UNIVERSITY OF THESSALY

MASTER OF SCIENCE

Modeling of Decision Making and Learning in a Business Simulation Game

---

Author:

Alkiviadis Vleioras

Supervisor:

Yeoryios Stamboulis

Dissertation

submitted in fulfillment of the requirements for the degree of

Master of Science

in

New Entrepreneurship, Innovation and Development

Department of Planning and Regional Development

Department of Mechanical Engineering

Department of Economics

May 25, 2020

Declaration of Authorship

I, Vleioras Alkiviadis, declare that this dissertation titled, “Modeling of Decision Making and Learning in a Business Simulation Game” and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a Master of Science degree at this University.
- Where any part of this dissertation has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the dissertation is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed my-self.

Signed: Date:

ΠΑΝΕΠΙΣΤΗΜΙΟ ΘΕΣΣΑΛΙΑΣ

Περίληψη

Τμήμα Μηχανικών Χωροταξίας, Πολεοδομίας και Περιφερειακής Ανάπτυξης

Τμήμα Μηχανολόγων Μηχανικών

Τμήμα Οικονομικών Επιστημών

Μεταπτυχιακό Δίπλωμα

Μοντελοποίηση της διαδικασίας λήψης αποφάσεων και μάθησης σε ένα παιχνίδι προσομοίωσης εφοδιαστικής αλυσίδας.

Βλειώρας Αλκιβιάδης

Με την ολοένα και αυξανόμενη χρήση της ηλεκτρονικής και εξ' αποστάσεως μάθησης, είναι επιβεβλημένη η ανάπτυξη κατάλληλων εργαλείων που θα βοηθήσουν τους διδάσκοντες να βελτιστοποιήσουν την εκπαιδευτική διαδικασία στις νέες συνθήκες του ψηφιακού περιβάλλοντος εκπαίδευσης. Σκοπός είναι η ανάπτυξη μιας μεθοδολογίας που θα δίνει στους διδάσκοντες μαθημάτων διοίκησης, τη δυνατότητα να βλέπουν πως εξελίσσεται η μάθηση των φοιτητών/τριών τους, καθώς και σε ποια σημεία του μαθήματος έχουν δυσκολίες στην κατανόηση. Χρησιμοποιήθηκαν στατιστικές μέθοδοι και τεχνικές μηχανικής μάθησης για να αποδοθούν γραφικά τα σημεία στα οποία δίνει σημασία ο φοιτητής/τρια κατά τη διάρκεια του πειράματος μέσω προσομοίωσης εφοδιαστικής αλυσίδας ζυθοποιίας. Η μεθοδολογία που αναπτύχθηκε μπορεί να εφαρμοσθεί και σε άλλες εκπαιδευτικές προσομοιώσεις, ανάλογα με τις ανάγκες της εκάστοτε περίπτωσης.

Λέξεις-κλειδιά: Εκπαιδευτική Προσομοίωση, Ανάλυση δεδομένων μάθησης, Ηλεκτρονική μάθηση, Μηχανική μάθηση, Ομαδοποίηση

UNIVERSITY OF THESSALY

Abstract

Department of Planning and Regional Development

Department of Mechanical Engineering

Department of Economics

Master of Science

Modeling of Decision Making and Learning in a Business Simulation Game

Vleioras Alkiviadis

With the rising interest in the use of e-learning and distance learning, the development of innovative tools that will help teachers adapt their teaching methods in the new digital landscape is a must. The aim, is to develop a methodology that will offer to the management courses tutors a way to track the learning process of their students, and to identify which specific parts they lack in comprehension and, thus, teaching should pay more attention to. I used statistical methods combined with machine learning techniques, to visualize the specifics that students pay attention to, during the experiment of simulating the supply chain of a beer factory. The developed process can be implemented in any other simulation game, according to the needs of the tutor.

Keywords: Learning Simulations, Learning analytics, e-learning, Machine learning, Clustering

Acknowledgements

Foremost, I would like to express my sincere gratitude to my advisor Yeoryios Stamboulis and for his continuous support of my MSc study and research, for his patience, motivation, enthusiasm, and immense knowledge.

Besides my advisor, I would like to thank Georgios Vleioras and Achilleas Barlas for their useful insights.

Finally, I must express my very profound gratitude to my family and friends for providing me with unfailing support and continuous encouragement through the process of researching and writing this dissertation. This accomplishment would not have been possible without them.

Thank you all!

Author

Vleioras Alkiviadis

Table of Contents

CHAPTER 1 MAPPING THE DISSERTATION

During the past years, a turn to e-learning platforms is emerging. Be it platforms like Edx or Udemy, or the recently-upscaled MS Teams and Zoom, an abundance of options for distance learning has emerged. While the content on these platforms is of the highest quality, they seem to be missing the necessary analytics tools that will improve the way this content is taught. Information like the attendance of students, clicks per question, or other similar information is available on most platforms, but more important data, like what each user pays attention to, or how the learning behavior changes in time, are not offered by the majority of platforms.

1.1 AIM OF THE DISSERTATION

In order for this gap to be filled, I will focus on business simulation games, and more specifically the beer game, for which I will try to develop some methods that will help visualize what each user sees in order to make his next moves on the game, and cluster the class into groups of students that have the same behavior.

In order to give instructors as much information as they can get to improve their teaching methods, the use of statistics and machine learning methods, can show us which parts of the teaching process are the most interesting to student groups, and how these groups change their behavior over time.

1.2 JUSTIFICATION OF THE RESEARCH TOPIC

Learning is a multifaceted process that individuals typically take for granted until they experience difficulty with a complex task. With the adoption of new technologies, the ways of learning have changed significantly during the past few years. E-learning platforms, use of multimedia processes, and cognitive learning are only a few of the structural changes the learning process has undergone. This leads to the necessity of mapping the new learning process to increase our teaching effectiveness. The use of technology in teaching has also provided us with a huge amount of data. As with many different industries that have the need to exploit the data provided by newly developed processes, the education industry needs to find ways to reinvent the communication between teachers and students.

The analysis of the data we get from a process, is a field that is currently undergoing a huge development. In regard to my research, learning analytics is a newly developed field that tries to use these data in favor of the learning process. Analytics in the education sector is already in use on all levels of the education, from the individual classroom, department, university, region, state/province, and international. Each level uses different kinds of data (in terms of quantity and diversity) and context, leading to a variety of questions and analytic lenses that can be applied to provide detailed and nuanced insight into each organizational layer of interest. In my case, I use the data extracted by the simulation of the "beer game" to answer the question of what each student pays attention to, and how a student changes his/her behavior overtime during the simulation process.

Moreover, the use of machine learning algorithms is common practice in research topics that want to discover hidden patterns or grouping in data. This kind of algorithms are called unsupervised learning algorithms and are used in this research to cluster the groups of students into groups of similar behavior, a methodology that isn't used until now in learning analytics tools.

1.3 STRUCTURE OF THE DISSERTATION

The objectives set out in the previous section also determine the structure of this paper. More specifically, each chapter deals separately with the following:

Chapter 2 presents the necessary information that is needed to further explore the subject of learning, e-learning, and learning analytics. I explain in depth the various methods that have been developed through the years, that model the learning process in various environments, as well as the use of analytics in the development of learning methodologies.

Chapter *3* depicts the methodology and processes of extracting conclusions of data. I present the data collection, the data pre-processing methods, and the analytics workflow. Also, I comment on the software tools I utilized for the analysis of the data.

In chapter 4 I analyze the aforementioned data, i.e. variables, regression tables, graphs, and clustering analysis. Chapter *5* summarizes the observations, concludes and suggests further related research directions

CHAPTER 2 AN OVERVIEW OF E-LEARNING

In this chapter I focus on two main issues. First, I review the literature on learning and e-learning. After defining the learning and e-learning process, I point out the seminal work of Argyris and Schon (2012) and Senge (2006) for the organizational learning that define how learning is viewed as a reflexive practice that results in the change of mental models. The second is the learning analytics sector. The necessary definitions are mentioned, along with the current trends and frameworks used on the subject. The review shows that there is a practical gap in the development of analytics methods and tools that can illustrate how learning – defined as change in mental models – takes place.

2.1 THEORIES OF LEARNING

In order to understand the learning process, we have to know what is learning, its difference with e-learning, and how these are achieved.

2.1.1 LEARNING AND E-LEARNING

2.1.1.1 Learning

> "Learning is a multifaceted process that individuals typically take for granted until they experience difficulty with a complex task. However, the capacity for learning is the characteristic that sets humans apart from all other species. Included are identifying objectives, projecting goals, constructing plans, organizing resources, and monitoring the consequences".

(Gredler, 2009).

Learning improves our understanding of the world and its processes. This information is projected in our minds as mental models; Mental models are how we understand the world. Not only do they shape what we think and how we understand but they shape the connections and opportunities that we see. Mental models are how we simplify complexity, why we consider some things more relevant than others, and how we reason. A mental model is simply a representation of how something works. We cannot keep all of the details of the world in our brains, so we use models to simplify the complex into understandable and organizable chunks.

> With the goal of integrating mental models into a comprehensive conceptual framework of learning and teaching, mental models mediate between preconceptions (defined as the initial states in the learning process) and causal explanations, defined as the desired final states in the learning process (Seel and Al-diban, 2000). Thus, the learning-dependent mental model progression can be identified as a specific kind of transition which mediates between preconceptions or misconceptions, which describe the initial states of the learning process (Ifenthaler and Seel, 2012).

The cognitive activity of learning is related to three unique aspects of human intelligence (Gredler, 1986).

> "First, humans are able to learn about the discoveries, inventions, and ideas of great thinkers and scientists of the past (referred to as inherited experience; Vygotsky, 1924/1979). Second, individuals can develop knowledge about places and events they have not experienced personally through the experiences of others. Third, humans adapt the environment to themselves, rather than merely adapting to it. This effort is accomplished by first planning new strategies or products in their heads. Examples include a variety of pursuits from quilt making to architecture. Vygotsky named this cognitive activity repeated experience"

(Gredler, 2009).

The process of learning has evolved through the years, and is dependent of the needs of each era; Huang et al.(2013), state that changes in the way we communicate in the age of social informatization has affected the way we live, work, and consequently, the ways in which we learn. This transformation requires a new way of thinking about learning. The essential difference between learning in a traditional manner, called nibbled learning, and information-based learning, also called connected learning, lies in the different understandings of knowledge processing. Nibbled learning is the process by which learners pass required tests according to standard requirements and a set order of knowledge units, so as to comprehensively master the learning contents within a specified period of time. Connected learning, with the characteristics of autonomy, inquiry, and collaboration, has been widely piloted and adopted in informal learning and training.

Research by Siegler (2007), reported by Kirkwood (2009)) delineates a number of distinct concepts of learning by students:

- Learning as the increase in knowledge
- Learning as memorization
- Learning as the acquisition of facts, procedures and so on, that can be retained and/or utilized in practice
- Learning as the abstraction of meaning
- Learning as an interpretive process aimed at the understanding of reality

In addition to the differences in conceptions of learning among students, according to Perry (1970) also referred to by Kirkwood, "conceptions also vary within students according to their stages of intellectual development". Kirkwood also states that "an individual's conception of learning will determine his or her expectations of, and approaches to, learning, for example in terms of surface-level (memorization and reproduction) or deep-level (developing and extending meaning and understanding) processing".

Seeking to unravel the links between practice and learning, agency and change, Senge (2004) made a fusion of 'systems thinking' and learning theories that led to a concept of organizational learning as a process of system-based organizational change. He concluded in five interrelated personal disciplines required to become a learning organization (the term discipline meaning a path of development for acquiring particular skills or competencies, to be studied, mastered, and put into practice):

- Personal mastery - the discipline of continually clarifying and deepening our personal vision, focusing energy, developing patience and seeing reality objectively.
- Mental models - an ability to describe and discuss our internal pictures of the organization, to enable open thinking and influence with others.

- Building shared vision - gaining a commitment to work towards the organizational goal(s).
- Team learning - where the combined output of the team exceeds that of the individuals. This produces extraordinary results, and rapid growth of individuals.
- Systems thinking - the four previous disciplines work together to create the necessary mind shift to become a learning organization. To discover how people create their reality, and how they can change it.

2.1.1.2 E-learning

Defined as “learning facilitated and supported through the use of information and communications technology”, e-learning may involve the use of some, or all, of the following technologies:

- desktop and laptop computers
- software, including assistive software
- interactive whiteboards
- digital cameras
- mobile and wireless tools, including mobile phones
- electronic communication tools, including email, discussion boards, chat facilities and video conferencing
- Virtual Learning Environments (VLEs)
- learning activity management systems

> “e-learning can cover a spectrum of activities from supporting learning, to blended learning (the combination of traditional and e-learning practices), to learning that is delivered entirely online. Whatever the technology, however, learning is the vital element. e-Learning is no longer simply associated with distance or remote learning, but forms part of a conscious choice of the best and most appropriate ways of promoting effective learning”.

