

# The Pragmatic Maxim as Learning Analytics Research Method

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## ABSTRACT

It is arguable that the chief aim of Learning Analytics is to use analytics for meaningful purposes in learning and teaching contexts, and that research in the field should advance this cause. However the field does not present a single clear understanding of what constitutes quality in Learning Analytics research.

In this paper we present the Pragmatic Inquiry for Learning Analytics Research (PILAR) method as one approach to conducting Learning Analytics research. Rather than creating a new method, we reintroduce an old method to a new field, drawing on the Pragmatic Maxim, proposed by Charles Sanders Peirce as a principle for making ideas clear. Our instantiation of the Pragmatic Maxim requires the researcher to situate Learning Analytics research within a clearly defined learning context and to consider the analytics in terms of the practical effects on learning. We propose three essential elements and a five step process for addressing them in research.

After presenting PILAR we address two potential limitations of the approach, and conclude with some implications for its future use in Learning Analytics research.

## CCS CONCEPTS

• **Human-centered computing** → **Interaction design process and methods**; *Interaction paradigms*; • **Applied computing** → **Education**;

## KEYWORDS

Research Methods, Learning Analytics, Pragmatism, Inquiry

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## 1 INTRODUCTION

Learning Analytics (LA) has embraced a definition that states the field's purpose as "understanding and optimising learning and the environments in which it occurs" [6]. While this has largely been uncontroversial amongst a community that aims to make a positive contribution to learning, there are non-trivial questions that the

definition leaves unanswered: To what end is 'understanding' to be directed? On what basis should 'optimising' occur? What is the scope of 'the environments'? These are big questions, and it is reasonable that they were left by the definition's authors to be answered by the LA community over time.

At the heart of these questions is the notion of LA quality. What makes good LA? What should be considered good LA research? We suggest that in order to address these questions, LA as a field needs to approach research in a way that grounds understandings of quality in the context in which it operates: Learning.

### 1.1 What are good Learning Analytics?

There appears to be no clear prescription for goodness within the LA literature. This is not surprising given the broad transdisciplinary character of the LA field, and the diversity of ideas that are embraced by it. While this diversity is arguably an important strength, philosophical differences between the contributing fields can result in conflicting models of quality, and competing perspectives on how to assess this quality. These perspectives tend to fall on a spectrum between a computational focus and a human focus. Human perspectives tend to result in research that utilises mostly qualitative methods, theory from the learning sciences and educational research, and data that is generally unstructured and small in quantity. In contrast, computationally focused work tends to be quantitatively driven with an analytical focus, and frequently operates on large amounts of highly structured data. Kop et al. [13, p. 319] concur, identifying that "a common definition of what makes good or poor evidence is not that obvious in the EDM and LA research community, which has brought together scientists from 'hard' (Computer Science) and 'soft' sciences (Education)."

Despite some commentary on the tendency to lean to the computational [7, 20], the LA community has generally navigated well the littoral zone between computer science and education, embracing the uniqueness of the contributing ecosystems while encouraging work that blends the two (see Section 1.2). The de facto reference for working between these perspectives has been the notion of a 'middle space' [21]. However, while this provides a useful construct for understanding the complexity of the field, it does not specifically address how to conduct research in this space, nor how the quality of work in this space should be determined.

Issues of interfacing of fields is not unique to LA, and lack of clarity can result in both overly optimistic hyperbole as well as push-back and scepticism - the rhetoric around sentient Artificial Intelligence is a current case in point. Similarly, LA also experiences this phenomena with commentary both championing [9] and condemning [5] the role of computers in learning, and in particular the increasing use of computation in assessment. We assert that these types of issues can be minimised by improving the clarity

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around how analytics and learning relate in *good* Learning Analytics. Further, we contend that strengthening LA research will aid in improving this clarity, and that a robust method for LA research could make a significant contribution.

## 1.2 LA Research Methods

Other more established fields derive their strength from deep philosophical foundations and respected research methodologies that have been tested over time. By contrast research in LA has been characterised more by its deference to other domains, or its willingness to tolerate exploration of ideas without requiring adherence to a particular stance. Recent research papers in the field show the diversity of research methods and the degree of acceptance of work without a research focus.

