Analogizing in Construction and Education Research: A Case Study

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Abstract

This paper is inspired by the concept of Analogizing. It explores the analogies between a concept from the Construction industry (Automated Project Performance Control – APPC) and a concept in Education (Organizational Learning Analytics – OLA). The APPC model deals with automating data collection and conversion from on-site construction projects in real-time to improve control and performance, while the OLA model expands the current application of learning analytics to managerial and strategic level decisions taken in higher education institutions (HEIs). By drawing connections between these two conceptual models, the paper demonstrates the innovative potential of Analogizing to identify novel solutions in one discipline using well established methods from an analogous, yet highly distinct, second discipline.

Keywords

Civil Engineering; Higher Education; Learning Analytics; Automation; Construction Project Performance Measurement

1 Introduction

Inspired by the concept of Analogizing, this paper presents a comparative case study of two conceptual models, one from Social Science and the second from Engineering.

The first model, known as Automated Project Performance Control (APPC), was developed to facilitate construction projects on-line control by automating the collection and conversion of field data from ongoing projects. The second model, currently under development, deals with learning analytics (LA). It aims to expand the application of LA beyond the classroom-level, which is its current focus. Thus, stakeholders outside the classroom-level will be able to make their decisions in alignment with HEI's overall organizational T&L. This model will be related to henceforth as organizational learning analytics (OLA).

The intention of this paper is to demonstrate how the concept of Analogizing can be used in a cross-disciplinary research, especially when researching new subjects. The authors use their experience in the development of the APPC and OLA models in a case study, which shows that the two, seemingly, distinct disciplines (the APPC and OLA models) share more commonalities than initially apparent. The concept of Analogizing, as well as the APPC and OLA models will be detailed in the following Sections.

2 Analogizing

Comparing dissimilar events, activities, or phenomena despite their differences characterizes analogical thinking, also known as Analogizing. This mental process is specifically designed to emphasize formal parallels across disparate contexts [1]. Zerubavel [1] illustrates this by pointing out that a female and an Afro-American professional in 1940s America are in parallel situations; both belong to low-status socio-ethnic groups while occupying high-status professional positions. He offers another cross-contextual example, highlighting the equivalence between gay individuals and those with disabilities, as both groups face societal "stigmatization." Sceptics often dismiss the possibility of finding equivalence among seemingly non-comparable items, asserting that it is like "comparing apples to oranges." However, Zerubavel [1] counters this argument by pointing out that even seemingly disparate entities, like apples and oranges, share commonalities, such as being fruits.

The Case Study will employ the Analogizing approach to underscore the shared characteristics between the OLA, utilized in the educational realm, and APPC in construction operations.

3 Automated Project Performance Control

This Section relates to the first of the two conceptual models – Automated Project Performance Control (APPC) from the construction industry.

Construction projects are complex and dynamic environments that prove challenging to monitor in real-time conditions [2]. Project Performance Control (PPC) broadly refers to the activities taken by the project management to ensure that the project's performance aligns as closely as possible with the initial plan. Performance is measured in terms of Project Performance Indicators (PPIs) such as cost, schedule, labor productivity, materials consumption, etc. [2], [3].

The reliance on manual data collection in traditional construction control methods inevitably leads to slow, inaccurate, and error-prone data collection processes [3], [4]. This, in turn, likely explains the prevalence of generic and infrequent control practices among construction managers. To achieve more timely and accurate control, project managers would need to dedicate an excessive amount of time to data collection, diverting their attention away from their primary responsibility of project management and supervision.

Automated Data Collection (ADC) technologies that can potentially measure performance indicators in real-time on construction sites are rapidly emerging with declining costs. However, the construction industry lags in adopting these technologies to measure performance indicators [2], [5], [6]. A key reason for this is that ADC technologies are unable to **directly** measure the required PPIs, they can only capture **indirect** metrics, raw data (RD) from the site [7], [8].

