in cases where they ask employees to wear sensors that track their every move, nearly 100 percent of employees consent (Pentland 2010; Waber 2018).

The responsibility to act ethically may take on even greater importance in the future. As Rachel Botsman, author of *Who Can You Trust* (2017), reminds us, the current generation's natural mistrust of machines will be reversed as today's children enter the workforce in years to come: *"The next generation will grow up in an age of autonomous agents making decisions in their homes, schools, hospitals and even their love lives. The question for them will not be, 'How will we trust robots?' but*

'Do we trust them too much?'" (Botsman 2017). Leaders must take it upon themselves to use AI and algorithms wisely and ethically. At work, the tools should be employed in the spirit of creating a more rewarding work environment and offering better services to customers.

Advances in machine learning naturally frighten people, making them think AI and robots will soon replace human workers. But this skips an important stage in the evolution of smart machines; AI will first supplement and augment human performance. AI will relieve employees of mundane tasks they aren't good at, like quantitative analyses and fast pattern-recognition based on processing millions of rows of data. This will free employees up to do the things they do better than machines, such as creative work and the enormous range of work that requires emotional intelligence.

For the foreseeable future, machine and human together are better than either alone. Even where analysis is concerned—though AI brings massive processing power with incredible pattern-matching and predictive abilities—humans are still needed to turn AI's analyses into actionable insights for the business (Housman 2018).

Implementing Predictive and Prescriptive Analytics in IRR

"It can take three to five years to build a strong talent analytics function and the same length of time, or longer, to develop a mindset and culture in which people make decisions based on data and not just instinct. It is important to start laying the groundwork. … seek out and conduct pilot projects focused on critical business and talent problems, invest in developing the analytics capabilities to drive the HR function going forward. Recognizing HR's reputation as a profession and function that shies away from numbers and data, it is critical to move from talk to action," (Deloitte Consulting 2015).

Regarding the elements above, HR has made progress since 2015, if mainly in the licensing of technologies with embedded AI. As of 2018, the quote above might better describe the incentive and rewards industry, members of which often struggle even to report return on investment in incentives programs (Schweyer, Thibault Landry, and Whillans 2018). Many reward program owners and their teams, including reward providers and consultants, are at stage one when it comes to analytics. Determining the first step for organizations hoping to build predictive analytics and machine learning capabilities depends on the culture of the organization. In their 2018 book, *Human + Machine: Reimagining Work in the Age of AI*, authors Paul Daugherty and James Wilson suggest an approach for beginners that they call "MELDS."

First, the authors advise, adopt a **M**indset of reinvention and unlimited possibility. Deeply define the primary problems to solve by using analytics and AI; think broadly about new processes that could do it better. Involve customers and employees in imagining new ways of doing things and then test the best ideas through **E**xperimentation, learning, and incremental improvement. Run frequent, small tests. Don't label experiments that fail as losses—they supply the data needed to learn, adjust, and try again. Visionary **L**eaders who aim to use AI for exponential gains are pivotal. Such leaders orchestrate machines and humans to work in concert, not at odds. Good leaders dispel fears and rumors of job losses and know that people don't naturally trust AI or algorithms (Ford 2015; Wellers, Elliott, and Noga 2017). They acknowledge the limitations of AI but encourage employees to appreciate the benefits, including reduction of tedious work. Another vital part of the process is to appreciate **D**ata as the fuel that drives burgeoning AI and algorithms. ML needs a lot of data at a high grade to perform well. Finally, employees must learn the necessary Skills to trust and work alongside AI—to leverage it to dramatically increase their productivity. According to the authors, employees will soon need to learn how to work as well with AI as they do with each other. To do this, they'll need to understand how AI thinks and decides (Daugherty and Wilson 2018).

