# 教育機関における学習分析の設計と導入のフレームワーク：文献レビュー

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# Frameworks of Designing and Implementing Learning Analytics in Educational Institutions: A Review

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**Abstract**

Learning analytics represents a transformative approach to understanding and enhancing the educational landscape. As higher education institutions recognize and embrace the potential of learning analytics, they unlock myriad benefits, fostering a more responsive and effective educational ecosystem. However, the design and implementation of learning analytics in the organization is a complicated process of planning, communicating, collaborating, and decision-making that involves multiple stakeholders, both inside and outside the organization. The paper examines 15 learning analytics models that discuss how to design and implement learning analytics in institutions. Four types of frameworks are identified: domain, process, level, and mixed. A holistic planner of organizational learning analytics is created because of the review.

## 1 Introduction

Learning analytics is defined as the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs [1]. Learning analytics aims to customize educational opportunities based on the specific needs and abilities of each learner, achieved through actions like intervening with at-risk students and offering feedback and instructional content [2]. The development and progress of this endeavor are intricate, interdependent, and constantly evolving, involving a diverse range of stakeholders throughout the institution [3]. However, limited research is available on perspectives and involvement of all stakeholder groups in institutional planning and implementation of learning analytics, and on the ways how institutions develop and enact strategies for the designing and implementation of learning analytics [4].

In 2022, the Center for IT-based Education (CITE) at Toyohashi University of Technology (TUT or Gikadai), a national university in Japan, decided to explore the possibility of integrating learning analytics into the university's Moodle-based learning management system (LMS). To accomplish this, discussions were held with several learning analytics solution providers. After a thorough evaluation and careful comparison, IntelliBoard, a vendor specializing in learning analytics for LMS platforms such as Moodle, was selected for a pilot initiative called TUT Learning Analytics (TUT–LA). The initiative aims at designing, deploying, and implementing learning analytics with the involvement of key stakeholders at TUT. Considering the practical intent and the existing research gap, it is our contention that undertaking a research investigation to document this university-led endeavor would yield significant advantages for both academic institutions and educational researchers with a shared interest in the domain of learning analytics within the higher education context.

Furthermore, in conjunction with the Gikadai–MDA (Mathematics, Data science, and AI education, or in Japanese as GIKADAI 数理・データサイエンス・AI 教育プログラム) program implemented at TUT, the TUT–LA initiative is of particular importance in the Japanese university context. After the release of the Cabinet Office’s AI Strategy policy in 2019 and the establishment of the MDASH (Mathematics, Data Science, and AI Smart Higher Education) Programs Certification System in 2021, an expectation has been set that graduates from Japanese universities, junior colleges, and technical colleges should possess a foundational understanding of mathematics, data science, and AI. As shown in Fig. 1, in response to this new policy, between 2021 and 2023, a total of 529 dedicated educational programs offered by higher education institutions in Japan received accreditation at the *MDASH Literacy Level* (リテラシーレベル: 382) and at the *MDASH Advanced Literacy Level* (応用基礎レベル: 147). Remarkably, some programs were specifically recognized at the *MDASH Literacy+ Level* (リテラシーレベルプラス: 25) and *MDASH Advanced Literacy+ Level* (応用基礎レベルプラス: 14) due to their innovative and distinctive ideas and characteristics [5].

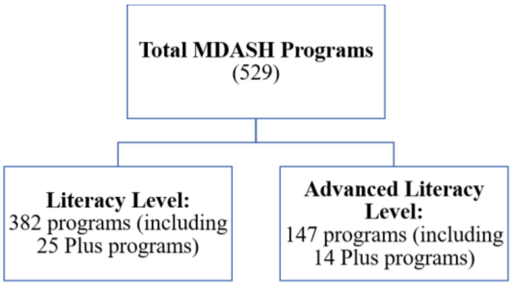


Fig. 1 MDASH programs by 2023 in Japan

In the Gikadai–MDA program, there are five courses at the *MDASH Literacy+ Level* including *Introduction to Information and Communication Technology*, *Introduction to Engineering*, *Engineering and Science Laboratory*, *Probability and Statistics*, and *Research Project*. They are for first- and second-year undergraduate students. There are two courses at the *MDASH Advanced Literacy Level* including *Data Science Exercise*, and *Advanced Data Science Exercise*. They are for third- and fourth-year undergraduate students. The latter two courses use interactive textbooks in Jupyter Notebook format, the *TK Basic series* and *TK Advanced series*, which were created in collaboration with KIKAGAKU Corporation—a provider of business training [6].

