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ABOUT JMP

Since 1989, JMP software has combined interactive visualization with powerful statistics to help scientists and engineers see their data more clearly. And when data is better understood, insight-driven improvements are sure to follow. It's spelled J-M-P but pronounced "jump," like a leap in insight. JMP is a SAS company.

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On the cover: Sky Alibhai and Zoe Jewell, WildTrack.

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One step at a time

The old adage of taking things one step at a time has extra significance for the scientists at WildTrack. Like many of us, they're good at breaking big tasks into small, achievable ones.

But the nonprofit's 30-year success in wildlife conservation has literally been built upon steps. Specifically, rhino steps. And then tiger steps. And since then, countless footprints of endangered species and other scientifically interesting animals.

WildTrack's success story (page 18) is one of many in the pages of this magazine. But Zoe Jewell and Sky Alibhai – WildTrack founders – have a long history with JMP and a shared passion for environmental conservation.

Excited by the prospect of taking the footprint identification technique that worked with black rhinos into other species, JMP employees dedicated Sunday after Sunday, year after year, to collecting tiger data for WildTrack. With the help of a North Carolina-based carnivore conservation group, JMP employees walked tigers through sand, measured and photographed prints, and helped build a database for testing the theory. In the end, it worked.

Of course, JMP doesn't make a habit of conducting experiments and building databases for its users. But we're all about empowering people to make the world better with their statistical discoveries.

If you're proud of the discoveries you make with JMP, tell us on jmp.com/impact. Maybe we can tell your story in a future issue of JMP Foreword.

Diana Levey

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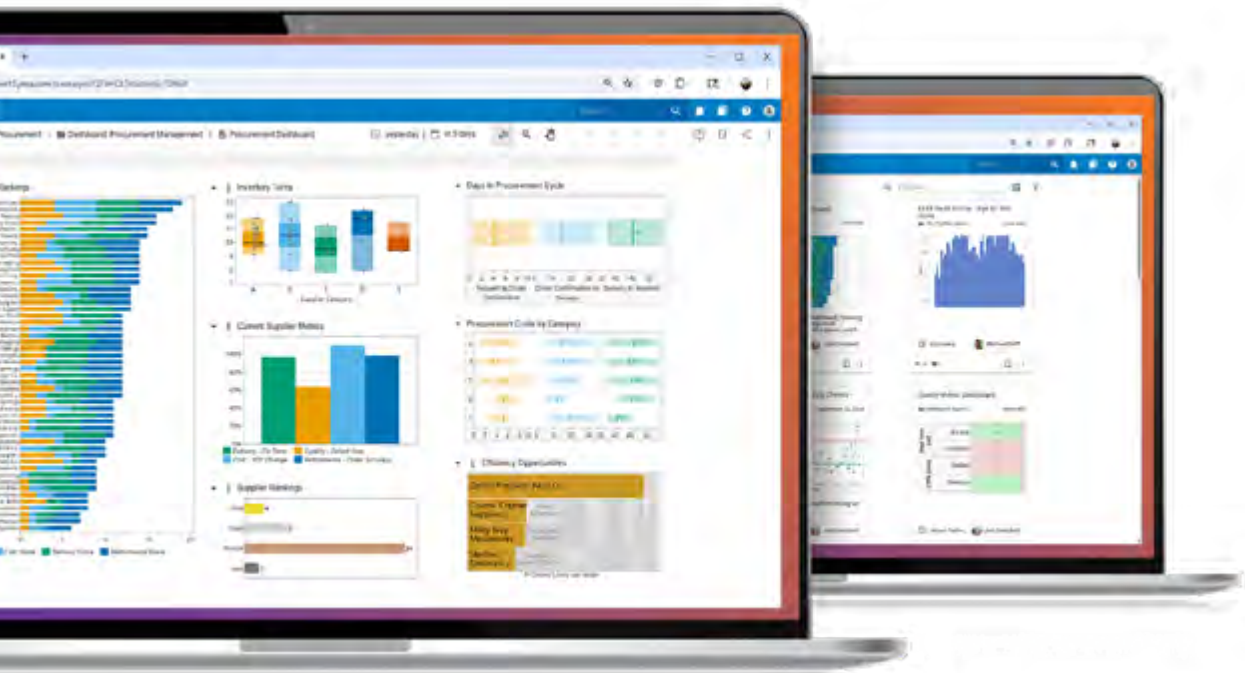
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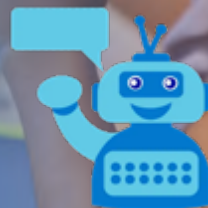
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Data analysis, generative AI, and the human factor

David Meintrup on FOBO in statistics

Have you heard of the acronym FOBO? It's the lesser-known little sister of FOMO (fear of missing out) and stands for "fear of becoming obsolete."

Let me share a quick example. On February 3, 2026, after Anthropic released specialized plugins for its Claude Cowork platform that were tailored to tackle legal tasks, stock prices for companies like Thomson Reuters and LegalZoom plummeted. Financial markets saw this launch as a direct threat to established software as a service (SaaS) providers. \$285 billion in market value was erased in a single day as the market feared SaaS vendors might become obsolete.

At its core, applied statistics is a service, and I see three main use cases: software packages like JMP offering statistical analysis as a service; statisticians helping scientists extract insights from data; and universities teaching statistics to future professionals. In all three domains, generative AI raises the question: Is it time for FOBO in statistics?

The end of statistics has been predicted before – for instance, in 2008 when Chris Anderson published "The End of Theory" in Wired, arguing that correlations were enough and statistical models were no longer needed: big data would speak for itself. The subtitle of his article was "The Data Deluge Makes the Scientific Method Obsolete." There it is again, that magic O word!

Even though neither theory nor statistical models have become obsolete today, looking back, one has to admit that Anderson had a point: large language models do not understand language through grammatical rules or other human-centered theories, but through brute-force statistical predictions from massive data sets (as Richard Sutton highlighted in his 2019 essay "The Bitter Lesson").

In May 2023, during his keynote speech at the Computex tech trade show in Taipei, NVIDIA CEO Jensen Huang famously declared: "Everyone is a programmer now – you just have to say something to the computer." Does the same hold true for



"Detailed knowledge is essential to validate AI outputs."

David Meintrup

Professor of Mathematics and Statistics
Ingolstadt University of Applied Sciences

statistics? Is everyone a statistician now? Can we just tell the computer what analysis we want and let generative AI take care of the rest? Let's test this hypothesis (even if that sounds suspiciously like the old-fashioned scientific method).

Design of the study

I set up a small study to test LLMs in applied data analysis. The workflow is promising: you upload a data set and prompt the model. Rather than searching the depths of its neural network for answers, the LLM converts the prompt into Python code, executes it, and displays the results. This approach significantly cuts down on typical AI errors, such as hallucinations.

I evaluated free versions of Gemini and Claude across five domains, using standard and non-standard data sets. The table below provides an overview.

"Deskilling is the greatest danger of the unreflective use of AI."

