TOPcast Episode 46: Empowering Humans Through Learning Analytics

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(musical transition)

Tom Cavanagh: From the University of Central Florida's Center for Distributed Learning, I’m Tom Cavanagh.

Kelvin Thompson: And I’m Kelvin Thompson.

Tom: And you are listening to TOPcast: The Teaching Online Podcast. Welcome, dear listener.

Kelvin: Just the one?

Tom: Yes, just the one.

Kelvin: (laughter) Just the one!

Tom: Just the one.

Kelvin: Boy, that is setting a low bar.

Tom: (laughter) “Low.”

Kelvin: (laughter)

Tom: Well, I mean, let’s make an assumption here that people are not listening in a vast crowd. It’s not being, you know, broadcast to a group. So, we are talking individually to a single listener.

Kelvin: It’s personalized learning, that’s what you’re saying. (laughter)

Tom: Yes, it is personalized learning. That’s right. It’s broadcasting many to one.

Kelvin: Although, as a potential teachable moment, right? Surely, that is a viable use case scenario. If you would like to assemble five, ten, fifteen, twenty of your dearest colleagues and sit around like old time radio. (laughter)

Tom: Yeah.

Kelvin: And we gather around the speaker and listen. We’d welcome that. Take a picture of us, send it to us. (laughter)
Tom: Tom and Kelvin, and little orphan Annie.

Kelvin: *(laughter)* Little orphan Annie, why did she have no irises?

Tom: You’re really getting off on a tangent there, Dr. Thompson.

Kelvin: Was I ever on the main road?

Tom: The phantom nose, yeah.

Kelvin: Ooh, I thought that was a shadow nose?

Tom: The shadow nose, you’re right. It is the shadow. I should know that.

Kelvin: Who knows what evil lurks in the hearts of men?

Tom: Of men, that’s right. My dad loved those.

Kelvin: The shadow nose.

Tom: Yeah.

Kelvin: But we digress. *(laughter)*

Tom: Do we? I don’t know.

Kelvin: *(laughter)*

Tom: So, as we were kind of digressing and talking, I did hear the delicate burbles of—

Kelvin: The delicate burbles? Is that like an adjacent possible to the dulcet gurgles?

Tom: The dulcet gurgles?

Kelvin: *(laughter)*

Tom: Yes, the delicate gurgles of a fine brew, I am sure.

Kelvin: Mhmm.

Tom: So, what am I stirring here, Kelvin?

Kelvin: Well, I brought in today, Tom, my go-to high end coffee blend, Storyville Coffee. We’ve had this coffee before, you might remember, on the show. This particular batch was hand delivered by our UCF colleague Bren Bedford after a trip to the Pike Place Storyville Café in Seattle. Bren—shout-out to the TOPcast Insiders—kind of coordinates the production of our TOPcast Insider newsletter. And hey, if you haven’t registered to get that monthly newsletter, you can do that rather easily. Just send us an email to topcast@ucf.edu. We’ll send you a link because I don’t remember the URL to it right this second.
Tom: *(laughter)* I’m sure it’ll be in the vast show notes.

Kelvin: The vast show notes, yes it will. But I’ve brought Storyville back in today for a very specific reason, Tom, not just because I didn’t have any other coffee because Lord knows I’ve got a lot of coffee. *(laughter)*

Tom: Yeah, and we do have. To anybody who’s actually sent us coffee—

Both: Thank you!

Tom: We will drink it all, at some point, on this show.

Kelvin: *(laughter)* That’s exactly right.

Tom: The problem is we’re only doing this once a month.

Kelvin: That’s right. It may force us, just to get through the coffee, to increase the productivity. But I brought this in for a reason, because I recently watched a one and half minute video in which the artistry and the humanness, I kid you not, the artistry and the humanness of the Storyville coffee blend creation and coffee roasting process are beautifully portrayed in an elegant, and I will even say poetic, manner. Although, full disclosure, a friend of mine who first introduced me to Storyville years ago, Vernon Raminwater, is the narrator of video. But it was beautiful. So, that’s the set-up, but here’s my hint. I’m adding a hint, Tom, because my Kung-Fu has been weak lately. My hint for today’s coffee connection is antithesis.

