

Chapter 1

Adoption of Learning Analytics



David Gibson and Dirk Ifenthaler 

1.1 Introduction

This book's theme – *Adoption of Learning Analytics in Higher Education Learning and Teaching* – brought to mind the seminal *Diffusion of Innovations* (Rogers, 1962), which for decades has shaped research on adoption of innovations. The reader may be familiar with his notion that there are five kinds of people involved in the diffusion of an innovation, innovators, early adopters, early majority, late majority, and laggards, and that a 'critical mass' is needed for full, sustainable implementation of innovation. But Rogers went beyond the *actors* of adoption and also set a larger *context* in which the innovation itself, communication channels, time and the encompassing social system were also key determinants of whether and how an innovation such as learning analytics would be adopted. Learning analytics is considered a creative innovation in learning and teaching for three reasons: novelty, effectiveness and wholistic impacts. Learning analytics can produce novel near real-time information to improve teaching decisions; it is proving to be an effective method of abstracting and modelling meaning from information, and it contributes to a more wholistic interpretation of data by expanding the number and types of measures.

The still emerging field of learning analytics has introduced new frameworks, methodological approaches and empirical investigations into educational research; for example, novel methods in educational research include machine learning,

D. Gibson
Curtin University, Bentley, WA, Australia

D. Ifenthaler (✉)
Curtin University, Bentley, WA, Australia

University of Mannheim, Mannheim, Germany
e-mail: dirk@ifenthaler.info

network analyses and empirical approaches based on computational modelling experiments. Learning analytics have been defined as the use of static and dynamic information about learners and learning environments, assessing, eliciting and analysing it, for real-time modelling, prediction and optimization of learning processes, learning environments as well as educational decision-making (Ifenthaler, 2015). The new frameworks and adoption models focusing on learning analytics are required for successful integration of learning analytics systems into higher education institutions (Buckingham Shum & McKay, 2018; Dyckhoff, Zielke, Bültmann, Chatti, & Schroeder, 2012). However, these models of practice and adoption vary across different institutions due to situational and historical conditions, within any individual organization due to disciplinary and contextual idiosyncrasies and across different countries due to these as well as cultural differences (Klasen & Ifenthaler, 2019; Schumacher, Klasen, & Ifenthaler, 2019).

In the next sections, we briefly review Rogers' model; those who are familiar with it may wish to skip to the discussion of examples, which will draw from our recent research and development activities. We also outline specific tactical applications where the adoption of learning analytics can add value to higher education, and we illustrate the cross-over between diffusion of learning analytics as an innovation and tactics developing within five major domains of higher education practice (marketing and recruitment, learner characteristics, curriculum, teaching and post-graduate community and communications) with examples from our and others' research.

1.2 Innovation Diffusion

1.2.1 *Six Characteristics of an Innovation*

Six characteristics of an innovation, according to Rogers (1962), include the (1) relative advantage compared to current tools and procedures, (2) compatibility with the pre-existing system, (3) complexity or difficulty to learn, (4) trialability or testability, (5) potential for reinvention and use for unintended purposes and (6) observed effects (see Table 1.1). If we establish an indicator scale from low to high (or little to ample) for each of these characteristics, we can imagine a minimum of 2^6 or 64 innovation configurations, as outlined in Table 1.1. This is surely a fraction of the myriad ways that learning analytics is actually evolving in higher education today, but perhaps offers a set of sufficiently unique categories to describe a range from 'little adoption' to 'full implementation' of the benefits of learning analytics.

Researchers might use these six characteristics of an innovation to reflect on the degree and extent of adoption of learning analytics in a higher education setting. For example, if the relative advantage of some innovation is high and the remaining five characteristics are all low, the innovation might still be deemed worth piloting for

Table 1.1 Six characteristics of an innovation

Characteristics	Low	High
Relative advantage compared to current tools or procedures	Little to no advantages	Large and evident advantages
Compatibility with the pre-existing system	Incompatible, does not integrate or requires significant reworking of the existing system	Highly compatible, works within or alongside the existing system, does not require significant reworking
Complexity or difficulty to learn	Simple to understand, easy to learn and apply	Complex or complicated, hard to learn and apply
Trialability or testability	Is difficult or costly to test or trial, trials do not result in definitive added value	Is easy or not costly to trial. Results from trials show definitive added value
Potential for reinvention and use for unintended purposes	Innovation is limited in scope of application	Innovation is flexible and can be applied to many varying cases.
Observed effects	Insignificant or limited effects	Significant and meaningful effects

adoption. The difficulties of overcoming the shortcomings of incompatibility with current systems, complexity, costliness and limited effects might be worth the effort, if the relative advantage is a matter of survival of the institution. In general, if the innovation has more high than low indicators, then it is easier and more worthwhile to adopt. The one indicator that seems to buck the trend is complexity, where at the low end, if easy to learn and simple to understand, it might be too simplistic and broad to be deeply helpful, as pointed out by researchers who have noted the issue of complexity as a challenge for leaders of analytics adoption (Dawson, Poquet, Colvin, Rogers, & Gašević, 2018; Gibson, 2012; Tsai, Poquet, Gašević, Dawson, & Pardo, 2019). In the context of Rogers' (1962) six characteristics, the degree and details of engagement by key actors can measure or characterize the diffusion of the innovation in some higher education context.

Other authors in this book point to the potential benefits of adopting learning analytics; to these we add that learning analytics has potential to disrupt and transform higher education learning and teaching across five major domains of higher educational practice: (1) acquiring students, (2) promoting learning, (3) offering timely relevant content, (4) using up-to-date delivery methods and (5) supporting learners as part of a network of successful alumni who continue to positively impact the world (Henry, Gibson, Flodin, & Ifenthaler, 2018; Mah, Yau, & Ifenthaler, 2019). Considering these domains of higher education practice in the sections to follow, we will outline 15 tactics that can influence the 5 domains, followed by case examples.