Area	Standard	Non-standard
Descriptive statistics	Visualize and describe small data set	Visualize and describe large data set, missing values
Hypothesis tests	One-way ANOVA all assumptions met	One-way ANOVA with outliers, missing values, heteroscedasticity
Linear models	Multiple regression with three factors	Anova with interaction, log-transform
Classification	Build classifier, small and clean data set	Build classifier, large data set, missing values, categorical and continuous factors
Design of experiments	Response surface design with three factors	Custom design for screening, with linear constraint, two continuous and two categorical factors

Finally, I had to decide how much statistical knowledge should go into the prompt. Here are three examples for an ANOVA comparing the weight of cars from three different countries:

- **Expert level:** Perform a one-way ANOVA of weight by country. Check the assumptions of normality and equal variances. Perform Tukey-HSD post-hoc tests if the ANOVA is significant. Create visualizations. Report and interpret the results. Print the Python code used to generate the analysis.
- **Student level:** Perform a one-way ANOVA with weight as response and country as factor. Report the results and visualize the data.
- **Zero-knowledge level:** Investigate statistically if weight differs for different levels of country.

To test the idea that “Everyone is a statistician now,” I used the zero-knowledge level and compared the AI reports against JMP’s output.

Results

The results were surprisingly good. For instance, the zero-knowledge prompt mentioned above was fully sufficient to trigger everything requested in the expert prompt. Missing values, large data sets, and violated assumptions were handled effortlessly.

The more complex the task, the “lazier” the AI became. For example, it occasionally skipped residual analyses in linear models – quite human, one might say. However, a quick follow-up prompt (“Add a residual analysis”) resolved this. Minor weakness-

es included slight inconsistencies across repeated queries, as well as rare, mild hallucinations in interpretation (such as adding a unit of measurement that wasn’t explicitly stated in the data set).

I was particularly curious about the results for design of experiments (DOE). Naturally, this kind of prompt needs more detail – otherwise a correct experimental design isn’t possible in the first place. The standard design created by the AI (a response surface design) was identical to JMP’s output. For the custom design, the AI generated a usable plan, albeit with some compromises compared to JMP’s optimal design. The D-efficiency dropped from 0.87 (JMP) to 0.73 because the linear constraint was not handled ideally. However, it is likely only a matter of time before it adjusts.

Conclusions

So, does it mean that we can now stop teaching statistics? Quite the opposite. First, the more domain knowledge you bring to the prompt, the more value you extract. Moreover, detailed knowledge is essential to validate AI outputs. For this reason, I am also not particularly worried about software packages like JMP: not only is JMP’s workflow unmatched in its smoothness compared to the back and forth of prompting an AI, but I can rely on the results – every single time.

In my view, deskilling is the greatest danger of the unreflective use of AI. Following the old principle “use it or lose it,” humans rapidly lose skills they no longer use, whether it is programmers who cannot code without AI or doctors unable to spot melanomas without automated aid. This development is

Perceptual constancy vs. Spurious correlations

Humans: high robustness



AI: low robustness



Human versus artificial intelligence

currently most dramatic among students, where AI often replaces the entire thought process. Seemingly perfect data analyses are presented, often without the slightest understanding. In my view, this is another strong argument for using JMP in teaching, since it forces students to create the analysis themselves. As Richard Feynman famously put it: "What I cannot create, I do not understand."

As statisticians, educators, and scientists, let us work together to view AI as a highly useful tool that enhances our capabilities, but one that should not replace human thinking, critical questioning, and our unique creativity.

Transparency

I wrote every single word of this article myself in my native German. The text was subsequently machine translated and edited.

About the author

David Meintrup is Professor of Mathematics and Statistics at Ingolstadt University of Applied Sciences in Germany. Alongside academia, he provides corporate training and consulting in applied statistics, design of experiments, and AI, empowering engineers and scientists to put modern data science to work. He is coauthor of several books on applied statistics using JMP.



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The art of framing your analysis

By Regina Nuzzo and Kristin Sainani



Regina Nuzzo is an award-winning science journalist and Gallaudet University professor who talks to audiences around the world about communicating statistics creatively. She's written for *Nature*, *New York Times*, *Reader's Digest*, *Scientific American*, *New Scientist*, *Science News*, and *ESPN the Magazine*, among others, including a column about the science of sex, dating, and relationships for the *Los Angeles Times*.



Kristin Sainani is a Stanford professor and science journalist who brings statistics and scientific writing to students and audiences worldwide. She teaches the popular Coursera course *Writing in the Sciences*, available in 22 languages, and offers an online medical statistics certificate program through Stanford Online.

Here's a scenario we see all the time as statisticians: An investigator walks into our office with a data set in hand and asks: "Which statistical analyses do I need to run on my data?"

Our response is always the same: "What question are you trying to answer?"

We invariably get a puzzled look in return.

"What question are you trying to answer?"

The fundamental mistake people make with statistics is believing that there is one "right" analysis for any given data set, that the entire process is just a mechanistic flowchart. But it isn't. Statistics is a way of thinking.

There is an art to framing your data analyses, and it starts with figuring out what question you want to ask.

For example, let's consider making toilet paper. (One of us, before becoming a Ph.D. statistician, interned at a toilet paper manufacturing plant.)

Let's imagine a simplified scenario, where we know the characteristics for every roll, such as production line; month, day, and time of operation; production shift; paper pulp source; machine speed; moisture level; finished roll weight; quality measures; and whether the roll passed final inspection.

In this scenario, you're an intern, and apparently too many rolls have been failing inspection lately. Your boss hands you six months of data and says, "Figure out what's going on with the toilet paper."

But what exactly are we trying to do here? Each possible question leads us on a different quest through the data analysis landscape. The key is understanding which quests to follow first.

Perhaps we're trying to describe what's going on: How common are defects, and what kinds are we seeing? Then we might want to visualize distributions, tabulate counts, or examine summary statistics.

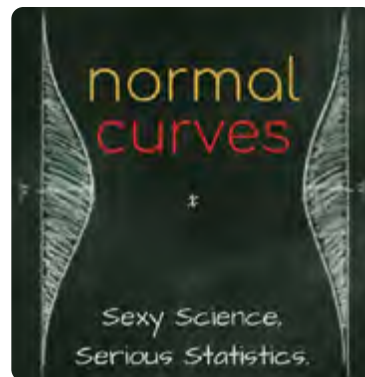
"Each possible question leads us on a different quest through the data analysis landscape."

Or we might be trying to explore simple relationships or compare situations: How do defect rates and quality measures differ across raw material sources? How has absorbency changed over the past six months? Here we could turn to exploring our data by building graphics and fitting simple models.

We could also ask how characteristics relate or co-occur: How does a roll's paper tensile strength relate to its absorben-

You can think of statistical analysis as a choice of quests. Which quest you choose first depends on your goal. Long projects often stack and combine quests!

- » **What happened?** You want to describe.
- » **How does it differ?** You want to explore/compare.
- » **What patterns exist?** You want to relate.
- » **What seems to matter most?** You want to model.
- » **What will happen next?** You want to forecast.
- » **What should we change?** You want to improve.



cy measures? Are there distinct subtypes of failure “personalities” in rolls that fail inspection? Advanced multivariate methods and clustering techniques can show us co-relational patterns and potential hidden relationships.

Often we want to model differences or understand drivers: Which factors interact to account for variation in absorbency? After controlling for machine speed, does moisture level still explain differences in softness? Which production line characteristics are associated with a roll passing its final inspection? Now we might look to fit models that let us compare the explanatory power of different variables in our data set, test competing hypotheses, and understand how multiple parameters jointly link to an outcome.

Or maybe we want to forecast: Which rolls will fail inspection? Can we get early warning about which production lines will veer off target? Here, we can use large amounts of data to train, test, and continually update complex models that project future outcomes from past experiences.