Tom: “Antithesis.”

Kelvin: Antithesis. So, that’s my set-up and that’s my hint. So, how’s the coffee and do you get some kind of a semblance of a connection to today’s topic?

Tom: The coffee is good. You do brew a strong cup of coffee. I will say that.

Kelvin: I was thinking—I don’t know what I did—this is stronger than normal.

Tom: It is, yeah.

Kelvin: I’m not sure what I—You know, my Kung-Fu in the coffee-making department may be weak too.

Tom: Well, maybe that’s the way you’re supposed to have it.

Kelvin: Yeah, it’s a little stronger than normal.

Tom: But it’s good, and as you know, I froufed it up with a whitener of some sort.

Kelvin: *(laughter)* It’s definitely a more delicate shade than the oily blackness in my cup that I’m drinking.
Tom: *(laughter)* But it’s good. And as far as the Kung-Fu goes, I’m working on it.

Kelvin: *(laughter)*

Tom: I happen to know what we’re talking about.

Kelvin: Yeah, that’s helpful. *(laughter)*

Tom: Yeah, that’s a hint.

Kelvin: Well, you can tell us the topic and I’ll try to make the connection if you want. That’s fine.

Tom: *(laughter)* Alright. So, there has been quite a bit of growing discussion and interest in—and I think rightfully so—the subject of analytics.

Kelvin: Mhmm.

Tom: And how do we identify students at risk and intervene to get them back on track before it’s too late?

Kelvin: Yeah, that is today’s topic. And in my antithetical set-up with the Storyville coffee and the humanness and the artistry of the blending and coffee roasting process was really just to underscore that with analytics, we tend to think scale and automatic, even, and kind of homogenizing and moving along in some sort of an almost AI kind of “Hey, we’re going to figure this all out” kind of way. And I’m just a little voice crying out in the wilderness like “Humans!”

Tom: *(laughter)*

Kelvin: Humans in the loop! Humans!

Tom: Okay, I get it now.

Kelvin: Yeah. So, thank you.

Tom: But yeah, I think you’re right. And I’ve even been in meetings where I or you or others have reminded people that “Hey, that report that you’re showing with all the numbers and colorful charts that says whether or not this student is likely to graduate in that major, let’s not forget that’s a human being.”

Kelvin: Yeah.

Tom: And that long spreadsheet with 60,000 of those represent 60,000 individuals here at UCF. Actually 68,000 here at UCF.

Kelvin: *(laughter)*

Tom: And so, you really, I think you make a good point. You can’t lose sight in the numbers in sort of these goals to move retention one percentage point or two
percentage points, or graduation by whatever. We are talking about human beings here.

Kelvin: Yeah. Yeah, what you said.

Tom: Yeah.

Kelvin: That’s exactly right. So, thank you for that. I agree. I’m with you. I think that this whole learning analytics trajectory is a very useful road to travel potentially.

Tom: Yeah, well, I’m on that bus. I’m totally for it. I think that it is an appropriate use of machine skills. (laughter)

Kelvin: Mhmm.

Tom: You know, let’s take advantage of the ability of computers to compute and interpret large quantities of data and find meaning in it. I feel the same way about healthcare.

Kelvin: Mhmm.

Tom: And I think we ought to be able to have computers help us diagnose things when it can be a tool to support a doctor.

Kelvin: Mhmm.

Tom: And I guess we would take the same kind of analogy or approach in analytics.

Kelvin: Mhmm.

Tom: At least, that’s my perspective. I use this example a lot. If you present a particular, I don’t know, let’s say a predication about a student. “Hey, you’re at risk. You are on track to fail this course.”