While requiring significant effort, bringing more people into better understanding of the complexities of the diffusion of learning analytics in higher education helps create conditions for a wider and deeper array of insights and more effective group and institutional responses, as noted by Rogers (1962). We will illustrate the innovation characteristics and specific tactics using some recent studies we have conducted or encountered.

1.2.2 Communication Channels

The degree of adoption of an innovation within an organization is a measure of the number of actors using the innovation or who have altered their practice because of the innovation. The process of the diffusion requires communication channels between potential actors, who then follow a well-known decision-making process (i.e. moving from unawareness to knowledge, then being persuaded that learning more will be beneficial, then trying out the change, then moving into routine implementation and finally creating confirmatory data and helping others) as the actors individually adopt or ignore the innovation. Influencers who wish to promote the adoption of the innovation must ensure and secure open communication channels and encourage people to start and stay on the journey of decision-making from awareness to action.

The ‘Concerns-Based Adoption Model’ (CBAM) emerged in the 1970s with survey metrics to help an educational organization self-assess its status on an innovation journey (Hall, 1974; Hall, Loucks, Rutherford, & Newlove, 1975). The tools track the percentage of staff who are sitting at each stage of the journey and offer a structured way to address the ‘next need’ of each group by focusing on moving people from their current state to the next decision-making focus. For example, if a large number of people do not know the benefits of learning analytics, the task is to first make them aware and have them develop knowledge, before they can become persuaded that adoption has any potential to make their life better. If a few early adopters are already implementing and providing confirmatory data, their ability to effectively model for others will be limited to the people who are already ready to decide to adopt. Communication channels are the riverbeds for the flow of energies from unawareness to action (Kotter, 2007). It goes without saying that the process takes time, so leaders who wish to influence and track adoption of learning analytics have to be ready to understand the processes and have patience – take the time needed – to allow the communication channels to work (Roll & Ifenthaler, 2017).

1.2.3 Encompassing Social Systems

The dynamics of communications that support the flow of adoption processes are part of the complex social networks in the encompassing social system contexts involved in higher education (Kozleski, Gibson, & Hynds, 2012). Learning analytics researchers are beginning to take note. As recently pointed out (Dawson et al., 2018), the existing conceptual models of the adoption of learning analytics in higher education fail to operationalize how key dimensions interact to inform the realities of the implementation process, leading to a need to rethink learning analytics adoption through complexity leadership theory and to develop systems understanding at leadership levels to enable the movement of boutique analytics projects into the enterprise. Among the issues in the encompassing social systems of higher educa-

tion, learning analytics adoption often faces a shortage of resources, barriers involving multiple stakeholder buy-in and the fears and paranoia of big data ethics as well as privacy concerns (Ifenthaler, 2017; Ifenthaler & Schumacher, 2016). Addressing these challenges requires agile leaders who are responsive to pressures in the environment, capable of managing conflicts and are capable of leveraging complex social systems for change (Gibson, 2000; Tsai et al., 2019).

Network analysis has emerged as one of the most promising methods for studying the complexities of social influence, layered hierarchies and the evolution of relationships. Network methods can be used (1) to define the spread and variety of behaviours, (2) to predict the pattern of diffusion of innovations, (3) for analysis of educational phenomena (Clariana, 2010; Ifenthaler, 2010; Ifenthaler, Gibson, & Dobozy, 2018), and (4) to identify opinion leaders and followers in order to better understand flows of information (Lazega, 2003). In the context of learning analytics, epistemic network analysis is of particular note (Gašević, Joksimović, Eagan, & Shaffer, 2019).

1.2.4 Summary of Innovation Diffusion

In summary, the diffusion of learning analytics in higher education is expected to involve:

- *Actors.* Levels of readiness of individuals and the emergent property that is the combined readiness of the social group of which those individuals are members
- *Innovation Configuration.* Six characteristics of learning analytics adoption as perceived by the individuals responsible for the innovation ((1) relative advantage compared to current tools and procedures, (2) compatibility with the pre-existing system, (3) complexity or difficulty to learn, (4) trialability or testability, (5) potential for reinvention and use for unintended purposes and (6) observed effects)
- *Communications.* Channel characteristics among the individuals and their social groups
- *Complexity Leadership.* Flexibility in the face of dynamic overlapping networks

1.3 Improving Higher Education with the Adoption of Learning Analytics

The five major domains of higher education practice, where adoption of learning analytics can improve both learning and educational organization, are as follows: (1) acquiring students, (2) promoting learning, (3) offering timely relevant content,

(4) using up-to-date delivery methods and (5) supporting learners as part of a network of successful alumni who continue to positively impact the world (Henry et al., 2018). In the sections below, we suggest 3 tactical areas for each domain – 15 tactical areas to consider when planning, undertaking or gauging the extent of adoption and influence of learning analytics in a higher education institution.

1.3.1 *Acquiring Students*

Market Understanding An analytics capability can generate profiles of in-demand skills in the market, track education trends and help the curriculum react accordingly by offering learning experiences and certifications that are sought by employers and entrepreneurs. For example, an analytics team can monitor and report on skills needs straight from a primary source such as highly dynamic job advertisements, using open source tools such as RapidMiner and R to gain insights from accessible online vacancy data (Berg, Branka, & Kismihók, 2018; Wowczko, 2015).

