Success-enablers of Learning Analytics Adoption in Higher Education: A Quantitative Ethnographic Study

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Abstract. This paper focuses on the area of success-enablers in learning analytics (LA) adoption from the perspective of senior managers in higher education institutions (HEIs). A significant body of academic literature exists about challenges in LA. However, to date, the success-enablers from the perspectives of institutional senior managers have received limited attention. This research aims to address this gap reporting on the findings of a study that conducted a series of semi-structure interviews with senior managers at 44 European HEIs. A detailed thematic analysis was conducted on the interviews to tease out the main success-enablers. Then, connections of different success-enablers were analyzed using epistemic network analysis (ENA). The analysis showed that the success-enablers in HEIs that had fully adopted LA depended on the involvement of high-level stakeholders, setting an embedded strategy, getting a technology support from the external partnership, or having a strategic analytical culture. The HEIs that were preparing or only partly adopted LA depended on success-enablers such as having a developing analytical culture or a delegation of expertise in LA related activity. The findings of this study can help HEIs create strategies that can support successful adoption of LA.

Keywords: Epistemic network analysis · Higher education · Learning Analytics · Success-enablers · Adoption scope

1 Introduction

Learning analytics (LA) is widely considered a promising approach to enhancing learning and teaching by harnessing vast amounts of data collected by contemporary learning technology. Examples of popular uses of LA include but are not limited to prediction and description of learning outcomes, measurement of 21st century skills, penalisation of learning experience and feedback at scale. While the interest in LA has been high for more than a decade now, the current pandemic situation with COVID-19 has forced many higher education institutions (HEIs) to accelerate the use of online learning at a large scale [9]. This in turn increased a demand for improving learning experience where LA can pay a significant role.

In spite of high interest, many studies show that systematic adoption of learning analytics in HEIs is still in early stages [32,8,26]. A European project

– SHEILA – investigated LA adoption in 46 European HEIs and found that only a third HEIs had implemented LA [32]. A similar situation was identified in the UK HEIs, where there were high desires toward LA but low LA adoption rate [22]. Saint Gutierrez [27] found that the main drivers of LA adoption in the UK were organisational factors because of possible advantages of student retention and tracking of progression. Sclater [28] investigated the state of LA in UK universities by conducting a series of interviews with staff in UK universities and found that UK universities had different objectives for using LA, whether to enhance students experience, provide better feedback, or improve student retention. Although many HEIs plan to adopt LA, a wide adoption of these tools might be a challenge. The results of the survey and interviews with institutional senior managers at European HEIs in a study reported in [32] show that over two thirds of institutions had implemented LA or were preparing to adopt LA. However, when asked if they had accomplished the objectives set out for LA, only few participants who had implemented LA were able to prove their success. A similar situation was observed in the UK HEIs, where most respondents hesitated to report any significant results from their LA activities [28]. The respondents in those studies [32,28] were senior managers in HEIs, who are some of the main stakeholders in LA adoption [11] and who are mostly interested in using LA to enhance institutional performance in European HEIs [36]. Previous studies that discussed LA adoption have focused more on challenges rather than on success enablers [21,23,20,16,13,36]. Gašević, Tsai, Dawson, and Pardo [14] discussed the success factors, such as cultural change and infrastructural upgrade. However, there is less discussion regarding success enablers and their related factors for LA adoption to answer why learning analytics adoption fails or succeeds. This is a critical perspectives to be considered in order to drive a strategic adoption in LA at HEIs.

To analyse the success-enablers factors that affect LA adoption and implementation process, there is a need to understand how success factors might vary among HEIs that were with different scope of adoption including those who are preparing, partially adopted or fully adopted LA. In order to address these gaps, the study reported in this paper was set out to address this research question:

What factors are associated with the success-enablers within different LA adoption scope?