Kelvin: Mhmm.

Tom: You show that exact same data and message to two different students in the same class, so that the message is neutral. Right?

Kelvin: Mhmm.

Tom: And it’s not customized.

Kelvin: Mhmm.

Tom: Each of those students can have a wildly different reaction to that information.

Kelvin: Mhmm.
Tom: One student could potentially get inspired by that and get their budding gear, and say, “Yeah, I need to improve.” And the other one could just get discouraged and drop out.

Kelvin: Right.

Tom: And it’s one reason why you have to call the doctor to get your test results, right?

Kelvin: Yeah, very good metaphor, Tom! Or is that an analogy, or a simile? I don’t know.

Tom: *(laughter)*

Kelvin: But it is good, whatever it is!

Tom: Yeah. Well, I mean, I think it’s true. And it’s the same thing here in education where the stakes maybe aren’t quite as high.

Kelvin: Right.

Tom: But are still pretty darn high when you’re talking about whether or not you’re going to stay in school. So, if analytics can be used as a tool for the human being to have an interaction with the student about, I think then it could be really useful.

Kelvin: We certainly want, to extend your medical metaphor, we certainly want to do no harm, right?

Tom: Right, yeah. The Hippocratic Oath of higher education, yeah. *(laughter)*

Kelvin: That’s right. And I guess just to, because we kind of assumed, I suppose that everybody’s on the same page with us. Might be maybe not a bad thing just to kind of say that what we’re saying to learning analytics here, this is all—let me throw out a cloud of words. You know, big data, data science, educational data mining, business intelligence, all of that. Baker and Siemens in 2014 made the phrase, “One can scan through large datasets to discover patterns.” And what we’re saying is yes, all of that broad brushstroke backdrop. But what I think we’re mostly concerned about, Tom, in our world and maybe for this particular episode is how to leverage real time learning management system data for student access in particular against the backdrop of all the other kinds of big data at our institutions. Would you agree?

Tom: Yeah, that’s true. Yeah, I think it’s good to kind of sharpen that pencil a little bit because there are all kinds of big data initiatives going on here and elsewhere that involve institutional data, SIS data, ERP data.

Kelvin: Mhmm.

Tom: And look at much more macro-patterns of predictive models and things like that. And the world that we live in, ours is much more granular at the course level and that’s what we’ve been spending a lot of our focus on.
Kelvin: Yeah.

Tom: Obviously, in collaboration with the folks on campus here who are doing things at the more institutional level.

Kelvin: Mhmm.

Tom: Trying to just make sure that everything we’re doing is complimentary for each other, and at some point, we’ll all talk to each other.

Kelvin: Yeah. And I’m totally going to put you on the spot here. You feel a little bit more comfortable in broad brushstrokes talking about the recent prototypical predictive model that we’ve been playing around with just a little bit? Because it does speak to SIS data and maybe the relationship to real-time LMS data, just as a toe in the water kind of thing.

Tom: Sure. This is obviously more vision than practice for us right now.

Kelvin: Mhmm. But as a concrete example.

Tom: Yeah, well. I mean, at the university, we do have some large-scale predictive analytic efforts going on, which is mostly using SIS data and looking at end of course grades and registration patterns and other kinds of factors to determine whether or not somebody’s at risk or will graduate in a particular major. And then what we’ve been doing at the course level is trying to look at what’s happening today with the particular student and go through some tools that we’ve built ourselves, as well as some things that are kind of out of the box or coming soon in the LMS that we happen to be using. We are trying to figure out ways that we can have those two systems talk to each other so that the faculty can send information to the advising community and everybody keeps using the platforms that they’re used to using. We don’t have to build some sort of middleware in-between that everybody’s going to log into because nobody is going to log into yet another thing.

Kelvin: No, that’s been made clear.

Tom: Yes, and I agree with it because I feel the exact same thing.