(JISC, 2004)

“E-learning” is still widely used to refer to the application of technology to learning. However, the term “technology-enhanced learning” is gaining favor since it emphasizes how technology adds value to learning by enabling:

Table 2.1: Added values to learning by technology enhanced learning

Connectivity to information and to others
24/7 access to learning resources
Greater choice over the time, place and pace of study
Alternative modes of study: distance, blended work-based, partially or wholly campus-based
Knowledge-sharing and co-authoring across multiple locations
Opportunities for reflection and planning in personal learning spaces
Rapid feedback on formative assessments
More active learning by means of interactive technologies and multimedia resources
Participation in communities of knowledge, inquiry and learning
Learning by discovery in virtual worlds
Development of skills for living and working in a digital age

Source: JISC, 2007

The hype about e-learning is typically related to its (perceived) benefits around fitting in with learners’ time requirements (any time), with overcoming problems around geographical distance (any place) or with offering increased flexibility (e.g. only for me or just in time), and thereby improving access and increasing convenience. According to Allen and Seaman (2008), around 1/4 of all students in post-secondary education within the USA were undertaking complete online courses in 2008 with a report by Monroe (2009) noting the figure rises to 44% when considering blended provision. Thus, the necessity for the development of a framework became eminent, with the one by HEFCE (2009) listing seven basic areas of e-learning activity at the institutional level. We are able to recognize that the reasons for the adoption of e-learning span across all aspects and dimensions of higher education activity:

Table 2.2: Seven Areas of e-learning Activity

Activity area	Strategic priorities
Pedagogy, curriculum design and development	Enhancing excellence and innovation in teaching and learning. Enhancing flexibility and choice for learners Enhancing student achievement. Improving employability and skills. Attracting and retaining learners. Supporting research-based or enquiry-based learning Engaging employers (or other stakeholders) in curriculum design and delivery. Improving efficiency of curriculum design and delivery processes.
Learning resources and environments	Enhancing flexibility and choice for learners Enhancing student achievement Improving employability and skills Widening participation and improving access Effective management of learning resources Designing and maintaining effective environments for learning
Lifelong learning processes and practices	Improving employability and skills Enhancing flexibility and choice for learners Widening participation and improving access to learning opportunities Supporting diverse learners' needs Retaining learners and meeting learners' expectations Co-operating with other institutions, colleges and campuses
Strategic management, human resources and capacity development	Enhancing excellence in teaching Enhancing excellence in research Workforce development Business/community links Improving efficiency and effectiveness of institutional processes
Quality	Institutional quality processes can support objectives and enhance benefits in all the other areas
Research and evaluation	Enhancing excellence in learning and teaching Enhancing excellence in research Enhancing understanding of learning and teaching processes Enhancing institutional processes (especially quality assurance and review)
Infrastructure and technical standards	Enhancing flexibility for learners Supporting diverse learners' needs Enhancing efficiency of institutional processes Enhancing the technical infrastructure Enhancing the information environment Ensuring effective ICT investments and effective use of existing ICT resources Sustainability ("green" computing)

Source: Pachler & Daly, Key Issues in e-learning

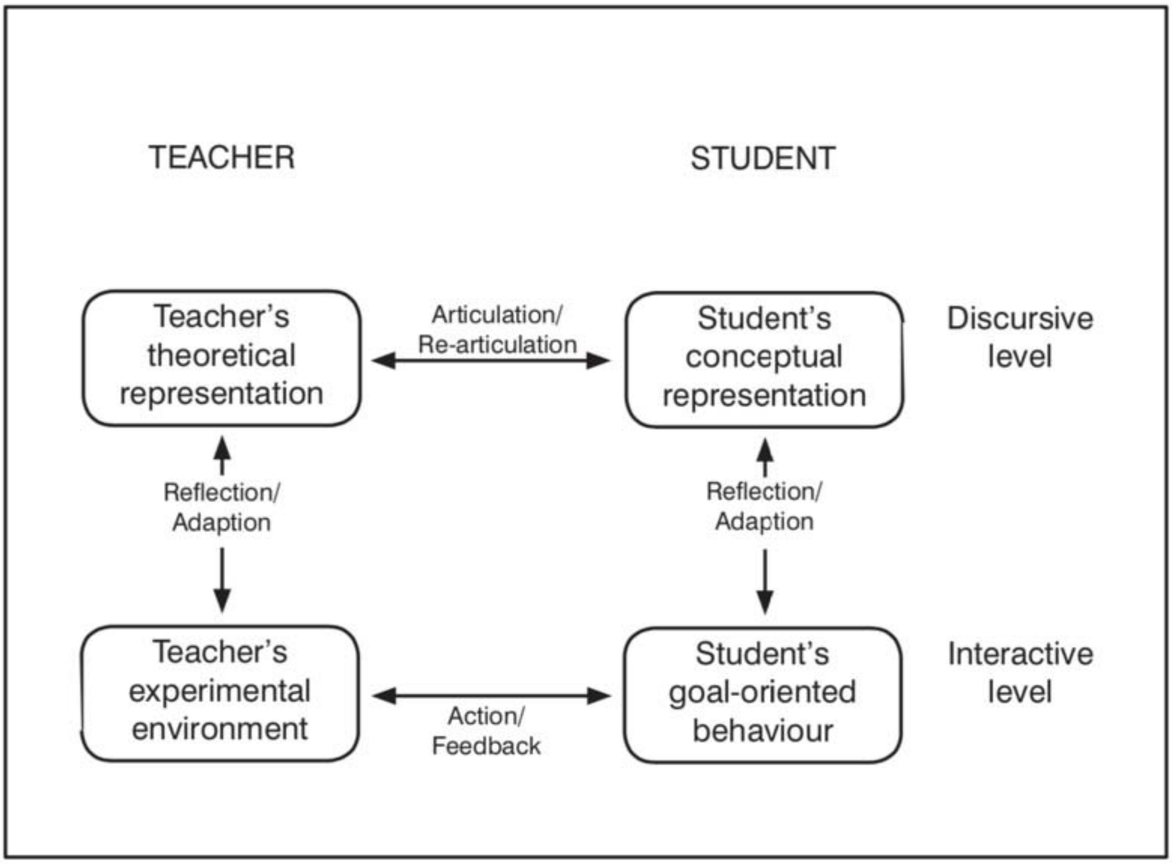
2.1.2 KEY COMPONENTS OF AN E-LEARNING FRAMEWORK

In order for us to understand how e-learning happens, we need to map the learning process. Several frameworks have been developed in the past, with the most important ones being listed below:

The seminal work of Diana Laurillard's discursive "conversational framework" model, which describes interrelationships between, and activities by, teachers and learners within the meaning-making process offers a clear view of the learning process. She (Laurillard, 2004) explains the learning process as "being akin to a conversation between the teacher and the student that operates at a discursive and interactive level linked by reflection and adaptation" (see Figures 1, 2).

The subject model is based on a recursive loop based on theorizing, design and evaluation. Learning is presented as a series of iterative conversations with various factors: the external world and its artifacts, with oneself and with other learners and teachers. Laurillard argues that learning is most successful when the learner takes control of the activity, being able to try out ideas by performing experiments, asking questions, collaborating with other people, seeking out new knowledge, and planning new actions (Pachler and Daly, 2011).

Figure 2.1: The conversational framework for the learning process

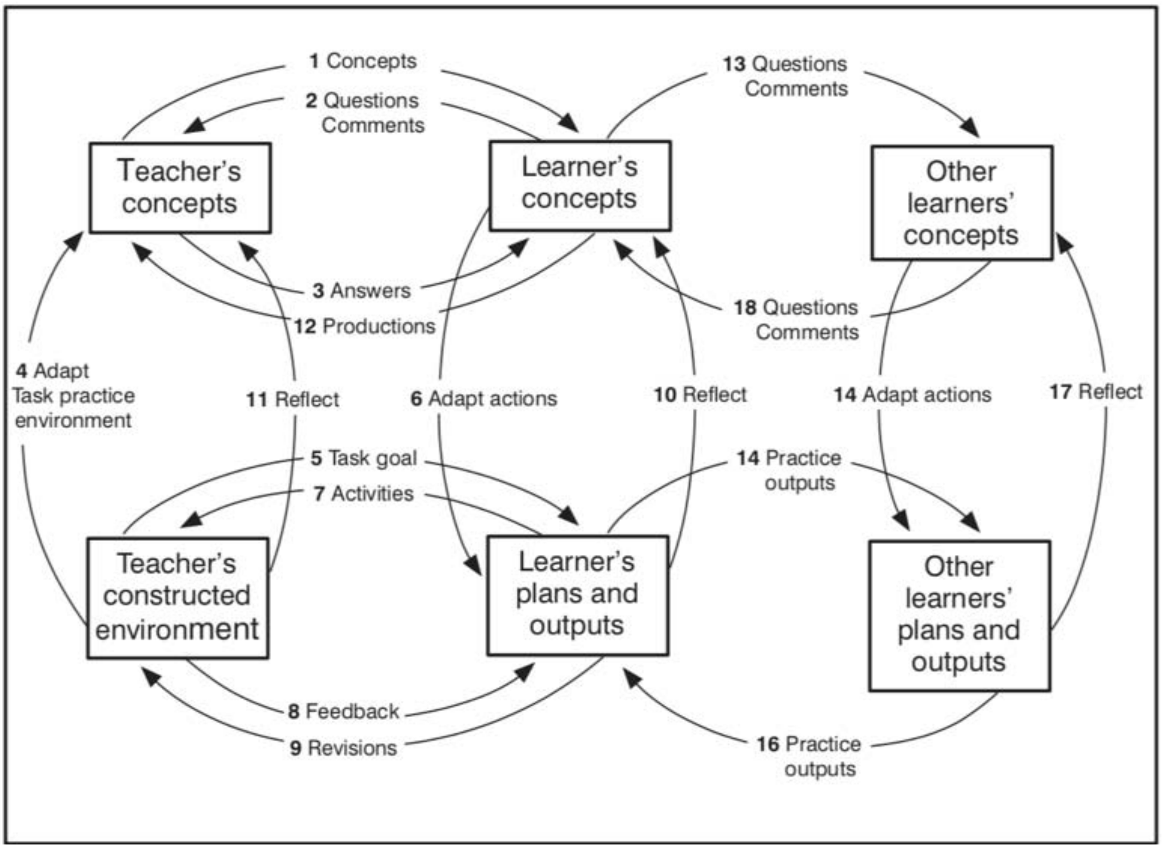


Source: Laurillard et al., 2000

This framework will become the basis of the process explained in Chapter 3, the conversation between teachers and learners, as well as with the classroom in its entirety, is the main issue seeking solution.

Pachler *et al.* (2009) argue that the notion of conversation, brings to the foreground the link to people at the expense of links to systems and media structures, asking themselves whether the term communication may better express these. Indeed, Pachler, Bachmair and Cook (2010: 25; see also (Pachler, 2010)) developed a socio-cultural ecological model in response to their previous question, comprising of agency, cultural practices and structures that enable an analytical engagement around educational uses of mobile learning technologies:

Figure 2.2: The conversational framework for supporting the formal learning process

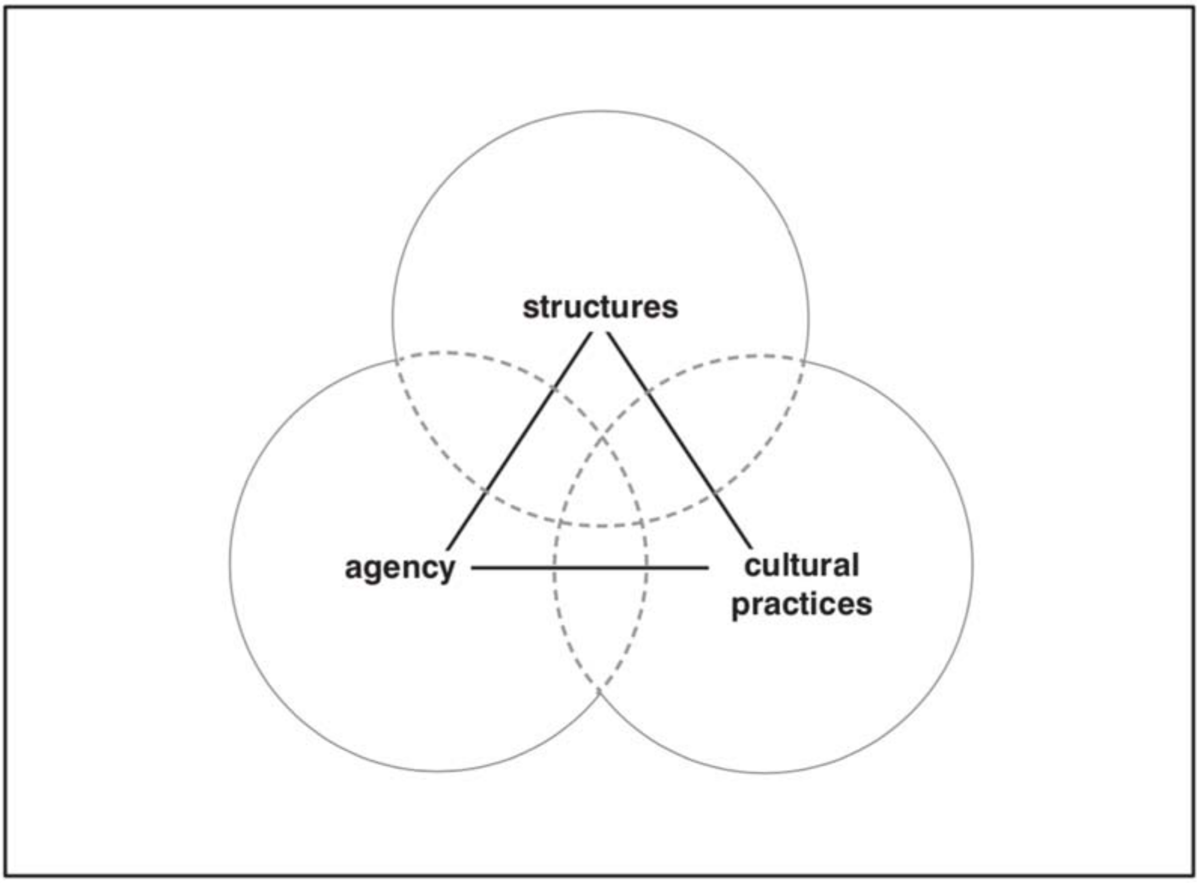


Source: Laurillard 2007: 160

- Agency: young people can be seen to increasingly display a new habitus of learning, in which they constantly see their lifeworld framed both as a challenge and as an environment and a potential resource for learning, in which their expertise is individually appropriated in relation to personal definitions of relevance and in which the world has become the curriculum populated by mobile device users in a constant state of expectancy and contingency.