Personalized Recommendations Student and market information can be used to aid course selection and align student expectations. A recent innovation at one university found that some students mistakenly sign up for classes that informally require prior knowledge from earlier in the curriculum. With better automated guidance, the university could save time and frustration and improve retention with analytics-driven recommendations (Parkin, Huband, Gibson, & Ifenthaler, 2018). Students could also find out the likelihood of employability for their current skill set and explore prospects for the future in their selected areas of study by an analytics-driven approach that combines market understanding with personalized recommendations (Berg et al., 2018).

Community Engagement Analytics-driven market knowledge can be reflected in the outward-facing marketing and community engagement of the university, but perhaps more important may be the engagement of the public in developing policy that impacts higher education. ‘Policy analytics’ has been suggested as an emergent use of computational approaches to understanding and dealing with five major complexities inherent to public decision-making: use of public resources, multiple stakeholders, long time horizon, legitimacy and accountability and public deliberation (Tsoukias, Montibeller, Lucertini, & Belton, 2013).

1.3.2 *Promoting Learning*

Adaptive Support With full implementation of learning analytics, learning services can use interaction history to learn and become tailored to individual learning differences and preferences. This adaptive capacity, automated and available at scale, is a key mechanism of one of the primary benefits (and part of the puzzle of the

emerging field) of the adoption of learning analytics – personalization of delivery (Gašević, Kovanović, & Joksimović, 2017; Ifenthaler & Widanapathirana, 2014; Schumacher & Ifenthaler, 2018). Model-based feedback that focuses on novice-to-expert differences can guide the adaptation of support (Ifenthaler, 2009, 2011).

Proactive Retention Management As many researchers are finding, students with high attrition risk can be identified early and receive targeted preventative interventions (de Freitas et al., 2015; Gibson, Huband, Ifenthaler, & Parkin, 2018; Glick et al., 2019; Ifenthaler, Mah, & Yau, 2019). Proactive retention is a prominent theme in the literature because it balances benefits to both learners and the educational system; for learners, it highlights that analytics can support decisions and develop human capabilities and at the same time can underpin organizational and educational efficiencies by saving time and money.

Personalized Communication With appropriate adoption of learning analytics, learning materials can be targeted to communicate with students based on learning characteristics, level of attainment and aspirations for achievement. Recent advances in analytics-driven applications include using network analysis to understand social and cognitive relationships in learning (Gašević et al., 2019) and creating conversational agents to enhance learning and the educational journey through higher education (Arthars et al., 2019).

1.3.3 Offering Timely Relevant Content

Adaptive Curriculum When the adoption level for learning analytics is high, curricula can be made dynamic, adapting in real time to employability needs, changes in global knowledge stores and student cognitive needs that are complementary to the personal learning process needs targeted by adaptive learning support, as well as to changing circumstances in the external environment. Systems can be designed around the semantic relationships of topic and subtopics (Li & Huang, 2006) as well as by using similarity measures among learning objects in relationship to decision modelling based on learner characteristics (Ifenthaler, Gibson, & Dobozy, 2018; Lockyer, Heathcote, & Dawson, 2013).

Scalable Delivery At advanced stages of adoption of learning analytics, which includes using machine learning methods to continuously discover, infer and feed information to adaptive curriculum and learning support systems, technologies using learning analytics can deliver content to all students and staff in a more participatory mode that allow ‘scalable pedagogies’ such as near-real time feedback and decision supports (Hickey, Kelley, & Shen, 2014).

Industry Integration Curricula in an analytics-driven system are designed to deliver in-demand competencies and support relevant work place learning, for example, via ‘challenge-based collaborative problem-solving’ (Gibson & Ifenthaler, 2018; Gibson, Irving, & Scott, 2018; Ifenthaler & Gibson, 2019).

1.3.4 *Delivery Methods*

World-Leading Pedagogy Analytical research into student cognition and teaching methods is used to define the higher education institution's practices and drive student self-awareness, in institutions with a high level of adoption. Signposts of the integration of analytics into teaching and the growth of the field can be found in the rapidly accumulating literature engendered by the Society for Learning Analytics Research (Gašević et al., 2017).

Adaptive Assessment In analytics-driven higher education environments, evidence of learning is measured continuously, allowing targeted, dynamic assessment that adapts to changing conditions and needs (Gibson & Webb, 2015; Gibson, Webb, & Ifenthaler, 2019; Ifenthaler, Greiff, & Gibson, 2018; Webb & Ifenthaler, 2018).

Managed Outcomes Framework With widespread adoption of learning analytics, students can be assessed against a granular framework, allowing for and supporting an iterative and formative approach to learning and recognition of micro-credentials (Mah, 2016; Mah, Bellin-Mularski, & Ifenthaler, 2016; Mah & Ifenthaler, 2019; West & Lockley, 2016).

1.3.5 *Supporting Alumni Networks*

Strategic Employment Similar to acquiring students with intensified and dynamic market analysis, an analytics-driven strategic employment strategy can utilize a unique assessment framework that assists students to find, prepare for and secure positions with high prestige employers. In one successful massively open online course at Curtin University, an Indian technology company guarantees a job interview for anyone who obtains a certificate from the experience.

Alumni and Lifelong Learning Communication Alumni and recurring learners can be engaged through better information on market and industry trends and via targeted and flexible opportunities for further study (Norris, Baer, Leonard, Pugliese, & Lefrere, 2008).

Targeted Recruitment into Research Engagement in needed research areas can be developed from better analysis of history, current status and more finely detailed student competency profiles that fit with and extend the skills of researchers. Finding and developing talent, driving fact-based planning, making decisions, executing on strategy, managing tactics, measuring and both eliciting and validating learning are all within the boundary of adoption of learning analytics and related disciplines (Berg et al., 2018; Kiron & Shockley, 2011).