A conceptual model for APPC was developed to enable automated measurement of the indirect RD, which after conversion to PPIs, are used for controlling construction projects [9]. As illustrated in Figure 1, this model outlines how a typical control cycle begins by measuring RD, which will later be converted to the PPIs like cost, progress, and resource consumption (resources such as materials, manpower, etc.) as of the data-collection date. These values are compared against planned, or updated plans, performance levels. If deviations are found, an analysis is conducted to understand the factors causing them. Corrective actions, like adding resources, adding workers, or authorizing overtime work are then decided upon based on this analysis. The final phase of the control cycle involves implementing these corrective measures.

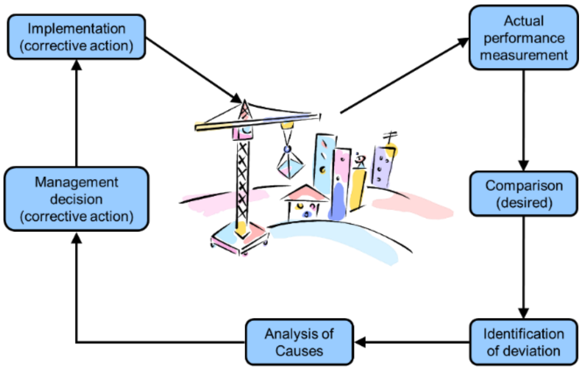

Figure 1. The Control cycle

The Achilles' heel of the automated construction control cycle lies in the real-time measurement of PPIs. The current absence of sensors capable of directly and automatically measuring PPIs creates a significant gap between the technologically capturable data on-site – RD – and the PPIs essential for real-time automated control. While automated data collection (ADC) technologies can measure various RD, project managers require, on the other hand, direct PPIs values to make informed decisions. This fundamental lack of direct PPI measurement sensors presents a major obstacle to achieving real-time automated control in construction projects.

To bridge the gap between RD collected from on-site construction projects in real-time and the necessary PPIs, Technion has developed conceptual conversion models. This approach aims to measure real-time values of indirect parameters (the RD) that can be captured on-site using existing technology. By converting these indirect parameters into the required PPIs, construction managers have actionable information to work with. The most important PPIs – cost and schedule, known as Key Performance Indicators (KPIs) – can now be compared in terms of actual performance against planned objectives. This enables timely course correction and improves project outcomes.

The specific indirect parameters likely differ across various types of activities (in building construction: skeleton activities, finishing activities, like flooring, in road construction: compacting, paving etc.). However, Technion models are often based on the fact that a "construction agent" – worker, earthmoving equipment or other – must be proximate to a building element, or the road section, to construct it. Thus, capturing the construction agent's location over time, combined with data from the Building Project Model (BPM), enables determining what activity the agent is performing.

By collecting location data at regular intervals, the construction-activity-specific algorithms developed in Technion can determine what the construction agent is doing at any given time. The model links measured locations to activities (e.g. flooring, painting, paving etc.) based on proximity of the construction agent to building elements – this is the novelty of the concept.

This conceptual model was implemented in proof-of-concept case studies and tested on-site with ADC, in various construction areas: manpower control [10], road construction [11], materials management [12], safety control [13], progress [14] and more. Subsequent efforts delved into enabling technologies and opportunities, reviewed the field's state-of-the-art, and proposed dashboards and concepts [2], [4]–[6], [15]–[18].

Like the OLA model that will be explored next Section, the APPC model demonstrates a data-driven approach to gaining insights for performance improvements.

4 Learning Analytics

Learning analytics (LA) is 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 [19]. The data available in the HEI's repository are students' participating in online courses, submitting assignments, engaging with learning resources, accessing the university websites and databases, activities in the libraries, number of students enrolled in each course and over time, number of students per class, distribution of grades across courses and departments, courses where students need additional support, faculty-to-student ratios, and more.

LA is instrumental in identifying students who may be at-risk of dropping out or failing a course and allows for the implementation of targeted interventions to help these students succeed [20]–[22]. When combined with machine learning methods, LA serves as a tool for early identification of students who may not submit their upcoming assignments or face potential failure [23], [24].