An examination of the last two years (2016-2017) of LAK papers<sup>1</sup> found that a quarter (56 of 224) specifically referred to research methods (i.e. 'methodology' or 'research methods') as opposed to other methods like computational techniques. Of these, just over half (32) could be classified as quantitative, experimental or empirical research. Only 8 were clearly qualitative (for example coding of interviews or focus groups), and the other 16 covered a variety of methods including design based methods (3 in LAK16), Social Network Analysis (3 in LAK17), general mixed methods (4), meta analysis (1), and other less common methods (5).

Notably, research methods that are commonly found in educational and social science research were not referred to in the papers. These included Action Research, Critical Theory, Phenomenology, Ethnography. An exception was Grounded Theory which appeared in one paper but not in the context of it being a specific research method. Although some papers may have implied research methods, even if they didn't explicitly state them, the general lack of method mentions appears to reflect the applied and developmental nature of the field.

While this diversity of research methods is not necessarily problematic, one might have expected the field to have cultivated an approach that is a custom fit, however this does not seem to be the case.

## 1.3 Determining LA quality

Just as other domains have addressed central questions of quality (e.g. What is good science? What is a substantive social theory? What is considered quality educational research?), so too LA needs to address the question: What is quality LA research?

When the perspectives of the practitioners of the field have largely been imported from other domains, arriving at a unique LA perspective is a non-trivial task. Those practitioners from fields that are dominated by statistical analysis will tend to affirm quality in terms of the rules of statistics, and dismiss work that does not play by these rules. Similarly, those from fields that are theory driven may affirm work that takes a particular theoretical lens, and dismiss that which is atheoretical.

As is the case in any academic community, much of these disagreements of perspective are invisible, hidden within the peer

review process. However, this risks marginalising some perspectives while baking others into the fabric of the field, gradually eroding diversity over time until there is only one prevailing view.

Ideally, a young field like LA would develop its own unique position that is able to accommodate a diversity of contributing perspectives without surrendering to any one perspective's demands. That is, accommodate both analytic and learning perspectives while being neither 'learning with analytic help' nor 'analytics with an application in learning'.

Questions of quality are also not easily resolved by examining how LA is currently used. Scheffell et al. [19] note that "there is no standardised instrument so far to evaluate the LA tools once implemented." Indeed, it appears that there is a lack of clarity on LA quality from both its foundational fields and in its application.

If it were possible to determine LA quality without deference to other domains, then issues with a single dominating perspective might be averted, paving the way towards uniquely LA research with its own consistent understanding of how to determine what is quality LA both as research and in application. This in turn would provide many benefits for those in the field including: a clarification of core concepts and principles, the ability to discern the quality of contributions to the field, the establishment of a distinct basis for the creation of new LA knowledge, and the development of a mechanism for evaluation.

This paper argues that a maxim proposed 140 years ago holds the potential to address current day LA. Adopted in logic, mathematics, science, psychology and education early in the 20th Century, and many other fields following, its heritage together with its trans-disciplinary nature gives it significant relevance for 21st Century LA. This is the Pragmatic Maxim originally described by Charles Sanders Peirce. A pragmatic approach to research is not new [4], nor is it novel in LA [14], however this paper applies the essence of Peirce's Pragmatic Maxim to LA research.

## 2 THE PRAGMATIC MAXIM

Consider what effects, that might conceivably have practical bearings, we conceive the object of our conception to have. Then, our conception of these effects is the whole of our conception of the object. [16]

This short quote from 'How to make our ideas clear' is commonly referred to as Peirce's Pragmatic Maxim, and although his contemporaries William James and John Dewey developed a full philosophy of Pragmatism, Peirce intended it to be applied in a more limited form [17]. Peirce essentially calls for the comprehension of a thing solely in terms of that thing's practical impact in the world.

For LA this means understanding analytics in terms of their effects on learning. While at first glance, this may appear to be self evident, consider a scenario where the LA researcher has a well established and validated computational model and yet does not know the effect the model may have on learning. In this situation Peirce would say that the understanding of the analytics is unclear (the conception of the effects on learning is the whole of the conception of the analytics). Similarly, if there is clear understanding of a learning process but uncertainty in the resulting analytics, then there is actually a lack of clarity of the learning process.

<sup>1</sup>The papers included in the proceedings given to delegates, including posters and workshops.