Kelvin: I don’t want to do anything more than I have to do. I’m already here. Why would I go somewhere else?

Tom: Right. And when you’re talking about scale, and you’ve got in some cases fairly large classes, and the most valuable resource a faculty member has is his or her time.

Kelvin: Mhmm.

Tom: We want them focused on the things that matter.

Kelvin: Mhmm.
Tom: And if they can focus on those students, that maybe if they just sent an extra message or invited them for office hours.

Kelvin: Mhmm.

Tom: Or whatever it might be, could make the difference, kind of elevating those students, to put right in front of their faces and say “Hey, here are a couple that I think you should probably pay attention to.” I think it’s well worth the effort.

Kelvin: Yeah, I think that’s right. And to that point, just as a—I don’t know, line in the sand, flag in the ground—I’m fascinated by what might influence faculty. We’re talking a lot about empowering decision makers, right? Especially faculty because they’re very strategic. Also, at the individual student level. You gave that example earlier, a few minutes ago. This is not a great example, but I think it serves as a placeholder. I read a study recently of Dutch primary teachers and their data-based decision-making actions, and the researchers concluded that study with a statement which I think is just kind of emblematic, right? “The present study indicates that teachers’ perceived control of data use, their attitude regarding its benefits and consequences, and their intention to use data positively influence their instructional data use.” So, I think that’s fascinating. There are human factors that affect human data use. And if we want to connect these humans—the faculty and the students—we’re going to connect to them actionable data, we’ve got to also be mindful about what are these other factors that are going to cause them to take action or not, or to dismiss it, or to do something with it? And that’s really…I’m not hearing a whole lot about that. I think it’s an area that we need to explore a little further.

Tom: Yeah, that is interesting, and it’s something that I was thinking about talking about. Probably jumping ahead in our conversation, but whatever, here we go.

Kelvin: (laughter)

Tom: The whole concept of ethics around the use of analytics data.

Kelvin: Yeah, big. That’s big.

Tom: It is big, and it’s probably worth its own discussion. But just to kind of touch on it, there are a number of kind of facets to it, and there’s been a lot published about it. You know, one area that I find fascinating is the kind of responsibility to act and kind of ethos, that if you do know something about a student, then you have a responsibility to do something with that. If you see a student through data that is going to fail and you don’t do anything about it, then you have a certain amount of culpability there.

Kelvin: Mhmm.

Tom: And I think there’s something to that.

Kelvin: Mhmm.
Tom: But it’s a fine line to walk because there’s an awful lot of questions of bias in here that you have to be careful about.

Kelvin: Right, yeah.

Tom: Whether it’s a student’s incoming social-economic status or whatever being correlated with students who struggle more or first time in college or first generation, or whatever.

Kelvin: Mhmm.

Tom: You don’t want to necessarily judge a student on anything other than their performance.

Kelvin: Mhmm.

Tom: Because that’s only fair. But you also want to be able to give them all the support that they might need.

Kelvin: Right.

Tom: You know, and how do you walk that line? And it can be difficult. And I think what we’re trying to do is err on the side of not pre-judging, obviously, like other schools around the country are doing.

Kelvin: Yeah. And I think phrases like self-fulfilling prophecy.

Tom: Yeah.

Kelvin: Right. You want to steer clear of that, and I think we’ve got a—it seems like to me. It’s been awhile since I’ve read this literature—but I think we’ve got a widely accepted literature base on the role of high expectations on student performance.

Tom: Mhmm.

Kelvin: You know, appropriate. Not unrealistic, not crazy, but appropriately high expectations.

Tom: Yeah.

Kelvin: So, you wouldn’t want to say, well, Tom was predicted not to do well anyway. *(laughter)* You wouldn’t want that right.

