Patterns of Successful Online Student Learning in a MOOC

Theodore W. Frick

Professor Emeritus

Department of Instructional Systems Technology

School of Education, Indiana University Bloomington, USA

Rodney D. Myers

Instructional Consultant

School of Education, Indiana University Bloomington, USA

Cesur Dagli

Research Analyst

Office of Analytics & Institutional Effectiveness

Virginia Polytechnic Institute and State University, USA

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Abstract (211 words)

In this naturalistic study, we tracked 172,108 learning journeys of students who were interacting with an online resource, the Indiana University Plagiarism Tutorials and Tests (IPTAT) at https://plagiarism.iu.edu. IPTAT was designed using First Principles of Instruction (FPI; Merrill, 2020). Students who used IPTAT were mostly from university and advanced high school courses taught in 186 countries and territories. Instructors expected their students to pass one of trillions of difficult Certification Tests (CT) provided through IPTAT. Each CT assessed student ability to classify samples of writing as word-for-word plagiarism, paraphrasing plagiarism, or no plagiarism—when given original source materials. In 51,738 successful learning journeys, students who had passed a CT viewed an average of 130 IPTAT webpages designed with FPI. In the 120,370 unsuccessful learning journeys, students had viewed an average of 26 webpages designed with FPI. Analysis of Patterns in Time (Frick, 1990) revealed that successful students were about 5 times as likely to have selected webpages designed with FPI when compared with those in unsuccessful learning journeys. These results support the extraordinary effectiveness of First Principles of Instruction for design of online learning in a massive, open, online course (MOOC). These findings further demonstrate the value of an innovative approach to learning analytics, Analysis of Patterns in Time (APT).

Keywords

Online learning; learning journeys; innovative learning analytics; MOOC; First Principles of Instruction; Analysis of Patterns in Time; instructional effectiveness; recognizing plagiarism; certification tests; mastery learning; web-based instruction.

Theoretical Framework

Michael Scriven (1967) has been often cited for first introducing the terms *formative* vs. *summative* methods when evaluating curriculum in education. Broadly conceived, these methods of evaluation are distinguished by their purpose. *Formative* evaluation is used to improve something during its development, whereas *summative* evaluation is used to determine its merit or worth when that development is completed. Worthen and Sanders (1987) also made this distinction, emphasizing that formative evaluation entails asking questions such as "What is working?", "What needs to be improved?", and "How can it be improved?" (p. 36). Reigeluth and Frick (1999) recommended ways that formative research methodology can be used to evaluate instructional-design theories. They stated:

> The underlying logic of formative research … is that if you create an accurate application of an instructional-design theory (or model), then any weaknesses that are found in the application may reflect weaknesses in the theory, and any improvements identified for the application may reflect ways to improve the theory. (p. 636)

The broader issue is praxiology in educology, according to Steiner (1988). In 1964 Steiner had introduced the term *educatology* for the study of education, but soon after shortened it to *educology* (e.g., see Frick, 2019, 2020). Disciplined inquiry about education, if adequate, results in qualitative, quantitative, and performative educology (Steiner, 1988). Educology is in essence "recorded signs of knowing about education" (Frick, 2021, p. 28).

Quantitative knowledge is comprised of *scientific*, *praxiological*, and *philosophical* theories which have been verified by appropriate research methods. These theories are about universals. Universals are not limited to time or place (Steiner, 1988). A praxiological theory is thus comprised of statements consisting of recorded signs about means-ends relationships that are universal. Such means-ends relationships are not limited to time or place. Instructional-design theories are, therefore, a type of praxiological educology. ID theories specify ways of effectively guiding student learning that can have broad generalizability (e.g., see Frick & Reigeluth, 1992).

David Merrill posited what he termed *First Principles of Instruction* (FPI; 2002, 2013, 2020). First Principles can be considered as an instructional-design theory, and hence also are part of praxiological theory in educology. Merrill (2020) defined a *principle*

> as a relationship between learning outcomes and instructional strategies that is always true under appropriate conditions regardless of the methods or models used to implement it. Rather than methods or models of instruction themselves, principles are the relationships that may underlie any model or method. (p. 2)

Overview of this Study

Merrill's First Principles of Instruction had been applied in 2015 when redesigning the online Indiana University Plagiarism Tutorials and Tests (IPTAT). The praxiological study described in this article is a form of *summative* evaluation (Scriven, 1967; Worthen & Sanders, 1987). We used a method to verify praxiological theory called *Analysis of Patterns in Time* (APT; Frick, 1990; Frick et al., 2021; Frick & Reigeluth, 1992; Myers & Frick, 2015). What is further innovative in this study is the use of Google Analytics 4 to track individual student interaction with IPTAT. GA4 created the temporal maps needed for APT—that is, big data collected on 172,108 learning journeys through IPTAT during early 2021. GA4 segmenting and matching tools were subsequently applied to count event patterns within those temporal maps which indicated student experience of First Principles of Instruction and their learning outcomes. Results from GA4 queries were then exported to a Microsoft Excel spreadsheet to perform further computations needed for APT.

Primary Research Question

Student learning achievement in IPTAT was measured by well-established and reliable Certification Tests (Frick & Dagli, 2016). These allowed us to address the primary research question:

> To what extent do First Principles of Instruction promote student learning achievement in IPTAT?

Merrill (2020) had further hypothesized that

> when a given instructional program or practice implements one or more of these First Principles, there will be an increase in learning and performance. Obviously, the support for this hypothesis can only come from evaluation studies for a given instructional product or research comparing the use and misuse of these principles. (p. 3)

Indeed, the IPTAT is “a given instructional product” which, in this case, happens to be a massive, open, online course (MOOC; Frick & Dagli, 2016).

Methods

Redesign of IPTAT in 2015

Frick et al. (2018) described 14 years of IPTAT development and use historically. While originally designed for students in the Instructional Technology program at Indiana University, IPTAT has subsequently been adopted by many instructors worldwide. These instructors want their students to avoid committing plagiarism, and typically they expect their students to pass an

IPTAT Certification Test as a course requirement. Frick et al. (2021) indicated that IPTAT had been accessed over 125 million times since its inception, and that from 2016 through 2020 nearly 750,000 students had passed one of trillions of IPTAT's difficult Certification Tests.

A team had significantly redesigned IPTAT in 2015 by applying First Principles of Instruction (Merrill, 2002, 2013, 2020). Merrill's First Principles of Instruction as applied to IPTAT included:

- *Authentic problems* or tasks for students to do, arranged from simple to complex (e.g., https://plagiarism.iu.edu/tutorials/index.html);
- *Activation* of student learning by helping students connect new learning with what they already know or believe (e.g., https://plagiarism.iu.edu/tutorials/task1/activation.html);
- *Demonstration* of what is to be learned, by showing a variety of examples (e.g., https://plagiarism.iu.edu/tutorials/task1/demonstration.html);
- *Application* of what is being learned, so students can try themselves and feedback is provided (e.g., https://plagiarism.iu.edu/practiceTest.php?task=1&item=1); and
- *Integration* of what has been learned into students' own lives (e.g., https://plagiarism.iu.edu/tutorials/task1/integration.html).