2   Literature Review

2.1   Learning analytics adoption

The previous studies in LA have led to the development of conceptual models and frameworks to understand main elements and dimension in LA adoption or readiness. For instance, Greller and Drachsler [15] proposed a framework that aims to guide the development of LA services. The framework included six different dimensions: (1) stakeholders,(2) objectives, (3) instrument, (4) data, (5) internal limitations, (6) external constraints. Within this framework, ethics

and privacy are the most important external constraints. Drachsler and Greller [12] also developed the "DELICATE" checklist that covers the most important ethics and privacy criteria that are relevant to establish 'trusted LA' and to help "overcome the fears connected to data aggregation and processing, policies" [p. 96]. Arnold, Lonn, and Pistilli [1] found five factors that are important for LA readiness including: (1) ability, (2) data, (3) culture and process, (4) governance and infrastructure, and (5) readiness perception. Colvin, Dawson, Wade, and Gašević [7] identified three models of LA implementation (i.e., input, output, and process) and conclude that the factors that have been discussed broadly in most models include technological readiness, leadership, organizational culture, staff and institutional capacity, and strategy. These factors could potentially be barriers or enablers of LA success.However, success-enablers are factors which could be interesting to investigate in order to better understand the LA adoption with respect to scope of LA adoption.

2.2   Success factors in learning analytics

Researchers differ in their perspectives about key factors of success that are associated with LA adoption. Tsai, Gašević, Whitelock-Wainwright[32] argued that expertise in data analytics, data culture, staff buy-in, and technological infrastructure are four key dimensions of institutional capacity to enable successful adoption of LA. Clark and Tuffley [6] conducted a study that aimed to find specific areas on which HEIs can concentrate to ensure a LA system is successfully implemented. The authors used Delone and McLean's (D&M) information system success model to measure LA success in three demographically different Australian universities. The model focuses on three main elements: (1) functionality, (2) usability, and (3) activity system or utility. The study findings show that LA has much potential in terms of improving teaching and learning. Another study by Clark et al., [5] propose a framework that seeks to define and explore the Critical Success Factors (CSFs) for the implementation of LA within the higher education sector. They explore the perspectives of higher education practitioners using mixed-methods that included factor analysis, profile analysis, and thematic analysis. In that study, the authors demonstrate five CSFs of LA implementation: (1) strategy and policy at organisational level, (2)information technological readiness, (3) performance and impact evaluation, (4) people's skills and expertise, and (5) data quality. Even so, the study did not prioritize the factors based on their importance to the LA adoption that may help to focus more on these factors in setting the strategy for LA adoption.

Recently, Tsai, Kovanović, and Gašević [33] conducted a study that looked at associations among factors that influence adoption processes or the change in priorities when institutional experience with LA increases. They identified connections between certain areas of success from less experienced institutions; that are, connections between the success in improving the data culture and gaining experience of LA. However, the authors have not explored factors that could contribute to success, and whether the phenomenon differs when adoption scopes vary. In this study, we address this gap by looking at three different adoption

scopes: (1) preparation – the HEI took some preparation steps such as development of an data warehouse, setting strategies, or developing a partnership with external stakeholders, but LA was not yet implemented; (2) partial implementation – LA was implemented in some parts of an HEI; and (3) full implementation – the implementation and strategies of LA cover the whole HEI. The objective of the study reported in this paper was to achieve a better understanding of the success-enablers of learning analytics by following the quantitative ethnographic methods through the use of semi-structured interviews and epistemic network analysis.

Based on the literature reviewed above [6,32], we may conclude that the common factors that can potentially become success-enablers are: analytical culture, analytical capabilities, stakeholders involvement, strategy, and technological infrastructure.The details of theses success factors have been discussed below.

Analytical culture Culture is defined in [17] as "the collective programming of the mind that distinguishes the members of one group or category of people from others."[p. 6]. Culture in LA looks at whether or not stakeholders are aware of and accept data-informed decision making [2]. It has been discussed as an important element in LA adoption [36], and in LA readiness [10,1,25], where Dawson et al. [10] identified staff culture in LA as "sharing and encouraging conversations around LA"[p. 241]. In addition, analytical culture has been considered a key facilitator of LA implementation [1,15]. Overall, LA should be adopted when institutions are ready to invest and commit based on supportive LA culture. In this paper, we consider 'analytical culture' as the culture of LA at HEIs.