Tom: Right! Yeah, and in fact, that’s come up in faculty discussions where the faculty that we talk to on advisory board and other kind of folk groups that we do. They’re awesome, and I have no worries about them, but they have raised the question that you know, you’ve got a lot of students and you’re trying to focus on everybody at the same time. It is possible that if some predictive algorithm popped up and said, well, gee, Kelvin is at risk of not succeeding, there is a
potential temptation by some, it’s human nature to write them off and say, “I’m going to focus my efforts on areas where I think it’s going to bear fruit,” and that’s really not fair.

Kelvin: No, that’s not what we want to be about at all. I think if we had to boil down what we want to be about, it’s about reinforcing agency really. Student agency, faculty agency. What can we do to support the excellence already going on there? It’s like an exosuit. It’s like Iron Man!

Tom: *(laughter)*

Kelvin: It’s like, you know? You’re going to go out there and still get up and move, and I don’t know, chop some wood, and pick up that obstacle in front of you, but the exosuit is just helping to support what you’re going to do anyways. It’s just giving you a little extra oomph.

Tom: I got a mental picture of Tony Stark chopping wood now in an Iron Man suit. It’s an odd image.

Kelvin: But hey! Evocative, maybe?

Tom: Evocative. Yeah, it is. *(laughter)*

Kelvin: *(laughter)*

Tom: A couple of years ago I was fortunate enough to participate in a convening in California. It was called Asilomar. It was in Monterey at this sort of conference center that they have. It was this beautiful area.

Kelvin: Mhmm.

Tom: But it was put together to talk about this—about ethics and the use of student data—and one of the organizers of that meeting is a Stanford researcher named Mitchell Stevens, and he talks about the concept of open futures. So, analytics and the use of student data shouldn’t limit opportunities for students, right?

Kelvin: Right.

Tom: It shouldn’t be used as something that closes doors for students, but it should be used instead to help open doors for students.

Kelvin: Excellent metaphor!

Tom: And I mean, it resonates with me because sometimes you have to have a really hard conversation with students. One of the systems we’re using here on campus kind of tells an advisor or somebody how likely it is a student is going to graduate in that major and it may be that it’s not very likely. So, you have to have an honest conversation with the student based on the data. It’s like, “Hey, maybe you’re not meant to be an aerospace engineer. It’s a hard major, but based on where you have been successful, let’s see where you can be successful and fulfilled and challenged and happy.” Without the data, you wouldn’t be able to
have that conversation, and it’s not about saying, “Close this door. Forget about aerospace engineering.” But it’s about opening another door—several other doors—to say, “Hey, have you thought about these because you seem to be really successful here?”

Kelvin: What I like about that a lot is that the context is a human conversation, right? You’re just supporting that, and I would like to imagine in the hypothetical that if the student was like, “Yes, I get it, but you know, I have a passion. I really want to. This is my vision., I want to pursue against all obstacles this goal of being an aerospace engineer,” then I mean, then that goes a certain direction with the advisor because you wouldn’t want to shut them down.

Tom: No, and that’s something that’s come up. So, what do you do? Well, okay, if that’s your decision, then here are some supplemental resources.

Kelvin: Yes.

Tom: Some tutoring or other kinds of things.

Kelvin: It’s going to be a rough road.

Tom: Yeah, know what you’re getting in for, but okay, here’s what you’re going to have to probably pursue, and it’s going to be you know, tutoring, extra resources, whatever it is that you’re going to have to add to try to get you to that goal.

Kelvin: Yeah.

Tom: But yeah, again, it’s a data-informed conversation that comes out of analytics.

Kelvin: But I love that opening doors, not closing. It’s not like you’re saying, “Oh yeah, the system said…” like some kind of dystopian Brave New World, Aldous Huxley thing like, “The system says you’re not likely to succeed, therefore (blip).”

Tom: Right.

Kelvin: Here’s your broom. You know? Some kind of horrible thing like that. It’s not that human conversation.

Tom: Yeah.