Examples of application of First Principles are illustrated by hyperlinks to webpages above. Since this design has been described in more detail elsewhere, readers are referred to Frick et al. (2018, 2021). Since IU technology services had discontinued their in-house Web statistics, the design team incorporated Google Analytics in the new version of IPTAT, which went live on January 2, 2016.

Analysis of Patterns in Time

The primary research method we used to evaluate the effectiveness of First Principles of Instruction in IPTAT was Analysis of Patterns in Time (Frick, 1990; Frick et al., 2021; Myers & Frick, 2015). APT is an innovative *learning analytics* method. APT has been used in many past studies (space prevents a detailed description here). Instead, we describe in detail below how we leveraged Google Analytics to do APT when supplemented by spreadsheet calculations.

Frick et al. (2021) used the metaphor of the Oregon Trail, comparing how early settlers followed it by walking and riding in covered wagons with how modern-day transportation systems can be used to make this trip. They introduced the concept of learning journeys and briefly summarized the limitations of traditional quantitative and qualitative approaches. They described APT as an alternative, which instead uses *temporal maps* as the primary data collection source. APT thus allows researchers to document what happens *during* learning journeys. If enough learning journeys are sampled, researchers can make predictions about patterns of student success and failure that are associated with various instructional strategies.

The important discovery in early 2020 by Frick et al. (2021) was that Google Analytics has been implementing many ideas from the original APT, which had been invented decades earlier (Frick, 1983, 1990). GA tracking effectively creates APT temporal maps, and if used creatively, GA can subsequently do segmenting and matching within temporal maps, resulting in counts of event occurrences that have been previously tracked on user interaction with a website such as IPTAT. Results from GA reports can then be transferred to a spreadsheet, where cell formulae are created to do further APT computations needed for forming likelihoods and odds ratios.

Google Analytics 4 for Collecting Big Data

Google Analytics 4 (GA4) was used for tracking student interaction with the IPTAT website. GA4 stored their interaction trails as client sessions. Session records are indeed temporal maps as described by Frick et al. (2008, 2021) and Myers and Frick (2015). GA4 allowed us to subsequently segment those student learning journeys based on their navigation through IPTAT and whether or not they passed Certification Tests (CTs). IPTAT also stored records of CT results, which served to triangulate our measures of student success.

Using GA4 to Carry Out APT Queries

Caveat: It took us some time to discover how to adapt GA4 in order to do Analysis of Patterns in Time. We were breaking new ground and not even sure we could do APT with GA4 when we started. Once we better understood how GA4 tracks and counts events, as well as how it identifies clients (active users), then we were able to proceed as described below. While GA4 by itself cannot do all of APT, it can greatly facilitate the counting process. Additional APT calculations such as means, likelihoods, and odds ratios can subsequently be calculated with a spreadsheet. We hope that our descriptions below will help guide others to use this approach to research on instructional effectiveness.

Setting up Website Tracking for GA4. IPTAT users were tracked since 2016 via Universal Analytics (UA), an earlier version of Google Analytics. Starting in early December, 2020, we connected the existing UA tracking system to the new GA4 tracking system, and then enabled new GA4 tracking records.

When initially setting up Google Analytics, a snippet of JavaScript code was provided that contained our unique website ID, which we inserted into our HTML templates for webpages to be tracked. Whenever anyone accesses a particular webpage, their browser executes the

JavaScript code when the page is displayed. This code sends information to Google's tracking system which includes the hashed client-ID of the user, webpage URL (path), HTML title of the page, IP address of the client device, and the current date and time. Specific website users remain anonymous, since their device's IP address and client-ID are encrypted in GA tracking records to help protect user privacy. GA normally can determine when the same device accesses a different webpage at a later time through use of browser cookies stored on that device. If users disable cookies or clear them from their browsers, then GA tracking methods are thwarted. Once tracking of a website is enabled, GA reporting tools can be used to analyze what users have done on the website. Google provides authentication methods for GA administration normally by using one's Gmail account. This further restricts who can access the tracking data on a particular website.

When we initially built the IPTAT website at https://plagiarism.iu.edu we created page names that corresponded to various First Principles of Instruction and other important activities (e.g., /activation*, /demonstration*, /masteryTest*, /practice*, /plagiarismTestUG*, /mail*, etc.). Note that the asterisks (*) used here are wildcards for variations of webpage filenames. For example, any filename that contained '/activation' would correspond to use of the FPI activation principle in IPTAT design.

We originally intended this file naming convention for our own benefit as website developers. Fortuitously, this also simplified subsequent APT queries with GA4 tools when specifying segments and matching conditions. For example, all FPI activation events can be identified by matching webpage filenames that contain the string, '/activation'. Or we can determine from GA4 that whenever a '/mail*' webpage was accessed, this meant that a student had just passed a Certification Test (CT) and clicked the button to email it to themselves. Note that this particular webpage can *only* be accessed immediately after a student has passed a CT.

GA4 Real-time Reports. As can be seen in Figure 1, GA4 tools include a real-time view of the IPTAT website. In this example, 104 different users (GA clients) had been accessing IPTAT in the previous 30 minutes. The world map indicates where the majority of those users are currently located. At 11:30 a.m. on March 25, 2021, most were from the U.S., Philippines, China, India, and Africa. Not shown in Figure 1 are additional statistics that include which webpages were accessed most frequently, conversion events, and more.

[Insert Fig. 1 about here.]

Figure 1

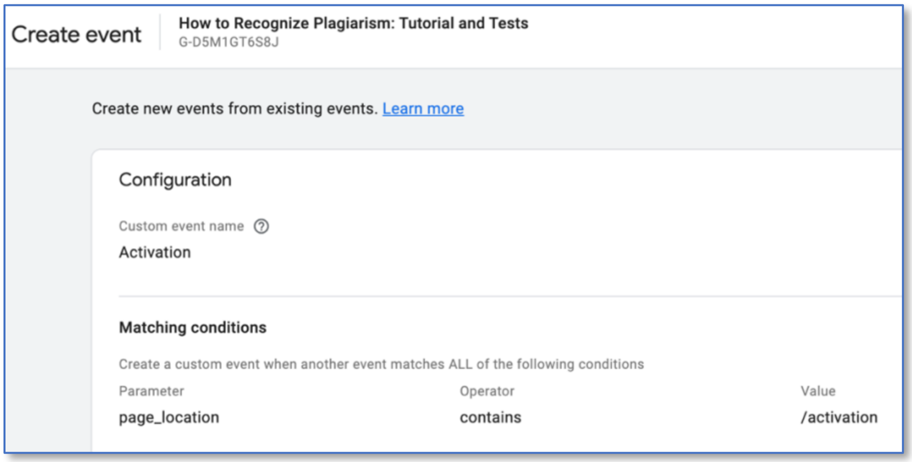
GA4 Realtime View of IPTAT Website Usage

Creating New GA4 Events and Conversions. GA4 tracks a number of events by default that include pageviews, clicks, scrolling, and client session starts. To do APT, we needed to create new events according to pageviews of First Principles of Instruction. For example, we created an event category called *Activation* as illustrated in Figure 2.

[Insert Fig. 2 about here.]