Sometimes we want to improve a process: Would slowing a machine’s processing speed

actually reduce defects? How would increasing the paper pulp density likely affect the tensile strength? How can we design an efficient experiment to test combinations of parameter effects? This leads us to exploring optimization, experimental design, quality and reliability.

The problem, of course, is that “analyze toilet paper” is not a single (or simple) question. Choosing an analysis without a guiding question is like choosing a surgery without knowing what’s wrong with the patient. You may finish the job and tidy everything up, but you probably didn’t solve the problem – and you likely made it much worse.

Likewise, the same data set can be used to answer many different questions, and each question leads to a different analysis.

Often the statistical quest starts with someone important saying, “Let’s figure out what’s going on here quantitatively.”

Well-meaning but inexperienced analysts interpret that as, “Uh oh, now I’ve got to run the one right set of statistical analyses for my data. Maybe a textbook will tell me what to do. Or AI will tell me what the answer is.”

Experienced statisticians like us immediately think, “First, I need to understand what the real question is and what the action will be at the end of it. If I don’t know, then I need to go talk to the people affected – the ones making the decisions or who will be implementing the new systems – until I know what I’m trying to do.” The analysis comes later.

Watch Stat Speaking with JMP to hear more from Regina Nuzzo and Kristin Sainani: jmp.com/statspeaking



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From Claude to coral reefs

By Anderson Mayfield



Dr. Anderson Mayfield, Ph.D., lead scientist at Coral Reef Diagnostics. He is a marine biologist from Nashville, interested in all things pertaining to coral reefs – particularly the framework-building animal-plant symbioses upon which these beautiful, high-biodiversity ecosystems are based. His long-term goal has been to develop diagnostic tools for coral health assessment in the face of global climate change and other anthropogenic impacts.

If you are proficient in both statistics and AI-driven approaches (e.g., computer vision, LLMs, etc.), you will be able to solve problems of great significance, and you will never lack for enthusiastic collaborators or become bored. The (data) world will indeed be your proverbial oyster, and you could end up saving the planet (or at least a coral reef; Fig. 1).

I say this because I fear there are many who believe that AI and statistical prowess are mutually exclusive. “I am an accomplished statistician; what can AI offer

me?” Or maybe: “I am AI-savvy and lack an interest in statistics; why should I learn how to use a product like JMP?”

As someone who spends 50% of his data analysis time with JMP Pro and the other half with Claude (Anthropic), I can safely say that AI has made me a better JMP user. And JMP, with which I am far more familiar (pushing 20 years!), has made me a far wiser and more prudent AI adopter.

There is adage among statisticians that goes something like “you spend 90% of your time formatting the data, with 10% spent on what most would consider the ‘fun’ and interesting parts: analyzing it.” JMP is actually an excellent tool for getting your raw, messy data ready for analysis, but I personally do not enjoy this part of the process. I prefer the exploratory steps that come afterward, which is where JMP truly shines.

As I write this, I am in Halmahera, Indonesia, on a field expedition to survey never-before-studied coral reefs (Fig. 1). I only have an hour between dives, but I still want to make progress on some data science projects. Could I “outsource” lengthy data preparation steps to Claude, then use JMP Pro to explore and analyze the data?

I have about 44,000 coral reef research articles on my computer, each with rich metadata: authors, countries, journal metrics, keywords, type of



Fig. 1. An uncharted coral reef in Halmahera's Bacan Strait in Indonesia.

“As someone who spends 50% of his data analysis time with JMP Pro and the other half with Claude (Anthropic), I can safely say that AI has made me a better JMP user. And JMP, with which I am far more familiar (pushing 20 years!), has made me a far wiser and more prudent AI adopter.”

zotero_key	doi	title
1. C0JCV5M	10.1016/j.jmbs.2015.05.005	Hoxolateral-to-apical host gene expression by injection...
2. M0R000C	10.1242/jeb.017730	Organic osmolytes as compatible, metabolic and osmotic...
3. T1U0V7J5	10.1016/j.jmbs.2015.05.005	Marine research in the post-genomic era...
4. H0F0V0R3	10.1016/j.jmbs.2015.05.005	Chlorine use of a K+ channel in Pterodroma perlegrina...
5. A2N0V2K6	10.1242/jeb.017730	The effects of a variable temperature regime on the phy...
6. H0F0V0R3	10.1016/j.jmbs.2015.05.005	Experimental evidence of the synergistic effects of warm...
7. P0V0M0M2	10.1016/j.jmbs.2015.05.005	Integrated physiological responses by four species of RH...
8. T0H0L0E1	10.1016/j.jmbs.2015.05.005	Disruptive heterochromatin is altering the trait landscape...
9. P0G0R0V0	10.1016/j.jmbs.2015.05.005	Effects of larval density and food concentration on Cr...
10. C0M0R0V0	10.1016/j.jmbs.2015.05.005	Climatological context for large-scale coral bleaching...
11. T0H0L0E1	10.1016/j.jmbs.2015.05.005	Comparative spatial ecology of farmed spiny lobsters Pa...
12. T0H0L0E1	10.1016/j.jmbs.2015.05.005	Ecology of a coral-reef gastropod, Conus caryoceras, in...
13. T0H0L0E1	10.1016/j.jmbs.2015.05.005	Long-term dynamics of coral reefs in 101, John, US Virgin...
14. T0H0L0E1	10.1016/j.jmbs.2015.05.005	Luminescent bioluminescence in corals from the Great Barrier Reef...
15. T0H0L0E1	10.1016/j.jmbs.2015.05.005	Sexual reproduction of the photosymbiont Symbiodinium...
16. T0H0L0E1	10.1016/j.jmbs.2015.05.005	Spatial distribution of benthic invertebrates on coral reefs...
17. T0H0L0E1	10.1016/j.jmbs.2015.05.005	Spectral discrimination of coral reef benthic communities...
18. T0H0L0E1	10.1016/j.jmbs.2015.05.005	Disease Diagnostics and Pathways Connections by Vibri...
19. T0H0L0E1	10.1016/j.jmbs.2015.05.005	The expansion of the Great Barrier Reef to oceanic...
20. T0H0L0E1	10.1016/j.jmbs.2015.05.005	The extended phenotypes of marine symbionts: ecology...
21. T0H0L0E1	10.1016/j.jmbs.2015.05.005	Warm, hot and cold temperatures contributed to a Late Mio...
22. T0H0L0E1	10.1016/j.jmbs.2015.05.005	Evidence for Autoinduction and Quorum Sensing in Vibri...
23. T0H0L0E1	10.1016/j.jmbs.2015.05.005	Larval Demographic Processes of Juvenile Corals in B...

Fig. 2. A portion of a JMP table featuring text and metadata (e.g., DOI) from 43,998 coral reef research articles published since ~1850. The columns feature parameters like field site latitude, methods used, author nationality, and coral studies.

research (e.g., ecological vs. physiological), and the like. I want to know how the coral reef research field has grown over time, as well as how research trends and priorities have changed. I'm certainly not going to read 44,000 abstracts!

Instead, I exported the metadata from my citation management library to a SQL file and asked Claude to add the manuscripts' text to a single (enormous) CSV file. A more advanced JMP user could surely have used JSL to do this, but I had to go diving, so Claude made the CSV file for me, and I imported it into JMP (Fig. 2).