1.3.6 Cases

In the following two *Cases*, we illustrate the six features and five domains with examples and findings from our research and development efforts. The examples provided here give a taste for the application of the six features of innovation across the five major domains of higher education practice.

1.3.6.1 Analytics Teams in Business Units of a University

The first case is from a large university in Australia where executive interest and awareness of learning analytics has been growing since a pilot study in 2010. A senior executive briefing paper was then produced in 2013 by the strategy and planning group and brought to the senior executives, outlining some of the issues and opportunities of learning analytics, leading to increased awareness of applying learning analytics and resulting in the 15 tactics outlined in Sects. 1.3.1, 1.3.2, 1.3.3, 1.3.4 and 1.3.5. Since then, analytics teams have been springing up across the campus and now reside in operations areas such as recruitment, marketing and finance; in service delivery areas such as teaching; and in research areas devoted to increasing the university's computational capabilities.

Beginning in 2010, the pilot study showed that behaviours of students in a school of business could be grouped together to better understand the drivers of retention (Deloitte, 2010). The resulting model, termed the *Student Discovery Model* (SDM), utilized a self-organizing map methodology (Kohonen, 1990) to create clusters of behaviours that helped analysts discover new relationships, raise additional research questions and test assumptions and hypotheses. The effort was extended in 2013 to the largest domestic campus of the university. This involved creating clusters among 52,000 students over a 5-year period (Gibson & de Freitas, 2016) drawing at the time from 15 data systems (e.g. finance, student records, learning management system) and was used to conduct initial exploration of hypotheses as well as to identify correlations that warranted deeper analysis.

In 2015, a project in predictive analytics used machine learning (Chai & Gibson, 2015) to help make the case for the return on investment of building the university's capability in student retention. An investment in data architecture simultaneously established how the new exploratory analytics would interact with managed data systems of the university. A data scientist was hired in 2016 to lead the analytics group in learning and teaching, and that team has grown to three people. The theme of return on investment led to a second paper (Gibson, Huband, et al., 2018) that focused on the capability developed and methods underpinning continuous on-demand production of analyses and insights aimed to stimulate inquiry and action to improve retention. Data analysts have also been added in student services, recruitment, finance and elsewhere. These groups have not yet been brought together into an ongoing community of practice and typically pursue their own agendas with

Table 1.2 Adoption profile of analytics teams in business units of a university in Case 1

Actors	<ol style="list-style-type: none"> 1. Innovators 2. Early adopters 3. Early majority 4. Late majority 5. Laggards 	<ol style="list-style-type: none"> 1. Data scientists, data analysts 2. Faculty level leaders, central learning and teaching staff, senior executives
Innovation configuration	<ol style="list-style-type: none"> 1. Relative advantage 2. Compatibility 3. Complexity 4. Testability 5. Reinvention potential 6. Observed effects 	<ol style="list-style-type: none"> 1. High (new BI insights) 2. High (skilled people) 3. High (knowledge gap high) 4. Low (no way to compare) 5. Low (isolated teams) 6. High (significant effects)
Communications	<p>Teams communicate primarily <i>within</i> rather than <i>across</i> the university. Informal communications are used as needed to solve local problems. There is as of yet no formal structure of communications <i>among</i> or <i>integrating</i> any of the teams</p>	
Complexity leadership	<p>University leadership has recently signalled that the central learning and teaching area is the entity now charged with learning and academic analytics. Leadership of all analytics is distributed, and separate teams work independently from each other without coordination to impact on other aspects of the student experience (e.g. recruitment, admissions, student life, finance, academic records, alumni networks)</p>	

different toolsets, varied levels of accessibility to university data, supported by informal working relationships among the groups.

Analysing the case story briefly with Rogers’ (1962) framework, in Table 1.2, one can see that the stage of adoption at the university is prior to ‘early majority’ – meaning that adoption is limited to a few innovators and early adopters. A dashboard capability for instructors is being introduced now and may help lead to an early majority of people using some form of learning and academic analytics to make decisions.

1.3.6.2 Adoption of Learning Analytics in Challenge-Based Learning Design

The second case illustrates how designers of challenge-based learning experiences have been building capability for adopting a data-driven approach to the design of scalable learning experiences. Challenge-based learning is a teaching model that incorporates aspects of collaborative problem-based learning, project-based learning and contextual teaching and learning while focusing on current real-world problems (Ifenthaler & Gibson, 2019; Johnson, Smith, Smythe, & Varon, 2009). The approach is particularly well-suited to industry integration and to extending formal learning into the community and world.

A digital learning experience platform – Challenge platform – has been developed to study the detailed time-sensitive user trails of interactions between a learner

and content and among groups of learners collaborating to solve problems (Gibson, Irving, & Scott, 2018). The platform supports self-directed learning at scale with automated feedback and assessment in real time, at the point of learning. It promotes active engagement to enable deeper learning, evidence of which is captured via fine-grained data collection by a learning analytics engine. Challenge has the capability, for example, to identify and track who does what during team work to promote individual responsibility among participants. It can also engage students in peer feedback, supporting development of critical thinking and reflection skills, as team members work toward solving a wide variety of challenges.

Studies of the platform have focused on the dynamics and impacts of learning engagement as a multidimensional concept. This includes an individual’s ability to behaviourally, cognitively, emotionally and motivationally engage in an ongoing learning process. Results indicate that engagement is positively related to learning performance (Ifenthaler, Gibson, & Zheng, 2018) and that team learning processes can be studied and related to performance using network analyses (Kerrigan, Feng, Vuthaluru, Ifenthaler, & Gibson, 2019; Vuthaluru, Feng, Kerrigan, Ifenthaler, & Gibson, 2019).