Figure 2

GA4 Event Creation for the FPI Activation Principle



The matching condition for an Activation event was whenever the ‘page_location’ parameter contained “/activation”. All of the IPTAT webpages that we specifically designed using the FPI Activation principle contain this string in their filename paths (e.g., https://plagiarism.iu.edu/tutorials/task4/activation2.html). In early December, 2020, we defined similar matching conditions accordingly for other FPI events. Once these new FPI events were created, they were further marked as GA4 conversions (i.e., FPI goals achieved by IPTAT users).

[Insert Table 1 about here.]

Table 1

GA4 Events Created and Marked as Conversions (Goals)

Event Name	Marked as conversion
Activation	TRUE
Application	TRUE
click	FALSE
Demonstration	TRUE
file_download	FALSE
first_visit	FALSE
Integration	TRUE

Mastery_Test	TRUE
page_view	TRUE
Pass_GR_Test	TRUE
Pass_UG_Test	TRUE
Plagiarism_Patterns	TRUE
Plagiarism_Test	TRUE
scroll	FALSE
session_start	FALSE
Test_Feedback	TRUE

Once these new FPI events (conversions) were created, then they could be tracked via GA4. In essence, by creating new events in GA4, we taught it how to classify various FPI webpages by appropriate categories (Frick, 1990; Myers & Frick, 2015). In Table 1, event names that begin with capital letters are ones we created, and uncapitalized event names are events that GA4 provides and tracks by default. Note, for example, we had created 'Activation' as new event and marked it as a conversion (= TRUE). We marked the GA4 event, 'page_view' also as a conversion, whereas other uncapitalized event names were not, such as 'scroll' (= FALSE). Once new GA4 events have been created, they will be tracked as such, unless they are later unmarked as conversions.

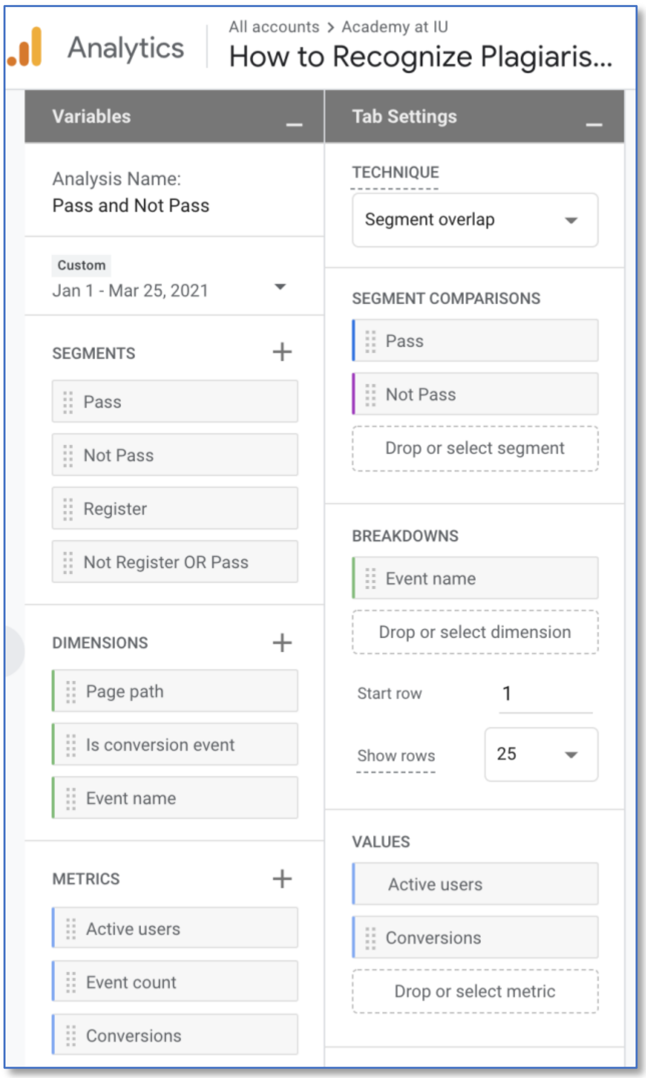
This was a very important initial step. Note further that the 'page_view' event is counted for all webpages tracked by GA4, including those which we did *not* classify as instances designed specifically using First Principles of Instruction. We initially configured GA4 this way because we later intended to do Analysis of Patterns in Time. This method of designing naturalistic research is an innovative approach via GA4, although APT itself is a research method that has been around for decades (Frick, 1990).

GA4 Analysis Reports. Once new events are created and tracked, as described above, the real power of GA4 can be utilized with its Analysis Tool. We illustrate here how we used the analytic technique "Segment overlap" in order to do APT of IPTAT usage.

[Insert Fig. 3 about here.]

Figure 3

GA4 Analysis Setup to Do APT of IPTAT



First, we named this analysis "Pass and Not Pass." We set the custom date range to cover IPTAT events between Jan. 1 and Mar. 25, 2021, illustrated in Figure 3.

Next, we added two segments: Pass and Not Pass. We segmented users according to whether their learning journeys were successful or not. See Figures 4 and 5.

[Insert Fig. 4 and 5 about here.]

Figure 4

GA4 Definition of Segment for Users Who Pass a CT

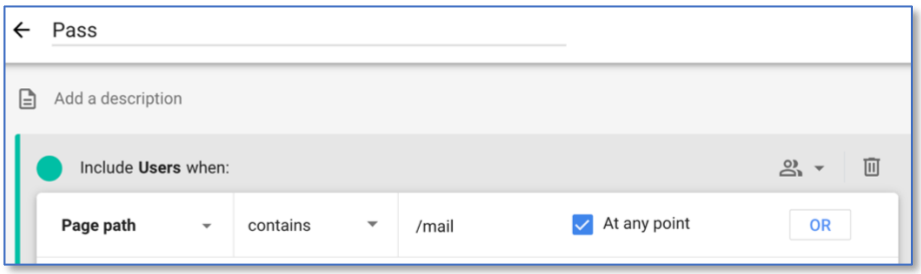
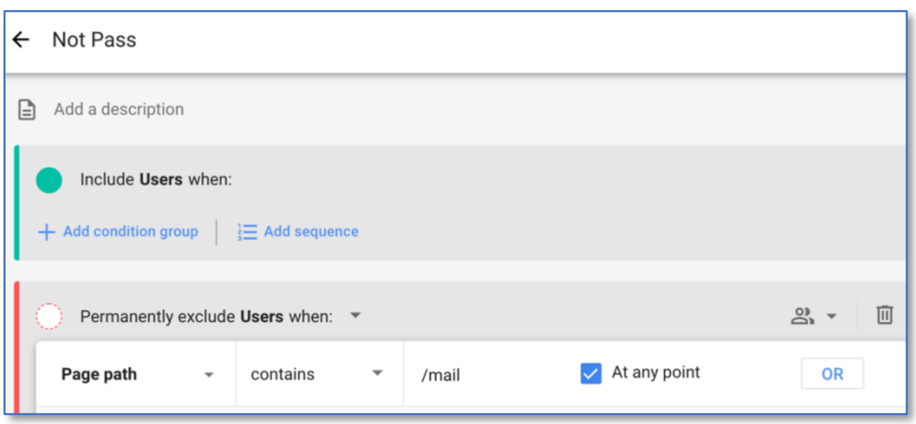


Figure 5

GA4 Definition for Users Who Do Not Pass a CT



The Pass segment *includes* users when their pageview path contains "/mail" at any point in their learning journeys. The Not Pass segment *excludes* users whose learning journeys contain "/mail" pageviews at any point. This results in two mutually exclusive and exhaustive subsets of users—those who passed a CT and those who did not.