- Cultural practices: mobile devices are increasingly used for social interaction, communication and sharing; learning is viewed as culturally situated meaning-making inside and outside of educational institutions and media use in everyday life has achieved cultural significance.
- Structures: young people increasingly live in a society of individualized risks, new social stratifications, individualized mobile mass communication and highly complex and proliferated technological infrastructure; their learning is significantly governed by the curricular frames of educational institutions with specific approaches towards the use of new cultural resources for learning (Pachler, 2010).

Figure 2.3: Key components of a socio-cultural ecological approach



Source: http://www.londonmobilelearning.net

Although this model was developed specifically for mobile technologies, in particular for smartphones, it can be seen to apply equally to e-learning. In e-learning, as in mobile learning, the agency of the learner can be seen to be of the utmost importance, given the relative lack of teacher intervention, be it in creating learning activities and tasks that help out learners, advising them with modeling and sustaining their learning process and so on. This model is inspired by the common practices of daily routine as well as education spaces (schools/universities) and the workplace, and at the same time being situated in the characteristics of their social environment and the technological infrastructure available to them (Pachler and Daly, 2011).

Krämer, B. (2001) delineate the potential of technology in education and learning as follows:

- The same content can be presented using different media types including text, two- and three-dimensional graphics, sound, image sequences, or simulations.
- Different perspectives and access to the same topic can be used to provide cognitive flexibility.
- Different media are synchronized into multi-modal presentations.
- Multimedia components can be networked to hypermedia learning applications according to logic, didactic, or other meaningful relationships among components.
- Different customized “tours” can be superimposed on a web of learning components with a view to maximize re-use and adapt existing contents to new courses and curricula.
- Education software development and knowledge modelling tools facilitate authoring of multimedia educational material and technology.
- Flexible navigation controls learners explore a networked information space at their own pace and orientation. But it can also provide rigid guidance including conditional selection of follow-on information and progress on successful completion of given learning tasks.
- Interaction facilities provide learners with opportunities for experimentation, context-dependent feedback, and constructive problem solving.
- Asynchronous and synchronous communication and collaboration facilities help to bridge geographical distance between course providers, teachers and students.
- Virtual laboratories and environments can be used to offer near authentic work situations, opportunities for hands-on experimentation and constructive problem solving.
- Operation sequences and preferred learning paths can be recorded, evaluated and reactivated if necessary. The students can add their own reference structures and personal notes to the course material.

They may stress that the role of technology in education is in many cases exaggerated, but they conclude that its judicious and pedagogically principled use can be seen to yield great potential. Indeed, research also shows that the extent to which both educators and students make use of the technology or its value, can also vary (Kirkwood, 2009).

An important factor of e-learning, in particular at a meso- and macro-policy-level, has been the belief in its ability to arouse productivity and performance. At a macro-level, for example, policy initiatives that aim in lifelong learning and widening participation, have seen e-learning as an integral mechanism of enabling an ever-increasing number of people to access learning throughout their lifespan. At a meso-level on the other hand, institutions have seen e-learning as a possible means of facing the diminishing of funding sources, as well as an opportunity for broadening their interest area for students beyond location-specific boundaries (Pachler and Daly, 2011). A meta-analysis published by the US Department of Education ((Means, B., Toyama, Y., Murphy, R., Bakia, M., and Jones, 2009) explored the question of the relative efficacy of online and face to face (f2f) instruction. Based on a several studies that examined web-based instruction with a random-assignment or controlled quasi-experimental design that focused only on effects for objective measures of student learning, as well as bearing in mind that only a handful of research studies on the matter have been published, it concluded in:

- Students who took all or part of their class online performed better, on average, than those taking the same course through traditional f2f instruction.
- Instruction combining online and f2f elements had a larger advantage relative to purely f2f instruction than did purely online instruction.
- Studies in which learners in the online condition spent more time on tasks than students in the f2f condition found a greater benefit for online learning.
- Most of the variations in the way in which different studies implemented online learning did not affect student learning outcomes significantly.
- The effectiveness of online learning approaches appears quite broad across different content and learner types.
- Effect sizes were larger for studies in which the online and f2f conditions varied in terms of curriculum materials and aspects of instructional approach in addition to the medium of instruction.
- Blended and purely online learning conditions implemented within a single study generally result in similar student learning outcomes.
- Elements such as video or online quizzes do not appear to influence the amount that students learn in online classes.
- Online learning can be enhanced by giving learners control of their interactions with media and prompting learner reflection.
- Providing guidance for learning for groups of students appears less successful than does using such mechanisms with individual learners.

The types of tangible benefits evidenced by the research of the British Educational Bureau are presented under the following headings:

Table 2.3: Tangible effects of learning (e.g. context, style, insight and reflective practice)

Effect on exam results
Effect on student personal development (e.g. skills, employability, confidence)
Student satisfaction with e-learning (e.g. effect on motivation, attendance and enjoyment, as shown in national survey, institutional survey, module evaluation, focus groups or other)
Innovation in teaching, learning and assessment (e.g. stimulus to creative approaches)
Influence on educational research
staff satisfaction with e-learning
Effect on staff personal development (e.g. skills, employability, confidence)
Influence on recruitment (students or staff: e.g. through greater accessibility, opening up new markets)
Influence on retention (e.g. students or staff)
Influence on policy (e.g. institutional, faculty/school, departmental or other extra-institutional body)
Effect on resources (e.g. effect on cost of delivery, time, applying full economic costing to teaching and learning)
Modifications to learning spaces (e.g. libraries, wireless networks, informal learning spaces)
Effect on management of learning assets (e.g. institutional IP, repositories)
Effect on a social justice agenda (e.g. widening participation, provision of space for consideration of differing or challenging perspectives).

Source: British Educational Bureau

2.1.3 REFLEXIVE LEARNING

Reflexive learning is an educational route of guiding people through the rapid changes, risks, and uncertainties of modernity. Reflexivity compels people to think afresh, to reflect on, and to engage with their social environment. (Gbenga, 2016)

The emphasis placed on reflexive practice as a primary competence for professional work Schön (1983) has forced a rethinking of educational processes for professional development, particularly in areas connected with the health profession (Mann, Gordon and MacLeod, 2009), the teaching profession; Kreber, 2005)), the training of psychologists ((Sax, 2006); (Mayo, 2004)) and management education (Cunliffe, 2004).

Although experimentation in higher education is extensive, it also appears to be rather fragmented. This could be because there is still no agreement about what is meant by reflection (Kember *et al.*, 2008; Kreber, 2005), nor about the methodology required to analyze and evaluate it (Mann, Gordon and MacLeod, 2009).

Under the general heading of reflection, there are various descriptions of its nature that suggest different educational approaches(Schön, 1983; Mezirow, 1991; Boud and Walker, 1998; Dewey, 2005).

It is possible to identify at least three general approaches to describing this concept.

In the first approach, “reflection is a form of mental process delineated as an inquiring attitude aiming at improving problem-solving. The focus is on goal-directed behaviors and cognitive activity, and less attention is paid to the role of the emotions” (Moon, 2013).

In the second approach, the emphasis is on awareness of self in action: “Reflection refers to the beliefs, values, feelings and implicit assumptions used in setting and solving a problem”(Mezirow, 1991). These aspects have led some scholars (Warin *et al.*, 2006) to recommend a shift from reflective practice to reflexive practice. “Reflexivity means considering the involvement of the practitioner’s professional and personal values and frames and their impact on his/her working activity” (Schön, 1983)

Recently, this approach was reappraised: Reflection is interpreted as a “socially situated, political, collective process that occurs within social and organizational contexts”(Reynolds and Vince 2004, p. 6). The emphasis would be merely on reflexivity as a dialogical and relational activity: “It is not an internal, cognitive process, but a form of knowledge that is built up through dialogue and negotiation” (Cunliffe, 2004).

2.1.4 REFLEXIVE PRACTICE AND MENTAL MAPPING

Fonagy and Target(1997) define the reflective function as “the whole of the psychological processes which sustain mentalization, i.e. the ability to use mental states to understand and to explain one’s own and others’ behavior” (for example, ‘I took this action because I thought...’; ‘He decided in that way because he believed... or because he felt angry...’). This ability provides us with the recognition that mental states are representations which can be fallible and can be altered because they are only based on a selection of a wide range of possible perspectives (Fonagy, Peter Target, 1996). According to these authors, “the mentalization and the theory of mind can be considered as synonymous: Displaying a mentalizing attitude means perceiving oneself and others as characterized by mental states. These mental states include both those with a non-epistemic nature (wishes, intentions, emotions) and those with an epistemic nature (beliefs, reasoning, inferences (Barnett and O’Mahony, 2006). These mental states include both those with a non-epistemic nature (wishes, intentions, emotions) and those with an epistemic nature such as beliefs, reasoning and inferences (Barnett and O’Mahony, 2006).

Moreover, the ability to mentalize implies both a self-reflexive component, concerning the attribution to the self of mental states and an interpersonal component, which refers to the process of conferring mental states on others.

Allen and Seaman(2008) suggest that “such an ability to mentalize is not a stable characteristic, but a situated process that can be activated and put to different uses depending on the relational contexts. It is an action: something we do or cannot do”. Consequently, he prefers the term ‘mentalizing’ rather than ‘mentalization’.

Following this theoretical framework, the reflexive practice can be defined as “the process of mentalizing, i.e. of attributing mental states to oneself and to others and of explaining one's own and others' actions with reference to those mental states"(Bruno, Galuppo and Gilardi, 2011).

"Reflexive practice—as a process of mentalizing—is useful for adults at work as it is closely related to social and communication skills and to the processes of knowledge construction. For example, an interaction based on mentalizing sustains cooperative negotiation and effective communication: If we mentalize, we consider the other as an autonomous person with a different perspective, and we will make an effort to understand and to influence each other. Without mentalization, the other is transformed into an object, dehumanized" (Allen and Seaman, 2008).

On the matter of knowledge construction, recent research has highlighted the relationship between theories of mind and epistemological beliefs (Fagnant and Crahay, 2011). Lalonde and Chandler(2002) state in effect that "the capacity to appreciate the interpretative nature of knowledge needs to encompass an understanding of the interpretative character of the mind".

Since in every profession reflexive practice appears to be necessary to deal with complex tasks and situations, it is, therefore, important to be aware of the methodologies suitable for evaluating whether an educational context activates and sustains such a practice.

2.1.5 HOW TO EVALUATE REFLEXIVE PRACTICE

For the evaluation of reflexive practice, educational literature suggests both quantitative tools, such as questionnaires(Kember *et al.*, 2000; Biggs, Kember and Leung, 2001; Sobral, 2001; Mamede and Schmidt, 2004) and qualitative techniques. The use of journals is often proposed in educational programs in order to sustain and assess reflexive thinking (Hubbs and Brand, 2005; Gleaves, A., Walker, C., & Grey, 2008). Reflective journals are often structured: a coding scheme is usually required for assessing the level of students' reflection (Wong *et al.*, 1995; Kember *et al.*, 2008).

The learning challenges as identified by mental models and cognitive maps can help instructors understand the difficult parts of the course materials from the students' perspective and take actions of address them, and therefore enhance teaching effectiveness (Shen, Tan and Siau, 2019).

Taking into account the above-shared knowledge, it is made clear that in order for us to evaluate the reflexive practice that comes with e-Learning, research should provide a method of Analytics that is relevant to the matter. This is defined as *learning analytics*.

2.2 LEARNING ANALYTICS

2.2.1 DEFINING LEARNING ANALYTICS

The most widely used definition of learning analytics was proposed during the 1st International Conference on Learning Analytics:

"Learning analytics is the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs".

Other definitions are less involved and draw language from business intelligence:

“Analytics is the process of developing actionable insights through problem definition and the application of statistical models and analysis against existing and/or simulated future data”. (Cooper, 2012).