Applying learning analytics in the MDASH programs can unveil a captivating possibility. Over years, despite the growing body of learning analytics research, its tangible impact on actual teaching and learning practices remains somewhat limited, primarily due to the prevailing prevalence of small-scale adoptions [3], [4], [7]. The research findings derived from this endeavor possess considerable potential to yield scalable experience and comparable research projects among all MDASH programs operating throughout Japan, which actively engage a wide range of stakeholders within the comprehensive landscape of Japanese higher education. This paper reports the experience from the TUT–LA project by sharing results of a selective review of the literature that proposed learning analytics models, which primarily visualize the learning analytics designing and implementation at the institutional level. The purpose of the review is to synthesize the accumulated intelligence on this topic and to offer a holistic and integrated view to inform the institutional designing and implementation actions of learning analytics at TUT.

## 2 Deploying learning analytics in educational institutions: A review of available frameworks

Numerous frameworks that aim at facilitating the designing and implementation of learning analytics within educational institutions are available. Two dedicated review studies exist on providing a holistic view of learning analytics models [8], [9]. This review is different from them because its focus is on reviewing learning analytics models that involve the designing and implementation of learning analytics at the institutional level. Our review resulted in a categorization of these frameworks into four distinct types: “domain” frameworks, “process” frameworks, “level” frameworks, and “mixed” frameworks. The domain type of frameworks is more dominant in the literature than the other three types (Table 1). The mixed type of frameworks typically mixes process and domain or level and domain. Hence, be aware that the count of the mixed type overlaps with the counts of the other three types in Table 1. An overview of these four types of frameworks is presented in Table 2. The subsequent paragraphs provide comprehensive details regarding each type.

Table 1. Number of frameworks by type

| Type | Number of frameworks |
|---|---|
| Domain | 11 |
| Process | 4 |
| Level | 3 |
| Mixed | 2 |

### 2.1 “Domain” type of frameworks

Domain frameworks offer comprehensive coverage of various components, aspects, or dimensions that necessitate consideration when designing learning analytics at the institutional level. This type is the most popular type among the reviewed frameworks. Out of eight domain frameworks, four common domains are synthesized and listed in Table 3, which are objectives, stakeholders, technology infrastructure, and institutional context.

*Objectives*. It is recommended that institutions set a maturity index to gauge learning analytics progression, set goals, and measure progress [10]. There are different objectives, which can be related to for instance awareness and reflection [11]–[14], behavioral change of students and educators during the learning processes [11], retention [3], supporting educational decisions [12], monitoring and analyzing [12], prediction and intervention [12], [13], tutoring and mentoring [12], assessment and feedback, adaptation [12], personalization and recommendation [12], identifying at-risk students/courses/subjects [14], informing educational practices [14], helping/advising students [14], developing new programs [14], holding academics accountable for student performance [14], scholarly research [14], and influencing faculty/university policy [14]. Defining objectives, which reflect back to the “purpose” of adopting learning analytics in the first place [15], will influence forthcoming choices and actions in other domains of consideration.

*Stakeholders*. This domain, on one hand define, who to involve in the learning analytics process, which may include both internal stakeholders (e.g., students, teaching staff, senior managers, researchers, study program leaders, IT officers, a working group made up of representatives from various units) and external stakeholders (e.g., learning analytics experts, data scientists, service/solution vendors, publishers, data governing bodies) [13], [15], [16]. Another suggestion is to divide stakeholders into data clients (beneficiaries of the learning analytics process to act upon the outcome, e.g., teachers) and data subjects (suppliers of data, through their browsing and interaction behaviors, e.g., students), and to expand stakeholder groups to also include computer agents (e.g., notification email sent by system) [13]. On the other hand, the domain of stakeholders is also related to assessing stakeholders’ perceptions, attitudes, willingness [17], motives, needs [3], skills [14], [17], providing them with necessary training to get start [3], [14], as well as monitoring and supporting them in practice [14]. For instance, it was suggested that learning analytics researchers should study and share experiences on the effects of integrating learning analytics into everyday practice [12]. The current lack of support and communication academics receive when faced with learning analytics should be improved [18].