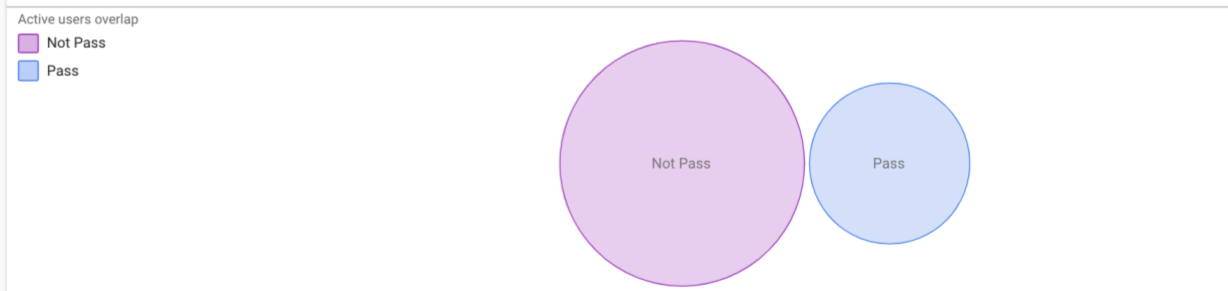
As illustrated in Figure 3, once these two new segments were defined, we dragged them to the right-hand column for SEGMENT COMPARISONS. We had already selected the

Segment overlap TECHNIQUE. We had dragged "Event name" into the BREAKDOWN area. For VALUES we had dragged "Active users" and "Conversions" to the VALUES area. These were the criteria used for creating the GA4 report illustrated in Figure 6.

[Insert Fig. 6 about here.]

Figure 6

Part of the GA4 Report from Segment Overlap Analysis of IPTAT Users Who Passed and Did Not Pass: Jan. 1–Mar. 25, 2021



Segment set		Not Pass		Not Pass ONLY		Pass		Pass ONLY	
Event name		Active users	Conversions	Active users	Conversions	Active users	Conversions	Active users	Conversions
	Totals*	120,370 69.2% of total	5,339,753 32.27% of total	120,370 69.2% of total	5,339,753 32.27% of total	51,738 29.75% of total	11,213,605 67.77% of total	51,738 29.75% of total	11,213,605 67.77% of total
6	Plagiarism_Test	32,637	541,670	32,637	541,670	51,664	1,015,221	51,664	1,015,221
7	Test_Feedback	23,952	544,265	23,952	544,265	51,648	1,158,220	51,648	1,158,220
8	Plagiarism_Patterns	17,692	327,080	17,692	327,080	33,606	750,651	33,606	750,651
9	Pass_UG_Test	0	0	0	0	40,685	103,373	40,685	103,373
10	Activation	14,213	132,964	14,213	132,964	21,416	281,842	21,416	281,842
11	Mastery_Test	13,726	269,600	13,726	269,600	21,488	554,058	21,488	554,058
12	Demonstration	12,659	122,563	12,659	122,563	21,207	248,741	21,207	248,741
13	Application	12,440	1,122,483	12,440	1,122,483	21,362	2,567,555	21,362	2,567,555
14	Integration	10,360	72,889	10,360	72,889	19,998	165,763	19,998	165,763

From the Venn diagram in Figure 6, we can see that the Not Pass segment and the Pass segment do not overlap. We can further see that there are a total of 120,370 Active users who did Not Pass. These numbers are identical for the Not Pass ONLY segment because Pass and Not Pass are non-overlapping sets (we had defined them this way in order to do APT properly).

We can further see that none of the active users included in the Not Pass segment had passed an Undergraduate Certification Test (Pass_UG_Test), as it should be. As discussed above, Conversion events were defined for respective webpages designed with First Principles of Instruction.

We can further see in Figure 6 that 51,738 Active users did Pass a CT who had 11,213,605 Conversions (as marked in Table 1). Note that 40,685 users passed an Undergraduate CT. Not all of the results are shown in Figure 6, the remainder of which can be viewed via scrolling the report in GA4 (including 11,195 Active users who passed a Graduate level CT). We now have the basic numbers to complete the APT.

In summary, we have described the methods by which we obtained results from 172,108 learning journeys through IPTAT between Jan. 1 and Mar. 25, 2021. We have provided considerable detail, since we needed to be rather creative in adapting use of GA4 in order to do APT. We would not expect most readers to know how to do this or to discover it by themselves. While we clearly understood our goals, it took considerable experimentation to get GA4 to count the patterns we needed for doing APT. This was made easier nonetheless by our webpage naming conventions which paralleled our application of First Principles of Instruction in redesigning IPTAT in 2015.

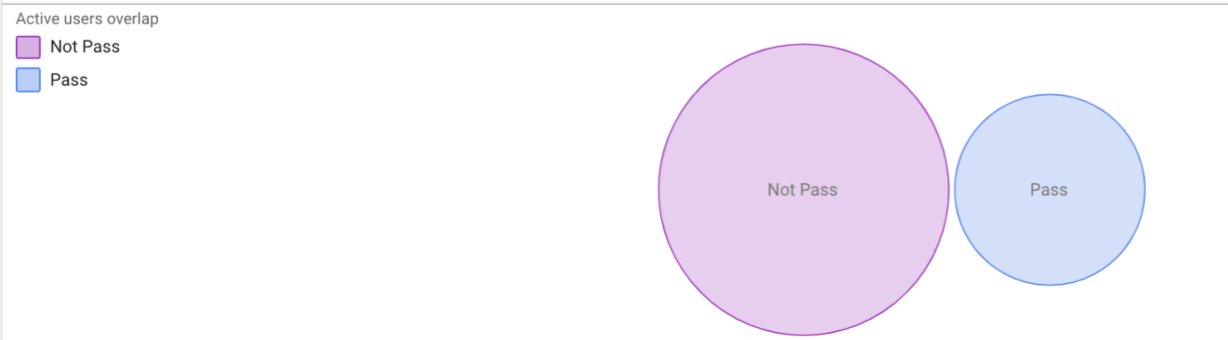
Results

While Figure 6 illustrates a breakdown of IPTAT results by event names, we had first done a more basic APT query, as illustrated in Figure 7. We used the GA4 Segment Overlap tool to produce the initial report. We set our SEGMENT COMPARISONS to Pass and Not Pass, but we did no BREAKDOWNs, and for VALUES we chose the METRICS: Active users, Sessions, Conversions, and User Engagement.

[Insert Figure 7 about here.]