Analytics in the education sector are already in use on all its levels, from individual classroom, department, university, region, state/province, and international. Buckingham Shum (2012) groups these organizational levels as micro-, meso-, and macro-analytics layers. Each level uses different kinds of data (in terms of quantity and diversity) and context, leading to a variety of questions and analytic lenses that can be applied to provide detailed and nuanced insight into each organizational layer of interest. For example, analytics for classrooms might include social network analysis and NLP (Natural Language Processing) that will assess individual engagement levels, whereas department-level analytics should focus on risk detection and intervention with support services. On the other hand, institution-level analytics would mainly focus on improving the efficiency of university operations, or comparing performance with other peer universities. Essentially, as the organizational level changes, so do the functions that are used for analyzing learner data. The same goes for the types of organizational challenges that analytics could address.

“Below we can find a brief summary of the diversity of fields and research activities within education that have contributed to the development of learning analytics (LA):

- *Citation analysis*: (Garfield, 1955) was an early pioneer in analytics in science by emphasizing how developments in science can be better understood by tracking the associations (citations) between articles. Through tracking citations, scientists can observe how research is disseminated and validated. PageRank, a key algorithm in Google’s early search engine, adopted Garfield’s model of analyzing and weighting links on the web in order to gain “an approximation to ‘importance’” of particular resources (Kumar, 2012)Educationally, citation or link analysis is important for mapping knowledge domains (detailed below in knowledge domain modeling).
- *Social network analysis* is prominent in sociology, dating back to the work by Reis, Sprecher and Fingerman (2013) and Milgram (1967). Wellman(1999), active in social net- work research since the early 1970s, transitioned into analysis of networks in digital settings. Haythornthwaite(2002)) has more recently explored the impact of media type on the development of social ties.
- *User modeling* is concerned with modeling users in their interaction with computing systems. User modeling contributed to a shift in computing where users were treated “as individuals with distinct personalities, goals, and so forth” (E Rich, 1979), rather than treating all users the same. User modeling has become important in research in human-computer interactions as it helps researchers to design better systems (Fischer, 2001) by understanding how users interact with software. As detailed later, recognizing unique traits, goals, and motivations of individuals remains an important activity in learning analytics.
- *Education/cognitive modeling* has been applied to tracing how learners develop knowledge. Cognitive models have historically attempted to develop systems that possess a “computational model capable of solving the problems that are given to

students in the ways students are expected to solve the problems(Anderson *et al.*, 1995). Cognitive modeling has contributed to the rise in popularity of intelligent or cognitive tutors. Once cognitive processes can be modeled, software (tutors) can be developed to support learners in the learning process.

- *Tutors*: Computers have been used in education for decades as learning tools. In 1989, Burns argued for the adoption and development of intelligent tutor systems that ultimately would pass three levels of "intelligence": domain knowledge, learner knowledge evaluation, and pedagogical intervention. These three levels continue to be relevant for researchers and educators.
- *Knowledge discovery in databases* (KDD) has been a research interest since at least the early 1990s. As with analytics today, KDD was "concerned with the development of methods and techniques for making sense of data" ((Fayyad, Piatetsky-Shapiro and Smyth, 1996). The Educational Data Mining (EDM) community has been heavily influenced by the vision of early KDD.
- *Adaptive hypermedia* builds on user modeling by increasing personalization of content and interaction. "Adaptive hypermedia systems build a model of the goals, preferences and knowledge of each user, in order to adapt to the needs of that user" (De Bra, Brusilovsky and Houben, 1999). As will be presented later in this article, personalization and adaptation of learning content is an important future direction the learning sciences.
- *E-learning*: The growth of online learning, particularly in higher education ((Ally, 2004); (Andrews and Haythornthwaite, 2019), has contributed to the advancement of LA as student data can be captured and made available for analysis. When learners use a Learning Management System (LMS), social media, or similar online tools, their clicks, navigation patterns, time on task, social networks, information flow, and concept development through discussions can be tracked. The rapid development of massive open online courses offers additional data for researchers to evaluate teaching and learning in online environments "

  (Chronicle of Higher Education, 2012).

A list of learning analytics tools and techniques that are common in various science fields, can be found in the following section.

2.2.2 LEARNING ANALYTICS TOOLS

The fields that have contributed to the advance of learning analytics as a discipline, reviewed in the previous section, were also integral to the development of a range of technologies and techniques that are now being used by learning analytics researchers and practitioners. Learning analytics tools can be broadly grouped into two main categories: commercial and research.

Commercial tools are far more developed, with companies like SAS and IBM investing heavily in adapting their analytics tools for use in the education market. Software versions of SPSS, Stata, and NVivo for learning analytics and modeling are used as an extension of the research activities that students and academics have previously conducted with these tools. Statistical software packages are equally important in analytics and in quantitative research.

A variety of education market vendors, such as Ellucian and Desire2Learn are both offering commercial versions of their software, providing student information systems, curriculum management software, and learning management systems that are already circulating in the education sector. By adding analytics layers to existing systems, they provide added value for education administrators, managers, and teachers. An abundance of prominent analytics tools already relies on data captured in an LMS. For example, Purdue University's Signals (Arnold, 2010) and University of Maryland–Baltimore County's "Check My Activity" both rely on data generated in Blackboard. Recommender systems, such as Degree Compass, similarly rely on data captured in existing information technology systems in universities. Web analytics tools, such as Google Analytics and Adobe's Digital Marketing Suite are also used for LA.

Considering the above, we can clearly see that the focus on analytics in education has been a motivating factor for existing commercial vendors to either modify or extend their range of features within established products. However, following the growth in this field we note the emergence of a new suite of commercial analytics tools and infrastructure. Key representatives are Tableau, Microsoft PowerBI, Oracle and more. These tools are designed specifically to remove the complexity surrounding many analytic tasks, such as data importing, cleaning, and visualization. These products are indicative of the fact that analytics is no longer a discrete specialized area, but can attract individuals with a vast array of skills, expertise, and background. By letting users upload text and data files and perform advanced analytics without the knowledge of programming languages or visualization skills, they offer ease of use, affordability, and accessibility that has increased the level of their adoption across the education community.

Research and open analytics tools are not as developed as commercial offerings and typically do not target systems-level adoption. Programming languages such as R and Python are focused on individual analytics tasks, but are getting more and more functional for researchers with little programming experience.

Learning analytics has two components: techniques and applications may overlap with each other but have distinct characteristics. The techniques component is structured from the specific algorithms and models that are required for conducting analytics. The applications component includes the manners in which the techniques components improve teaching and learning. For example, a technique would be the recommendation algorithm of additional course content for learners. This technique, or a learner dropout risk prediction, often leads to the development of an application, such as personalized learning content that reflects learners' comfort with the subject area. The two components are not mutually exclusive, and they reflect the focus of researchers. A researcher specialized in statistics would be more interested in the creation of probability models for the identification of student performance (technique), whereas someone working on the social sciences would be more interested in the evaluation of how social networks form, based on technologies used in a course (application). Both cases though are of importance in the advance of learning analytics as a field (Siemens, 2013).

Baker and Yacef(2009) address the technique dimension of learning analytics/EDM in listing five primary areas of analysis:

- Prediction
- Clustering
- Relationship mining
- Distillation of data for human judgment
- Discovery with models

Bienkowski, Feng and Means (2014) offer five areas of learning analytics/EDM application:

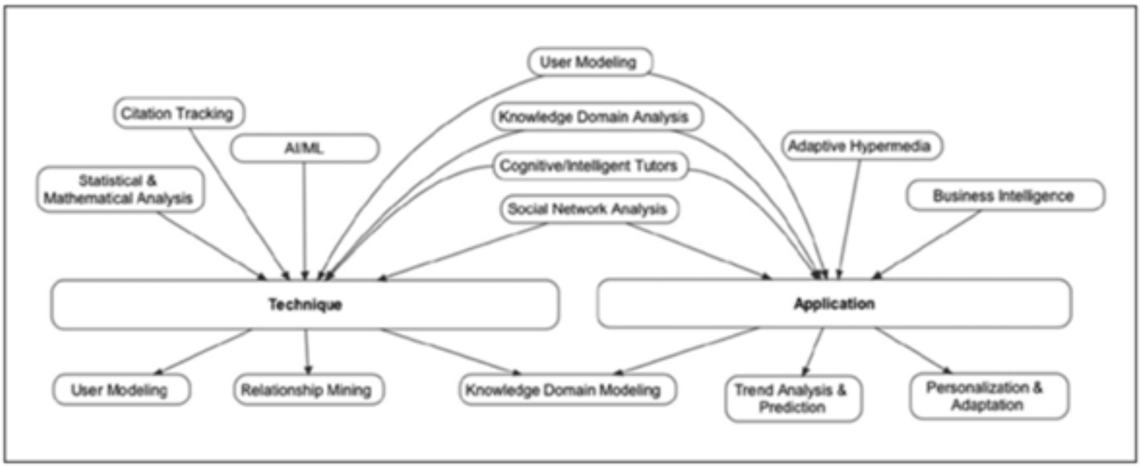
- Modeling user knowledge, behavior, and experience
- Creating profiles of users
- Modeling knowledge domains
- Trend analysis
- Personalization and adaptation

Baker and Yacef's (2009) model highlights various types of data mining activity that a researcher could conduct, while on the other hand, Bienkowski et al.'s (2014) model focuses on application on the above mentioned fields. The variations between the two models, assess the fact that we still find it difficult to make definitions and taxonomies of analytics. The lack of maturity of techniques and analytics models reflects the youth of learning analytics as a discipline (Siemens, 2013)

Techniques, especially those prominent in EDM, require tech savviness and make use mostly of machine learning and AI algorithms. Using statistical analysis, neural networks, and so on, we are able to gather data-based insights into learner behavior. This can be considered as basic research where discoveries are made through the use of models and algorithms. The discoveries made this way, then serve to the development of applications (Hershkovitz *et al.*, 2013).

Application areas of learning analytics involve user modeling, knowledge domain modeling, analysis of trends and patterns, and personalization and adaptation. Application areas are of great influence to the development of curriculum (such as ontologies that can be automatically evaluated against learner-produced work), social network analysis, and discourse analysis. The multidisciplinary roots of learning analytics and the current techniques and applications are detailed in Figure 6 (Siemens, 2013).

Figure 2.4: Historical influences in development of learning analytics.



Source: Siemens, 2004

Prominent analytics techniques are presented in Figure 5. We should note that analytics models and approaches are based mainly on traditional fields, as presented in Figure 5. More recent analytics models that target learning are being developed by learning analytics researchers, such as those tracking behavior, persistence, achievement (Macfadyen and Dawson, 2012), attention metadata (Wolpers *et al.*, 2007), participatory and peer learning (Clow and Makriyannis, 2011), and social learning analytics (Buckingham Shum, 2012).

2.2.3 DATA CAPTURE

A successful analytics activity requires data sources that can capture the complexity of the learning process. Activities such as success prediction of students or identification at-risk learners, intervention strategies, and adaptive learning require an analytics system that requires “quality” data. Ideally, data that are captured in the process of authentic learning (where collection is unobtrusive), that will provide researchers with a more detailed insight into the social and pedagogical dimensions of learner performance. To this day, learning analytics has relied mainly on two sources: student information systems (SIS; in generating learner profiles) and learning management systems (in tracking learner behavior and using it for prediction) (Siemens, 2013).

The expansion of data beyond SIS and LMS into a broad range of sources, including the physical interactions that currently do not leave data trails, is important in increasing the quality and depth of analysis (Siemens, 2013). One approach to increase data capture is through “sensor-based modeling of human communication networks” (Choudhury and Pentland, 2003). Sensor-based modeling involves wearable computing devices that capture social connections and conversations. Other approaches include “passive acquisition” of “physical activity data” through “pedometers, heart rate monitors, accelerometers, and distance trackers” (Lee and Thomas, 2011). With the emergence of mobile devices and wearable computing, such as smart watches, the quality of data available to analyzed has increased to levels never previously met.

Table 2.4: Learning Analytics (LA) techniques and applications.

LA Approach	Examples
Techniques	
Modeling	Attention metadata
	Learner modeling
	Behavior modeling
	User profile development
Relationship mining	Discourse analysis
	Sentiment analysis
	A/B testing
	Neural networks
Knowledge domain modeling	Natural language processing
	Ontology development
	Assessment (matching user knowledge with knowledge domain)
Applications	
Trend analysis and prediction	Early warning, risk identification
	Measuring impact of interventions
	Changes in learner behavior, course discussions, identification of error propagation
Personalization/adaptive learning	Recommendations: Content and social connections
	Adaptive content provision to learners
	Attention metadata
Structural analysis	Social network analysis
	Latent semantic analysis
	Information flow analysis

Source: Siemens, 2013

The role of real time data collection and human interaction with, and evaluation of, data before visualization and presentation are reflected in the process of making Google maps. In addition to collecting images through Google Street View cars, data and images are evaluated and updated by people in order to create maps that are current and accurate: “The sheer amount of human effort that goes into Google’s maps is just mind-boggling”(Madrigal, 2012). The majority of learning analytics models nowadays rely on data automatically collected, whose accessible data points, especially in relation to the learning context, often provide only static snapshots in time. To make a more effective, holistic, and transferable use of them, future analytics projects should have the capacity to include additional data through observation and human manipulation of the existing data sets (Siemens, 2013).