Analytic capabilities Higher education found it difficult to take advantage of data due to the lack of data analytic expertise [35]. The expertise required for data analytics involves the ability to extract valuable information out of educational data and determine which data is more beneficial to achieve organizations goals within a time frame [38]. Clark et al. [5] identified people's skills and expertise, as a success factors in LA. The authors included three items under 'people skills' dimensions including team competence and expertise. In this paper, we focus on evaluating the institution's analytical capabilities and actions taken to improve them.

Stakeholders Involvement Stakeholders involvement has important implications for LA adoption. Adopting new computer systems requires reorganizing business processes and organisational environment to ensure that the stakeholders welcome and cooperate with the change. Thus, stakeholder involvement has been considered a challenge [35,15,20,36,31] and at the same time it can be crucial to the success of LA deployment [33]. Stakeholders involvement can improve the process of LA and having a system that provides educational benefits that reflect stakeholders' expectations and needs[18]. Thus, stakeholders should

be allowed to take part in decision-making that affects them.In this paper, we consider the extent to which the planning and or implementation of LA have involved consultations with stakeholders at various levels (e.g., high-level, student, teachers).

Strategy In organizational settings, IT tools are often used strategically to achieve a defined business goal. According to Nguyen [24], many organizations adopt new IT to keep up with emerging technology trends that other organizations have already implemented. However, the lack of definition or strategy for the purpose of adopting IT tools can lead to the failure of the business. In HEI settings, LA adoption need a strategy to achieve educational goals. The result of the interviews with the participants from three Australian universities shows that having clear strategies can be a success-enabler in LA adoption [6]. Dawson et al. [10] categorized the strategy in LA adoption as iterative and preceding based on the empirical research of over 20 HEIs in Australia. In this paper, we focus on broad meaning of strategies on the institutional level whether they involve initial piloting, extensions of existing learning and teaching strategies, or specially dedicated strategies for LA.

Technology Technology features have been considered as "foundation elements" in the LA implementation [3, p. 258]. Technology infrastructure supports collecting, storing, processing, managing and visualizing educational data [21]. Clark et al. [5] argue that the adoption of LA requires a technology infrastructure upgrade to enable adoption and enhance scalability. They identified five items that can be used to measure the success in technology: (1) technologies used for implementation readiness, (2) condition of equipment, (3) system complexity issues, (4) type of hardware and software chosen, and (5) usability of software. In this paper, we focus on the actions that have been taken to prepare a technological infrastructure for LA.

3   Methodology

The research was carried out through a series of semi-structured interviews with senior managers at the 46 European HEIs between August 2016 and February 2017. We excluded two institutions in this study because they expressed no engagement with LA at the time of the interview. This resulted in 44 interviews used for ENA. The participants included Deans of Learning and Teaching to Heads of IT, Directors of E-learning Centres, and positions established especially for LA research and development. An opportunistic sampling [30] method was adopted because access to population is easy and inexpensive with getting benefit from the researchers' existing network and influence. The literature review that was done by [blinded for review]was the basic of coding scheme process. New themes were emerged during coding process.The final coding scheme ends up with two types of variables - implementation and readiness variables [blinded

for review].The current study focuses on success enabler and how this code was used alongside previous study on LA adoption in European HEIs. Thus, the main factor in this study is the success-enablers, which is one of the sub-code of success and it was identified as 'enablers for the success in learning analytics'. It was used alongside other codes to understand what factors were identified as success-enablers by senior manager in European HEIs. Using ENA, we identified association of the 'success-enabler' code with other codes including analytical culture, analytical capabilities, stakeholders involvement, strategy, and technology (for further information about the themes, see `http://bit.ly/la_std_codes`).