When learning and analytics is brought together in LA, learning can no longer be conceptualised separate from analytics, nor can analytics be conceptualised separately to the learning. According to the Pragmatic Maxim, both would need to be understood in terms of their practical effects on the other.

An example from James [11, p. 12] also reinforces the significance of the principle:

To take in the importance of Peirce's principle, one must get accustomed to applying it to concrete cases. I found a few years ago that Ostwald, the illustrious Leipzig chemist, had been making perfectly distinct use of the principle of pragmatism in his lectures on the philosophy of science, tho he had not called it by that name. "All realities influence our practice," he wrote me, "and that influence is their meaning for us. I am accustomed to put questions to my classes in this way: In what respects would the world be different if this alternative or that were true? If I can find nothing that would become different, then the alternative has no sense."

The Pragmatic Maxim essentially poses the same question for LA: In what respects would the learning be different if this LA was working? However with LA, it can also be said that if there is no difference (or if the difference is worse for the learner), then the LA has no sense!

Hill [10] suggests that the Maxim is best understood in terms of some of Peirce's later thinking on three categories: "Reason, or rational law, is the third of Peirce's categories; his name for it is Thirdness. It takes potentiality (Firstness) and transforms it into actual existence (Secondness)." For LA, right thinking or reason is required in order take the potential of an analytic and transform it into a learning effect. This brings into focus how the Pragmatic Maxim might improve the rigour of LA research. Not only does it clarify the potential and provide for practical effects in the learning, it does this via a well-reasoned approach.

### 3 PILAR

Based on the application of the Pragmatic Maxim in LA research, we propose **PILAR** (Pragmatic Inquiry for Learning Analytics Research) as a research method encompassing three key elements (potentiality, actuality, and reason) and a five step process (contextualise, clarify, hypothesise, apply, and evaluate). The method is detailed in the following sections.

#### 3.1 Potentiality

The first of the three PILAR elements is potentiality, the beginning of inquiry. Peirce states that an irritation of doubt gives rise to a struggle for belief, which he refers to as inquiry [15]. In doubt, there is the potentiality for a resolution in practical effects. There is potentiality for ideas to "fulfill their purpose in the world" [18, CP 5.197]. However, finding the purpose or potentiality requires one "to refer to the situation in which these ideas/statements are produced" [12].

LA potentiality is found when the analytics are embedded in a learning context. Without the learning context, there is only

analysis. This may still have some research value, yet it cannot reasonably address concerns of quality in LA if it is not situated in a way that makes its usefulness apparent. Thus, a particular LA of concern will have maximum potential when it arises from the irritation of doubt, and is comprehended both in terms of its practical effects on learning, and the context of those effects.

#### 3.2 Actuality

Actuality is found in the practical effects. It is the result of the process of inquiry. The importance of actuality in LA is highlighted by Beck and Xiong [2, p. 7] who explored the value of improvements in accuracy in an Intelligent Tutoring System (ITS). They state that "While larger datasets enable us to estimate such minuscule quantities quite precisely (thus, the low p-value), it raises the question of whether this result is useful in any way?". In this situation the precision of the algorithm was the goal of the work rather than identified practical effects on student learning. Beck and Xiong [2, p. 7] go further in their critique stating that "Ironically, as a field we have settled on a common test problem that has little impact on tutorial decision making or on informing the science of learning." Consideration of actuality guards against this situation as the researchers would need to take into account how any improvement in precision would *actually* impact the learning.

Further, the Pragmatic Maxim states that how we conceive of these actual effects is the *whole* of our conception of the LA. This means ultimately that the extent to which our research is actually LA (rather than computer science for example) depends on the extent to which it is understood in terms of the actuality of practical effects.

#### 3.3 Reason

Potentiality and actuality cannot exist on their own. The identification of LA potentiality required consideration of practical effects, and actuality is the manifestation of what we posit as potentiality. Peirce claims that what connects the two is 'right thinking', a law of reason. He makes it clear that this is a cognitive process: "The method prescribed in the maxim is to trace out in the imagination the conceivable practical consequences" [18, CP 8.191].

In the connection between potentiality and actuality lies the relationship between pragmatism and the mode of reasoning Peirce called abduction. This connection has been explored in LA by Gibson [8] who showed the significance of abductive reasoning for LA, and its value for justifying the approaches that we take in connecting the potential to the actual.