Figure 7

GA4 Initial Segmenting Report on IPTAT Usage: Jan. 1–Mar. 25, 2021



	Segment set	↓Active users	Sessions	Conversions	User engagement
	Totals*	173,936 100% of total	361,809 100% of total	16,547,092 100% of total	11y 110d 100% of total
1	Not Pass	120,370	206,479	5,339,753	3y 200d
2	Not Pass ONLY	120,370	206,479	5,339,753	3y 200d
3	Pass	51,738	151,883	11,213,605	7y 275d
4	Pass ONLY	51,738	151,883	11,213,605	7y 275d
5	Pass + Not Pass	0	0	0	0m 00s

As can been seen in Figure 7, Not Pass and Not Pass ONLY have equivalent results, as well as do Pass and Pass ONLY. This is because the Pass and Not Pass segments were defined to be mutually exclusive and exhaustive. Thus, "Segment set" 5 (Pass + Not Pass) shows zero Active users, etc. If they were *not* mutually exclusive, there would be overlap of the segments where some users would be in both. In mathematical set theory, two sets are mutually exclusive if their intersection is the empty set; and they are exhaustive if every element can be placed in one of the sets. Thus, every element is a member of one and only one set. Here the elements are learning journeys. APT requires such classifications in order to form mathematical likelihoods. See Frick (1983, pp. 100-104).

We then downloaded the report in Figure 7 to a CSV file and imported it into Excel as a new worksheet. Then we removed the redundant information, as illustrated in Table 2.

[Insert Table 2 about here.]

Table 2

GA4 Results from Segment Overlay Analysis on IPTAT Usage Jan. 1–Mar. 25, 2021

GA4 Segment	Student Learning Journeys	Sessions (Temporal Maps)	IPTAT Conversions (Goals)	IPTAT User Engagement (Total Seconds)
Not Pass	120,370	206,479	5,339,753	111,972,074
Pass	51,738	151,883	11,213,605	244,731,764
Grand Total	172,108	358,362	16,553,358	356,703,838

We also adjusted the totals by computing them in Excel. According to GA4, the "Totals*" reported in Figures 6 and 7 "may include duplicate values and may differ slightly from other reports." Presumably, the counts of events within segments are accurate. We discuss this further in the section below on how GA4 determines Active users. We prefer to call these student learning journeys that contain one or more APT temporal maps.

Cross-Validation of GA4 Results with IPTAT Records

We wondered about the accuracy of GA4 tracking, so we triangulated GA4 data with IPTAT data collected by PHP scripts and stored in a MySQL database on Indiana University computers completely independent of GA tracking, which stores sessions on Google's servers.

We first used the GA4 User Explorer tool to look at unique user sessions. We were able to match IU records by searching for the date and time that the user activated their IPTAT registration, which executes a script, https://plagiarism.iu.edu/mainLogin.php?action=activate*. By searching our MySQL record of the date and time the user activation was completed with the

GA4 date and time when this webpage was accessed, we could identify the specific user by finding a match. Our records include the user's e-mail and name when registering, as well as when they passed a Certification Test if they had done so. It is important to note that GA does not store this information in their tracking records, and so does not identify the actual clients. We do, however, in our MySQL database.

We did find matches of randomly selected GA sessions via the User Explorer tool and our IU MySQL records. We also wanted to determine if the Active user counts matched our MySQL counts for the same time intervals. Between Jan. 1 and Mar. 25, our MySQL records indicated that 56,328 users had passed a CT. We note that GA4 determined that there were 51,738 Active users who were segmented on the basis of whether they accessed the /mailCertificate*.php file when clicking the button after passing the test. Thus, the GA4 count is an underestimate of the actual number of IPTAT users who passed a CT. Our PHP scripts record this certificate information in MySQL regardless of whether or not a user clicks the button to e-mail their certificate. Not all users do so, since they know that they can also do this later via IPTAT's "Retrieve and Validate Certificates" functionality. Moreover, users can thwart GA tracking by using Web browsers that disable or block cookies or by other software that does so (e.g., Bitdefender plugins).

The good news is that GA4 underestimates the number of successful Active users by a relatively small percentage (by about eight percent in this study). If GA4 had overestimated this number, that would be problematic. This cross-validation of GA4 results through triangulation with IU MySQL records was reassuring. We could not do this kind of triangulation for unsuccessful users, since IPTAT does not keep records of users who do not register, and who therefore cannot pass a CT. We assume that the GA4 counts of unsuccessful Active users would likewise be a small underestimate. In any case, with such large numbers of users these underestimates would not likely make appreciable differences in likelihood (or odds) ratios determined via APT methods.

Using Excel to Compute APT Likelihood Ratios

We next created Excel cell formulae that generated results reported in Table 3.

[Insert Table 3 here]

Table 3

Further Excel Results Computed from Table 2 to Derive Measures for APT of IPTAT Usage

GA4 Segment	Mean GA4 Sessions (Temporal Maps)	Mean IPTAT Goals per User	Mean User Engagement (Minutes)	IPTAT Conversions (Goals) Odds (P:NP)	IPTAT Engagement Odds (P:NP)
Not Pass (NP)	1.715	44.361	15.504	1	1
Pass (P)	2.936	216.738	78.837	4.886	5.085
Grand Total	2.076	95.901	34.443	~	~

In Table 3, learning journeys in which users passed a CT contained an average of 216.7 conversions, compared with 44.4 IPTAT goals achieved during unsuccessful learning journeys where no CTs were passed. These means were computed by dividing the IPTAT conversions in Table 2 by the respective numbers of student learning journeys for each segment type. The means for temporal maps and user engagement were similarly computed. Thus, we can see that for learning journeys in which a CT was passed, users viewed nearly 4.9 times as many IPTAT webpages as did those in which a CT was not passed (216.738/44.361). Similarly, successful learning journeys were about 5.1 times longer in duration on average than were unsuccessful ones.

Readers should note the IPTAT conversions (goals achieved) included not only views of webpages designed with First Principles of Instruction, but also other IPTAT webpages (page_views). See Table 1.

As illustrated in Figure 6, we had done a more refined analysis of successful and unsuccessful learning journeys, where we obtained counts of specific types of FPI webpages. These results were likewise exported to a spreadsheet. See Table 4.

[Insert Table 4 about here.]

Table 4

GA4 Results on First Principles of Instruction (FPI) Goals Achieved: Jan. 1–Mar. 25, 2021

Segment Event Type	**Not Pass Conversions (NP)**	**Pass Conversions (P)**
Activation	132,964	281,842
Demonstration	122,563	248,741
Application	1,122,483	2,567,555
Integration	72,889	165,763
Mastery_Test	269,600	554,058
Plagiarism_Test	541,670	1,015,221
Test_Feedback	544,265	1,158,220
Plagiarism_Patterns	327,080	750,651
FPI Totals	3,133,514	6,742,051
Total Learning Journeys (Active Users)	120,370	51,738
FPI Conversions per Journey	26.032	130.311
FPI Odds (P:NP)		5.006

It is evident in Table 4 that the FPI Application principle was experienced more often than other FPI principles in both successful and unsuccessful student learning journeys. But the number of learning journeys for students who did *not* pass a CT (120,370) was much greater than those for students who did pass (51,738). This is why we need to compute FPI conversions *per* *learning journey*, prior to computing APT odds ratios. Students who did not pass a CT viewed an average of 26 IPTAT webpages designed with First Principles of Instruction, whereas those who *did* pass a CT viewed about 130 FPI-designed webpages. Thus, successful student learners experienced about five times as many First Principles in their learning journeys through IPTAT. It is not that unsuccessful students did not view any FPI webpages, but their learning journeys were much shorter (about 15 minutes per journey) and they selected about one-fifth as many FPI-designed pages, whereas successful students spent nearly 79 minutes on average, as indicated in Table 3. These results are consistent with Merrill's hypothesis that "when a given instructional program or practice implements one or more of these First Principles, there will be an increase in learning and performance" (2020, p. 3).