The innovating actors in this second case are application developers who are also researching the impacts of the innovation and advocating for others in the university to use the application to promote collaborative problem-solving and group projects in classes. Early adopters of the innovation have been a handful of individual instructors (e.g. one instructor in architecture, another in business and law) and student services units (e.g. the career counselling service centre). Currently, one faculty area has committed to widespread adoption the application in 2020, so the number of early adopters is expected to increase (Table 1.3).

Table 1.3 Adoption profile of analytics in challenge-based learning in Case 2

Actors	<ol style="list-style-type: none"> 1. Innovators 2. Early adopters 3. Early majority 4. Late majority 5. Laggards 	<ol style="list-style-type: none"> 1. Application developers, data analysts 2. Individual instructors; business and law faculty 3. Student services content delivery
Innovation configuration	<ol style="list-style-type: none"> 1. Relative advantage 2. Compatibility 3. Complexity 4. Testability 5. Reinvention potential 6. Observed effects 	<ol style="list-style-type: none"> 1. High (collaborative learning improved) 2. High (capstone projects supported) 3. High (easy authoring) 4. High (research on learning and teaching) 5. High (team learning innovations) 6. High (significant effects)
Communications	The current challenge is how to share the opportunity and help people to use the platform, including how to interpret and utilize the learning analytics information	
Complexity leadership	A group with the central learning and teaching unit is managing the infrastructure, budget, staffing and software development	

The innovation configuration profile in the second case is assessed to be primarily high. New collaborative learning knowledge is being published and is leading to new embeddings of automated analyses such as the cognitive and educational benefits of the challenge-based approach.

1.4 Discussion and Outlook

There are many different ways to improve higher education through learning analytics, and institutions are most likely to develop unique innovation configuration profiles based on their current circumstances, histories and priorities. Importantly, understanding an institution's learning analytics adoption profile needs to be framed with specific knowledge of the particular aspects of learning analytics applied to tactics such as those outlined in Sects. 1.3.1, 1.3.2, 1.3.3, 1.3.4 and 1.3.5. For example, an institution might be in an early stage in alumni relations while highly advanced in recruitment or adapting the curriculum. In addition, for an institution to be adopting learning analytics at scale does not necessarily mean covering all the aspects mentioned in the previous sections. Institutions will set priorities and may decide to make progress on only a subset of the possibilities.

The two cases discussed briefly above lead to observations about three user roles: (1) *informal* educators, those who provide student services and extension programs outside of the formal curriculum, who seek ways to go to scale; (2) *formal* educators who instruct classes and are interested in seeing the impacts of learning analytics on team-based classroom and curriculum projects; and (3) data and information science *experts* without a background in traditional instructional design who are helping people in roles 1 and 2 to create new digital learning experiences on the Challenge platform. Table 1.4 utilizes the Rogers (1962) framework to compare observations across these user role groups.

In one university, informal educators using analytics to drive design and deployment are about 2 years ahead of the formal educators and the experts. Formal instructors heard about the analytics and, as innovators, wanted to see if they could benefit. In one school setting, the success of the pilot innovator teacher has led to three other early adopters. Experts were added to the platform support team to continuously drive new innovations based on data analytics, so are considered innovators. Most striking in the comparison of informal with formal educators is that the former have built a team approach and have more of a strategic vision based in observed effects such as highly efficient scalability and the reinvention potential. This has led the team to significantly expand to impact nearly all students of the University. The formal educators, in contrast, work alone in their classrooms and have not had opportunities yet to write conference papers, conduct localized research or influence others in their fields of knowledge.

Table 1.4 Comparing user roles in higher education adoption of learning analytics

		Informal	Formal	Experts
Actors	1. Innovators 2. Early adopters 3. Early majority 4. Late majority 5. Laggards	1. Two 2. n/a 3. Four	1. Two 2. Two	1. Two
Innovation configuration	1. Relative advantage 2. Compatibility 3. Complexity 4. Testability 5. Reinvention potential 6. Observed effects	1. High 2. High 3. Low 4. High 5. High 6. High	1. Low 2. High 3. Low 4. High 5. Low 6. Low	1. High 2. High 3. High 4. High 5. High 6. High
Communications		Within team and bilateral with experts; small community of practice within the team	1:1 with experts; no community of practice has emerged	Small team communicates with all users, plus external researchers; community of practice is international
Complexity leadership		Relative advantages outweigh other considerations; commitment to innovation has led to team development	Time-poor and focused on pragmatic operations rather than theoretic advances; individual instructors are 'on their own'	Highly adaptable to other users, balancing time between helping others and creating insights from data

Use of analytics across these three groups varies in this instance. The informal team uses analytics to determine effectiveness of the *structure of their offerings* as well as the *extent of implementation*, for example, counting the number of 'compliance' experience expected to reach masses. In contrast, the formal educators are loners within their faculty areas, who are interested in innovation in their own teaching. They use the analytics to *understand team problem-solving* and especially *individual contribution to team products* in projects where in the past they had no visibility. Their observations about impacts on student learning are limited to one or

two classes of their teaching load. The expert group utilizes data in these and several other ways, driven in part by the needs and foci of the informal and formal users, but also driven by *research questions and external feedback* from interested and collaborating international researchers.

At the level of small teams, even when a ‘critical mass’ is achieved in the actor network, such as in the informal team, adoption is shaped and limited by communications. In the formal instructors’ experience, almost all communications are one-to-one with the supporting expert team, not with peers and not with any expectation from or knowledge shared by executive leadership in their faculty area. In contrast, the informal team has been empowered by the executive leadership to do as much as possible with the assets, experience and analytics.

The profile of the adoption of learning analytics that emerges from this brief cross-case analysis illustrates details that help explain the ‘early-stage’ status of adoption within the higher education institution. The two cases presented demonstrate the potential of Rogers’ (1962) framework as a useful reflective tool in thinking about the processes and status of adoption of learning analytics.