Leaders must also construct rules and governance around the data to be collected and used. Though big data (vast, fast flowing, and high variety) is needed, even small organizations can capture and store enormous amounts of data using inexpensive cloud-based services. In large firms, reward program owners often suffer not from a lack of data but a dispersion of data across simultaneous programs running in various departments, all labeled differently. Marketing, sales, incentives, HR, compensation, and other players must define common terms and taxonomies for data, and then share it so that the algorithms see the entire picture (Wolfersberger 2018).

"The data and analysis models don't have to be perfect, just better than what we have now using experience and intuition alone," (Scherbaum 2018).

Sometimes, bringing all the data together from multiple sources and "normalizing" it, will prove impractical. For example, in 2012, the SVP of global HR operations at PepsiCo was asked to digitalize HR. He first brought stakeholders together (from across HR, compensation, and IT). But with 260,000 employees, Pepsi had many HR silos around the world, and dozens of different systems in place. The SVP tried to consolidate the data but learned that it would be virtually impossible due to inconsistencies in data labels and poor data quality generally. Instead, he started from scratch. After identifying the data needed and crafting a data taxonomy and governance rules, his team created one platform—a data lake—for all HR information. This took an enormous amount of work because, in many cases, data had to be entered into the universal system by hand. But as of 2017, HR data was in one place and accurate. Pepsi has since added predictive analytics and AI to their analytics capability, including "robotic process automation" that has saved the company significant work and has more than paid back the investment. Today, Pepsi has real-time data and its HR is fully digital (Charan, Barton, and Carey 2018).

"I think we are leaving the age of experience and moving into the age of evidence. One of my big goals professionally is to get more leaders to stop acting on intuition and experience—and instead be data-driven,"(Adam Grant, as quoted in McGregor 2016).

After mapping and organizing data and platforms for analysis, organizations should turn their attention to building an analytics team, as Daugherty and Wilson suggest. Unfortunately, seven years ago McKinsey researchers declared data scientists, and those who manage them, the hardest jobs to fill in business (Manyika, et al. 2011). Despite the emergence of new university degree and private certificate programs in the field, the market for data scientists has grown even more competitive since then (Bloomberg 2018).

A Practical, if Temporary Shortcut: Third-Party Platforms

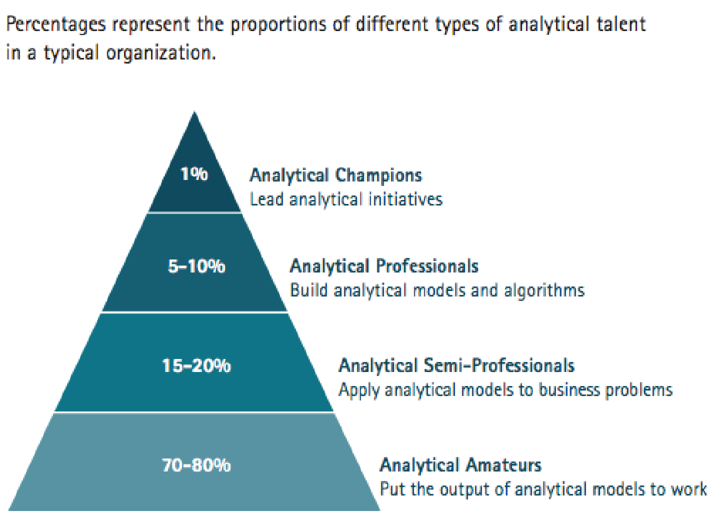
Given the difficulty, cost, and learning curve involved in building a capable analytics operation, reward program owners should strongly consider insourcing their needs to other parts of the organizations (those that have advanced analytics capabilities) or outsourcing. Alternatively, they might follow the lead of HR in procuring off-the-shelf tools with machine learning and analytics built in. This approach may present the most practical shortcut to leveraging powerful, if not entirely customizable analytics.

According to the VP of client strategy and marketing for a major IRR firm, *"We ride the fence* *between positioning for the future, and responding to our client's immediate program and data needs. Advancing analytics is a formally scoped component of our product roadmap, and we're weighing the pros and cons of building more robust predictive capabilities in house, or partnering with outside AI expertise to address our growing client performance management needs."* (McWilliams 2018).