At this point I have spent about five minutes of "hands-on" time on my computer. Starting from the 43-column (article metadata+text content) by 43,998-row (the articles) JMP data table (Fig. 2), I first wanted to simply see how publication output and authorship has changed over time. I dragged "year" into the X-axis of Graph Builder and immediately got the larger plot shown in Fig. 3. Five seconds of work.

There has been an absolute explosion in coral reef research since I began my career in 2002. In a given year, there are now as many coral reef articles published as had been published cumulatively between 1850 and when I started graduate school. Since 2009, when I published my second paper, 32,000 of the 44,000 coral reef articles in my database were published, meaning that nearly 75% of all coral reef-related articles have been published in the past 16 years.

I also suspected that, given that science is becoming increasingly more interdisciplinary, the number of authors per article has increased over time. I opened another Graph Builder window, dragged "year" into the X-axis drop zone and "author count" into the Y-axis drop zone, and I got the inset of Fig. 3; for much of the history of our field, articles featured a single researcher, or at most two. However, the average is now 8-10 authors/paper, which is probably good news, assuming the majority merited authorship.

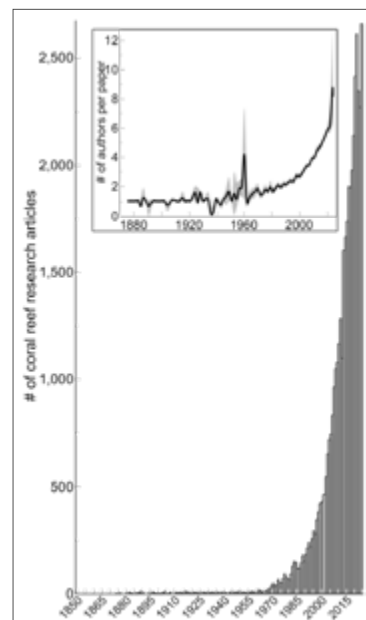


Fig. 3. Increase in number of coral reef publications and number per article (inset showing a spline plot with 95% confidence intervals as gray shading) over time.

To see how research priorities and trends have changed over time, I next used Text Explorer to analyze the half a billion words in the data table. One good thing about Text Explorer is that it already knows to ignore very common words (e.g., "the," "a," "an"). Manually adding additional "stop words" is fast and easy; these are terms, such as "coral reefs," that you expect to be present at high frequencies and which will not be of interest in this comparison. I spent about 5-10 minutes removing stop words, though you can still see words like "described," "source," and "science" in the word cloud of Fig. 4. These terms do not tell us much about how coral reef research has changed though are generally "harmless" as we proceed toward more advanced topics.



Fig. 4. The most common words found in coral reef research articles. “Corals,” “coral reefs,” and several other very common words were removed (stop words). The top 10 remaining terms are highlighted in blue.

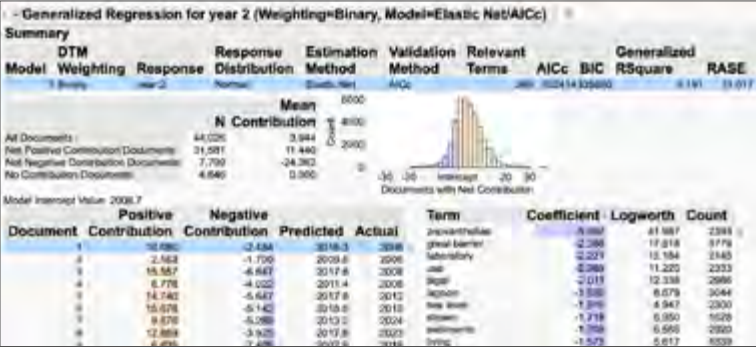


Fig. 5. Text Explorer's Term Selection output. This display is dense by design because I aim to show how rich the output is. The yellow and purple terms are those that are becoming more and less common, respectively, in the coral reef literature, over time.

I next used the Term Selection tool under the Text Explorer red triangle menu and set “year” as the response column. I used the default modeling conditions to identify research themes that are becoming significantly more or less common over time (Figs. 5-6). This analysis took 5-10 seconds on my Macbook Pro (M1) with 64 GB of RAM.

One of the most dramatically decreasing terms is “zooxanthellae,” which was the old, nonspecific name for the dinoflagellate algae living within all reef-building corals. The preferred nomenclature

for the past 10 years or so is to use the family name for these photosynthetic mutualists: Symbiodiniaceae. This result was expected and reflects our fieldwide push to use more taxonomically accurate nomenclature, and “Symbiodiniaceae” is the term that is increasingly used in publications to the greatest extent (Fig. 6). Both “USA” and “Florida” are decreasing in frequency (Fig. 5), as work in Indonesia (Fig. 6) increases. This result reflects the slow-but-sure shift from developed country-centric research to those developing nations that possess the majority (~75%) of the planet’s coral reefs.

Term	Coefficient	Logworth	Count
symbiodiniaceae	0.001	142.62	2038
restoration	0.001	62.939	2458
connectivity	0.001	18.633	1742
ecosystem	0.001	18.659	11422
underwater	0.001	11.510	1838
Indonesia	0.001	12.437	1742
macroalgae	0.001	16.546	2574
gpr	0.001	8.537	2506
genes	0.001	16.568	2707
reef	0.001	24.142	2007
performance	0.001	16.931	2004

Fig. 6. Coral reef research themes and terms increasing in popularity over time.

Another theme that is rising significantly is “restoration” (Fig. 6), whereby a habitat is rehabilitated through, most popularly, planting corals. As of mid-2026, it is indeed the hot topic in our field, and the literature trend supports its emergence. Connectivity plays a critical role in restoration efforts; perhaps a restored reef could repopulate others in the vicinity through spawning of thermotolerant or otherwise more resilient larvae. It stands, then, that research focused on connectivity has also increased over time (Fig. 6). These are just a few of the interesting trends I was able to discover through tinkering with Text Explorer in less than an hour.

So that raises an interesting question. Do we already have enough data to save the world, data that are just sitting within a black box awaiting to be analyzed properly? Sure, we can always do more experiments in more places with more species using better technology, but in the case of coral reefs, which are highly threatened by rapidly rising seawater temperatures, we now need to evaluate the data we already have to see if we can optimize conservation and even restoration approaches (the topic of my JMP Discovery Summit 2026 presentation).

But now that we can meta-analyze research trends spanning decades and thousands of

papers in a matter of minutes, we might be surprised to learn how much we can use preexisting data to make important discoveries that could change the way we view (or save) the world. (In the future, we can also look at many more parameters of interest, including efficacy of coral reef intervention or whether a particular approach better fosters coral resilience.)

By being savvy with AI and JMP, I completed a rudimentary meta-analysis of 44,000 coral reef research papers in an afternoon, an effort that might have taken months just a few

years ago. Let AI do some of the “dirty” work for you so that you can spend more time using JMP to really explore some of these massive, complex, but incredibly under-served data sets out there; you might be surprised what you uncover.

Mayfield presented a paper at Discovery Summit 2025. Check it out:



“Let AI do some of the ‘dirty’ work for you so that you can spend more time using JMP to really explore some of these massive, complex, but incredibly under-served data sets out there; you might be surprised what you uncover.”