Currently, LA primarily focuses on informing professors about their students for teaching and learning (T&L) improvement [22], [25]. However, this approach only utilizes a fraction of the valuable data available within HEIs' repositories. The activities and decisions of other stakeholders, including department heads, administrative staff, presidents or provosts, and vice presidents, etc., all have a significant impact on the academic conduct and the quality of T&L. These stakeholders often focus on performance metrics specific to their individual roles, such as marketing, budgeting and finances, faculty recruitment, student enrolment, fundraising, etc. rather than metrics aligned with the institution's broader goals.

This demonstrates the gap between LA's potential and actual usage [26], [27]. In order to narrow this gap, The Open University of Israel is currently conducting a research study to develop a conceptual model which will empower a broader range of stakeholders, both within and outside HEIs, to effectively utilize LA to improve T&L – as mentioned in the Introduction, this conceptual model is called organizational learning analytics (OLA). The conceptual model adapts principles from management science models, demonstrating the Analogizing concept. An initial conceptual model was presented last year [28].

Ethical considerations still challenge LA researchers [22], [29], [30]. Expanding LA applications to more stakeholders could raise additional ethical issues. Therefore, the new OLA conceptual model will need to carefully account for ethical implications during its development.

As highlighted in the previous APPC model Section, the OLA approach also relies heavily on data analytics to derive decisions and outcomes.

Having outlined the key concepts within the APPC and OLA models, this paper now turns to analyze the disparities and commonalities between them.

5 Case Study

Construction project performance measurement and organizational learning analytics (OLA) operate in distinct contextual circumstances with unrelated objectives. Educational institutions function within structured environments defined by clear plans, such as curricula, and typically adhere closely to these plans. Conversely, construction projects, conducted in external environments, are subject to harsh weather conditions and other dynamic factors, making it challenging to adhere rigidly to initial plans.

In educational institutions, the key stakeholders – the students – exhibit stability by adhering to the curriculum, usually thorough the whole year or the entire program duration measured in terms of years. In contrast, construction workers rarely stay on a single project for an extended period, spanning only days, weeks, or occasionally, months. The differences between these contexts are significant, and in Zerubavel's [1] terms, attempting to find cross-contextual equivalence between OLA and APPC would be like to comparing apples to oranges.

As in the case of apples and oranges, despite these apparent disparities, a more profound comparative analysis uncovers noteworthy commonalities between OLA and APPC. Both models rely on data to derive actionable insights. They both measure indirect, proxy, raw data interpreted by powerful algorithmic processes to generate Key Performance Indicators (KPIs).

OLA leverages raw data such as grades, student course participation, assignment submissions, engagement with learning resources, etc. These data are not direct indicators of the quality of teaching and learning (T&L). Direct KPIs might include, for example, the number of students successfully completing a course or graduating. Similarly, the APPC model tracks the locations of "construction agents" at regular intervals, associating them with building, or other construction elements based on schedule data and Building Information Model (BIM). However, the resulting information, such as the construction agent's activity, does not directly represent KPIs like cost and schedule.

Both OLA and APPC share a common limitation: the outputs of their algorithmic processes may not accurately reflect the actual activities they are intended to represent. In OLA, student participation metrics may not necessarily correlate with genuine engagement in the learning process. Similarly, in APPC, a worker's presence near a specific building element may not always indicate that work is being performed on that element. Conversely, a worker's absence from a particular area (despite having been there shortly before and returning shortly after) should not be interpreted as a lack of work on that element. The worker may still be engaged in tasks contributing to actual work being performed on that element, such as fetching materials or preparing tools, despite not being physically proximate to it.

Another cross-contextual commonality is the involvement of diverse stakeholders in both construction and HEIs, including internal and external parties. Project management stakeholders range from project managers, clients, owner/entrepreneurs, architects, engineers, main- and sub-contractors, and materials suppliers, to local authorities and regulators. This stakeholder network expands at the company level, emphasizing the complexity of project management. In HEIs, stakeholders span from students, professors, department heads, administrative staff, presidents, vice presidents etc., to external authorities like local/national authority and regulators.