For Peirce, abduction is most closely related to hypothesis which he saw as central to inquiry [12]. We also see this centrality of hypothesis as essential for LA, and capture this in a proposed method for LA research based on the Pragmatic Maxim.

#### 3.4 The Process

The method at the heart of PILAR is not new or novel. Indeed James [11] stated, "There is absolutely nothing new in the pragmatic method. Socrates was an adept at it. Aristotle used it methodically. Locke, Berkeley and Hume made momentous contributions to truth by its means." What is new is the application of the core ideas from the Pragmatic Maxim in LA research. PILAR presents this not only

through the elements previously described, but also as a five step method as follows.

- (1) **Contextualise** irritation or doubt within a clearly designated learning situation.
- (2) **Clarify** the analytics to investigate based on practical learning effects.
- (3) **Hypothesise** how the analytics will result in the anticipated practical effects.
- (4) **Apply** the hypothesis by putting it to the test in the learning context.
- (5) **Evaluate** the extent to which the hypothesis is true.

Although PILAR is presented here as a single process, more complex programmes of research are likely to use the process iteratively. Further explanation of the process is described in the following sections.

**3.4.1 Contextualise.** PILAR requires that the research is situated within a specific learning context. This ensures that the potentiality is identified not according to its intrinsic merits, but according to how it may result in practical effects within the identified context. For example, many computational techniques used in LA have been developed in other fields, so the potentiality for those fields are well known. The contextualise step would require such a technique to be reconsidered in terms of the learning context that is the subject of the research.

**3.4.2 Clarify.** Once the LA has been contextualised in terms of a specific learning context, the potentiality of the LA needs to be identified and clarified in terms of anticipated practical effects for the learning. This involves considering the potential analytics in terms of learning effects and the potential learning in terms of analytics effects. Through this process, LA is clarified in a way that provides focus on practical results rather than other non-relevant features. For example, if a computational feature cannot be clarified in terms of a practical learning effect, then that feature may be modified or omitted. Similarly, if a particular learning activity cannot be captured in the analytics then it may be removed from the research.

**3.4.3 Hypothesise.** The hypothesis in PILAR is a potential explanation of how the LA might result in the anticipated practical effects. There is a creative element to the hypothesis, where the researcher draws on insight to arrive at a new idea on how potentiality might resolve to actuality. However, this creative hypothesising is still grounded in the learning context of the inquiry. Aliseda [1, p. 4] notes that “for Peirce, three aspects determine whether a hypothesis is promising: it must be *explanatory*, *testable*, and *economic*.”. Each of these aspects is grounded in the practical reality of the learning. The hypothesis’ explanation should be relevant to the learning, it should be possible to apply the hypothesis within the learning context, and its application should be achievable within the resources of the learning context.

**3.4.4 Apply.** The fourth step of PILAR is to apply the hypothesis in the learning context. This application needs to be designed to test the truth of the hypothesis, determining the extent to which the LA results in the anticipated practical learning effects. The application of the hypothesis should realise potentiality and result in actuality.

**3.4.5 Evaluate.** Finally, PILAR requires that the whole process be evaluated. As this is LA research, evaluation is more than assessing the results of the application of our hypothesis. It also involves judging the extent to which our whole approach to LA is robust and defensible. Rigorous defensible research with PILAR will show clear potentiality connected to actuality through good reasoning, with the all elements situated in a clearly articulated learning context. Existing LA work on the Evaluative Framework for LA (EFLA) by Scheffel et al. [19] could provide a high quality approach to this step.

## 3.5 Aggregate and Constituent Research

It is important to recognise that PILAR is a method of inquiry and therefore is only complete to the extent to which it leaves no further doubt in the line of inquiry. This of course is dependent on how the line of inquiry is scoped, and as James [11] states is less likely to present in a solution than a programme of work:

But if you follow the pragmatic method, you cannot look on any such word as closing your quest. You must bring out of each word its practical cash-value, set it at work within the stream of your experience. It appears less as a solution, then, than as a program for more work, and more particularly as an indication of the ways in which existing realities may be CHANGED.

For this reason another important aspect of PILAR is transparency on how the research work might contribute to what might be considered a fully complete LA. To this end, we suggest that researchers articulate the extent to which their work is *constituent* and contributes to an existing or future LA agenda, and/or it is *aggregate* and incorporates prior LA constituent research in order to deliver a more complete LA. Some within the LA community have described this as closing the loop [3].