Career conversations

You want proximity to the problems, but you're drawn to the data

By Wendy Tseng



Wendy Tseng is a Principal Systems Engineer at JMP, where she helps engineers, scientists, and business analysts accelerate their impact in their projects, organizations, and careers through data and analytics. With degrees in biomedical engineering and applied statistics, she transitioned into analytics-focused roles, building a career that spans engineering, statistics, and business analytics.

Two years after starting my first job as an engineer, I knew I wanted to do something different. Initially, it was interesting to be a part of getting products to market. But after the first product launch, I started to notice how much of the job was paperwork and processes that were uninspiring.

The aspects of the job I loved were those that involved data: analyzing test method validation data, performing root cause analysis on failures, quantifying process variation for critical dimensions. I saw statistics as a process for learning and making

sound decisions and, as a result, a way to make an impact as a young engineer.

What kept resurfacing was a pivotal experience I had during a year-long internship working alongside a biostatistician and retinal surgeon. The retinal surgeon was the principal investigator in a study to evaluate a drug implant to treat an inflammatory retinal disease. He developed the hypotheses and understood the disease progression, but the biostatistician was the one interpreting the study data because of her knowledge of statistics. This experience showed me two key things:

- Knowledge of statistics is powerful.
- Strong collaboration between a statistician and a domain expert accelerates learning.

I knew I wanted to do more of what I liked and less of what I didn't like. So, I started a part-time master's degree program in applied statistics. I wasn't 100% sure I wanted to change careers, but I knew I had to take the first step by getting formal education. Also, I thought whether I decided to pursue a career change or not, the coursework would help me as an engineer. Getting a degree as a part-time student allowed me to learn more about statistics as I continued to work as an engineer.

Eventually, I did commit to making a career change from engineer to statistician. But looking back, I didn't know there were alternative paths. After

“I saw statistics as a process for learning and making sound decisions and, as a result, a way to make an impact as a young engineer.”

decades of working in different industries as a statistician, I realized that making the career switch is one of many career paths for a “data person.”

I've met several scientists and engineers who advanced their careers through applied statistics – without switching career paths. They took the initiative to advance their knowledge in statistics and increased the impact of statistics in their organizations by applying that knowledge. They advanced innovation in two ways: directly as technical experts and indirectly by advancing the statistical competency of colleagues.

As scientists and engineers, they stayed close to the problems and identified more problems that could be solved with data analysis, making decisions that directly impacted projects.

Seeing this proximity to the problems and solutions made me reflect on how I might have made a different decision two decades ago had I known that I could have evolved my work as an engineer – versus completely pivoting.

I wanted to know how other scientists and engineers who've had similar life-changing moments with applied statistics navigated it in their careers. Why have some technical experts chosen to stay and others to pivot? I spoke to several scientists and engineers that were the data people in their organizations about their careers. These conversations helped me understand myself better. Click on the QR code at the end to read more about these conversations.

Reflecting on career leaps

I have often looked back and questioned my decision to move away from engineering. Witnessing data people who evolved their roles to incorporate their passion for data while still staying in their professions highlighted the trade-offs I made with leaving. As a statistician/consultant, I often felt an uncomfortable distance from the problems and decisions. I wish I had known there was another path I could have considered.

Even so, conversations with others in similar situations helped to put words to a feeling I always had about the various career changes I've made. At the core, I also loved new challenges and solving problems. Understanding one's core motivations is crucial to be able to take career leaps that lead to drastically new experiences, growth, and more opportunities. I think the path I've taken has scratched the itch I've always had for novelty, challenge, and problem solving.

One conversation reminded me how intense some of the feelings that I had as a young engineer were, new to the workplace. I'd forgotten how strongly I felt about things I loved

and things that I disliked and how ambitious I was to build a career.

The conversation to have

If you are a data person thinking about how to evolve your career, I want to leave you with some questions to ponder.

- What drives you at your core? What kinds of problems or questions do you find yourself coming back to repeatedly?
- What brings you the most satisfaction? Building a new product; discovering underlying mechanisms or insights; helping others uncover insights with data and statistics?
- Can you reshape your current role to include more of what you enjoy and less of what you don't? Would the incremental changes be enough (or too little) to be fulfilling?
- Do you need formal education to evolve your career or to explore the idea of evolving it? There are many affordable, flexible options for master's programs in applied statistics (e.g., Purdue, University of Michigan). Outside of degree-granting programs, Coursera, Udacity, ASQ, and JMP (to name a few) have many excellent opportunities to build your skills.
- Would you be satisfied to be a statistician or to do more statistical work without the title? There are far more job postings for engineers and scientists than statisticians.

As you think through these questions, it may be valuable to seek out other data people to exchange stories and ideas. Attending conferences like JMP Discovery

Summit are a great way to connect with other data people.

The experiment is yours

There are many ways to design a fulfilling career as a data person. If you find yourself drawn to data, asking deeper questions, or wanting to understand "why" just a little more than those around you, don't ignore it. Practical constraints you may have (e.g., time, money, family) will inevitably shape your path, much like constraints shape a well-designed experiment. And like experiments, careers evolve sequentially, with each experience informing the next iteration.

"If you find yourself drawn to data, asking deeper questions, or wanting to understand 'why' just a little more than those around you, don't ignore it."

Check out Tseng's Discovery Summit Online plenary where she is joined by Research Scientist Cara Happe of Promega and Rebecca Breuer, Senior Statistician at Francis Medical, for more inspiring stories on becoming the data person. You'll find it on community.jmp.com and in the new JMP for Stats app.

Tseng explores the topic further – complete with interview – on The Analytic Advantage blog: jmp.com/analyticsadvantage

Distinguish a real signal from a fortunate coincidence

By Ryan Lekivetz



Ryan Lekivetz is a Director of Advanced Analytics R&D at JMP, heading the Design of Experiments (DOE) and Reliability Development team. Lekivetz earned his doctorate in statistics from Simon Fraser University in Burnaby, British Columbia. He has published papers on DOE topics in peer-reviewed journals and holds many patents that he shares with his team members.

This year marks the 100th anniversary of Ronald Fisher's 1926 paper, "The Arrangement of Field Experiments." This article started where many discussions of Fisher usually begin: $p < 0.05$.

After all, the paper contains one of Fisher's early discussions of what would become the familiar 5% significance threshold. Fisher described the point at which "either there is something in the treatment, or a coincidence has occurred such as does not occur more than once in twenty trials."

Reading his paper a century later, I was struck with how casu-

ally Fisher treats what would later become one of the most famous numbers in science. If one-in-twenty did not seem convincing enough, he suggested using one-in-fifty or one-in-one-hundred instead. We could easily be living in a world that obsesses over 0.02 or 0.01 instead of 0.05. But after revisiting the paper, I found myself much less interested in discussing the significance threshold itself than in everything else going on around it.

The paper feels less like the introduction of a single idea and more like a collection of several important ideas coming together: randomization, replication, blocking, factorial experimentation, and valid estimation of error.

A framework for learning

Many of these concepts were already being developed through the work happening at Rothamsted. What Fisher did was assemble them into a framework for learning from data.

One passage that stood out to me was Fisher's observation that: "One way of making sure that a valid estimate of error will be obtained is to arrange the plots deliberately at random."

Today, randomization is so familiar that it can feel almost obvious. But the idea reflects a deeper principle. If we want trustworthy conclusions, we have to think about how the data are generated before we worry about how they will be analyzed.