Others in the industry who regularly advise clients how they should build advanced analytics capabilities remind reward program owners that should they license capabilities from others, they must still grow in-house knowledge of AI: *"IRR leaders hear about AI in the news but they don't know what it means for them. My advice to them is that it takes people who 'get it.' In other words, it's not going to be as simple as licensing an out-of-the-box solution and stopping there. As more people in the IRR group start to build AI expertise and knowledge, a real game-changing potential arises because they can rethink the business through the lens of AI. They can discover and experiment with ways to use AI to reinvent the way they design, deliver, and measure incentive, reward, and recognition programs"* (Wolfersberger 2018).

External expertise and platforms may reduce the need for internal resources, but to eventually "get AI," and even to use the analyses that third-party firms and tools provide, organizations will need internal business experts to interpret and contextualize analysis and insights from outsourced partners. Whether filling the roles internally or externally, reward program owners should try to build capacity along the lines of the pyramid model in Figure Two.

Figure Two: Distribution of Analytical Talent



"Analytical champions" and those who create predictive models, algorithms, and machine learning need not be "data scientists." Leaders should look for talent widely, not focus entirely on education or experience, nor fixate on titles. A wider internal and external search, looking foremost for competence and aptitude, will yield more results at lower costs. Excel, R (programming language), and Python experts exist at all levels, as do individuals with the ability to learn rapidly.

Reward program owners should find people who are comfortable with data throughout the business. No algorithm works without business experts to interpret the analyses and turn them into insights. Ideally, every manager and senior leader should grow comfortable interpreting data. Finally, whether the most advanced analytics is performed in house or is outsourced, reward program owners should work toward instilling a data culture in which everyone uses evidence drawn from analysis in their decision making.

Starting with the right questions, data, and analytics, tools do much of the heavy lifting in terms of statistical and mathematical calculations, and in identifying patterns and correlations. But for now, true value in analytics is delivered by smart, experienced people who can build statistical models and algorithms and then make sense of the patterns revealed through analysis. Only qualified and experienced people can quickly reject the irrelevant, see the critical elements, draw insights, and then communicate them clearly to decision makers (more information on building analytics capabilities is included in Appendix B).

"They are a frugal but ambitious lot, less excited by climbing walls and en-suite kitchens than by career development. Most critically, they expect to be treated as individuals. Students raised amid the tailored analytics of online retailers or college recruiters presume that anything put in front of them is customized for them, … group designations evolving into 'segments of one." — How a recent *New York Times* article described incoming freshmen at American colleges in 2018 (Pappano 2018).

Conclusions

Advances in ML and AI are limited by innovation, data availability, and computer processing power. As discussed, virtually every organization now possesses or can obtain adequate data. Innovations in AI are accelerating at an incredible pace. That leaves processing power as a potential choke point. Moore's Law, which predicts a doubling of microchip capacity and power every two years, held true for 50 years following its pronouncement in 1965. Moore's Law may be showing signs of wear today, but the cloud, more efficient algorithms, and massively parallel computing are, so far, more than making up for limitations in the amount of processing power designers can pack into a microchip (Simonite 2016).

Thus, it appears advances in AI will not be curtailed by limitations in computing power, data, nor human capacity to innovate anytime soon.[4] Indeed, significantly improved people management and reward program design using AI is already possible and deployable. For example, existing platforms, like Genome, Zoomi, Joberate, Watson, and others make AI people management applications easier to adapt and use for organizations that can afford the licensing fees. A widespread ability to tailor experiences to each person, to know precisely which rewards will work best for whom, and under what circumstances, appears on the verge of reality. These tools and many other algorithms will make rewards immeasurably more engaging and meaningful (Johansen 2017).