The institutions varied in terms of location, size, subject coverage, ranking, and nature of their LA adoption scope. In this study, we focused on comparing success enablers by the scope of LA adoption. Almost 50% of institutions (n= 20) had not adopted LA or had plans for this (scope = none). Eleven institutions had implemented LA throughout the institution (scope = full), followed by 10 institutions that had adopted LA in only part of the institution (scope = partial), and four institutions had taken certain action in preparation for LA implementations (scope = prep). For further information about the sample see `http://bit.ly/la_std_sample`). In this study, we excluded the institutions from our analysis that reported no LA adoption (scope = none) because ENA did not show any connections between success enables and the factors studied in this paper. The reasons for this result is that it might be early for those institutions to report any success or there was no existing project to be considered successful at the time data was collected from those institutions.

We analyzed the data by using epistemic network analysis (ENA), which is "a collection of techniques for identifying and measuring the connections between elements in coded data and representing them in dynamic network models" [29, p. 9]. ENA works by revealing the co-occurrence of codes within chunks of text excerpts called 'stanzas' and within each of the units of analysis [19,33]. The units of analysis in this paper correspond to the different interviewed HEIs and stanzas correspond to conversation utterances during an interview, which are two consecutive conversation utterances in our case. To answer the research question, we used ENA to analyze the strength of connection between success-enablers and other codes, and in turn, examine the most important success-enablers related subcategories that should be taken into consideration in the strategy for LA adoption.

4   Results

4.1   Pairwise analysis of thematic groups

Success-enablers and analytical culture The 'Analytics culture' code identifies the culture for learning analytics at the institution. It includes the following sub-codes: *Immature* – HEI in general has limited knowledge of LA, *Strategic* – there are initiatives to strategically improve institutional culture by offering workshops or address existing related to cultural challenges to the implementation of LA, *Developing* – HEI in general shows interest in applying LA to

improve teaching practice and promote students' learning, *Resistant* – the culture in which some stakeholders have clear resistance to LA because of various concerns (e.g., ethical concerns), and *Developed* – HEI in general has fairly good understanding of LA and acknowledge the potential of LA. As shown in Figure 1, HEIs that fully adopted LA demonstrated strong connection between success-enablers and strategic culture (Fig. 1b). This suggests that the level of success can be improved in LA adoption by addressing cultural considerations and offering workshops and seminars related to LA. Moreover, the results show that the success-enablers had strong connection with the developing culture in the HEIs that were preparing or having partial LA adoption (Fig. 1a). This suggests that interest in applying LA to enhance teaching and support students' learning plays an important role in the success of the LA implementation. The U08 interviewee explained this points as:

> I guess the willingness from the director to try to improve our learning capabilities and student learning capabilities, looking at data and working on data, on facts and not on impressions. *-U08*
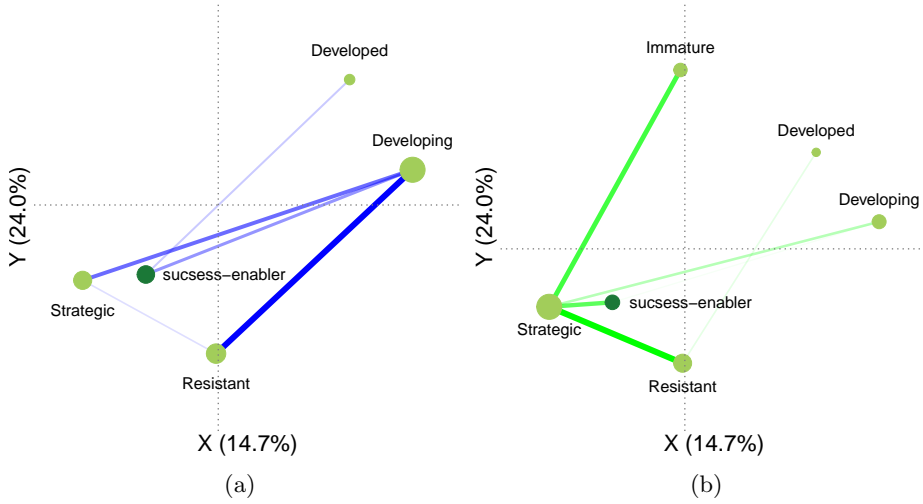