"If we want trustworthy conclusions, we have to think about how the data are generated before we worry about how they will be analyzed."

That idea resonates strongly with me because it is still the problem we face today.

We live in a world of machine learning, AI, automated model building, and nearly unlimited computing power. We can fit models faster than ever. We can optimize objectives at massive scale. Yet many of the biggest mistakes still occur long before any model is built. Was the data representative? Were the right questions asked? Did we create the conditions necessary to learn something meaningful?

In other words, are we designing for discovery, or are we simply collecting data and hoping discovery happens afterward?

"Are we designing for discovery, or are we simply collecting data and hoping discovery happens afterward?"

Another passage in the paper feels surprisingly modern: “In reconciling thus the two desiderata of the reduction of error and of the valid estimation of error, it should be emphasised that no principle is in the smallest degree compromised.”

A century later, I wouldn’t be able to phrase that challenge quite so eloquently, but it remains fundamentally the same. We want to reduce uncertainty as much as possible while also having an honest assessment of the uncertainty that remains.

“We want to reduce uncertainty as much as possible while also having an honest assessment of the uncertainty that remains.”

The challenge is not simply producing answers. It’s knowing when those answers deserve our confidence. That’s one reason I think the paper remains relevant today. Its lasting contribution wasn’t the 5% threshold, nor even a specific experimental design. It was the recognition that credible conclusions begin with thoughtful data generation.

As someone who spends much of my time thinking about experimentation, predictive modeling, and how organizations learn from data, that message feels every bit as important in 2026 as it was in 1926.

The tools have changed dramatically.

The underlying challenge has not.

A century later, we’re still trying to answer the same question Fisher was asking in a field experiment: how do we create the conditions

to distinguish a real signal from a fortunate coincidence?

And it turns out, that’s a pretty timeless question.

References

Fisher, Ronald Aylmer (1926) *The arrangement of field experiments*. Journal of the Ministry of Agriculture, 33. pp. 503-515. 10.23637/rothamsted.8v61q

Ryan Lekivetz is among the statistical thought leaders interviewed on Stat Speaking with JMP: jmp.com/statspeaking



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If the foot fits

WildTrack's data-driven conservation, one step at a time

Every footprint tells a story. We just need the right tools to understand it. From the rainforests in South America to the deserts of southern Africa, to the tracks left in sand, snow, and soil, our planet is constantly revealing clues about the life it holds. WildTrack is turning clues into data and helping protect endangered species in ways that are both innovative and noninvasive.

We spoke with WildTrack's co-founders Zoe Jewell and Sky Alibhai to learn how the organization is using analytics, community collaboration, and technology to help protect endangered species around the world. Because what if the key to protecting our planet isn't just what we can see, but what we can measure?

A mission rooted in every step

What if you could protect a species without ever touching it? That's the vision behind WildTrack.

WildTrack is a nonprofit organization that uses data from animal footprint tracking to help monitor endangered species without harming them. Using a unique synergy of noninvasive footprint tracking that combines advanced analytics and traditional ecological knowledge, it can decode animal tracks into rich biodiverse data. Each track it records is a

data point that can help keep a species from sliding toward extinction.

The premise sounds almost impossible: no collars, no tranquilizers, and no disruption of any ecosystems. However, the science behind it is rigorous. WildTrack's footprint identification technology (FIT) has been used to monitor such species as rhinos, lions, leopards, polar bears, and others – with more than 90% classification accuracy.

These outcomes weren't inevitable. When WildTrack first began, nearly all scientists were skeptical and reluctant to believe that traditional ecological knowledge could be translated into science and results. The data it collected changed that. Not through argument, but through results and data visualization tools that made it possible to see clearly and communicate convincingly.

In southern Africa, WildTrack's data on cheetahs, lions, and leopards helped wildlife conservation managers understand how these endangered species use protected and unprotected areas so that conflict mitigation measures could be implemented. It has a multitude of success stories, ranging from tracking small mammal species like sengi to helping authorities in northeast China track the Amur tiger.

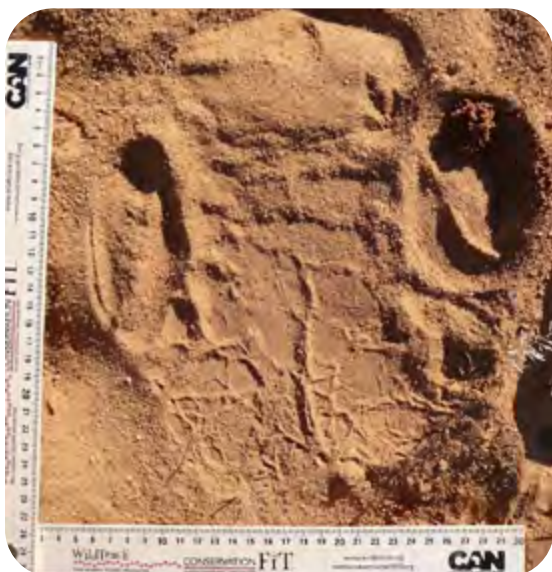


“What starts as a mark in the mud becomes a data point, and enough data points become a population.”



“Biodiversity loss is accelerating faster than our capacity to monitor it.”

Sky Alibhai
Co-founder
WildTrack



There is also a misconception worth addressing: that footprints are somehow “less scientific” than GPS collars. WildTrack’s analyses disproved that notion pretty soundly, showing higher accuracy and richer ecological detail. Instead of tracking a select few animals wearing collars, FIT creates a record of where all the animals in a population roam. No other wildlife monitoring tool can do this cost-effectively at landscape scale.

How does it actually work?

The process begins with a single photograph. A tracker captures an image of a footprint in the field, which is then fed into FIT, WildTrack’s custom-built platform on JMP. FIT automatically extracts more than 120 measurements from the print. It

extracts things like toe spacing, pad shape, and overall geometry and runs them through classification models built from a library of known species and individuals. What starts as a mark in the mud becomes a data point, and enough data points become a population.

A race against disappearance

But WildTrack is working against the clock. “Biodiversity loss is accelerating faster than our capacity to monitor it; many species are disappearing before we have basic data on their populations and ranges,” Alibhai said. Conventional monitoring tools like collars, GPS tags, and camera traps are expensive, physically disruptive, and difficult to deploy at scale across large landscapes and multiple species at once.

Making things harder, the data that does exist is rarely unified. Jewell said that “Conservation data are often fragmented across organizations, formats, and methods, making it difficult to see the big picture in time to act.” WildTrack’s innovation of a cost-effective, community-focused, landscape-scaled application within JMP is a direct response to that problem, and it produces results that hold up under scrutiny.

“Conservation data are often fragmented across organizations, formats, and methods, making it difficult to see the big picture in time to act.”

Zoe Jewell
Co-founder
WildTrack



The pattern recognition technology behind WildTrack's footprint analysis has potential far beyond wildlife. In medicine, the same approach of reading subtle variations from a single source over time could flag early signs of arrhythmias or microvascular changes before symptoms even appear. In industry, it could detect the first microshifts in a turbine or pump that signal a failure, days or weeks before it happens. In computer science, behavioral biometrics, like how someone types or swipes on their phone, could be tracked the same way WildTrack tracks a paw print, keeping systems secure without invasive monitoring. Even in humanitarian settings, anonymous movement patterns along community routes could reveal when something has changed. Whether it's a new conflict zone, a flooding path, a dangerous wildlife presence, we would know without ever recording a name or face.