Hidden factors undoubtedly exist that will prove another law—Hofstadter's Law—which says things will take longer than expected (Hofstadter 2011). Nevertheless, reward program owners should move quickly. The first, practical step for many will be the use of ML in third-party software, combined with a deliberate effort to nurture among team members an understanding of AI and its potential.

By whatever means, reward program owners should take the lead in understanding and applying advanced analytics and AI to the field of human motivation, engagement, and performance. If they don't, others almost certainly will.

4 Data privacy and protection laws, like GDPR, might curtail data collection and limit its allowable uses. However, such laws and regulations do not apply to the collection or uses of workplace data by employers based in the US and in many other parts of the world.

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Appendix A: Glossary of Terms Not Defined

Aggregate Analysis: Imagine you run a wedding business. An aggregate analysis tells you that most of your customers live in Oregon and are women in their early 30s. These insights let you narrow in on advertising vehicles that reach that audience most efficiently.

Correlation: Correlations demonstrate the link between two variables. For example, in your business, which of the advertising vehicles you use produce the most leads? A correlation analysis using Excel can reveal the links between lead generation and advertising vehicles very quickly, allowing you to eliminate some and invest more heavily in others.

Trends Analysis: The continued tracking of correlations over time.

Sizing and Estimation: Educated guesses about the potential of a market, for example, using knowledge, experience, and the data at hand—a common and sometimes valuable practice.

Segmentation: When you divide your customers or employees into groups, you may do so to study their specific characteristics and behaviors so that you can tailor your offerings. You might also segment products to determine which ones sell well and identify their various levels of profitability, or rewards to see which resonate best and drive the desired behaviors.

Customer/Employee Life Cycle (CLC) Analysis: Studying customer or employee behavior at various stages, to determine things such as how long it takes a customer to upgrade from a free to a paid subscription on a website or for an employee to lose some of the initial enthusiasm/ engagement they brought to the organization when they joined.

Ambient or Passive Data (aka "Data Exhaust): "There are two types of data: self-reported and ambient. Self-reported data involves filling out time sheets, surveys, performance evaluations, and expense reports—all examples of this type of data. Ambient data is information about a behavior that is automatically collected without the user's having to actively enter each data point. Swiping into work with an active RFID badge, sending emails, making calls, and even adding events to an electronic calendar are all examples of ambient data" (Segal et al. 2014).

Datafication, or Digitization: Refers to taking information about all things under the sun—including elements we never used to think of as information at all, such as a person's location, the vibrations of an engine, or the stress on a bridge—and transforming it into a data format to make it quantified. This allows us to use the information in new ways, such as predictive analytics: detecting that an engine is prone to a breakdown based on the heat or vibrations that it produces. As a result, we can unlock the implicit, latent value of the information.

Descriptive Analytics: The first and easiest type of analytics; the one most organizations perform, looks back at what happened in the past. These descriptive analytics uncover trends and typically display them in charts or on dashboards. The information can alert leaders to future problems or opportunities. Good descriptive analysis results from asking questions about the variables and how they might affect one another. Many questions might lead to one or a few valuable insights, but those insights can have tremendous impact. For example, you might learn that sales revenue is more a function of opportunities raised, combination of products pitched, and attendance at a particular course, than tenure of sales rep, size of territory, and past performance. Analysts must take caution not to influence the results by seeking data that fits their hypotheses. Go beyond descriptive analytics to better understand why variables impact each other and to avoid relying on imperfect conclusions from what is the least rigorous of the four levels of analysis.

Diagnostic Analytics: At this stage, you ask why something happened. Here you'll use more advanced statistical techniques to uncover the connections between data. For example, by using techniques to isolate dozens of variables against just one, you can often determine which causes the effect. Diagnostic analyses helps you determine, for example, what makes some of your sales reps highly effective while others languish. With this information, you can design better training, coach reps in the precise areas they require help, and hire new reps in a more targeted fashion.