Fig. 1: Associations of success-enabler and analytical culture sub-codes . In graph (a), the prep-partial HEI showed a strong connection between the success-enablers and the developing analytical culture (Developing). In graph (b), the LA fully-adopted institutions, demonstrate particularly strong connections among the success-enablers and analytical culture (Strategic)

Success-enablers and analytical capabilities The analytical capabilities can be described as institution's analytical capabilities of LA and the actions

taken to improve them. It contains four sub-codes of analytical capabilities: *AnaCap.Teacher* – training for teaching/support staff has been provided or is acknowledged as necessary to use and interpret data or LA tools, *AnaCap.Student* – training for students has been provided or is acknowledged as necessary to use and interpret data or LA tools, *AnaCap.Experts* – there are delegated experts to facilitate data analysis, take relevant activities related to LA, or mediate between the university and primary users), and *AnaCap.Gaps* – there is recognition of gaps existing in the understanding of LA and skills for it among stakeholders at various levels.

The result of the ENA models of fully LA adopted HEIs in Figure 2b shows connection between success-enablers and the gap of the analytical capabilities. This suggests that the full adoption group have involved more stakeholders and could see the needs to address the gaps in understanding of LA among different stakeholders. The HEIs that were preparing or had partial LA adoption emphasized the connection between success-enablers and experts (shown in Figure 2a). This suggests that the institutions with narrow scope of adoption relied on experts when implementing LA. For example, the interviewee from U25, one of the institutions that had a partial LA adoption, claimed that having experts in LA contributed to the success of LA:

> One of the things that I'm most pleased about is the education developer. Not, and no harm to them but not a computer scientist. Not an engineer but someone for whom education's at the heart of what happens. And we need, so if we keep that focus that's a real plus. *-U25*

Success-enablers and stakeholder involvement The stakeholder involvement theme identified the process by which HEIs communicated and consulted different stakeholders in the planning or implementation of LA. This code had six sub-codes: *High.Level* – i.e., senior managers, *Support.Level* - e.g., IT units and student services, *Primary.Teachers* – primary stakeholders teachers, *Primary.Students* – primary stakeholders students, *External.Stakeholders* – i.e., LA service providers, and *Limited*, where there was little evidence of consultation with or involvement of any stakeholders.

HEIs that fully adopted LA demonstrated strong connection between success-enablers and high-level stakeholders (Fig 3b). This suggests that the institutions with full adoption has a significant engagement with senior managers and potentially support from them. For example, one of interviewees from U39 (fully adopted LA) pointed out the importance of a supportive decisions and acceptance by the high-level stakeholders and how they might enable the success in LA adoption:

> We've had very, very strong and positive support from university senior managers, and that makes a difference because we have not, I think from the very outset the, the relevant pro-vice chancellor has seen the potential benefits to this and has been interested in this as a resource for staff, so I think there's a really strong kind of interest there. *- U39*
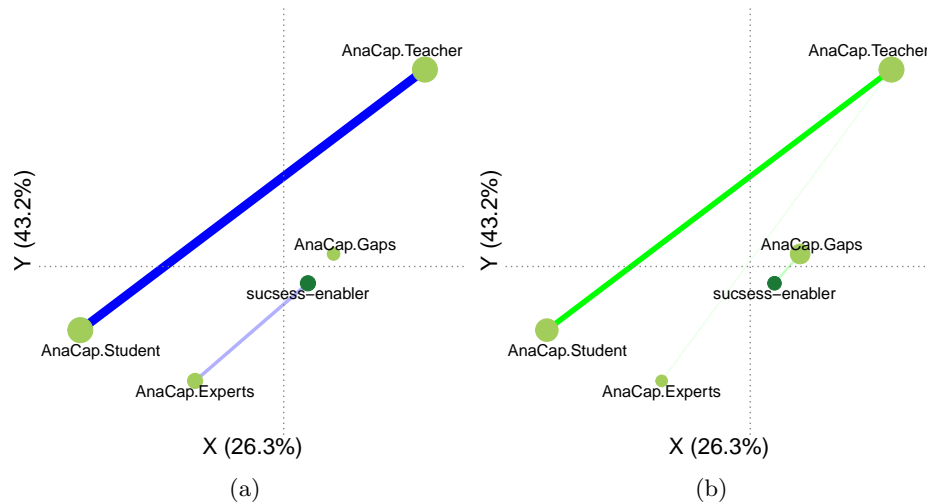
Fig. 2: Associations success-enabler and analytical capability sub-codes. (a) The prep-partial HEIs showed a strong connection between the success-enablers and the experts in the analytical capabilities, whereas (b) the HEIs that fully adopted LA demonstrated particularly strong connections among the success-enablers and the gaps in analytical capabilities