Importantly, there is no suggestion here that constituent research is somehow inadequate, but that it should be distinguished from aggregate research in its contribution to the field. Further it may be that some programmes of research make both a constituent and aggregate contribution and this should also be acknowledged.

It is anticipated that making the distinction clear between aggregate and constituent research will assist LA researchers in identifying the way that their work contributes to the new knowledge of the field.

## 4 PROVOCATIONS AND RESPONSES

At this point, we recognise that some may be sceptical of our proposal of PILAR as a research method for LA, and so we address what we consider to be two significant arguments against this approach in the form of provocations and address each with a response.

### 4.1 PILAR is unnecessarily restrictive

**4.1.1 Provocation:** The Pragmatic Maxim restricts inference by tethering it to those outcomes that can be perceived (read: measured). What’s more, it defines constructs with respect to measured outcomes. The immediate ramifications of this approach are that those areas without easily measured outcomes are ignored leading to a dearth of exploration in areas that may be important. But more seriously, it may hinder the generalizability of any finding that

as measures, which will define constructs, may not be replicable across contexts. An extreme version being that each course would need its own measures and constructs, a version of the Psychology of Lykken in which every human requires their own version of psychology to be understood. This would shrink the practical utility of learning analytics to an unusable extent.

**4.1.2 Response:** While it is true that PILAR is restricted to anticipated practical effects, the limitation is imposed not so much by the method, than by the imagination of the researcher. Peirce addresses the point as follows:

It allows any flight of imagination, provided this imagination ultimately alights upon a possible practical effect; and thus many hypotheses may seem at first glance to be excluded by the pragmatical maxim that are not really so excluded. (1903; Peirce 1997:249-50)

Further, there is an assumption in the provocation that a practical effect must be 'measured' and by inference quantified, however PILAR only requires that the effect be identifiable and be attributable to the application of the hypothesis. In a learning context, there may well be a positive impact on the learning from the application of a hypothesis without that impact being measurable. For example, a student may respond more enthusiastically to an activity. This may be qualitatively identifiable even if it is not measurable.

## 4.2 PILAR depends on causality

**4.2.1 Provocation:** A great deal of educational research involves probabilistic modelling, and many of the concepts involved in probability theory were not available to Peirce at the time he wrote the Pragmatic Maxim or had not been applied to behavioural research. And it is unclear whether the Pragmatic Maxim is compatible with a probabilistic methodology.

PILAR asserts strong links between observation and construct but no assumption of causality demonstrated by antecedent. Rather theories are measured as valid through their applicability to desired outcomes and can be applied when the measurement and the construct it measures can both be interpreted as probabilistic. If we are unsure about both whether the measurement is accurate and whether we are observing the thing we intended to, the PILAR may not be applicable or very few analytic methods may meet its stringent limitations.

**4.2.2 Response:** Once again there is an assumption that practical effects means quantifiable and directly linked. However, in both the writings of Peirce and James a main concern of Pragmatism was to resolve metaphysical disputes without any idea of dismissing a perspective that was not measurable or quantifiable. As a case in point, James introduces the idea of Pragmatism through an example of resolving a metaphysical dispute about a squirrel and a tree [11]. This illustration is entirely behavioural, and does not appeal to measurement as a mechanism for determining practical effects. Rather, the point of view of the observer determines how the dispute is resolved.

Likewise PILAR does not depend on a quantified understanding of causality in order to make the link between LA and practical effects. Rather it grounds the approach in a perspective that is relevant to the learning context, whether that be behaviour that is

qualitatively observed, a feature that is statistically modelled or some element that is directly measurable.

## 5 CONCLUSION

The transdisciplinary nature of LA has meant that much of the research to date has drawn on methods from contributing fields. This has enabled the field to grow, but presents difficulties to researchers attempting to answer questions of quality.

In response to this issue, we outlined PILAR, a research method for LA that is drawn from Peirce's Pragmatic Maxim. PILAR forces us to confront the relationship between analytics and learning that is central to LA. It requires research to address how LA might result in practical learning effects, as opposed to more information about learning with little practical consequence.

In turn, we hope that PILAR will make a contribution to addressing questions of quality within LA research and to the ongoing development of the field.

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