Predictive Analytics: The four levels of analysis don't necessarily work only in sequence. Normally, however, you'll graduate from descriptive to diagnostic to predictive, because after you know what and why, you'll want to leverage the data into even more valuable insights. By running your data through thousands, even millions of possible connections and correlations, algorithms can make startlingly accurate projections about the future. In sales, this might include predictions about which prospects will buy what products, and even why. To achieve this level of insight, use large datasets to "train" your predictive models. You might have a year's worth of data about particular KPIs concerning your sales reps, for example. Suppose you want to test how accurately performance against those KPIs predicts actual sales. To do so, take the first six months of KPIs for half your sales reps (first half) and add the full year of actual sales data concerning those reps. Process the data to determine the strength of the connection between the KPIs and sales, this becomes your predictive model. If your predictive model is strong enough, you'll want to use it to make decisions. But you need to test it first. To do so, take the KPI data for the other (second) half of your reps and run that against the same model. Separately, run your second half reps' KPI data against their own full year sales results data. The smaller the difference in outcomes between the two, the more valid your predictive model.

Prescriptive Analytics: Knowing what happened, why it happened and what might happen next leads to the logical question, what should we do about it? Prescriptive analytics uses highly sophisticated algorithms to build on predictive data to suggest optimal decisions and their consequences. The results from prescriptive analytics can give individual sales reps personalized action plans, for example, detailing exactly what they should do to make more sales. For example, which products to bundle for which customers, what training classes to attend and when and which prospects to prioritize based on probability models that forecast likelihood of closing.

Social Listening: "Many brands now employ artificial intelligence to monitor social media platforms, a practice known as social listening. With a sophisticated understanding of human language, AI can analyze social media trends to detect changes in conversations, alerting human operatives to changes in conversations about the brand or gathering information about the feelings of their customers." (Digiday; sysomos, 2017)

Organizational Network Analysis (AKA Social Network Analysis): For at least the past two decades, organizations have been able to gain deep insight into the way information and knowledge flows in their organizations through ONA (Cross and Parker, The Hidden Power of Social Networks: Understanding How Work Really Gets Done in Organizations, 2004). A typical ONA might collect data from email records and/or an employee survey, possibly even wearable sensors to build a map of the real networks at play inside organizations, including who talks to who, where people are isolated, etc. (see Figure Two, on following page)

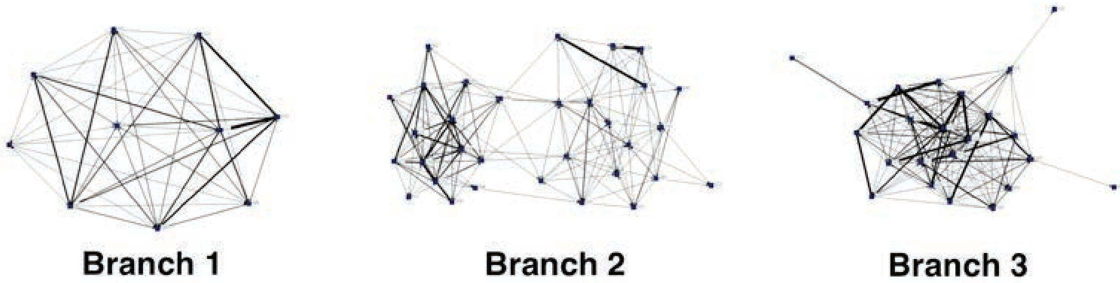

Figure Two: ONA Maps for Three Bank Branches

To illustrate the usefulness of ONA, Figure Two depicts three bank branches that do the same work in locations across a region. Branch 1outperforms Branch 2 by about 250% and Branch 3 by a little bit less. The ONA gives us clues. In Branch 1 managers had implemented an informal reward program, a target for the whole branch that if hit, earned everyone a bonus. The rewards incentivized employees to share information and they did. That is visible in the ONA map for Branch 1 where there are many connections and no outliers.