Additional data sets for researchers can be found from the use of open online courses. With the development of new models of learning (Downes, 2005), the adoption of active learning models has influenced the types of data available for analysis. Lecture hall data are limited to a few variables: who attended, seating patterns, student response system data, and observational data recorded by faculty or teaching assistants. On the contrary, when learners watch a video lecture, data are far more resourceful, providing data such as frequency of access, playback, pauses, and so on. With the use of an interactive learning system, such as edX, Codecademy or DataCamp, additional data can be provided about student errors or returns to videos for review. Anant Agarwal has stated that these platforms are a “particle accelerator for collecting data on learners and helping researchers to understand the learning process.”

When trying to capture learning as a holistic and social process, we ought to use more than a single data source or analytics method. A variety of analytic approaches can provide more information to educators and students than single data sources. In fields of network analysis, researchers are using multiple methods to evaluate activity within a network, including detailing different node types, direction of interaction, and human and computer nodes (Suthers and Rosen, 2011). These same techniques, drawing on multiple entities and sources of data and user interactions, must be adopted and evolved in learning analytics to further advance the field (Siemens, 2013).

A novel approach using big data, is often used in online courses delivered to grade school or college learners. Specifically, massive open online courses use learning analytics data to detect levels of engagement, track learner progress, and assign badges documenting achievement (Pecaric *et al.*, 2017).

2.3 GAMIFICATION IN E-LEARNING

E-learning is now considered as an integral part of the learning process of students involved in higher education. It doesn’t affect only universities that are involved in remote learning but is also systematically integrated into the student learning experience by predominately campus-based universities (Ellis, Ginns, & Piggott, 2009). E-learning, helps institutions achieve effects, such as a high degree of satisfaction, motivation, effectiveness and student efficacy. Nevertheless, many e-learning platforms do not actually meet these objectives due to the lack of knowledge of techniques and methods for the development of online information systems. Information system research states that user satisfaction is one of the most important factors in assessing the success of system implementation (Delon & Mclean, 1992). Students satisfaction in an e-learning environment, is affected by various factors. A variety of authors (Lewis, 2002; Arbaugh & Duray, 2002; Chen & Bagakas, 2003) have found that there are six factors that have an impact on satisfaction: students, teachers, course, technology, system design and environmental factors. Many others (Laurillard, 2002; Goodyear, Jones, Asensio, Hodgson, & Steeples, 2005), have researched e-learning in higher education and students experience. There are several reasons for poor efficiency, effectiveness, satisfaction and motivation of students in e-learning, with some of them being poorly managed projects, ignoring the main stages of the development of e-learning (analysis, planning, development, implementation and evaluation), the use of inappropriate motivational techniques, inadequate technical and technological implementation of e-learning, inappropriately selected personnel, incorrect data on demographic and other characteristics of students, and wrong graphical interface. Increasing the efficiency, effectiveness, motivation and engagement of students in e-learning can be achieved by gamification (Urh et al, 2014). Gamification applies elements associated with video games (game mechanics and game dynamics) in non-game applications. It aims to increase people’s engagement and to promote certain behaviors (Simões, Redondo, & Vilas, 2013). Attending to its technological nature, one of the fields where gamification may have a greater impact is online learning (Dominguez et al., 2013). The use of gamification in the field of e-learning is growing and gaining in popularity.

2.4 SUMMARY

In the preceded analysis, I review the definitions for learning and e-learning, along with the ones for key issues of this research, such as reflexive learning, tacit knowledge, and learning analytics. I pointed out the main frameworks on which I based my analysis, such as Laurillard's conversational framework for supporting the formal learning process, McClory's organizational learning loop, as well as the primary areas of analysis of the Learning Analytics sector. Additionally, I introduce the knowledge modelling concept of personalizing the learning process for individual students, a key element of the analysis that follows. The main conclusion of this literature review, is that what is missing from the application of analytics in e-learning, is the absence of a method that could easily improve the learning process and help the tutor realize if his teaching method has system failures, or teaching failures. This is what the following analysis will try to develop.

CHAPTER 3 METHODOLOGICAL APPROACH

In this research project, I aim to develop a method for modeling the learning process of students. During the simulation of the "beer game", the user has to keep track of 14 different variables that affect his two decisions: Decision for order, and Decision for production. The goal is to find a way to visualize the mental map the user makes during the simulation:

The student has assumed the role of the manager of a beer factory. His job is to control the weekly production of beer, in a way that maximizes the profit of the company throughout the two years of the simulation. The value of the variable "***Balance***" is each user's score.

In order to gather sufficient data, I performed two lab sessions with students from the University of Thessaly. These data will help me perform the necessary statistical and machine learning functions chosen to develop my method. Afterwards, I will attempt to cluster the users according to their learning behavior.

3.1 DATA COLLECTION AND PRE-PROCESSING

I used data from a number of students that ran the "beer game" in the Powersim simulation environment during the winter semester of 2019. 40 students of the undergraduate program of the Economics dpt. and the postgraduate program in "Applied Economics" assumed the role of production manager in a game simulating the operations of a beer making factory during the course of two years.

The simulation was developed by Vasilios Babaletsos (2018) during his undergraduate dissertation "Analysis of user decisions in educational game using python programming language". It includes a list of variables that the user observes in order to make decisions regarding the amount of production and the amount of orders.

Variables definition

Below I list all the variables of the experiment. Divided in Independent and Dependent, these are all the variables that are used for the simulation experiment, accompanied by the instructions given to the users before they participated in the experiment.

Independent Variables (results of the decisions the user makes and what he/she pays attention to in order to make his future decisions)

Table 3.1: List of independent variables

Beer Supply	Kegs
Cost of keeping beer	Euro/kegs/week
Completion of beer maturation	Kegs/week
Weekly lost sales	Kegs/week
Weekly income	Euro/week
Balance	Euro
Weekly sales	Kegs/week
Weekly cost	Euro/week
Total lost sales	Kegs
Cost of keeping raw materials	Euro/graincases/week
Reserve of raw materials	Graincases
Production process	Graincases/week
Production capacity of supplier	Graincases/week
Receipt of raw materials	Graincases/week
Reserve of raw materials	Graincases
Production process	Kegs/week
Weekly lost income	Euro/week
Weekly losses from lost sales	Euro/week
Delivery time of raw materials	weeks
Production cost	euro/keg

Dependent Variables (Decisions the user makes regarding the operation of the beer factory)

- Decision for production
- Decision for order

In order to produce one keg of beer, 4 cases of grains are required. Each week, an order is placed for the desired amount of raw materials. The supplier has to provide raw materials to other customers, so he can deliver a certain amount of raw materials (*Production capacity of supplier*). The amount of raw materials the supplier can provide is not the same throughout the year. The supplier always delivers the order **3 weeks** after it's been placed. The raw materials delivered, are added to the supply of raw materials the user already has. The time required for the production of beer is **4 weeks.**

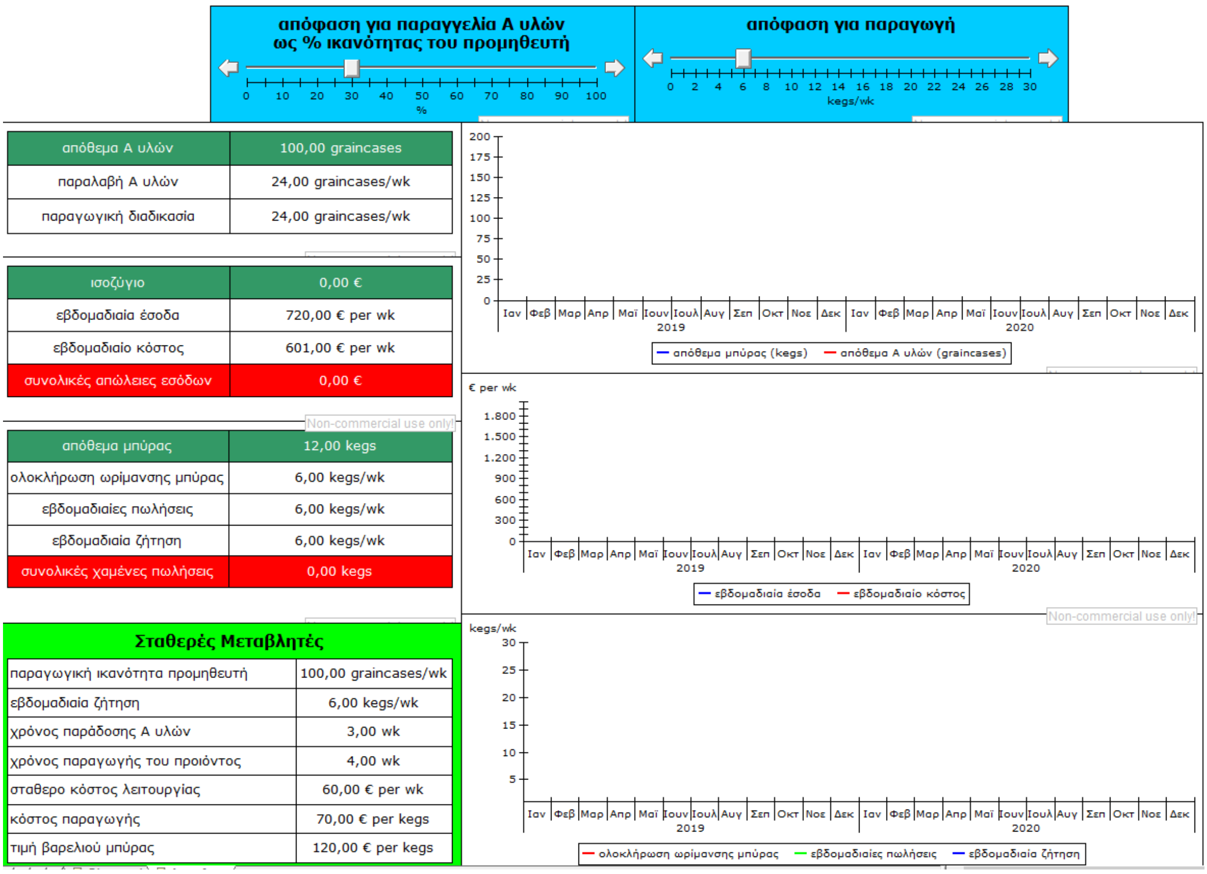
- Lost sales are the result of the weekly demand being bigger than the Beer supply. The difference between weekly demand and weekly sales gives the user the Lost Sales variable.
- Weekly demand differs from week to week due to seasonality.

Table 3.2: Simulation Variables Values

Selling price of each barrel (keg)	120 €
Production cost for each barrel	70 €
Cost of keeping beer *(per keg)*	Up to 20 kegs → 6€ 20 to 25 kegs → 8€ 25 to 30 kegs → 10€ 30 and more → 13€
Cost of raw materials	Decision <50% production capacity of supplier → 1,20€ Decision >50% → 1€ Decision > 75% → 0,85 €
Cost of keeping raw materials	Up to 100 materials → 0,25€ 100 and more → 0,50 €
Weekly cost of operation	60 €

Figure 3.1: Beer Game Simulation in Powersim

Source: Vasileios Babaletsos, Analysis of user decisions in educational game using python programming language



I filter out any users that did not run the simulation according to the instructions given or didn't make any decisions during the simulation. I then conclude to a data set derived from 18 students that was later used for the analysis.

- Number of initial users: 40
- Number of users that ran the simulation according to the instructions: 25
- Number of users that their results derived from non-singular regressions: 18

3.2 SOFTWARE TOOLS

For this study I used the following software:

- **Powersim**

  Powersim is a tool for modelling and simulation of dynamic systems. It can be used to study time continuous progress in a great number of areas, for example biology, economics, physics and ecology. The modelling is done by constructing a Powersim diagram, which is then used for simulating the research case.

- **R**

R is a programming language and free software environment for statistical computing and graphics supported by the R Foundation for Statistical Computing. The R language is widely used among statisticians and data miners for developing statistical software and data analysis. The libraries we used are the ones that offer linear and beta regression models, and the ones that are used for creating graphs.