Success-enablers and strategy The *Strategy* code had three sub-codes: *embedded* –the implementation of LA is part of extant teaching, learning and business processes *independent* – HEIs had a complete and independent strategy for LA adoption, and *nascent* – a pilot study in LA is part of the LA adoption strategy. The networks of prepared or partial adopters (Fig. 4a) did not display strong connections between success-enablers and any types of strategy. The results (Fig. 4b) showed that HEIs with full LA adoption tended to associate success-enablers with the embedded strategy. This suggests that with high-level stakeholders involved in the LA activities, these institutions were more likely to be able to embed LA into their existing strategy thus increasing the priority of LA in the institutions and potentially being able to dedicate more resources to LA too. For example, one interview U40 (from a full-adopter HEI) explained that analytics was always a part of their strategic objectives both in relation to learning and teaching which enable the success of LA adoption.

Success-enablers and technology The *Technology* code identified actions that the HEIs took to prepare themselves for LA technological infrastructure. Technology code had four sub-codes: *External.partnership* – e.g., making a partnership with LA service providers, *Enhancement* – install and develop IT systems, *Evaluation* – the HEIs carried out an evaluation of the existing IT system necessary for LA implementation, and *no technology evaluation* – there were no evaluations yet on the capacities of existing IT systems and software needed to
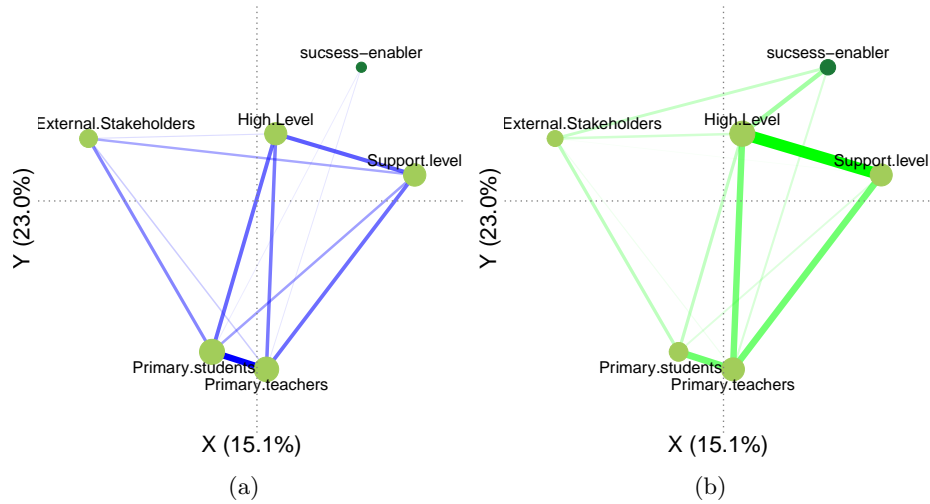
Fig. 3: Associations between success-enabler and stakeholder involvement sub-codes. (a) The HEIs with prep-partial adoption did not show a strong connection between the success-enablers and any stakeholders types, whereas (b) that shows the ENA of the full LA adoption HEIs demonstrated particularly strong connections among the success-enablers and the involvement of high-level stakeholders

implement LA, or evaluations on the potential of different types of data. The results showed that the institutions that were prepared or had partial LA adoption (Fig. 5a), had no obvious connections between success-enablers with any sub-codes of technology. The full adopter HEIs (Fig. 5b) had strong connections between success-enablers and external partnership. Such connections suggest that the external partnerships may help scale up the LA adoption scope.For example, one of the interviewees from U37 (fully adopted LA) indicated:

> I think having the investment in, having the Blackboard analytics product has been very helpful because that's allowed us to implement something and start working with that data. we do need to bring other data sets in from the business intelligence data sets. But it's allowed something solid to be taking place and to allow that engagement with stakeholders as well where we can be in front of them during the last twelve months.-*U37*

5   Discussion

From the existing literature, several factors affecting the success of LA adoption and can be viewed as enablers including analytical capabilities, analytical
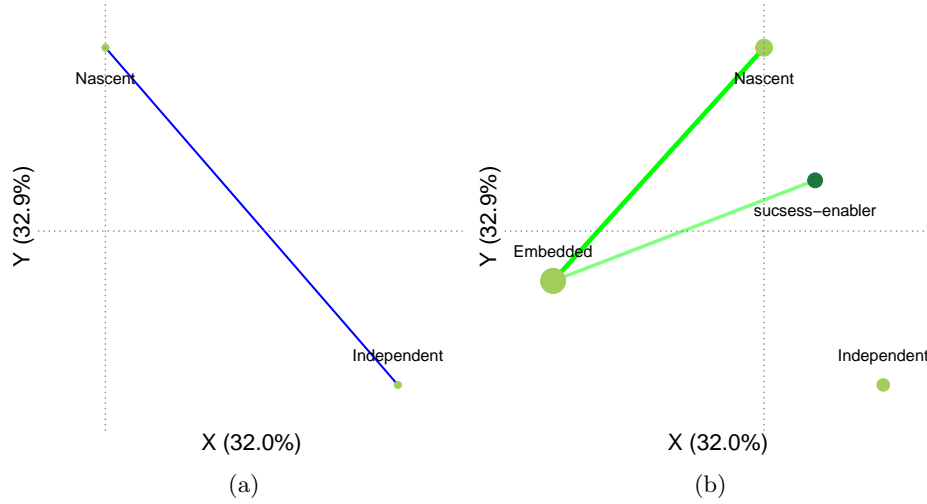
Fig. 4: Associations between success-enabler and strategy sub-codes. (a) The prep-partial LA adopters institutions did not show a strong connection between the success-enablers with any strategy types, whereas (b) the full LA adopter HEIs demonstrated particularly strong connections among the success-enablers and the embedded strategy

culture, stakeholders involvement, strategy, technology, policies,and evaluations [5,32]. However, this paper excluded policies and evaluation because the findings from the ENA models did not show connections between success-enablers and the sub-codes of policies and evaluations.

To answer the research question "What factors are associated with the success-enablers within different LA adoption scope", related to success-enablers have been discussed based on the results of ENA and as supported by quotes retrieved from the semi-structure interviews according to the relevant themes. Specifically, ENA revealed intriguing connections between the success-enablers and other factors among institutions that had different scope of LA adoption at the time of the interviews (full adopted vs prep-partial adopted LA).