Kelvin: The other thing that I loved—can I throw this out there? We both have talked about a ReplyAll mini-series called Crime Machine Part 1 and Part 2, and I thought that was fascinating.

Tom: I did too. I loved that.

Kelvin: But two things that really stood out to me…The originator of CompStat, that big kind of law enforcement database kind of thing. I think there was a version of that that was talked about in the Craig T. Nelson The District TV show a few
years ago. The originator was a beat cop, Jack Maple, and he had what just sounded like an interesting way of just interpreting events around him and seeing patterns, and there was this moment that they talk about in this episode, he recognized there an exit from the department store into the subway system at a certain time of day. He recognized that pickpockets were there, so he brought his little protégé along, and there he was picking up pickpockets left and right because he got that. That’s beautiful, and so helping other people discern those kinds of patterns would be a useful thing as opposed to abuses of the system.

Tom: Yeah and that two-part series of ReplyAll—I’ll send a link to it—is a fascinating case study in both the good and bad of analytics.

Kelvin: For sure.

Tom: And on the good side, I think it was a tool for human intervention.

Kelvin: Yeah.

Tom: And where Jack Mable was able to use the data and then put people in the subway cars and whatever and decoys and everything else that they had.

Kelvin: There was some great stories in there!

Tom: Oh, it’s fascinating. Yeah. But when it moves out of the realm of “Okay, how can we use that for human intervention?” to just a “We need to show certain numbers on the spreadsheet,” then it seems to not be working as well, and as a result, there are real abuses going on, I think.

Kelvin: Gaming the system.

Tom: Yeah.

Kelvin: Generating false data. There was one of the interviewees I think maybe in the second part of that little mini-series that talked about the misuse as a—it’s a very interesting phrase—management tool. When you’re using it to manage like “Okay, you got to see the numbers,” and they talk about examples of like the shift commander or whatever saying, “Alright, we need more jaywalkers today. Ignore other stuff. Just look for jaywalkers.”

Tom: Yeah, it’s terrible.

Kelvin: That’s crazy! (laughter) That’s insane.

Tom: And as I was listening, I couldn’t help but sort of think of it as an analogy to education.

Kelvin: Sure.

Tom: In the world that we live in.
Kelvin: Yeah.

Tom: And when you think about… I don’t know. We’ll pick a particular punching bag that we like to pick on which is US News and World Report

Kelvin: *(laughter)* Not that we’re not appreciative!

Tom: No, not that we’re not. But kind of at the macro level, there are—because of the influence of that algorithm—

Kelvin: Yeah.

Tom: It privileges schools to get a lot of applicants so they can turn them down so that they can increase their school activity, and the fewer students you admit, the better you look, and that’s not what we’re about here at UCF.

Kelvin: Right.

Tom: We’re about educating as many people as we possibly can, not trying to keep people out, so I’ll get off that high horse.

Kelvin: No, I think that makes sense. That’s good. I think going forward against—you know, we’ve been talking kind of at a broad brushstroke level—I think what we need as a sector—in our higher ed technology mediated impowered sector—is more concrete examples that fit within that big backdrop of all the caveats that we’ve issued in this episode, right? We need more concrete examples. I think a lot of our listeners are probably familiar, a few years back it got a lot of attention, Purdue’s signals project.

Tom: Mhmm.

Kelvin: Kind of the red light, yellow light, green light, kind of thing. Everything good, warning, warning, warning. And you know, a lot has been said about that, positive and negative. Michigan’s got the MyAnalytics thing recently.

Tom: It was Degree Compass that came out of Austin Peay.

Kelvin: Yeah. We use more of those. We’ve got a few, and we’ll link to those in the show notes, like our Student Performance Dashboard—which is still very beta—and we did stand up our Performance Insight Tool, different LMS providers are coming up with their own stuff as well. And you know, we’ve seen more of those examples in figuring out what’s working well with them and what’s working not well about them but gosh, I’m going to say it again, it’s all got to be about humans in the loop connecting to other humans. The data just help.