- **R libraries**

The R libraries we used are the ones that are used to perform regression analysis and draw graphs:

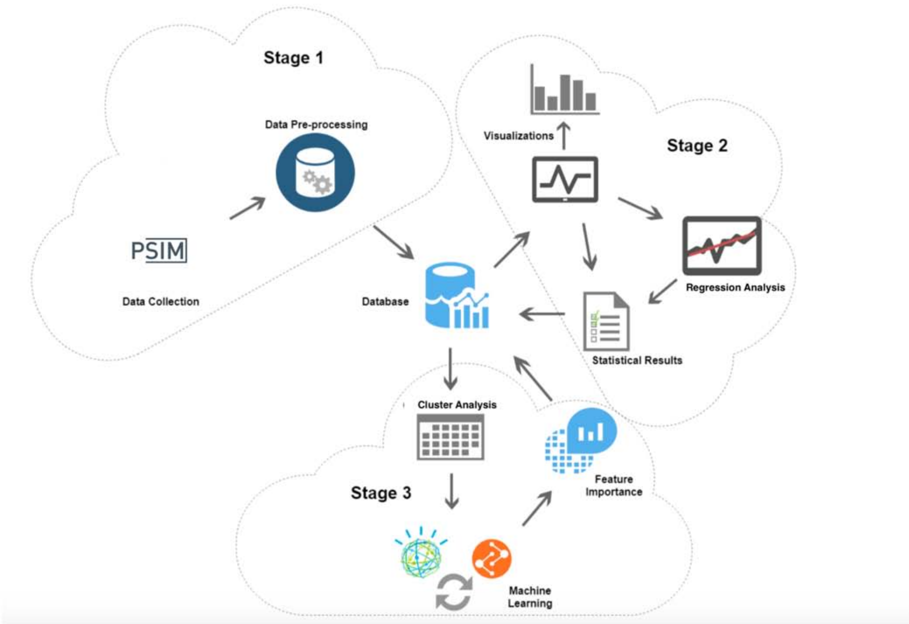
- **library(tidyverse)**
    - The "tidyverse" library collects some of the most versatile R packages: ggplot2, dplyr, tidyr, readr, purrr, and tibble. The packages work in harmony to clean, process, model, and visualize data.
    - We use the ggplot2 package: ggplot2 is an implementation of Leland Wilkinson's Grammar of Graphics—a general scheme for data visualization which breaks up graphs into semantic components such as scales and layers.
- **library (betareg)**
    - Beta regression for modeling beta-distributed dependent variables, e.g., rates and proportions. In addition to maximum likelihood regression (for both mean and precision of a beta-distributed response), bias-corrected and bias-reduced estimation as well as finite mixture models and recursive partitioning for beta regressions are provided.
- **library(RColorBrewer)**
    - Color palette for R graphs
- **library(readxl)**
    - Read Excel Files
- **library(FactoMineR)**
    - FactoMineR is an R package dedicated to multivariate Exploratory Data Anysis. It performs classical principal component methods: Principal Components Analysis (PCA), Correspondence analysis (CA), Multiple Correspondence Analysis (MCA) and clustering

- **library(factoextra)**
    - It provides some easy-to-use functions to extract and visualize the output of multivariate data analyses, including 'PCA' (Principal Component Analysis), 'CA' (Correspondence Analysis), 'MCA' (Multiple Correspondence Analysis), 'FAMD' (Factor Analysis of Mixed Data), 'MFA' (Multiple Factor Analysis) and 'HMFA' (Hierarchical Multiple Factor Analysis) functions from different R packages. It contains also functions for simplifying some clustering analysis steps and provides 'ggplot2' - based elegant data visualization.

3.3 ANALYTICS WORK-FLOW & METHODOLOGY

The analytics process is separated in three main stages.

Figure 3.2: Analytics Work-flow & Methodology



I. ***First stage - pre-processing***

a. The first stage of deals with the data acquisition and preprocessing. We collected the data during two lab sessions for undergrads and postgrads respectively.

II. ***Second stage - statistical analysis***

The second stage consists of the statistical analysis of the time series data we gathered. For each dependent variable we perform a regression analysis.

i. *Multiple regression*

In statistics, linear regression is a linear approach to modeling the relationship between a scalar response and one or more explanatory variables. The case of one explanatory variable is called simple linear regression. For more than one explanatory variable, the process is called multiple linear regression

ii. *Beta regression*

The beta regression model is useful for situations where the variable of interest is continuous and restricted to the interval (0, 1) and is related to other variables through a regression structure. These regressions will help us visualize the decisions each user made.

iii. Principal Components Analysis (PCA)

Principal Component Analysis (PCA) is an extremely powerful tool for compressing and synthesizing information, very useful when there is a large amount of quantitative data to process and interpret.

PCA is a factor analysis, in the sense that it produces factors (or main axes) which are linear combinations of the initial variables, hierarchical and independent of each other. These factors are sometimes called "latent dimensions". The main objective of the PCA is to detect the gatherings and the divergences between the individuals of the population studied, in this case we will seek the gatherings between the users, ie which are the users who are similar and which have a clear divergence.

III. ***Third Stage- Machine Learning Third Stage- unsupervised learning***

Unsupervised learning is a type of machine learning that looks for previously undetected patterns in a data set with no pre-existing labels and with a minimum of human supervision. In contrast to supervised learning that usually makes use of human-labeled data, unsupervised learning, also known as self-organization allows for modeling of probability densities over inputs. It forms one of the three main categories of machine learning, along with supervised and reinforcement learning. Semi-supervised learning a related variant, makes use of supervised and unsupervised techniques.

Two of the main methods used in unsupervised learning are principal component and cluster analysis. Cluster analysis is used in unsupervised learning to group, or segment, datasets with shared attributes in order to extrapolate algorithmic relationships. Cluster analysis is a branch of machine learning that groups the data that has not been labelled, classified or categorized. Instead of responding to feedback, cluster analysis identifies commonalities in the data and reacts based on the presence or absence of such commonalities in each new piece of data. This approach helps detect anomalous data points that do not fit into either group.

3.4 SUMMARY

These previous paragraphs were used to further explain our experiment and the actions that will be taken for the Data Analysis that will follow. Firstly, we saw the details of the experiment that we conducted, added by a list of the software that was used. An extensive catalog of software libraries is mentioned, as well as the three stages of the workflow of this research. In the next chapter this methodology is applied on the data gathered from the experiment. Visualizations of each user and the ensemble of the class, will show a representation of the learning process for this simulation.

CHAPTER 4 DATA ANALYSIS

Using the methods described above, I will try to develop the model in question. 3 methods were used to perform this analysis: multiple regression will help me model the first dependent variable and construct a spider graph for each user's decision during his/her simulation. Beta regression is used for the modeling of the second dependent variable and the construction of the spider graphs for each run of each user's simulation. Finally, the PCA method is used to cluster the users into groups according to their behavior.

4.1 MULTIPLE REGRESSION FOR DECISION FOR PRODUCTION

For the first dependent variable, multiple regression is used to extract the normalized regression coefficient to plot a spider graph. These coefficients allow the computation of the degree that each independent variable is taken into account by the decision maker (i.e. the student); the variable with the largest standard coefficient influences the variation of the dependent variable (the decision) more than the other independent variables and so on.

Some coefficients are left out of the model because of singularities. When some of the variables have perfect collinearity (some of the categorical variables occur together 100% of the time), we have to leave them out of the model selection. Finally, the best fit is selected (model selection), and with the use of the normalized regression coefficient the spider graph is created.

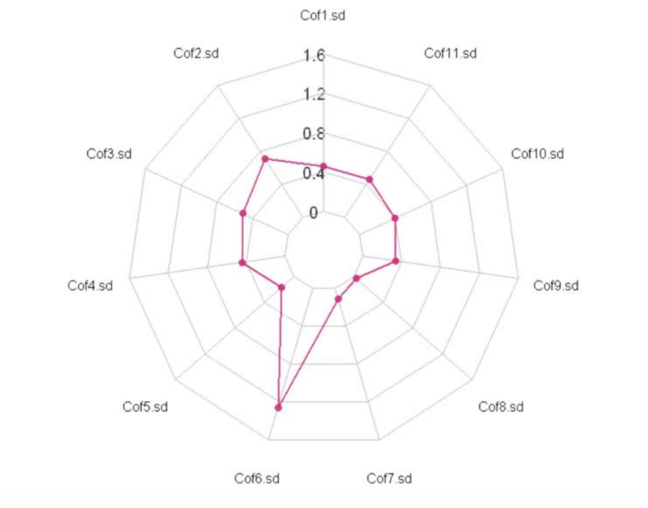
Table 4.1: Coefficient – Variable definition for Multiple Regression

Cof1.sd	Beer Supply
Cof2.sd	Completion of beer maturation
Cof3.sd	Weekly lost sales
Cof4.sd	Weekly income
Cof5.sd	Balance
Cof6.sd	Weekly Cost
Cof7.sd	Total lost sales
Cof8.sd	Cost of keeping raw materials
Cof9.sd	Receipt of raw materials
Cof10.sd	Reserve of raw materials
Cof11.sd	Production process
Cof12.sd	Production capacity of supplier

4.1.1 Measuring the factors affecting Decision for production

By using the beta coefficient of each variable, I create a spider graph that represents all the user's actions during the full duration of the simulation. The bigger the coefficient, the more this variable mattered to user's decision.

Figure 4.1: Decision for production Spider Graph



The spider graphs adds to the understanding of each user's behavior. Each variable (that is represented by a coefficient of the regression), has a point on the graph. The bigger the coefficient, the bigger the point, leading to the result that this variable has a bigger influence on the user's decision. On the above figure, the user pays attention to Coefficient 6, the weekly cost variable, that mostly shaped his ***Decision For Production***.

Some patterns can easily be derived from the behavior of students. There is a group that paid attention mostly to the ***Reserve of Raw Materials*** and ***Beer Supply***. A second group that took into account the ***Weekly Cost*** variable more than the others. A third one paying attention to **Weekly Lo*st Sales, Production Process, Receipt Of Raw Materials*** and ***Total Lost Sales***. Two users paid almost equal attention to all the variables. And finally, one user that considered ***Weekly Lost Sales*** and ***Total Lost Sales*** for his decision. The spider graphs for this decision of all the users are located in Appendix A.

The second dependent variable is a percentage variable. Thus, a beta regression is performed to calculate the beta coefficients that will be used to draw the spider-graphs for each simulation run of the user.

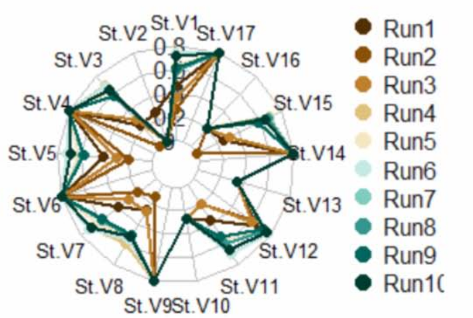
Table 4.2: Coefficient – Variable definition for Beta Regression

St.V1	Beer Supply
St.V2	Cost of keeping beer
St.V3	Completion of beer maturation
St.V4	Weekly lost sales
St.V5	Weekly income
St.V6	Balance
St.V7	Weekly sales
St.V8	Weekly cost
St.V9	Total lost sales
St.V10	Cost of keeping raw materials
St.V11	Receipt of raw materials
St.V12	Reserve of raw materials
St.V13	Weekly demand
St.V14	Weekly lost income
St.V15	Production process
St.V16	Production capacity of supplier
St.V17	Weekly losses from lost sales

4.1.2 Measuring the factors affecting Decision for order

By using the beta coefficient of each variable, a spider graph that represents all the user's actions during each run of the simulation is created. The bigger the coefficient, the more this variable mattered to user's decision.

Figure 4.2: Decision for order Spider Graph



This spider graph visualizes the user behavior for each of the runs the user did during the simulation. Each run is represented by a different color, and each variable by a different coefficient. This graph helps to better understand the evolution of the user's decisions during the simulation. From the above figure, a clear pattern on the variables the user takes into account can be extracted. The ones he/she pays less attention, are ***Production capacity of the supplier***, ***Weekly demand***, ***Cost of keeping raw materials***, and ***Cost of keeping beer***. Apart from this, there is an evolution on the value of the coefficients of some variables. For example, ***Weekly***

income plays a smaller role on the user decision during the early runs, but its importance rises as time passes by. On the other hand, the user's attention on the ***Balance*** variable is unchanged and high.

For this decision variable, the users are grouped into 3 distinct groups:

- The first one consists of users that don't change their actions much during each run and pay attention to the same variables through and through.
- The second one is the one that experiments during each run, delivering some extreme values on their spider graphs.
- The third is the residual user, who is kept in the final results as a reminder that there is always someone that doesn't coincide with the group.

The spider graphs for this decision of all the users are located in Appendix B.
The next paragraph shows how the users are clustered. The observations of the clustering analysis are in line with the observations of this paragraph, confirming the initial speculation for the grouping of the participants in 3 different groups of behavior.

4.2 CLUSTERING OF USER BEHAVIOR

To cluster the users into groups of similar behaviors, a principal components analysis is performed. R provides functions to draw the scree plot of eigenvalues, the correlation circle, and the graph of individuals. Then the Factor map of the individuals is created, that separates the users into 3 groups.

The scree plot of eigenvalues is used to decide the number of clusters that will be used. 3 is the number that comes up, which is then approved by the results of the correlation circle.

- The first cluster of variables, is the one that includes the ***Production Process*** and ***Balance***.
- Another cluster is the one that includes ***Weekly Lost Sales***, ***Total Lost Sales*** and ***Production Capacity of Supplier***.
- The third one includes all the others.

The Individuals factor map concludes to two main groups and the residuals, a result that coincides with the observations of the previous paragraph.
Some notes on the following plots:

Figure 10 represents the Scree plot of eigenvalues; In multivariate statistics, a scree plot is a line plot of the eigenvalues of factors or principal components in an analysis. The procedure of finding statistically significant factors or components using a scree plot is also known as a scree test.

Figures 11 and 12 represent the correlation circles of variables and individuals respectively; In every correlation circle, each measured variable is shown as a vector, which signals the combined strength of the relationships between the measured variable and two PCs (vector length) and whether these relationships are positive or negative (vector direction).

Figure 13 represents the variables factor map which presents the amount of variance from each parameter on the total variance in the PCA.