While additional commonalities, such as the competitive environments in which both domains operate, exist, this paper focuses on the highlighted examples to underscore the strength of the Analogizing concept in this case study.

Having examined the concepts of the APPC and OLA models, along with their distinct features and their commonalities, this paper now transitions to its concluding remarks.

6 Concluding Remarks

This paper underscores the significance of cross-disciplinary analogies in the face of researching new subjects. Through the APPC and OLA case study, it becomes evident that these seemingly distinct disciplines share more commonalities than initially apparent. The case study effectively highlights these cross-contextual connections.

The Concept of Analogizing emphasizes the recognition of shared patterns despite variations in domains. Examining the case study reveals several common principles between OLA and APPC models. Both models rely on collecting data to derive insights for informed decision-making. They utilize indirect, raw data that requires sophisticated analysis methodologies. Additionally, both operate within complex stakeholder environments.

These shared elements highlight the potential of analogical thinking to support concept-driven developments. Even without directly implementing ideas from other contexts, this approach can facilitate brainstorming, promote the exchange of ideas, and enable the reuse of methodologies, building blocks, and approaches across disciplines.

The use of the concept of Analogizing in construction, as well as in education research, is novel. The benefits of using such an approach for future construction research are unmistakable, especially when dealing with advanced technologies, such as automation and robotics (A&R). The construction industry lags in adopting A&R technologies, although these technologies have been discussed in the construction realm for the last four decades and even longer. The idea of using Analogizing in these circumstances may help break through this deadlock.

This paper advocates for the proactive extraction of lessons from broader contexts during the conceptualization phase. Further exploration of cross-disciplinary analogies holds promise for continual advancement.

References

[1] Zerubavel E. *Generally speaking: An invitation to concept-driven sociology*. Oxford University Press, 2020.

[2] Carmona et al. A. M. Instrumentation and data collection methodology to enhance productivity in construction sites using embedded systems and IoT technologies. In *Proceedings of the 35th CIB W78 2018 Conference: IT in Design, Construction and Management*, Springer, 2019: 637–644.

[3] Navon R. Research in automated measurement of project performance indicators. *Automation in Construction*, 16(2): 176–188, 2007.

[4] Cha H. and Kim J. A study on 3D/BIM-based on-site performance measurement system for building construction. *Journal of Asian Architecture and Building Engineering*, (19)6: 574–585, 2020.

[5] Munawar H. S. Ullah Qayyum F. S. and Shahzad D. Big Data in Construction: Current Applications and Future Opportunities. *Big Data and Cognitive Computing*, (6)1. 2022.

[6] Murguia D. Chen Q. Van Vuuren T. J. Rathnayake A. Vilde V. and Middleton C. Digital Measurement of Construction Performance: Data-to-dashboard strategy. In *IOP Conference Series: Earth and Environmental Science*, IOP Publishing, 2022, p. 092009.

[7] Griffin R. Navon R. Brecher A. Livingston D. Haas C. and Bullock D. Emerging technologies for transportation construction. *Transportation in the New Millennium*, 2000.

[8] Navon R. and Goldschmidt E. Monitoring labor inputs: automated-data-collection model and enabling technologies. *Automation in construction*, (12)2: 185–199, 2003.

[9] Navon R. Automated project performance control (APPC) of construction resources. In *ISARC 2003 The Future Site*, Eindhoven, The Netherlands, 2003, pages 79–82.

[10] Navon R. and Goldschmidt E. Can labor Inputs be measured and controlled automatically?" *Journal of Construction Engineering and Management*, (129)4: 437–445, 2003.

[11] Navon R. and Shpatnitsky Y. A model for automated monitoring of road construction. *Construction Management and Economics*, (23)9: 941–951, 2005.

[12] Navon R. and Berkovich O. An automated model for materials management and control. *Construction Management and Economics* (24)6: 635–646, 2006.