What comes next

WildTrack sees conservation moving in a clear direction – toward real-time decision support, where data from footprints, sensors, and images feeds continuously into platforms that can guide action as conditions shift on the ground. WildTrack is already using AI in JMP that can identify species, individuals, sex, and age-class from a single footprint, opening new possibilities in noninvasive monitoring. Cloud infrastructure is making it feasible to scale footprint analytics globally while keeping the collection process as simple as taking a photograph.

Longer term, the team expects the field to move from single-species analysis toward something more ambitious like multispecies, landscape-level views that reveal how whole ecosystems are responding to pressure. WildTrack's tools are already well suited to that shift, with predictive modeling and model comparison capabilities built to handle the kind of algorithmic complexity that future conservation science will routinely require.



When asked what they'd build with unlimited resources, WildTrack's answer was a "real-time interactive atlas" of the planet, mapping the movements of multiple species across continents using nothing more than tracks in sand, snow, and soil. Beyond that, it would use footprints as early-warning indicators of how species respond to climate change and habitat shifts. It would also build the tools in partnership with Indigenous and local communities, so those communities can ask their own questions about their data.



Decades of partnership

WildTrack's relationship with JMP goes back to the organization's earliest work and has deepened ever since. "Our collaboration with the JMP family, particularly the developers, has been the foundation of all our work over the years," Alibhai says. Together, JMP and WildTrack built FIT, a platform based on JMP that automates feature extraction from footprint images and processes extraction data through a full analytical pipeline to give conservation teams a workflow they can use in both lab and field settings.

That partnership has allowed WildTrack to grow from its initial rhino monitoring projects into a global footprint AI initiative, while keeping the tools accessible enough for field biologists who may not have a data science background. In early 2026, WildTrack hosted a workshop at JMP, gathering conservation biologists, data engineers, and statisticians to push the work forward. The developers brought new ideas to the table, such as spherometrics for footprint classification, design of experiments approaches for interviewing traditional trackers, and new machine learning options for species identification.

Visit the WildTrack website to learn more, donate, or participate: wildtrack.org



Watch the video about WildTrack and its use of JMP:



Measurable gains at Novo Nordisk Engineering

Turning audit pressure into real-time control

Within pharmaceutical manufacturing, few priorities outrank compliance. At the heart of that scrutiny are validation and the robustness of the statistical methods used in drug development and manufacturing that are crucial for getting the green light from auditors. But for many teams, the challenge is structural, with chemists and engineers not necessarily having the advanced statistical training needed to construct dependable, validated workflows from the ground up. The result can be a gap between scientific ambition and regulatory expectation, one that auditors are quick to flag.

It is in that space that consultants at Novo Nordisk Engineering (NNE) step in. By building robust, repeatable statistical frameworks, NNE helps companies turn fragile processes into systems that auditors can trust – and ultimately, approve.

Audit-ready workflows

Per Vase, Managing Consultant at NNE, has spent more than a decade supporting statistical frameworks in the pharmaceutical industry. While reproducibility and validation are core values of a good statistical workflow, both from the perspective of the manufacturer and auditor, the problem, Vase argues, lies in the tools. In environments such as Excel, scientists and engineers can end up doing a lot of programming themselves, creating bespoke solutions that may work in practice but fall short under regulatory scrutiny. For auditors, it raises a red flag: processes that are difficult to validate are, by definition, difficult to trust.



“There’s a lot of focus on cost today that wasn’t there ten years ago.”

Per Vase
Managing Consultant
Novo Nordisk Engineering

In contrast, JMP offers a different route. Tools such as the Workflow Builder use predeveloped, validated scripts embedded at each stage of a protocol, removing the need for manual coding. The result is not just efficiency, but transparency, and something auditors can interrogate with confidence: “It’s very easy for the auditor to feel comfortable because they can see exactly what you have done,” Vase says.

Optimizing before costs scale

But compliance is only part of the story. Increasingly, pressures also come from driving down costs. Pharmaceutical manufacturers that fail to properly optimize their processes risk poor yields or unnecessarily long run times when running them at scale. The consequence is not just technical inefficiency but financial drag. As Vase puts it, “there’s a lot of focus on cost today that wasn’t there ten years ago.” For companies looking to extract real value from their R&D investment, it often means circling back to revisit and reoptimize production steps that should have been right the first time.





In Vase's view, though, the real gains come from acting earlier. "Ideally, we should prevent bad things from happening and do preventative actions," he says, though concedes that such work is "much more difficult to sell" to management given the lag time between investment and visible return. Therefore, Vase says, it's key to focus initial efforts on what he calls "burning platforms," the areas of production with established need for an efficiency boost. "This way of working creates value," Vase continues, "and then at the next step, you can go for more long-term preventative things." Tools such as design of experiments (DOE) in JMP make that shift possible by enabling quick, targeted improvements that help to build a case for a more systematic, preventative approach. And crucially, they help to win the confidence of those holding the budget.

Once that preventative mindset takes hold, the focus shifts again, this time to measurement. For Vase, robust measurement systems are as critical as reliable production methods. "If you cannot measure, then you cannot see where you are," he says. Without that visibility, production can become guesswork. Teams that optimize their measurement processes before tackling production stand a far better chance of catching deviations early – rather than reacting after quality has already begun to drift, as it inevitably does in any pharmaceutical manufacturing process. The payoff is both practical and persuasive: fewer surprises, less wasted time, and a stronger case for investment.

Watch the video: jmp.com/nne



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A new data-forward paradigm across the enterprise

Energywith turns data visualization into a catalyst for digital transformation

Though batteries often fly under the radar, they are one of the most crucial pieces of infrastructure enabling the global transition to long-term energy storage. Batteries support innovations related to sustainable energy development, energy transport, and the efficient usage of electrical energy, among other industrial and domestic applications. With batteries expected to play key roles as energy storage devices at the grid scale, the research surrounding battery development has also changed. Part of this new research paradigm is Energywith, a battery development company that focuses on delivering large-scale energy transport and storage solutions.

Kei Hasegawa, a Manager in the DX and Data Strategy Promotion Groups at Energywith, says the company is in the process of transitioning from battery manufacturer to energy storage solution provider. As part of this shift, there is strong momentum to build out a data-driven culture with transformative potential.

Notably, Hasegawa adds, at Energywith, data-driven decision making is not limited to engineers; “visualized graphs are powerful features that allow salespeople or managers” to more intuitively see trends in their data. When visualization makes those trends more apparent, Hasegawa says “small successes arise, and [the teams] can spontaneously decide what actions they want to take.” In that way, democratized data visualization is the initial factor that accelerates things toward digital transformation, he says.

Data-driven decisions

In business decisions, there is an overarching need for certainty in lieu of guesswork. Hasegawa says that learning to visualize data across all sectors of the business, from sales to management to fabrication, has allowed the company to achieve some level of certainty.

“By analyzing the data rather than just speculating,” he says, leaders at Energywith “become aware of blind spots that reveal what is actually happening.” The cyclic nature of “formulating hypotheses from



“By analyzing the data rather than just speculating, [leaders] become aware of blind spots that reveal what is actually happening.”

Kei Hasegawa

Manager, DX and Data Strategy Promotion Groups
Energywith

the field’s perspective and then analyzing the data to see what happens” has allowed for new improvements at Energywith, Hasegawa continues, because new suggestions made to management are all backed up with data.