Our APT results on IPTAT usage indicate a *five-fold increase* in pages viewed that were designed with First Principles of Instruction in learning journeys where students pass a difficult Certification Test, when compared with students who do not pass. This is a large difference. Each CT is comprised of ten randomly selected questions from a large pool of items. There are literally trillions of unique CTs. The tests are difficult for most students—on average, about 14 percent of CT's attempted are passed. To pass a CT a student must answer at least nine questions correctly. Students who correctly answer fewer than nine questions do not pass.

IPTAT utilizes a mastery learning approach. Students are free to navigate IPTAT however they choose, and they can take as many CTs as needed until they pass. The large majority of students who use IPTAT do so because it is an assignment by their teacher or school. Historically, about 81 percent of those students eventually do pass a CT. As Table 4 indicates, those learning journeys which end in passing a Certification Test are, on average, associated with student selection of about five times as many IPTAT webpages designed with First Principles and spend about five times as much time learning. Student persistence and effort matter, and instruction designed with First Principles matters too.

What Are GA4 Active Users, APT Temporal Maps, and IPTAT Learning Journeys?

As discussed earlier, as users continue from one session to the next on the same device and browser, GA4 utilizes a hashed client-ID, normally stored in a browser cookie. However, if the same person changes devices and locations, they may be recognized with a different client-ID by GA4. IPTAT does not share user login information with GA4 tracking (see https://plagiarism.iu.edu/privacy.html). Thus, in the present study, we follow Frick et al. (2021) by referring to student learning journeys, which consist of one or more temporal maps. A user with the same GA4 client-ID may have one or more sessions in which they interact with IPTAT. "A session ends after 30 minutes of inactivity on the part of the user" (Google Analytics 4, 2020).

APT has referred to temporal maps historically, which is a record of a sequence of temporal events for a given person or situation. For examples of temporal maps, see Frick et al. (2008), Frick and Myers (2015), and Frick et al. (2021). Thus, it makes sense to treat GA4 sessions as APT temporal maps. In Table 3 the segment of users who pass an IPTAT CT interact with IPTAT on average for 2.9 sessions (temporal maps), when compared with users who do not pass a CT who experience on average 1.7 temporal maps per learning journey.

GA4 refers to Active users as unique users who have initiated sessions within a specified time frame. Uniqueness is determined by client-ID as discussed above. In the present study, we treat an IPTAT learning journey as a set of one or more GA4 sessions (i.e., temporal maps) with the same client-ID. An IPTAT learning journey is thus associated with a unique client-ID during the timeframe beginning on January 1 through March 25, 2021.

Discussion

Generalizability of Findings

Results from the present study are consistent with an earlier two-year Big Study that Frick et al. (2021) conducted on IPTAT using a prior version of Google Analytics, known as Universal Analytics (UA). On the other hand, we used GA4, a relatively new version of GA that became available in October, 2020.

In the Frick et al. (2021) study, they reported results on more than 936,000 learning journeys. According to UA tracking, those students were located in 213 countries and territories worldwide. Those 390,000+ users who registered for IPTAT reported ages mostly between 14 and 44 years old. In the present study, GA4 tracked more than 172,000 IPTAT learning journeys (Active users) for nearly three months, with 65,000+ IPTAT registrants. Notably, there were nearly twice as many other students who did not register to take IPTAT tests. According to GA4 tracking, these users were located in 186 different countries and territories worldwide. In both studies, when students registered for IPTAT, the large majority were doing so because it was a requirement by their teacher or school, and they were mostly college and advanced high school students (adults).

Frick et al. (2021) reported that successful students were between three and four times as likely to choose webpages designed with First Principles, when compared with those who did not pass Certification Tests. On the other hand, with GA4, we found the same odds ratio to be about *five to one*. Why the difference? In UA, when doing APT, Frick et al. (2021) used *unique* pageviews. In other words, if a user viewed the same webpage two or more times in a given GA session (APT temporal map), it was counted as one page view. They noted that pageviews were typically much higher than unique pageviews, but preferred to count the latter in their analyses.

In the present study, we used GA4, which does not provide unique pageview statistics in results. *All* pageview events are counted in GA4 results, most likely because GA4 is not limited to websites.

GA4 can be used with all kinds of apps; and the broader concept is *views*. Looking at a webpage is but one kind of view event. In GA4, a view could be when a user looks at a particular screen display on their smartphone while using a grocery shopping app to order food for later pickup—that is, not using a Web browser such as Safari or Chrome at all.

We are not overly concerned about the differences in approaches in UA and GA4. The patterns are clear and consistently repeatable across time. Students who pass CTs view many more webpages designed with FPI—whether it is four or five times more likely, it still makes a very large practical difference. After all, if you were purchasing a car and had a choice between a model that is four or five times more likely to get you to your destination, when compared to other models, which car would you choose?

We note that the reliability of a car is a highly important consideration (e.g., not breaking down and needing to be repaired as often), but it is not the only criterion for making a decision between models. Perhaps one would choose the car with the nicer sound system and posh leather seats. Perhaps one would be willing to spend more money on car repairs and take longer to arrive at their destination because of more mechanical breakdowns. But if the goal is to get there with the least amount of car repairs and frustration, a rational person would choose the car with greater reliability—that is, a car which is more effective and efficient. This is a praxiological issue, as discussed in the earlier theoretical framework.

A further difference between the present study and Frick et al. (2021) is the average amount of engagement time per learning journey. In our study, we found that engagement averaged about 79 minutes per journey, whereas Frick et al. reported a mean of about 98 minutes for successful students, and we found that unsuccessful students spent about 15 minutes, whereas they found about 21 minutes on average per learning journey. These appear to be substantial differences on use of the same MOOC. We note however that GA4 tracks user engagement somewhat more precisely—referring to *engaged sessions*. GA4 can apparently discriminate whether the app being used is the user's focus. When a user switches away from the app being tracked, GA4 does not consider this to be active user engagement. For example, during IPTAT, a student might switch away to read and respond to their text messages or e-mail for several minutes, and then resume interacting with IPTAT. In UA this would not be specifically tracked, unless the user had switched away for more than 30 minutes, in which case the IPTAT session would be terminated (as it also would be in GA4). However, in GA4 engaged time will apparently only accrue when the app being tracked is the user's focus. We believe that this is the most likely explanation of the differences between our results and those of Frick et al. (2021). Thus, we conclude here that the GA4 results are better indicators than UA when student engagement time is being considered.

If generalizability of empirical research results is considered with respect to repeatability of findings and applicability to a wide range of student learners, then results from the present study and the Frick et al. (2021) study can be considered as highly generalizable. When taken together, based on more than two years of IPTAT usage, these APT results apply to a worldwide audience of adult learners who can read and comprehend English and who have computer technology to access the World Wide Web. These observed learning patterns have been highly consistent since 2016, as Frick et al. (2021) have noted.

Statistical inference, as a form of generalizability, is discussed below.