*Technology infrastructure*. It comprises the “basic enterprise technology environment for individual institutions, including the combination of data, information, reporting, and analytics capabilities” [17, p. 31]. This domain covers consideration aspects such as what data will be collected [10], [12], [15], [19], what systems and environments will generate these data [12], [15], what analytics tools, techniques, and methods will be used to analyze the collected data [10], [12], [13], [19], what technical solutions/services are available (what can/cannot be technically achieved) [15], what is the data policy to guarantee a satisfying level of ethics, privacy, and data stewardship [3], [11], [13], [16], and how sustainable are the learning analytics solutions. The various objectives need the support of tailored set of performance indicators and metrics so that they can become easier to measure, monitor, and evaluate [12]. This domain has several challenges to address. For instance, the scope of data (e.g., collect data that did not accurately reflect student activities) [18], the quality of data (e.g., data accuracy, data reliability, data completion) [3], [14], [18], stakeholders’ understanding and trust of the benefits of using learning analytics are required to ensure the sustainability of these tools [20], choosing the right format to present the data and insight effectively to stakeholders [3], and system’s interface being not user-friendly enough [3].

*Institutional context*. This domain covers “hard” tangible context such as human resources [3], [15], financial resources [10], and administrative processes [17], and “soft” intangible context such as governance [10], [21], policies [14], [17], strategies [3], [14], leadership or top management support [14], [16], [22], culture/conventions/norms [3], [10], [14], [21]. It’s worth noting that some elements, like governance, policies, and strategy, can be seen as straddling between soft and hard contexts. For instance, while strategy might emerge from intangible organizational values and perspectives, it often gets codified into tangible plans and actions. Institutions are recommended to perform an audit of various contextual components such as policy, processes, and practices to see what supports student success and what has become an impediment [17].

Table 2. Frameworks of deploying learning analytics at the institutional level

| | Framework | Year | Type | Components | Instrument |
|---|---|---|---|---|---|
| 1 | Four-level analytics sophistication [23] | 2007 | Level | descriptive analytics; predictive analytics; prescriptive analytics; autonomous analytics | – |
| 2 | The five steps of analytics [16] | 2007 | Process | capturing; reporting; predicting; acting; refining | – |
| | | | Domain | stakeholders; information technology; goals and expectations; organizational readiness | |
| 3 | Learning analytics process [12] | 2012 | Process | data collection and pre-processing; analysis and action; post-processing | – |
| 4 | Four-component reference model for learning analytics [12] | 2012 | Domain | why; what; who; how | – |
| 5 | Six-dimension generic design framework for learning analytics [13] | 2012 | Domain | stakeholders; objective; data; instruments; external limitations; internal limitations | – |
| 6 | EDUCAUSE learning analytics model [10] | 2012 | Domain | culture/process; data/reporting/tools; investment; expertise; governance/infrastructure | ECAR analytics survey 2012 |
| 7 | Learning analytics cycle [24] | 2012 | Process | learners; data; metrics; interventions | – |
| 8 | Learning Analytics Sophistication Model [7] | 2013 | Level | awareness; experimentation; adoption; organizational transformation; sector transformation | – |
| 9 | Stages of student success analytics [17] | 2013 | Mixed: Level | static reporting (2-3 years); dynamic analysis and intervention (3-5 years); optimization. | – |
| | | | Mixed: Domain | technology infrastructure, analytic tools and applications; policies, processes, practices, and workflows; values and skills of stakeholders; culture and behaviors; leadership | |
| 10 | Learning Analytics Readiness Instrument (LARI) [21] | 2014 | Domain | governance and infrastructure; ability; data; culture and process; overall readiness of perception | LARI instrument (90 items) |
| 11 | Let's Talk Learning Analytics Framework [3] | 2016 | Domain | institutional context; transitional institutional elements; learning analytics infrastructure; transitional retention elements; learning analytics for retention; intervention and reflection | Academic level survey |
| 12 | SHEILA framework [15] | 2018 | Domain | purpose; methodology; management; stakeholder engagement; ethics and privacy; data management; human resources; internal and external support; financial resources; infrastructure; culture; capabilities; policy management; evaluation; policy management | SHEILA: a web tool |
| 13 | Quality indicators for learning analytics [11] | 2019 | Domain | objectives; learning support; learning measures and output; data aspects; organizational aspects | – |
| 14 | Five critical success factors for learning analytics implementation [14] | 2020 | Domain | strategy and policy at the organizational level; information technological readiness; performance and impact evaluation; people's skills and expertise; data quality | Survey instrument |
| 15 | Learning analytics framework [19] | 2021 | Mixed: Process | design; development; analysis; assessment | – |
| | | | Mixed: Domain | identification of the key stakeholders; identification of the needs; mapping the available data; metrics and indicators definition; data collection approach; data analysis methods; visualization techniques | |