From visualization to discovery

A poignant example of data-driven decision making is in quality control (QC), where vast amounts of data can cloud detailed manual analysis. Hasegawa explains that by using data visualization in QC, the team was able to extract much more meaning from the raw data as opposed to manually analyzing it for trends. Additionally, data visualization allows the teams at Energywith to better understand the battery operation data of their customers.

“By using JMP, the data can be visualized quickly, making it easier to understand overall conditions,” Hasegawa says. If there are any excursions from limits in QC or in customer satisfaction, he explains that “JMP allows users to drill down and investi-



gate the underlying phenomena that caused the anomaly.” In this way, JMP enables teams at Energywith to extract more insight from their data, while also gleaning that insight faster.

The analytical efficiency and depth of insight that JMP has enabled at Energywith has driven wide-spread adoption of data visualization. Across sales, inventory, and manufacturing groups, “visualizing data often leads to unexpected discoveries,” Hasegawa observes. Importantly, he explains that sometimes the “results are consistent with the engineers’ knowledge; other times, there are results that contradict the engineers’ knowledge.” Only by adopting JMP can these genuinely novel insights be uncovered – a reality which ultimately helps strengthen the technical skills across teams of domain experts at Energywith.

Toward enterprise intelligence

Beyond each individual team, JMP has made possible a paradigm shift from siloed expertise to data-driven enterprise. Hasegawa emphasizes “there aren’t many tools out there that make it this easy to move data back and forth,” underscoring the vital role JMP plays in democratizing data science. And as Energywith strives to become a player in energy storage and sustainability, adopting JMP companywide has allowed it to become more efficient and sustainable as well.

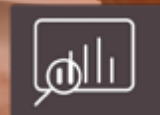
“In a sense,” Hasegawa reasons, “we can say that we are able to eliminate waste, and I think that being able to do that is the biggest achievement.”

Watch the video: jmp.com/energywith



“STIPS is excellent in balancing statistical theory and the practical hands-on use of JMP to solve common problems that many organizations deal with on a routine basis.”

Pete Cannon, NVIDIA



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Here's to discovering new ways to solve problems!



Friendlier skies

Lockheed Martin engineers take a statistical approach to aircraft departure noise

If you've ever stood in the vicinity of a fighter jet as it ascends from a runway – or lived anywhere near an airbase – you can appreciate the importance of Jeanette Elliott's work.

Elliott works for Lockheed Martin Aeronautics Company in Ft. Worth, TX, as an aeronautical engineer with the conceptual design group, helping optimize aircraft design. Most of the group's work occurs in the early stages of development, but once the planes are developed, engineers take another look to determine how the use of the aircraft can be improved. The group's primary clients are military agencies.

Elliott and her colleagues have been recognized nationally for a project that involved studying the flight patterns of fighter jets to minimize the noise that affects surrounding neighborhoods. JMP Statistical Discovery helped the researchers evaluate flight patterns in the vicinity of a base, and the project won the Distinguished Engineering Project Achievement Award from the Engineers' Council.

The complete process, Rapid Profile Development Methodology (RPDM), not only produces accurate results quickly, but it stimulates creative solutions. The Contour Profiler shows contours for a fitted model for two factors at a time and illustrates a feasibility region.

"The development of this methodology allowed us to rapidly change airplane parameters and flight conditions and then look at the resulting impact on the noise for the community," Elliott explains.

Transforming data into understanding

Aircraft noise is not only an annoyance; it can affect housing values as well. Addressing the issue helps the military maintain good relations with its neighbors. The Lockheed Martin team developed a process to establish community-friendly and pilot-friendly procedures that reveal the optimal "takeoff profile" for various types of fighter aircraft at specific airbases. Community concerns about noise need to be evaluated in conjunction with pilots' concerns about flight safety.

"Not only does this process reduce manual input errors, but we can accomplish in seconds what used to take hours or days to perform previously."

Jeanette Elliott
Aeronautical Engineer
Lockheed Martin

The ongoing process integrates such aircraft performance measures as takeoff distance and rate of climb. JMP regression equations are linked to computer programs from the U.S. Air Force and the Federal Aviation Administration to calculate noise levels to determine the noise-reduction potential of proposed changes to flight procedures.

Pilots then test the effects of each profile in a simulator to learn which might have the most positive effect for a particular setting. Testing has been performed on the F-35 and can be easily performed on any legacy aircraft, such as Lockheed Martin's F-16. The team's research has shown that adjustments to power settings, climb angles, and other parameters can significantly turn down the volume. Elliott uses JMP to make the process of discovery more expeditious and efficient. Her primary task, she says, is to "transform data into understanding and help make better decisions."





From the analysis results, her team can look at the impact of the change in the aircraft profile on the noise contours and suggest ways to alter flight profiles. “We can link that flight profile into the noise code, and you can pretty much immediately see the effect,” Elliott says. “This process is just much quicker and easier using JMP.”

“Not only does this process reduce manual input errors, but we can accomplish in seconds what used to take hours or days to perform previously.”

In addition, having the analysis results in JMP means that new profiles can be developed without having to delve back into the detailed analysis code. “You don’t have to be an expert in the code anymore,” she says, “meaning the results can be used by a lot more people. It allows you to rapidly construct a new profile without having to go back to the detailed code.”

Pinpointing optimal design

Elliott also uses JMP in the early stages of design. After an initial aircraft is drawn, engineers design experiments and perform multidisciplinary design optimization (MDO) to determine the best combination of variables for a design. They evaluate, for example, how changing the aircraft’s length or wing characteristics affect performance, cost, or any other measure.

Elliott explores possible combinations of factor settings using cutting-edge features for design of experiments (DOE) in JMP. “I generate data and then take that data into JMP to generate regressions and get curve fits,” Elliott says. “That allows us to look at a number of different scenarios and to change requirements and re-optimize without having to go back to the detailed analysis codes.”

Elliott can use the JMP Profiler to demonstrate how a change to one characteristic affects the others. “Let’s say I have a hundred different airplane designs, different ranges and different weights and mission times,” Elliott says. “I can set my constraints and say, ‘Give me the lightest-weight airplane that goes this far.’ And I can use JMP to pinpoint that design.”

Ultimately, this process yields the optimal design of the aircraft. “What’s nice is that if someone comes back and says that they want to change something – maybe they want it to be able to travel a little farther – I don’t have to go back and rerun everything. I can just change my constraint in the optimizer and then show how that affects the new design.” JMP helps her find the optimal point: “I don’t know how I would do that otherwise.”

Designing the design space

Elliott also uses JMP for stepwise regression to determine which variables are significant and therefore must be included in a design equation. Sometimes, as with the aircraft design, she can remove lower-order variables from the equation. “Having a smaller equation is definitely better, especially the more variables you have,” she explains. “It’s just too overwhelming to include everything.”

She’s also begun using the JMP Contour Profiler, which shows contours for a fitted model for two factors at a time. And she uses Fit Y by X capabilities in the software to look at her data before curve-fitting it to detect trends. Elliott continues to learn new applications for JMP. She is exploring recent enhancements to the software for drag-and-drop graph building, analyzing quality and reliability data, designing efficient experiments, interactively comparing models, and creating customized applications.

The bottom line, Elliott says, is simple: “JMP helps me design my design space and then make more efficient use of my data and time.”

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