Figure 4.3: Scree plot of eigenvalues

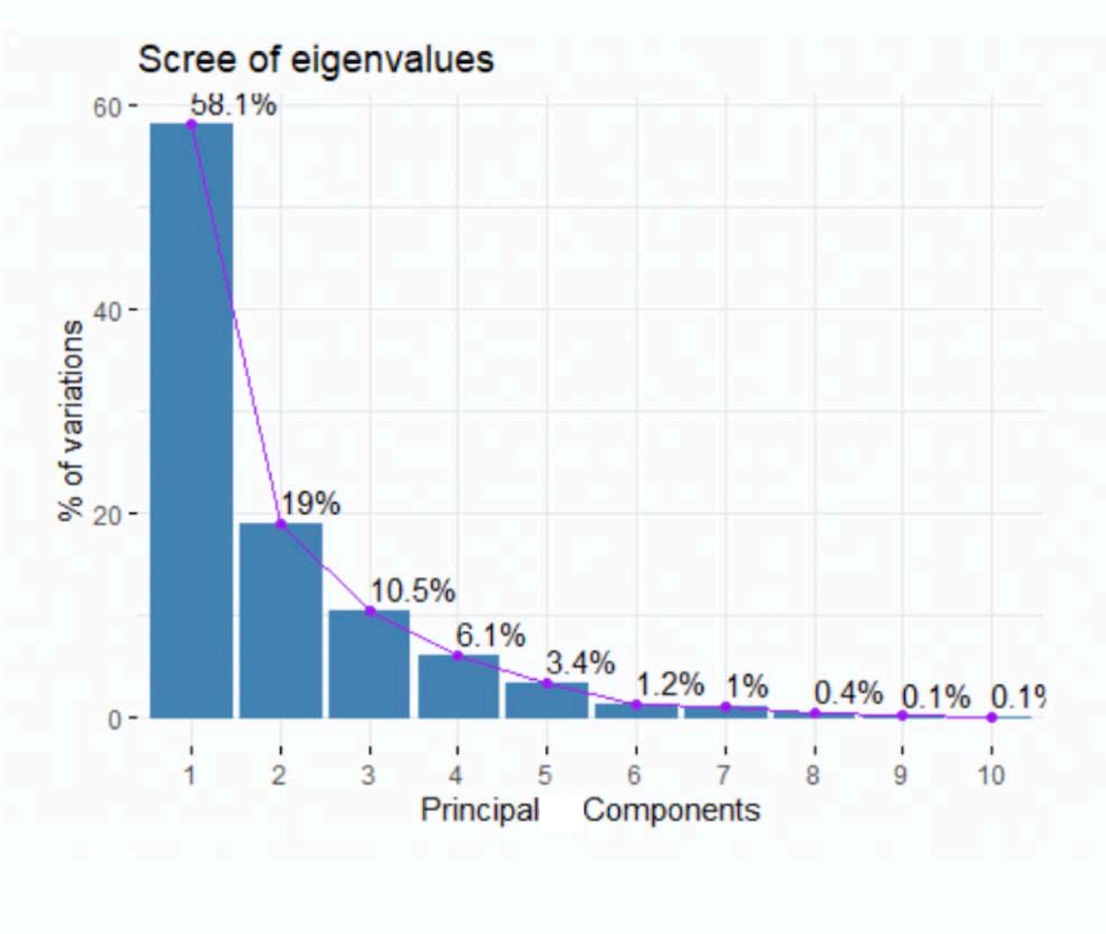


Figure 4.4: Correlation circle of variables

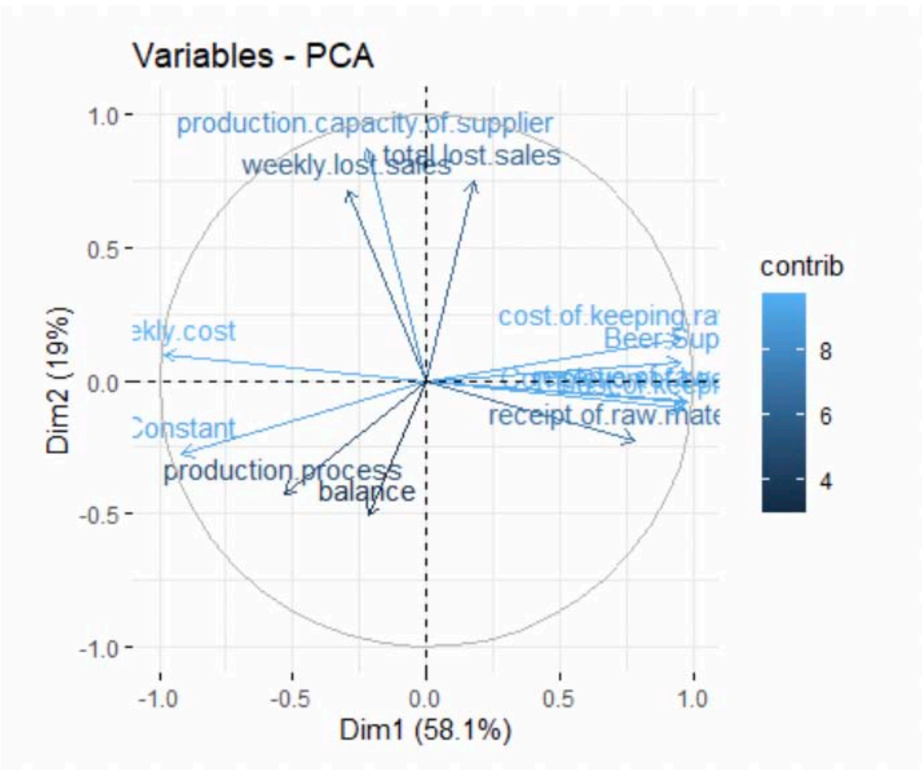


Figure 4.5: Correlation circle of individuals

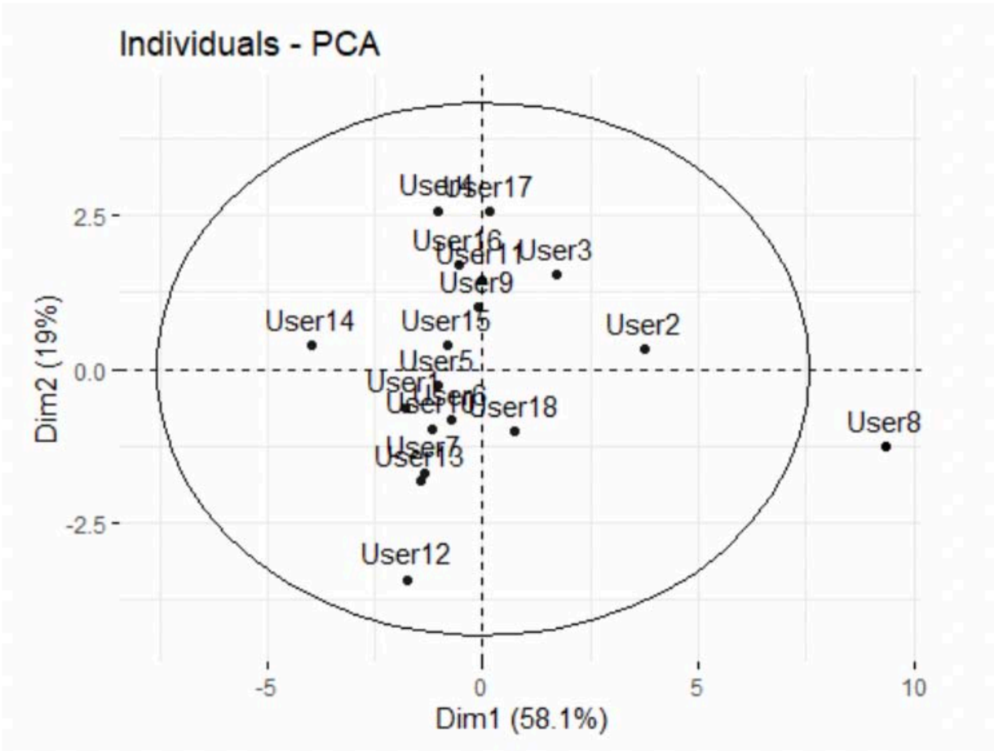
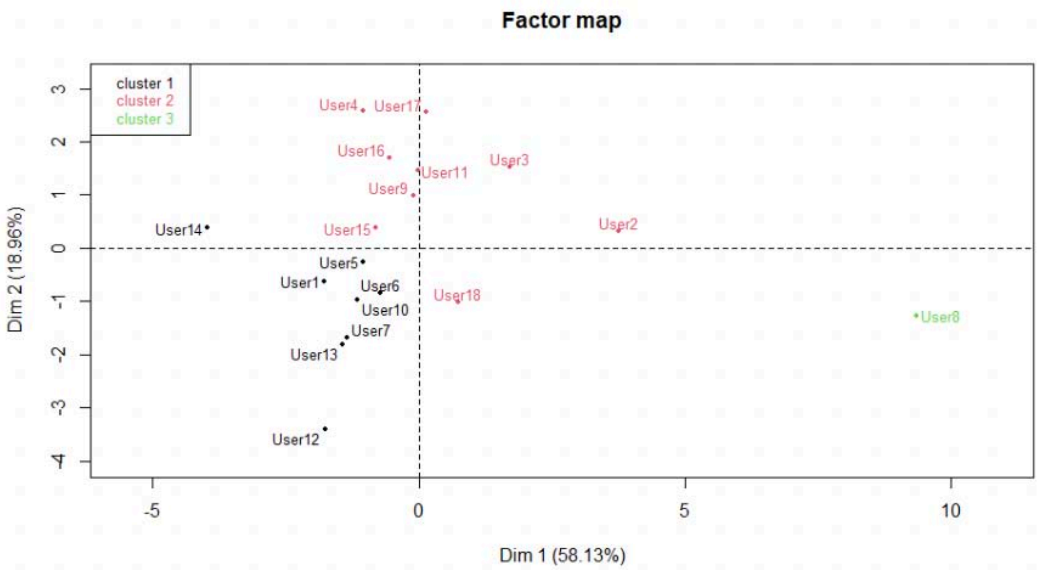


Figure 4.6: Factor map of the individuals



4.3 SUMMARY

This chapter listed 3 different options of visualization of the learning process during the beer game simulation. The use of the regression coefficients to better understand and measure the impact of the independent variables on the user decisions; In the case of the first dependent variable, the coefficient derived from multiple regression and on the second from beta regression. Finally, user behaviors were grouped in clusters with PCA, and in our case study, users were grouped in 3 clusters.

CHAPTER 5 CONCLUSIONS

In this dissertation, I tried to find a meaningful way of modelling the learning process of a student and/or a “classroom”. First, I reviewed the literature on the relevant theoretical framework. Laurillard’s learning process model is where this whole analysis is based upon, together with the 5 disciplines of Senge, supported by Siemens’s research on Learning Analytics processes and tools. Subsequently, I described the main methods that were used for the data analysis. there are many different software options, such as SPSS, eViews, or Tableau, but in order to make the method easier for further development, I decided to use the R programming language, that is mainly used for Machine Learning processes.

The code developed, performs three main actions:

- Draw spider-graphs that show what each user “sees” during all the simulation runs (regression analysis for the first dependent variable).
- Draw spider-graphs that show what each user “sees” during each run of the simulation (beta regression of the second dependent variable).
- Draw the factor map that shows how the “classroom” is separated into different groups of behaviors.

The results helped me conclude that there are 2 distinct groups of users, each running the simulation with a different perspective. This helps the tutor conclude in what the “classroom” knows, and how the behavior of each user excels throughout the simulation. The users appear to learn from run to run, developing a more efficient strategy. This finding coincides with the literature which states that learning can become more efficient with experience, as stated in the reflexive learning tradition with Argyris, Senge and Laurillard.

SUGGESTIONS FOR FUTURE RESEARCH

This dissertation was a first step towards the analysis of data provided by learning simulations. There is a lot of work to be made in order for it to have a market value, including: The development of a user-friendly simulation interface is of the essence since it will help the students concentrate on the learning process, and not to spend time to understand the use of the platform.

The use of fewer variables, for a less complex regression model to be made. This requires a much bigger number of users and simulation runs, along with collaboration between tutors to decide the most important parts of the simulation.

The development of a platform that will include a variety of simulations, backed by the developed algorithm, that will automate the process of information sharing to the tutor. The final step would be an automated process through which a “classroom” runs a simulation and the tutor gets several results, such as:

- Clustering of the students
- Learning development of the “classroom”
- Learning development of each user

REFERENCES

Allen, I. E. and Seaman, J. (2008) *Staying the course. Online Education in the United States, 2008, Sloam Consortium*. doi: 10.1242/jeb.049304.

Ally, M. (2004) *Foundations of Educational Theory for Online Learning*, *Theory and practice of online learning*. doi: 10.1007/978-1-4020-8299-3_8.

Anderson, J. R. *et al.* (1995) 'Cognitive Tutors: Lessons Learned', *Journal of the Learning Sciences*, 4(2), pp. 167–207. doi: 10.1207/s15327809jls0402_2.

Andrews, R. and Haythornthwaite, C. (2019) 'The Sage Handbook of E-learning Research', (April).

Arbaugh, J. B., & Duray, R. (2002). Technological and structural characteristics, student learning and satisfaction with web-based courses – An exploratory study of two on-line MBA programs. Management Learning, 33(3), 331–347.