Table 3. Four domains to consider when deploying learning analytics at the institutional level

| **Domain** | **Details** | [3] | [11] | [10] | [12] | [13] | [14] | [15] | [16] | [17] | [19] | [21] |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Objectives | what goals, (success/performance) | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | | | |
| Stakeholders | who, perception and motives, readiness, abilities, training and support | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Technology infrastructure | data (raw data, indicators, metrics, data sources: systems and environments), instruments (analytics tools, techniques, methods), vendors' provided services and solutions, ethics/privacy/stewardship, sustainability | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Institutional context | soft context (e.g., governance, policies, strategy, leadership, culture/conventions/norms), hard context (e.g., human resources, financial resources, administrative processes) | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ |

### 2.2 "Process" type of frameworks

Process frameworks elucidate sequential steps or procedures that facilitate the effective designing and implementation of learning analytics. This type has a vertical focus on data management, in comparison to the domain type that casts a horizontal view to reach different domains of consideration. Table 4 compared five process frameworks and discovered four common steps in the process of implementing learning analytics. They are data collection, data analysis and predicting, interventions, and assessing and refining.

*Data collection*. It collects educational data from environments and systems [12]. Previous studies identified 17 areas of data [10] or 8 types of data [16] collected by institutions. However, many institutions have not matured to use these collected data for prediction or strategic actions [10]. The decision of what data is to be collected often takes place in the initial design stage of a learning analytics project, which needs to be informed by domains of consideration [19].

*Data analysis*. It needs to consider objectives, data types, tools, and analytic techniques [12]. The data analysis can be executed for the purpose of analysis for understanding the current situations in the educational contexts (e.g., descriptive statistics), or analysis for predicting the future behaviors or developments (e.g., predictive modeling) [16], [24].

*Acting*. Taking actions is the primary aim of the whole learning analytics process [12]. Actions may range from information to inventions. [16] For instance, the analytic insights can be communicated with involved stakeholders using adequate visualization techniques, such as traditional reports or visualized dashboards to users (reporting) [16], [19]. Other acting can include triggering an automatic (e.g., email alerts) or manual intervention (e.g., personal phone calls) [16], [24].

*Assessing and refining*. This self-improvement step takes place at the end of one iteration of the learning analytics process. It aims to improve methods and results of the learning analytics practice [19]. The team needs to reflect on the whole process, evaluate the performance and effectiveness of current practice, and decide on what refinements should be implemented in the practice's next iteration. The refinements can take place in areas such as dataset, attributes, metrics/indicators, variables of analysis, analytic methods, processes, statistical models [12], [16].