The field of learning analytics is generating growing interest in data and computer science as well as educational science, hence becoming an important aspect of modern digital learning environments (Ifenthaler & Widanapathirana, 2014). Despite the high interest, the adoption of learning analytics in higher education institutions requires capabilities not yet fully developed (Ifenthaler, 2017). International perspectives on adoption models (Nouri et al., 2019) as well as on policy recommendations (Ifenthaler & Yau, 2019) may help to move the innovative efforts on learning analytics forward.

Acknowledgements This research is supported by Curtin University’s UNESCO Chair of Data Science in Higher Education Learning and Teaching (<https://research.curtin.edu.au/unesco/>).

References

- Arthars, N., Dollinger, M., Vigentini, L., Liu, D. Y., Kondo, E., & King, D. M. (2019). Empowering teachers to personalize learning support. In D. Ifenthaler, D.-K. Mah, & J. Y.-K. Yau (Eds.), *Utilizing learning analytics to support study success* (pp. 223–248). Cham, Switzerland: Springer.
- Berg, A. M., Branka, J., & Kismihók, G. (2018). Combining learning analytics with job market intelligence to support learning at the workplace. In D. Ifenthaler (Ed.), *Digital workplace learning. Bridging formal and informal learning with digital technologies* (pp. 129–148). Cham, Switzerland: Springer.
- Buckingham Shum, S., & McKay, T. A. (2018). Architecting for learning analytics. *Innovating for sustainable impact. Educause Review*, 53(2), 25–37.
- Chai, K. E. K., & Gibson, D. C. (2015). Predicting the risk of attrition for undergraduate students with time based modelling. In D. G. Sampson, J. M. Spector, D. Ifenthaler, & P. Isaias (Eds.), *Proceedings of cognition and exploratory learning in the digital age* (pp. 109–116). Maynooth, Ireland: IADIS Press.

- Clariana, R. B. (2010). Deriving individual and group knowledge structure from network diagrams and from essays. In D. Ifenthaler, P. Pirnay-Dummer, & N. M. Seel (Eds.), *Computer-based diagnostics and systematic analysis of knowledge* (pp. 117–130). New York: Springer.
- Dawson, S., Poquet, O., Colvin, C., Rogers, Pardo A., & Gašević, D. (2018). *Rethinking learning analytics adoption through complexity leadership theory*. Paper presented at the 8th International Conference on Learning Analytics and Knowledge, Sydney, NSW, Australia.
- de Freitas, S., Gibson, D. C., du Plessis, C., Halloran, P., Williams, E., Ambrose, M., et al. (2015). Foundations of dynamic learning analytics: Using university student data to increase retention. *British Journal of Educational Technology*, 46(6), 1175–1188. <https://doi.org/10.1111/bjet.12212>
- Deloitte. (2010). *Student retention analytics in the Curtin business school*. Bentley, WA: Curtin University.
- Dyckhoff, A. L., Zielke, D., Bültmann, M., Chatti, M. A., & Schroeder, U. (2012). Design and implementation of a learning analytics toolkit for teachers. *Educational Technology & Society*, 15(3), 58–76.
- Gašević, D., Joksimović, S., Eagan, B. R., & Shaffer, D. W. (2019). SENS: Network analytics to combine social and cognitive perspectives of collaborative learning. *Computers in Human Behavior*, 92, 562–577. <https://doi.org/10.1016/j.chb.2018.07.003>
- Gašević, D., Kovanović, V., & Joksimović, S. (2017). Piecing the learning analytics puzzle: A consolidated model of a field of research and practice. *Learning: Research and Practice*, 3(1), 63–78. <https://doi.org/10.1080/23735082.2017.1286142>
- Gibson, D. C. (2000). *Complexity theory as a leadership framework*. Retrieved from Montpelier, VT: <http://www.vismtorg/Pub/ComplexityandLeadershippdf>
- Gibson, D. C. (2012). Game changers for transforming learning environments. In F. Miller (Ed.), *Transforming learning environments: Strategies to shape the next generation* (pp. 215–235). Bingley, UK: Emerald Group Publishing Ltd.
- Gibson, D. C., & de Freitas, S. (2016). Exploratory analysis in learning analytics. *Technology, Knowledge and Learning*, 21(1), 5–19. <https://doi.org/10.1007/s10758-015-9249-5>
- Gibson, D. C., Huband, S., Ifenthaler, D., & Parkin, E. (2018). *Return on investment in higher education retention: Systematic focus on actionable information from data analytics*. Paper presented at the ascilite Conference, Geelong, VIC, Australia, 25 Nov 2018.
- Gibson, D. C., & Ifenthaler, D. (2018). Analysing performance in authentic digital scenarios. In T.-W. Chang, R. Huang, & Kinshuk (Eds.), *Authentic learning through advances in technologies* (pp. 17–27). New York: Springer.
- Gibson, D. C., Irving, L., & Scott, K. (2018). Technology-enabled challenge-based learning in a global context. In M. Schonfeld & D. C. Gibson (Eds.), *Collaborative learning in a global world*. Charlotte, NC: Information Age Publishers.
- Gibson, D. C., & Webb, M. (2015). Data science in educational assessment. *Education and Information Technologies*, 20(4), 697–713. <https://doi.org/10.1007/s10639-015-9411-7>
- Gibson, D. C., Webb, M., & Ifenthaler, D. (2019). Measurement challenges of interactive educational assessment. In D. G. Sampson, J. M. Spector, D. Ifenthaler, P. Isaias, & S. Sergis (Eds.), *Learning technologies for transforming teaching, learning and assessment at large scale* (pp. 19–33). New York: Springer.
- Glick, D., Cohen, A., Festinger, E., Xu, D., Li, Q., & Warschauer, M. (2019). Predicting success, preventing failure. In D. Ifenthaler, D.-K. Mah, & J. Y.-K. Yau (Eds.), *Utilizing learning analytics to support study success* (pp. 249–273). Cham, Switzerland: Springer.
- Hall, G. (1974). *The concerns-base adoption model: a developmental conceptualization of the adoption process within educational institutions*. Paper presented at the Annual Meeting of the American Educational Research Association, Chicago, IL.
- Hall, G., Loucks, S., Rutherford, W., & Newlove, B. (1975). Levels of use of the innovation: A framework for analyzing innovation adoption. *Journal of Teacher Education*, 26(1), 52–56.