Temporal Retrodiction from APT, Not Causal Inferences

Frick (1990) noted that causal inferences are not warranted from APT results unless additional factors are considered. He provided the example of dawn and sunrise. Dawn is a good predictor of sunrise, but dawn does not necessarily cause sunrise. Scientific theory that involves Newton's laws and optical refraction of light is preferable for explaining cause and effect of dawn and sunrise. Nonetheless, sunrise is highly predictable following dawn. And we can make decisions based on predictability of events, even if we cannot provide causal explanations.

Thus, we should not conclude that First Principles of Instruction *cause* student learning success (passing a Certification Test). But from APT results, we can conclude that success is more likely when students have greater exposure to instruction designed with First Principles, at least for IPTAT usage.

APT queries can be predictive or retrodictive, as explained by Frick et al. (2021). Based on present conditions, prediction is forecasting what is likely to happen in the future. Meteorologists do this when predicting that there is a 40% chance of rain tomorrow evening in Toronto.

On the other hand, retrodiction is looking backward in time. Given that some event is observed now, what has happened at an earlier time? This is what we did in the present study. We observed when students passed a Certification Test during their learning journeys and compared them to others who did not pass in their learning journeys. Then we looked backwards in time and counted how often each of these two groups chose parts of IPTAT designed with FPI. Myers and Frick (2015) likewise did this in their study of the Diffusion Simulation Game. They classified how well each student had done at the end of a game, categorizing them according to how many adopters each player had achieved. Then they observed prior game strategies players utilized. This also was a retrodictive approach to APT.

In short, APT is a descriptive-correlational approach to empirical research, not unlike what epidemiologists do when attempting to predict whether someone is likely to get cancer. What events precede cancer? For decades, epidemiologists and medical scientists knew that people who smoked cigarettes heavily earlier in their lives were between five and ten times more likely to contract lung cancer later in their lives than were nonsmokers. However, proving the causal relationship was more challenging until the role of carcinogens was identified as a significant factor, when researchers had a better understanding of biochemistry, pathology, and cell biology. Nonetheless, people were advised to refrain from smoking based on the temporal relationship.

Causal inferences are not warranted by correlation alone, as research methodologists and statisticians have reminded us for decades (e.g., Kirk, 1999).

Descriptive versus Inferential Statistics

Statisticians distinguish between descriptive and inferential statistical methods (e.g., Kirk, 2013; Tabachnick & Fidell, 2018). “Descriptive statistics are tools for depicting or summarizing data so that they can be more readily comprehended” (Kirk, 1999, p. 7). He goes on to say that

> it is usually impossible for researchers to observe all the elements of a population. Instead they observe a sample of elements and generalize from the sample to all the elements—a process called **induction**. They are aided in this process by **inferential statistics**, which are tools for inferring the properties of

> one or more populations from an inspection of samples drawn from the population. (pp. 7–8)

While APT clearly is a form of descriptive statistics, with such big data as collected via GA4 on IPTAT usage, the question of inductive inference arises. While the sample in this study is quite large, it was not *randomly* selected from the population of all potential students who might use IPTAT. Therefore, inferential statistics do not appear to be applicable.

In the present study, we did not estimate standard errors of means by using theoretical sampling distributions (such as Gaussian), which are based on sample size and expected variation among samples. One might ask, is the difference between those who pass and those who do not pass with respect to their use of FPI statistically significant? This is another way to ask: to what extent would the observed results be expected to occur by chance, and the difference we are seeing is due to sampling error?

We do not believe that this is the most important question. Teachers and instructional designers often want to know whether or not what they do is effective. Does it work? Or how well does it work? As in a weather forecast, we typically want to know if it is accurate—whether we can depend on it and make plans accordingly. This is the more relevant question. In our study, we emphasize practical significance rather than statistical significance. In real life, something that is five times more effective is a big difference, practically speaking. When sample sizes are extremely large, trivial differences can be statistically significant—that is, have no practical consequences.

In the case of implementation of First Principles of Instruction in IPTAT, they have worked well for over five years. At the time of this writing, over one million students have registered for IPTAT and over 800,000 have passed one or more Certification Tests since 2016.

This is a very large sample, though not random. Is it the population? No, but the predictions in terms of odds ratios have been very stable. Will the sun rise tomorrow morning? We do not know for sure, but it is highly predictable, based on a very large number of past observations.

Moreover, as Frick (1983) noted, the standard error of estimate decreases as a function of sample size—inversely proportional to the square root of the number of elements in the sample (see Kirk, 1999, p. 289). In the present study, we have 172,108 elements. Since GA4 does not provide standard deviations, we can compute a margin of error estimate for proportions, similar to that reported in survey results. If we convert the rates within passing and not passing segments to proportions, the likelihood of experiencing an FPI event in a successful learning journey is 0.83333 (130/156) and for an unsuccessful one is 0.16667 (26/156). See Table 3. The likelihood ratio is still 5:1, as it should be. The margin of error is 0.00176 for these proportions at the 95% confidence interval (with N = 172,108). See, for example, Kirk (1999, p. 365).

From a Bayesian perspective of probability theory, we are stating the following about the likelihood ratio, LR, assuming a flat prior distribution (e.g., see Schmitt, 1969, pp. 83-89):

$$p\ (\text{FPI} \mid \text{Pass}) = 0.8333$$

$$p\ (\text{FPI} \mid \text{Not Pass}) = 0.1667$$

$$LR = 0.8333/0.1667 = 5.0$$

APT is grounded in set theory and probability theory in mathematics. The margin of error in estimating the likelihoods (p) is very small in our study, plus or minus 0.00176, based on observed proportions with an overall sample size of 172,108 learning journeys.

APT and Praxiological Theory

Analysis of Patterns in Time does not identify patterns all by itself. Researchers must specify APT queries, and then APT accordingly segments temporal maps, finds matches, and counts occurrences of those events. While examining individual temporal maps may provide leads on what patterns to tell APT to look for, theory should be driving the process. Kurt Lewin has been often quoted for saying, "Nothing is as practical as a good theory" (Greenwood & Levin, 1998, p. 19).

The present study was guided by instructional theory—in particular, First Principles of Instruction. And design of instruction was driven by a practical need: IPTAT was designed with the goal of helping students learn to recognize basic kinds of plagiarism from non-plagiarism. Designers wanted IPTAT to be effective, that is, achieve its goal, and they wanted it to work via the Web so it would be easily accessible by students in the Instructional Systems Technology program at Indiana University. When IPTAT was designed in 2002, instructional theory about how to teach concepts was applied. In 2015, when IPTAT was redesigned, the design team specifically chose First Principles of Instruction for theoretical guidance. And most importantly, that FPI theory not only influenced how we structured our website and named webpages in 2015, it also guided which patterns we specified in APT to be counted in the present study.

The results provided in Table 4 did not "emerge from the data," nor did artificial intelligence algorithms discover those patterns. The segment event types listed in Table 4 are identified by names of First Principles. The additional mastery tests and Certification Tests were designed to assess how well students had learned to recognize plagiarism. The tests themselves and feedback on test results are further instantiations of the FPI Application principle. The plagiarism patterns to which test feedback adaptively links are further instances of the FPI Demonstration principle.