Our study looked at associations of analytical culture with success enablers. Analytical culture encompasses data culture, staff culture, or institutional culture. Oster et al. [25] showed that institutions that are more focused on teaching could have a perceived culture to implement learning analytics for practice of learning and teaching rather than for research . However, based on our ENA results, the success-enablers of the institutions that were prepared or partially adopted LA focused on the developing culture,which demonstrate that recognizing the potential of LA could scale up the success of LA adoption. Thus, cultural acceptance is necessary in a way that the institutions can achieve its potential benefits of LA [1]. In terms of analytical capabilities, the result of the ENA reported in the current paper showed a strong connections between
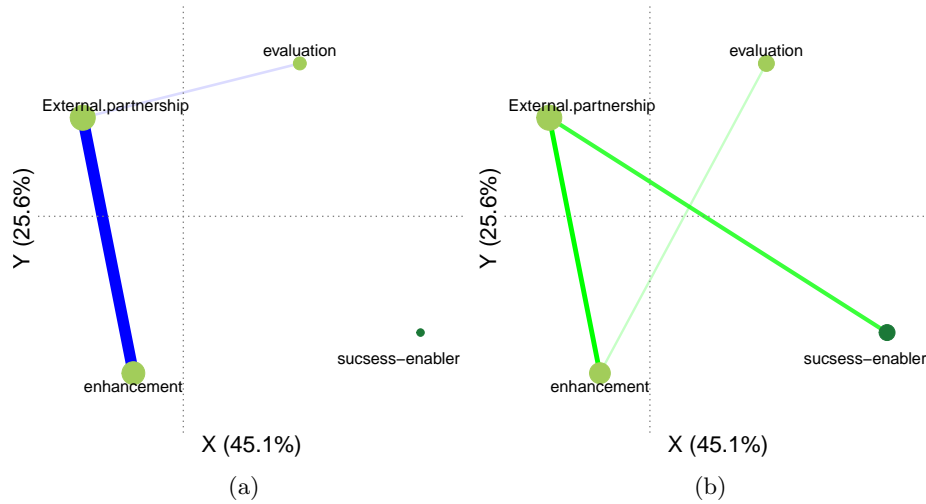
Fig. 5: Associations between success-enabler and technology sub-codes In graph (a), the prep-partial institutions does not show a strong connection between the success-enablers with any technology types, whereas the LA fully-adopted institutions demonstrate particularly strong connections among the success-enablers and the external partnership

success-enablers and expertise in LA. This means that a successful LA project required experts teams that have various expertise and having skills in LA [4].

Stakeholder engagement has previously been identified in the literature as a significant element for LA adoption. A survey study conducted a survey study with 45 senior managers, as reported in [37], found that the 'senior managers buy-in' ranked as the most important element that might affect achieving the potential of LA. In this study, the results of the ENA reported in the current paper showed that the connections between success-enablers and stakeholders involvement revealed that success-enablers were related to involvement of high-level stakeholders. This finding suggests that the institutions with full LA adoption tended to emphasize the engagement of high-level stakeholders to deliver LA project successfully.

On the organizational level, there is a need for strategic support for LA adoption. The results of ENA reported in the current paper showed that the fully adopted LA institutions depended on the embedded strategy as a success enabler of LA adoption, which has also been considered as an antecedent for use of LA in learning and teaching practice [10]. This means that the HEIs with full LA adoption showed interest in developing an LA strategy that is derived from existing teaching or learning strategies. Clark et al. [5] also emphasize this point as a critical success factor in LA adoption.

Several studies described the important role of technology infrastructure in LA adoption. LA adoption requires upgrading existing technology infrastructure

and system processes [34]. The literature refers to software and hardware [5] as key elements of technology infrastructure. However, the findings from ENA used in the current study showed a connection between success-enablers and external partnership, which means that obtaining LA support services from third-parties was strongly associated with the success of LA, especially among institutions that have university-wide adoption of LA. A possible reason for this is the HEIs did not have sufficient technology infrastructure to support LA adoption and thus they turned to relevant service providers for partnerships.

6   Conclusion

This study contributes to the field of LA by examining the potential success enabler of LA adoption practices. Based on the interviews with senior managers from European HEIs, we identified, analysed, and prioritised the most dominant success-enablers of LA adoption among different success factors. We found that high-level stakeholders' engagement, embedded strategy, partnership with technology third-party, strategic analytical culture, as key success enablers of the HEIs who fully adopted LA. We further found that developing analytical culture as well as a delegation of expertise in LA, to play a role in enabling a success to adopt LA in the HEIs that were preparing or partly adopted LA. This research lays the foundations for HEIs who are thinking to lunch LA at a wide scale or HEIs that have implemented LA to consider these success-enablers that could help them to adopt LA successfully.

The current study had limitations. This study is based on the European HEIs; as such, further research is need to understand the success-enablers in HEIs in different regions or within different experience in LA. Future research should also explore other factors that can enable success, as the current study focused on five success factors only.

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