- Henry, M., Gibson, D. C., Flodin, C., & Ifenthaler, D. (2018). Learning innovations for identifying and developing talent for university. In *Innovations in higher education – Cases on transforming and advancing practice*. London: IntechOpen.
- Hickey, D., Kelley, T., & Shen, X. (2014). *Small to big before massive: Scaling up participatory learning analytics*. Paper presented at the Fourth International Conference on Learning Analytics And Knowledge, Indianapolis, IN, USA.
- Ifenthaler, D. (2009). Model-based feedback for improving expertise and expert performance. *Technology, Instruction, Cognition and Learning*, 7(2), 83–101.
- Ifenthaler, D. (2010). Scope of graphical indices in educational diagnostics. In D. Ifenthaler, P. Pirnay-Dummer, & N. M. Seel (Eds.), *Computer-based diagnostics and systematic analysis of knowledge* (pp. 213–234). New York: Springer.
- Ifenthaler, D. (2011). Intelligent model-based feedback. Helping students to monitor their individual learning progress. In S. Graf, F. Lin, Kinshuk, & R. McGreal (Eds.), *Intelligent and adaptive systems: Technology enhanced support for learners and teachers* (pp. 88–100). Hershey, PA: IGI Global.
- Ifenthaler, D. (2015). Learning analytics. In J. M. Spector (Ed.), *The SAGE encyclopedia of educational technology* (Vol. 2, pp. 447–451). Thousand Oaks, CA: Sage.
- Ifenthaler, D. (2017). Are higher education institutions prepared for learning analytics? *TechTrends*, 61(4), 366–371. <https://doi.org/10.1007/s11528-016-0154-0>
- Ifenthaler, D., & Gibson, D. C. (2019). Opportunities of analytics in challenge-based learning. In A. Tlili & M. Chang (Eds.), *Data analytics approaches in educational games and gamification systems* (pp. 55–68). Cham, Switzerland: Springer.
- Ifenthaler, D., Gibson, D. C., & Dobozy, E. (2018). Informing learning design through analytics: Applying network graph analysis. *Australasian Journal of Educational Technology*, 34(2), 117–132. <https://doi.org/10.14742/ajet.3767>
- Ifenthaler, D., Gibson, D. C., & Zheng, L. (2018). *The dynamics of learning engagement in challenge-based online learning*. Paper presented at the 18th IEEE International Conference on Advanced Learning Technologies, Mumbai, India, 9 July 2018.
- Ifenthaler, D., Greiff, S., & Gibson, D. C. (2018). Making use of data for assessments: Harnessing analytics and data science. In J. Voogt, G. Knezek, R. Christensen, & K.-W. Lai (Eds.), *International handbook of IT in primary and secondary education* (2nd ed., pp. 649–663). New York: Springer.
- Ifenthaler, D., Mah, D.-K., & Yau, J. Y.-K. (2019). Utilising learning analytics for study success. Reflections on current empirical findings. In D. Ifenthaler, J. Y.-K. Yau, & D.-K. Mah (Eds.), *Utilizing learning analytics to support study success* (pp. 27–36). New York: Springer.
- Ifenthaler, D., & Schumacher, C. (2016). Student perceptions of privacy principles for learning analytics. *Educational Technology Research and Development*, 64(5), 923–938. <https://doi.org/10.1007/s11423-016-9477-y>
- Ifenthaler, D., & Widanapathirana, C. (2014). Development and validation of a learning analytics framework: Two case studies using support vector machines. *Technology, Knowledge and Learning*, 19(1–2), 221–240. <https://doi.org/10.1007/s10758-014-9226-4>
- Ifenthaler, D., & Yau, J. (2019). Higher education stakeholders' views on learning analytics policy recommendations for supporting study success. *International Journal of Learning Analytics and Artificial Intelligence for Education*, 1(1), 28–42. <https://doi.org/10.3991/ijai.v1i1.10978>
- Johnson, L., Smith, R., Smythe, J., & Varon, R. (2009). *Challenge-based learning: An approach for our time*. Austin, TX: The New Media Consortium.
- Kerrigan, S., Feng, S., Vuthaluru, R., Ifenthaler, D., & Gibson, D. C. (2019). *Network analytics of collaborative problem-solving*. Paper presented at the CELDA Conference, Cagliari, Italy, 7 Nov 2019.
- Kiron, D., & Shockley, R. (2011). Creating business value with analytics. *MIT Sloan Management Review*, 53(1).