Tom: Right, yeah. I wonder if maybe before we wrapped up, it would be worthwhile to kind of just define the different kinds of analytics.

Kelvin: Oh good!
Tom: Like their purposes.
Kelvin: Yeah, that’s good.
Tom: And I like to plagiarize from my colleague and former boss, Joel Hartman.
Kelvin: *(laughter)* Well, at least if you’re going to do it, pick a good one.
Tom: I’m going to plagiarize and give citation credit!
Kelvin: Is that possible?
Tom: I don’t know. But I think he’s had a really good way of defining data usage, particularly at an educational context as the descriptive, diagnostic, predictive and prescriptive.
Kelvin: Mhmm.
Tom: So, descriptive data are data that tell you what happened.
Kelvin: Mhmm.
Tom: Like, how many students retained from spring to fall or whatever.
Kelvin: Mhmm.
Tom: Diagnostic data tell you why it happened. Predictive data is, “Okay, what do you think will happen? What’s the model? What’s Kelvin’s likelihood of success in this major or in this course?”
Kelvin: Slim.
Tom: *(laughter)* And then prescriptive data—which is I think where we all want to get to but also where it’s fraught with all sorts of ethical considerations—
Kelvin: Mhmm.
Tom: It’s how can we make it happen?
Kelvin: Yeah.
Tom: How can we craft a particular outcome? In the case of higher education, it’s like how many students can we get to do well in class and graduate and have the majors that they want, the jobs that they want, and all of that? I think having that sort of spectrum of data definitions really helps us to figure out which thing are we working on here?
Kelvin: Yeah.
Tom: And how does this relate to these other things? Because they each have different use cases.

Kelvin: I think that’s excellent. You shared that with me a while back and I thought it was great. I’ve been pondering it, so I want to lay over and talk about one other broad construct and that is there’s kind of I think all of one, two, three, four of those things there’s historic data and there’s real-time data. Right? Because the four things—the descriptive, the diagnostic, the predictive, the prescriptive—can be true of either of those big pools, the historic stuff, which I’ve been thinking of as slow data and the real-time like in our LMS as the fast data, the fast-moving stuff. And it’s good to kind of know what data pool you’re pulling into because the historic stuff can be useful as well. It can tell you what happened, why did it happen, what will happen. You can kind of base predictive models—and some companies do—on historic data only.

Tom: Netflix, Spotify.

Kelvin: Exactly.

Tom: Amazon.

Kelvin: Versus the real-time, fast-moving kind of stuff. I think we all are sort of enamored with the fast-moving stuff, but hey, starting somewhere, the historic data is not a bad place to start as well.

Tom: Yeah.

Kelvin: Yeah.

Tom: Maybe one last comment?

Kelvin: Mhmm/

Tom: I’ll give another shout out to a colleague of ours, Kyle Bowen at Penn State.

Kelvin: He’s a good guy.

Tom: I heard him say one time that analytics is just math with good PR.

Kelvin: *(laughter)* That is Bowen--esque.

Tom: Yeah, and I thought you know, he’s right because I think it’s consistent with what we said that it’s really a tool for human interaction.

Kelvin: Yeah, now that’s excellent. Well, you want to land this plane and we can get on with our day?

Tom: Sure, so maybe we can say that empowering the decision making of students and instructors and administrators and senior administrative leaders with insights
gleamed from historic and real-time data does have the potential to positively affect student success but learning analytics is not a panacea.

Kelvin: Mhmm.

Tom: Nor should it be pursued without humans in the loop or ethics at the front of mind.

Kelvin: Yes!

Tom: Okay, any other business we need to attend to?

Kelvin: No, we’ve used up all of our time and our listener’s attention.

Tom: Okay, well then, until next time for TOPcast, I’m Tom.

Kelvin: I’m Kelvin.

Tom: See ya.