Table 4. Process of learning analytics

| | Step | Details | [12] | [16] | [19] | [24] |
|---|---|---|---|---|---|---|
| 1 | Data collection and pre-processing | data sources; data format | ✓ | ✓ | ✓ | ✓ |
| 2 | Data analysis | use analytic tools and statistical techniques to run analysis for understanding or analysis for prediction | ✓ | ✓ | ✓ | ✓ |
| 3 | Acting | reporting to stakeholders; trigger interventions | ✓ | ✓ | ✓ | ✓ |
| 4 | Assessing and refining | reflect on the whole process to assess the existing practice and make adjustment for future practice | ✓ | ✓ | ✓ | |

### 2.3 "Level" type of frameworks

Level frameworks depict the varying complexity and maturity levels of institutional learning analytics' development. It is expected that an institution will need a couple of years to progress from an immature organization in learning analytics to a mature one. Only three frameworks discussed this progression.

Davenport and Harris [23] introduced a taxonomy comprising four levels of analytics that reflect the sophistication of the intelligence they provide. Although their work is not directly addressing learning analytics, due to its high citations in the learning analytics research community and repeated appearances in EDUCAUSE publications such as [10], [17], it is included in this review. The lowest level, descriptive analytics, can be achieved by standard reports, ad hoc reports, query/drill down capabilities, and alerts. Moving up the hierarchy, predictive analytics involves statistical analysis, forecasting/extrapolation, and predictive modeling. Prescriptive analytics encompasses experimental design and optimization. Autonomous analytics can be attained through the utilization of machine learning techniques to extract insights from the data, enabling a deeper understanding of patterns and trends.

Siemens et al. [7] proposed the five-level Learning Analytics Sophistication Model, which includes: awareness, experimentation, adoption, organizational transformation, and sector transformation. However, this model lacks explanation and elaboration, which hinders its application in practices.

After surveying 40 higher education institutions in the USA, the three-level Stages of Student Success Analytics was proposed to "characterize the current status of organizational capacity for analytics in higher education as three stages of development" [17, p. 40]. They include Leve 1: static reporting, focuses on data and reporting; Level 2: dynamic analysis and intervention, focuses on supporting evidence-based decision making, and Level 3: optimization, focuses on making learning analytics a strategic imperative for the institution. The jump from Level 1 to Level 2 can take two to three years, and that from Level 2 to Level 3 can take three to five years. It is worth noting that the differentiation of these three development level borrowed insights of five-factor organizational capacities of analytics, namely leadership, technology infrastructure, processes and practices, skills and values, and culture and behaviors [17, p. 31]. These five factors are greatly overlapping with the four domains of consideration presented in Table 3, which suggests that when designing learning analytics at the institutional level considering the organizational capacity is one primary effort that cannot be overlooked. Comparing the three "level" type of frameworks, the most relevant and actionable framework will be this one.

### 2.4 "Mixed" type of frameworks

Two mixed frameworks [17], [19] blends level and domain, and process and domain, respectively. The first mixed framework [17] displays the development status of five factors of organizational capacity (or five domains) in each of the three levels (Level 1, 2, and 3). The second mixed framework [19] proposes a four-component continuous cycle process of learning analytics (design, development, analysis, and assessment), and suggests seven stages in the design component (or seven domains). Domains often serve as repositories for gathering factors to examine and discuss when designing and implementing the learning analytics process, as well as assessing an organization's level of learning analytics capacity. So far, no mixed framework blends three types (domain, process, level) into one entity.

## 3 A holistic planner to design and implement organizational learning analytics

Considering the context of Japan, this study has created a holistic planner that helps to empower evidence-based practice of designing and implementing organizational learning analytics through the PDCA cycle (Fig. 1). The PDCA cycle, developed for quality control modeled after the Toyota Method, has also been applied to the development of actionable learning analytics [25]. This planner integrates intelligence innated in four types of frameworks and adds to the literature a new mixed framework that blends three types of frameworks instead of two types. The planner can serve as an instructive guide and a stakeholder engagement tool in a learning analytics project. In this planner, the four domains are considered in the "plan" stage of the PDCA cycle, the four-stage process is planted into the "do", "check", and "act" stages. This PDCA cycle is repeated in order to level up the organizational capacity of learning analytics from the low Level 1 to the advanced Level 3 over years.