Managers in Branches A and B used individual incentives based on more traditional and quantifiable performance outcomes, such as loans underwritten. Where group incentives caused people to share in Branch 1, individual incentives have the opposite effect in the other Branches. Branch A outperformed Branches 2 and 3 significantly based on the same direct, quantifiable measures the other branches tried to incentivize.

From this, the bank surmised that group incentives, at least in this case, work better than individual ones. All of the bank's branches now use the same team-based incentives as Branch A. Sales have increased across the bank by more than one billion euros each year since (Waber, President & CEO, Humanyze, visiting scientist MIT Labs, 2018).

Appendix B: Datafication Next Steps (Continued from paper)

IRR professionals must develop advanced analytics capabilities; however, remember that the great majority of data problems do not require advanced analytics nor data scientists to solve them. And many problems that could be solved using predictive analytics and AI should not be, because the benefits do not match the effort and resources that must be put in. Choose data projects wisely.

First, identify the problem the business needs solved. For example, "customer engagement" might be low. If so, canvass experts in the organization to get their thoughts. Next, test their hypotheses with the data. Data analysis will eliminate all but the best ideas and reveal insights into actions and decisions to take. Finally, implement the solution on a trial basis, test it, and then roll it out. (Jain and Sharma 2014)

Faced with many difficult problems and a lack of time and resources, an organization can attempt to randomly hit on a solution or can analyze the situation, narrow the focus, and dramatically increase the odds of solving the problem. Around 2000, when Circuit City faced financial problems, it responded by releasing top talent, moving from prime locations to cheaper suburban spots, and by closing its home appliance business. Each of these decisions was made and implemented without analysis or evidence and each proved disastrous, contributing to the collapse of the company (Carlberg 2018).

Instead of acting on hunches, analyze. About 80 percent of business problems can be solved using basic business analytics, like those provided in Excel. The rest—a small minority—require predictive analytics and the skills of an advanced data analyst. Use the following five analytics techniques to discover insights and improve decision-making.

The BADIR Approach (Jain and Sharma 2014)

Follow these five steps in order. Combine analysis and insights with knowledge of the business.

1. **The Business Question** – First, pinpoint the question or questions the analysis will answer. Ask the five W's. Who wants the information and why? What is the problem it will address? When and where is the problem occurring? By what date is the analysis needed? Who does it impact? Take the time to find the right questions; solving the wrong ones wastes time.

2. **Analysis Plan** – Start by setting goals for the analysis. Next, assemble the people closest to the problem – the stakeholders. Ask them their thoughts on the causes and solutions to the problem and questions at hand. Bring the group together a second time to rank and prioritize the various hypotheses that will be tested. Next, choose the analytical technique best suited to the problem. Then identify the data that is needed and in what form and granularity. For example, in analyzing a sales problem, is sales data needed by the week, month, or year? Collect data only after the analysis plan is agreed to. Finally, document a project plan that identifies resources, responsibilities, timelines, risks, phases, and priorities.

3. **Data Collection** – After the plan is approved, collect data from the sources according to the plan. Test small samples to make sure the data pulled meets expectations. Next, validate the data to screen for missing and bad information.

4. **Insights** – Now focus on analysis and insights. Perhaps use Aggregate Analysis to look for the

components of the organization's customer base that account for the most sales and revenue, for example. Once it is determined that young people with smart phones buy more than older customers using laptops, for example, calculate the increase in revenues one might expect if more of the marketing budget were spent on targeting young smart phone users.

5. **Recommendations** – The analysis and investigation should result in insights. With the insights, present a concise set of credible and supported recommendations to stakeholders. Know the intimate details but focus on the broader story unless asked to delve deeper. Include an executive summary with short points covering the problem, main insights from the analysis, recommendations, and suggested next steps. Subsequent slides should go into more depth around insights and recommendations, all supporting the main conclusion (Jain and Sharma 2014).

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