[13] Navon R. and Kolton O. Model for automated monitoring of fall hazards in building construction. *Journal of Construction Engineering and Management*, (132)7: 733–740, 2006.

[14] Navon R. and Haskaya I. Is detailed progress monitoring possible without designated manual data collection? *Construction Management and Economics*, (24)12: 1225–1229, 2007.

[15] Alizadehsalehi S. and Yitmen I. A concept for automated construction progress monitoring: technologies adoption for benchmarking project performance control. *Arabian Journal for Science and Engineering*, (44): 4993–5008.

[16] Bhagwat K. and Delhi V. S. K. Review of construction safety performance measurement methods and practices: a science mapping approach. *International Journal of Construction Management*, (23)4: 729–743, 2023.

[17] Sardroud J. M. Perceptions of automated data collection technology use in the construction industry. *Journal of Civil Engineering and Management*, (21)1: 54–66, 2015.

[18] Woo J. Shin S. A. Asutosh T. Li J. and Kibert C. J. An Overview of State-of-the-Art Technologies for Data-Driven Construction. in *Proceedings of the 18th International Conference on Computing in Civil and Building Engineering*, Toledo-Santos E. and Scheer S. Eds. pages 1323–1334 Springer International Publishing, 2021.

[19] What is Learning Analytics? What is Learning Analytics? Society for Learning Analytics Research (SoLAR). [Online]. Available: https://www.solaresearch.org/about/what-is-learning-analytics/ Accessed: 09/11/2023.

[20] Montuori L. Alcazar-Ortega M. Vargas-Salgado C. and Alfonso-Solar D. Learning Analytics as Data driven decision making in High Education: a case study. 2023.

[21] Dawson S. Pardo Salehian-Kia A. F. and Panadero E. An Integrated Model of Feedback and Assessment: From fine grained to holistic programmatic review. in *13th International Learning Analytics and Knowledge Conference*, 2023, pages 579–584.

[22] Rets I. Herodotou C. and Gillespie A. Six Practical Recommendations Enabling Ethical Use of Predictive Learning Analytics in Distance Education. *Journal of Learning Analytics*, (10)1, 2023.

[23] Herodotou C. Hlosta M. Boroowa A. Rienties B. Zdrahal Z. and Mangafa C. Empowering online teachers through predictive learning analytics.

British Journal of Educational Technology, (50)6: 3064–3079, 2019.

[24] Lin, J. Dai, W. Lim, L.-A. Tsai, Y.-S. Mello, R. F. Khosravi, H. Gasevic, D. & Chen, G. Learner-centred analytics of feedback content in higher education. in *13th International Learning Analytics and Knowledge Conference*, 2023, pages 100–110.

[25] Ouyang F. Wu M. Zheng L. Zhang L. and Jiao P. Integration of artificial intelligence performance prediction and learning analytics to improve student learning in online engineering course. *International Journal of Educational Technology in Higher Education*, 20)1: 1–23, 2023.

[26] Kalman Y. M. A theoretical framework for organizational learning analytics. *Mini LAK Theory Workshop in Learning Analytics and Knowledge Conference (LAK). (Online due to COVID-19).* 2020.

[27] Kalman Y. M. Learning analytics in higher education (in Hebrew)." *The Open University, Israel, Seminar*, 26/05/2022.

[28] Navon R. and Kalman Y. Organizational Learning Analytics for Higher Education Institutions: A Novel Theoretical Framework (in Hebrew). In *The 18th Chais Conference on the Study of Innovation and Learning Technologies: Learning in the Digital Era*, Ra'anana, Israel, 02/2023.

[29] Cerratto Pargman T. and McGrath C. Mapping the ethics of learning analytics in higher education: A systematic literature review of empirical research. *Journal of Learning Analytics*, (8)2: 123–139, 2021.

[30] Tzimas D. and Demetriadis S. Ethical issues in learning analytics: a review of the field. *Educational Technology Research and Development*, (69): 1101–1133, 2021.