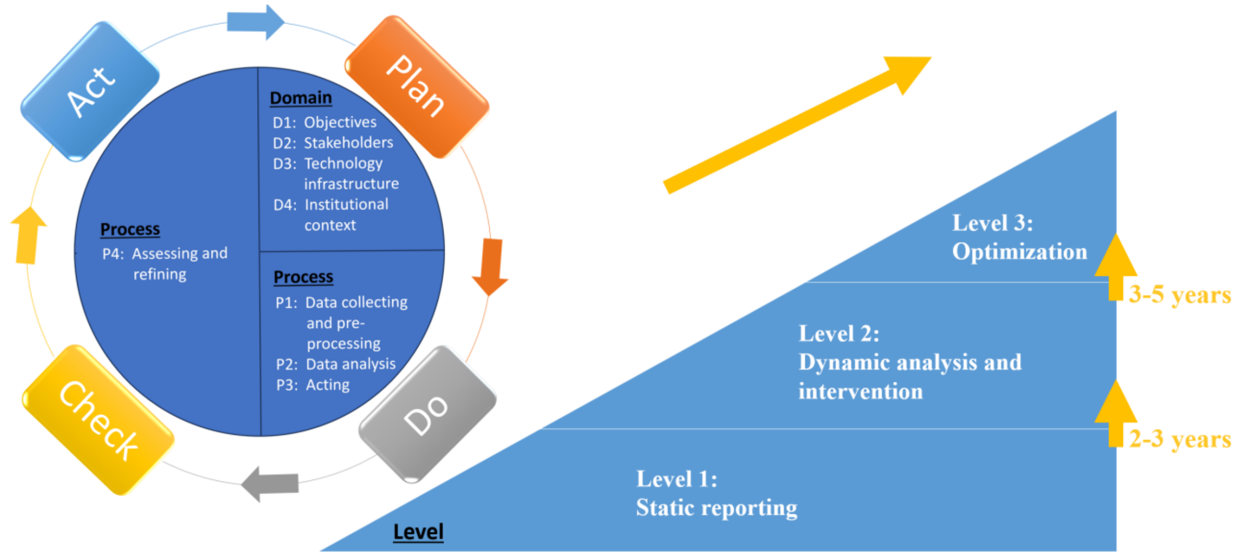


Fig. 1. A holistic planner of designing and implementing organizational learning analytics

## 4 Final remarks

To utilize this holistic planner, it is crucial for an educational institution to assemble a multidisciplinary team. Such a team should include not only educators and administrators but also data scientists, IT specialists, and even student representatives. This diversity allows for a richer understanding of the intricacies involved in deploying learning analytics, ensuring that both technical and pedagogical aspects are adequately addressed. For example, while data scientists can focus on analytics algorithms and data integrity, educators can provide insights into how the analytics can be most useful in a classroom setting. Administrators can oversee the implementation process, ensuring it aligns with institutional objectives and policies.

The necessity of establishing a team is not limited to the organizational level of designing and implementing learning analytics but also to the national level of a similar effort. We propose the establishment of a national steering group for guiding the designing of learning analytics in MDASH programs. This group would bring together experts from academia, government, and technology sectors to collaboratively work on the standardization, adoption, designing, and implementation of learning analytics in MDASH programs nationwide. By acting as a unifying body, the group could facilitate the sharing of best practices, offer recommendations for policy and technology integration, and ensure that learning analytics are employed ethically and effectively across various educational institutions. The creation of such a group would signify a national commitment to harnessing the full potential of learning analytics for the betterment of educational outcomes regarding mathematics, data science, and AI education in Japan.

## 5 Conclusion

This paper reviewed and synthesized fifteen learning analytics frameworks at the organizational level. It discovered four types of frameworks in the literature: domain, process, level, and mixed. It created a holistic planner tool to inform organizational practice of designing and implementing learning analytics. The purpose of this paper did not entail conducting an exhaustive examination of all frameworks pertaining to learning analytics. Instead, it raises the awareness of practitioners and researchers on the clustering of these frameworks under the four types. It is recommended that future researchers undertake additional investigations to supplement the existing body of knowledge within the four identified types.

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