In short, theory not only guided the instructional design of IPTAT, that instructional theory also guided the search for patterns of instructional effectiveness. APT was the particular research methodology that guided how to find those patterns, and APT in turn was developed retroductively from general systems theory, information theory, and set theory and probability theory from mathematics (Frick, 1983, 1990). The patterns themselves are qualitative—the event patterns are not numbers, rather they are *named*. The results of APT are quantitative—numerical counts of patterns of event occurrences in temporal maps. Those counts are used to form proportions (or likelihoods) and likelihood ratios (odds).

Numerous researchers have noted the need to leverage the power of learning analytics for evaluating instructional designs (Gašević et al., 2015; Ifenthaler, 2017; Klein & Hess, 2019; Mangaroska & Giannakos, 2019; Phillips & Ozogul, 2020). By explicitly designing the IPTAT using FPI and showing that successful learners experienced more instances of instruction based on FPI than unsuccessful learners, we have added support to Merrill's hypothesis regarding the effectiveness of FPI while also demonstrating how learning analytics (in the form of APT) can be used to test instructional design theory. Recent reviews of learning analytics research have noted the need to integrate education theories and learning analytics (Phillips & Ozogul, 2020; Romero & Ventura, 2020; Wong et al., 2019), and the present study illustrates a pathway toward "a synergistic relationship between instructional design and learning analytics" (Ifenthaler, 2017, p. 202).

Conclusion

What's New?

Frick et al. (2021) described Analysis of Patterns in Time as an innovative learning analytics method to evaluate instructional effectiveness. They illustrated the use of Google Analytics for doing APT on IPTAT website usage in 2019 and 2020. Specifically, they used Universal Analytics (UA) tools to do the counting.

The present study was conducted in early 2021, providing new data. More importantly, our study utilized a newer version, referred to as Google Analytics 4 (GA4), to do both tracking of user interactions with IPTAT in 2021 and for subsequent analytic procedures. To our knowledge, this has never been done before in educational research.

We found similar patterns as did Frick et al. (2021). In this sense our study is a replication. However, APT odds ratios were based on total pageviews, rather than unique pageviews as did Frick et al. Odds ratios in our study were about five to one, whereas they were between three and four to one in the earlier study. We further found smaller average engagement times than did Frick et al., most likely explained by GA4's more precise tracking methods, which can detect when IPTAT was the user's focus and excludes time spent using other apps when switching away from IPTAT for short intervals of time.

Perhaps most important, we have demonstrated how GA4 can be used to do APT when supplemented by additional spreadsheet computations. We have gone into considerable detail in describing our methods, since they are likewise innovative, further extending those discovered by Frick et al. (2021).

Overall IPTAT Success: Considerations for Future Studies

An additional question that we have not addressed thus far: Of those IPTAT users who tried a Certification Test, what proportion passed one? This question is a bit tricky, because it depends on the timeframe selected. There will be some students who registered for IPTAT and tried Certification Tests *during* the timeframe, did not pass a CT in that interval, but may pass at a later date. For example, a student could register on March 24, try a test, and not pass. This student works on IPTAT tutorials, takes more tests, and finally passes one on April 15 on their fourth attempt, spreading their effort over several weeks. This is an ultimately successful student, but who was not successful during the timeframe selected in a GA4 analysis, January 1 through March 25, 2021, and hence was counted in the 'Not Pass' segment. There were also students who registered prior to the timeframe, for example, on December 28, 2020 and took some tests and did tutorials, but did not pass a test until January 2. These students were successful during the selected timeframe, but who did most of the work with IPTAT before that timeframe.

Thus, we need to ask this question more carefully. Of those IPTAT users who tried a Certification Test between January 1 and March 25, 2021, how many passed? We did a further GA4 analysis and found that there were 56,511 students who tried one or more CTs during that timeframe, and of those, 51,738 passed a CT. When segmenting in GA4, this is a subset relationship. Those Active users who passed are a subset of those who attempted CTs (i.e., who were segmented by "Test Feedback" conversions in their learning journeys—see Table 1). This is an overall success rate of 91.6% according to GA4 tracking during this timeframe. However, there could be students who did not pass a CT during that timeframe, but who pass at a later date. If so, how long should we wait? We have observed some students who register for IPTAT at the beginning of the semester but do not pass a CT until the end of the semester. We know also that GA4 tracking results can be underestimates, as discussed above, and that some students use multiple devices at different locations and who may be tracked as different active users in GA4.

If we use our MySQL records, we observe that 65,420 students successfully registered for IPTAT, and we further know that 56,328 users passed one or more CTs during the same timeframe (Jan. 1 through Mar. 25). From this perspective, 86.1% were successful who had registered during this timeframe. We have included students who registered but did not pass during that time frame, but who may later pass a CT afterwards—hence, they were considered unsuccessful during the selected timeframe. Those students were eventually successful, just not in the timeframe in which we had segmented them.

And what about students who do not register with IPTAT and who never take any CTs? They may do most of the tutorials and learn to recognize plagiarism, but we have no MySQL records on them. From a GA4 perspective these kinds of students were included in the Not Pass segment. We cannot separate those who may later intend to register to take CTs from those who have no interest in passing a CT and never register for IPTAT. In any case, since they did not register, IPTAT has no records of these users, whereas GA4 does track them.

Although relatively minor when there are such large numbers overall, these are some of the limitations of the IPTAT analyses in the current summative evaluation study. In future studies, users could be required to register for IPTAT before being allowed to do any of the tutorials. It would also be possible to share IPTAT registration data with Google Analytics by setting up GA4 tracking to make this possible. This, however, then raises a privacy issue for IPTAT users who currently remain anonymous in GA4. IPTAT could be modified, as Frick and Dagli (2016) suggested, so that it does *all* the tracking instead of leveraging Google Analytics to do so. But then this would mean that further APT software would need to be developed in order to do the kinds of analyses that we have done in this study with GA4. These are all possibilities, but there are tradeoffs and considerable development expenses to consider. With such big data, it is unlikely that these minor limitations would make a practical difference in the conclusions reached. These observed patterns are further consistent with the Big Study done by Frick et al. (2021), which was based on two years of IPTAT usage, and nearly two million temporal maps with over 390,000 registered users, which in turn was consistent with usage patterns in the three years before that.

Final Remarks

Our goal has been to help students learn to recognize plagiarism. We have provided IPTAT as a MOOC since 2002 at no charge to users. The current version of IPTAT has been effective for about 92 percent of students who used it and tried the Certification Tests in early 2021. Students who passed a test selected and interacted with about five times as many IPTAT webpages designed with First Principles of Instruction, when compared with those students who had not passed. Student effort and engagement matter, and so do First Principles of Instruction.

Compliance with Ethical Standards

- *Disclosure of potential conflicts of interest*. The authors have no conflicts of interest to declare that are relevant to the content of this article. This study was not funded. The authors did not receive support from any organization for conducting this study.
- *Research involving human participants and/or animals*. This study has been approved and granted exemption for human subjects research by the Indiana University Institutional Review Board, Protocol No. 1304011238.
- *Informed consent*. No informed consent was required for this study by the Indiana University Institutional Review Board, Protocol No. 1304011238. The Privacy Policy for the Indiana University Plagiarism Tutorials and Tests is stated at https://plagiarism.iu.edu/privacy.html. In compliance with the Privacy Policy, we share only aggregate, non-personally identifiable information about participants in this study.

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