- Klasen, D., & Ifenthaler, D. (2019). Implementing learning analytics into existing higher education legacy systems. In D. Ifenthaler, J. Y.-K. Yau, & D.-K. Mah (Eds.), *Utilizing learning analytics to support study success* (pp. 61–72). New York: Springer.
- Kohonen, T. (1990). The self-organizing map. *Proceedings of the IEEE*, 78. <https://doi.org/10.1109/5.58325>
- Kotter, J. P. (2007). Leading change: Why transformation efforts fail. *Harvard Business Review*, January, 96–103.
- Kozleski, E., Gibson, D. C., & Hynds, A. (2012). Changing complex educational systems: Frameworks for collaborative social justice leadership. In C. Gersti-Pepin & J. Aiken (Eds.), *Defining social justice leadership in a global context* (pp. 263–286). Charlotte, NC: Information Age Publishing.
- Lazega, E. (2003). Rationalité, discipline sociale et structure. *Revue Française de Sociologie*, 44, 305–330. <https://doi.org/10.2307/3322457>
- Li, Y., & Huang, R. (2006). Topic-centered adaptive curriculum for e-learning. In V. P. Wade, H. Ashman, & B. Smyth (Eds.), *Adaptive hypermedia and adaptive web-based systems* (Vol. 4018, pp. 350–353). Berlin, Germany: Springer.
- Lockyer, L., Heathcote, E., & Dawson, S. (2013). Informing pedagogical action: Aligning learning analytics with learning design. *American Behavioral Scientist*, 57(10), 1439–1459. <https://doi.org/10.1177/0002764213479367>
- Mah, D.-K. (2016). Learning analytics and digital badges: Potential impact on student retention in higher education. *Technology, Knowledge and Learning*, 21(3), 285–305. <https://doi.org/10.1007/s10758-016-9286-8>
- Mah, D.-K., Bellin-Mularski, N., & Ifenthaler, D. (2016). Moving forward with digital badges in education. In D. Ifenthaler, N. Bellin-Mularski, & D.-K. Mah (Eds.), *Foundations of digital badges and micro-credentials* (pp. 511–517). New York: Springer.
- Mah, D.-K., & Ifenthaler, D. (2019). What do first-year students need? Digital badges for academic support to enhance student retention. *Journal of Applied Research in Higher Education*, 12, 86–96. <https://doi.org/10.1108/JARHE-12-2018-0258>
- Mah, D.-K., Yau, J. Y.-K., & Ifenthaler, D. (2019). Future directions on learning analytics to enhance study success. In D. Ifenthaler, J. Y.-K. Yau, & D.-K. Mah (Eds.), *Utilizing learning analytics to support study success* (pp. 313–321). Cham, Switzerland: Springer.
- Mishra, P., Henriksen, D., & Group, D. P. R. (2013). A NEW approach to defining and measuring creativity: Rethinking technology & creativity in the 21st century. *TechTrends*, 57(5), 10–13. <https://doi.org/10.1007/s11528-013-0685-6>
- Norris, D., Baer, L., Leonard, J., Pugliese, L., & Lefrere, P. (2008). Action analytics. Measuring and improving performance that matters in higher education. *Educause Review*, 43(1), 42–67.
- Nouri, J., Ebner, M., Ifenthaler, D., Saqr, M., Malmberg, J., Khalil, M., et al. (2019). Efforts in Europe for data-driven improvement of education: A review of learning analytics research in seven countries. *International Journal of Learning Analytics and Artificial Intelligence for Education*, 1(1), 8–27. <https://doi.org/10.3991/ijai.v1i1.11053>
- Parkin, E., Huband, S., Gibson, D. C., & Ifenthaler, D. (2018). *Analysing university student academic performance at the unit level*. Paper presented at the CELDA Conference, Budapest, Hungary, 21 Oct 2018.
- Rogers, E. M. (1962). *Diffusion of innovations* (1st ed.). New York: Free Press of Glencoe.
- Roll, M., & Ifenthaler, D. (2017). *Leading change towards implementation of learning analytics*. Paper presented at the AECT International Convention, Jacksonville, FL, USA, 6 Nov 2017.
- Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behavior*, 78, 397–407. <https://doi.org/10.1016/j.chb.2017.06.030>
- Schumacher, C., Klasen, D., & Ifenthaler, D. (2019). Implementation of a learning analytics system in a productive higher education environment. In M. S. Khine (Ed.), *Emerging trends in learning analytics* (pp. 177–199). Leiden, NL: Brill.

- Tsai, Y.-S., Poquet, S., Gašević, D., Dawson, S., & Pardo, A. (2019). Complexity leadership in learning analytics: drivers, challenges, and opportunities. *British Journal of Educational Technology*, 1–16. <https://doi.org/10.1111/bjet.12846>.
- Tsoukias, A., Montibeller, G., Lucertini, G., & Belton, V. (2013). Policy analytics: An agenda for research and practice. *EURO Journal on Decision Processes*, 1(1–2), 115–134. <https://doi.org/10.1007/s40070-013-0008-3>
- Vuthaluru, R., Feng, S., Kerrigan, S., Ifenthaler, D., & Gibson, D. C. (2019). *Visualising learner behaviours with network graphs and sankey diagrams*. Paper presented at the 10th International Science, Mathematics & Technology Education Conference, Reduit, Mauritius, 6 Nov 2019.
- Webb, M., & Ifenthaler, D. (2018). Assessment as, for and of 21st century learning using information technology: An overview. In J. Voogt, G. Knezek, R. Christensen, & K.-W. Lai (Eds.), *International handbook of IT in primary and secondary education* (2nd ed., pp. 1–20). Cham, Switzerland: Springer.
- West, D., & Lockley, A. (2016). Implementing digital badges in Australia: The importance of institutional context. In D. Ifenthaler, N. Bellin-Mularski, & D.-K. Mah (Eds.), *Foundations of digital badges and micro-credentials* (pp. 467–482). New York: Springer.
- Wowczko, I. (2015). Skills and vacancy analysis with data mining techniques. *Informatics*, 2, 31–49. <https://doi.org/10.3390/informatics2040031>