Argyris, C. and Schon, D. A. (2012) *Organizational Learning Theory*, *Encyclopedia of the Sciences of Learning*. doi: 10.1007/978-1-4419-1428-6_5176.

Arnold, K. (2010) *Signals: Applying Academic Analytics*, *EDUCAUSE*.

Baker, R. S. J. D. and Yacef, K. (2009) 'The State of Educational Data Mining in 2009 : A Review and Future Visions', *Journal of Educational Data Mining*, 1(1), pp. 3–16. doi: http://doi.ieeecomputersociety.org/10.1109/ASE.2003.1240314.

Barnett, B. G. and O'Mahony, G. R. (2006) 'Developing a culture of reflection: implications for school improvement', *Reflective Practice*, 7(4), pp. 499–523. doi: 10.1080/14623940600987130.

Bienkowski, M., Feng, M. and Means, B. (2014) 'Enhancing teaching and learning through educational data mining and learning analytics: An issue brief', *Educational Improvement Through Data Mining and Analytics*, pp. 1–60.

Biggs, J., Kember, D. and Leung, D. Y. P. (2001) 'The revised two-factor Study Process Questionnaire: R-SPQ-2F', *The British journal of educational psychology*, 71, pp. 133–149. doi: 10.1348/000709901158433.

Börner, K., Chen, C. and Boyack, K. W. (2003) 'Visualizing knowledge domains', *Annual Review of Information Science and Technology*, 37, pp. 179–255. doi: 10.1002/aris.1440370106.

Boud, D. and Walker, D. (1998) 'Promoting Reflection in Professional Courses: The challenge of context', *Studies in Higher Education*, 23(2), pp. 191–206. doi: 10.1080/03075079812331380384.

De Bra, P., Brusilovsky, P. and Houben, G.-J. (1999) 'Adaptive hypermedia', *ACM Computing Surveys (CSUR)*, 31(4es), p. 12. doi: 10.1145/345966.345996.

Bruno, A., Galuppo, L. and Gilardi, S. (2011) 'Evaluating the reflexive practices in a learning experience', *European Journal of Psychology of Education*, 26(4), pp. 527–543. doi: 10.1007/s10212-011-0061-x.

Buckingham Shum, S. (2012) 'Learning Analytics: Policy Briefing', (November), pp. 1–12. Available at: http://iite.unesco.org/files/policy_briefs/pdf/en/learning_analytics.pdf.

Chen, W. L. C., & Bagakas, J. G. (2003). Understanding the dimensions of self-exploration in web-based learning environments. Journal of Research on Technology in Education, 34(3), 364–373.

Chen, C. and Paul, R. J. (2001) 'Visualizing a knowledge domain's intellectual structure', *Computer*, 34(3), pp. 65–71. doi: 10.1109/2.910895.

Choudhury, T. and Pentland, A. (2003) 'Sensing and modeling human networks using the sociometer', *Proceedings - International Symposium on Wearable Computers, ISWC*, pp. 216–222. doi: 10.1109/iswc.2003.1241414.

Clow, D. and Makriyannis, E. (2011) 'ISpot analysed: Participatory learning and reputation', *ACM International Conference Proceeding Series*, pp. 34–43. doi: 10.1145/2090116.2090121.

Cooper, A. (2012) 'A Brief History of Analytics', *CETIS Analytics Series*, 1(9), pp. 1–21. Available at: http://publications.cetis.ac.uk/t/analytics.

Cunliffe, A. L. (2004) 'On becoming a critically reflexive practitioner', *Journal of Management Education*, 28(4), pp. 407–426. doi: 10.1177/1052562904264440.

Delon, W., & Mclean, E. (1992). Information systems success: The quest for the dependent variable. Information Systems Research, 3(1), 60–95.

Dewey, J. (2005) 'The Copernican revolution (1929)', *James and Dewey on Belief and Experience*.

Dominguez, A., Saenz-De-Navarrete, J., De-Marcos, L., Fernández-Sanz, L., Pages, C., & Martinez-Herráiz, J. J. (2013). Gamifying learning experiences: practical implications and outcomes. Computers & Education, 63, 380–392.

Downes, S. (2005) *E-learning 2.0, eLearn Magazine*.

E Rich (1979) 'User modeling via stereotypes', *Cognitive Science*, 354(3597), pp. 329–354. Available at: https://www.sciencedirect.com/science/article/pii/S0364021379800129.

Ellis, R. A., Ginns, P., & Piggott, L. (2009). E-learning in higher education: some key aspects and their relationship to approaches to study. Higher Education Research & Development, 28(3), 303–318.

Fagnant, A. and Crahay, M. (2011) 'Theories of mind and personal epistemology: Their interrelation and connection with the concept of metacognition', *European Journal of Psychology of Education*, 26(2), pp. 257–271. doi: 10.1007/s10212-010-0045-2.

Fayyad, U., Piatetsky-Shapiro, G. and Smyth, P. (1996) 'From Data Mining to Knowledge Discovery in Databases', *AI Magazine*.

Fischer, G. (2001) 'User modeling in human-computer interaction', *User Modeling and User-Adapted Interaction*, 11(1–2), pp. 65–86. doi: 10.1023/A:1011145532042.

Fonagy, Peter Target, M. (1996) 'Playing with reality: I. Theory of mind and the normal development of psychic reality.', *The International Journal of Psychoanalysis*.

Fonagy, P. and Target, M. (1997) 'Attachment and reflective function: Their role in self-organization', *Development and Psychopathology*, 9(4), pp. 679–700. doi: 10.1017/s0954579497001399.

Garfield, E. (1955) ‘Citation indexes for science’, *Science*, 122(3159), pp. 108–111. doi: 10.1126/science.122.3159.108.

Gleaves, A., Walker, C., & Grey, J. (2008) ‘Using digital and paper diaries for assessment and learning purposes in higher education: A case of critical reflection or constrained compliance?’, *Assessment & Evaluation in Higher Education*.

Goodyear, P., Jones, C., Asensio, M., Hodgson, V., & Steeples, C. (2005). Networked learning in higher education: Students’ expectations and experiences. Higher Education, 50, 473–508.

Gredler, M. (2009) *Learning and instruction: Theory into Practice, Learning and Instruction*.

Haythornthwaite, C. (2002) ‘Strong, weak, and latent ties and the impact of new media’, *Information Society*, 18(5), pp. 385–401. doi: 10.1080/01972240290108195.

HEFCE (2009) *Enhancing learning and teaching through the use of technology: A revised approach to HEFCE’s strategy for e-learning.*

Hershkovitz, A. *et al.* (2013) ‘Discovery With Models’, *American Behavioral Scientist*, 57(10), pp. 1480–1499. doi: 10.1177/0002764213479365.

Hubbs, D. L. and Brand, C. F. (2005) ‘The Paper Mirror: Understanding Reflective Journaling’, *Journal of Experiential Education*, 28(1), pp. 60–71. doi: 10.1177/105382590502800107.

Ifenthaler, D. and Seel, N. M. (2012) ‘Encyclopedia of the Sciences of Learning’, *Encyclopedia of the Sciences of Learning*, (January). doi: 10.1007/978-1-4419-1428-6.

JISC (2004) *Effective practice with e-learning: A good practice guide in designing for learning.*

Kember, D. *et al.* (2000) ‘Development of a questionnaire to measure the level of reflective thinking’, *Assessment and Evaluation in Higher Education*, 25(4), pp. 381–395. doi: 10.1080/713611442.

Kember, D. *et al.* (2008) ‘A four-category scheme for coding and assessing the level of reflection in written work’, *Assessment and Evaluation in Higher Education*, 33(4), pp. 369–379. doi: 10.1080/02602930701293355.

Kirkwood, J. (2009) ‘Motivational factors in a push-pull theory of entrepreneurship’, *Gender in Management*, 24(5), pp. 346–364. doi: 10.1108/17542410910968805.

Krämer, B., and S. (2001) ‘Components and tools for on-line education.’, *European Journal of Education 36(2):195– 222.*

Kreber, C. (2005) ‘Reflection on teaching and the scholarship of teaching: Focus on science instructors’, *Higher Education*, 50(2), pp. 323–359. doi: 10.1007/s10734-004-6360-2.

Kumar, S. (2012) ‘Analyzing the Facebook workload’, *Proceedings - 2012 IEEE International Symposium on Workload Characterization, IISWC 2012*, pp. 111–112. doi: 10.1109/IISWC.2012.6402911.

Lalonde, C. E. and Chandler, M. J. (2002) ‘Children’s understanding of interpretation’, *New Ideas in Psychology*, 20(2–3), pp. 163–198. doi: 10.1016/S0732-118X(02)00007-7.

Laurillard, D. (2004) *Rethinking university teaching, a conventional framework for the effective use of learning technologies, 2nd edition (Book).*, *Teaching in Higher Education*. Available at: http://search.ebscohost.com/login.aspx?direct=true&AuthType=ip,cookie,shib&db=ehh&AN

=12531726&site=eds-live&scope=site&custid=ncirlib.

Lee, V. R. and Thomas, J. M. (2011) ‘Integrating physical activity data technologies into elementary school classrooms’, *Educational Technology Research and Development*, 59(6), pp. 865–884. doi: 10.1007/s11423-011-9210-9.

Lewis, C. (2002). Driving factors for e-Learning: an organizational perspective. Perspectives, 6(2), 50–54.

Macfadyen, L. P. and Dawson, S. (2012) ‘Why e-Learning Analytics Fail’, 15, pp. 149–163.

Madrigal, A. (2012) ‘How Google Builds Its Maps—and What It Means for the Future of Everything’, *The Atlantic*.

Mamede, S. and Schmidt, H. G. (2004) ‘The structure of reflective in medicine’, *Medical Education*, 38(12), pp. 1302–1308. doi: 10.1111/j.1365-2929.2004.01917.x.

Mann, K., Gordon, J. and MacLeod, A. (2009) ‘Reflection and reflective practice in health professions education: A systematic review’, *Advances in Health Sciences Education*, 14(4), pp. 595–621. doi: 10.1007/s10459-007-9090-2.

Mayo, J. A. (2004) ‘Using miniautobiographical narration in applied psychology to personalize course content and improve conceptual application’, *Journal of Constructivist Psychology*, 17(3), pp. 237–246. doi: 10.1080/10720530490447149.

Means, B., Toyama, Y., Murphy, R., Bakia, M., and Jones, K. (2009) ‘Evaluation of evidence-based practices in online learning: A meta-analysis and review of online learning studies.’, *Washington, DC: US Department of Education.*

Mezirow, J. (1991) ‘Transformative Dimensions of Adult Learning’, *Adult Education Quarterly*.

Milgram, S. (1967) ‘The Small World Problem’, *Psychology Today*.

Monroe, W. (2009) ‘Ambient Insight Research, US self-paced e-learning market’.

Moon, J. A. (2013) *A Handbook of Reflective and Experiential Learning, A Handbook of Reflective and Experiential Learning*. doi: 10.4324/9780203416150.

Pachler, N. *et al.* (2009) *Mobile Learning: Structures, Agency, Practices: Struktures, Agency, Practices [Gebundene Ausgabe]*. Available at: http://www.amazon.de/Mobile-Learning-Structures-Practices-Struktures/dp/1441905847/ref=sr_1_cc_1?s=aps&ie=UTF8&qid=1327279574&sr=1-1-catcorr.

Pachler, N. (2010) ‘The socio-cultural ecological approach to mobile learning: An overview.”’.

Pachler, N. and Daly, C. (2011) *Key Issues in e-Learning: Research and Practice*.

Pecaric, M. *et al.* (2017) ‘A big data and learning analytics approach to process-level feedback in cognitive simulations’, *Academic Medicine*, 92(2), pp. 175–184. doi: 10.1097/ACM.0000000000001234.

Perry, W. (1970) *Forms of intellectual and ethical development in the college years: A scheme.*

Reis, H., Sprecher, S. and Fingerman, K. L. (2013) ‘Weak Ties’, *Encyclopedia of Human Relationships*, 78(6), pp. 1360–1380. doi: 10.4135/9781412958479.n556.

Ronghuai Huang • Kinshuk • J. Michael Spector (2013) *Reshaping Learning*.

Sax, P. (2006) 'Developing Preferred Stories of Identity as Reflective Practitioners', *Journal of Systemic Therapies*, 25(4), pp. 59–72. doi: 10.1521/jsyt.2006.25.4.59.

Schön, D. A. (1983) *The Reflective Practitioner: How Professionals Think in Action, New York: Basic Books*.

Seel, N. M. and Al-diban, S. (2000) 'Mental Models & Instructional Planning', *Integrated and Holistic Perspectives on Learning, Instruction and Technology*, pp. 129–158.

Senge, P. M. (2004) 'The Fifth Discipline:The Art And Practice Of The Learning Organization'.

Shen, Z., Tan, S. and Siau, K. (2019) 'Use of mental models and cognitive maps to understand students' learning challenges', *Journal of Education for Business*. Routledge, 94(5), pp. 281–289. doi: 10.1080/08832323.2018.1527748.

Siegler, R. S. (2007) 'Learning about learning', *Appraising The Human Developmental Sciences: Essays in Honor of Merrill-Palmer Quarterly*, 8, pp. 67–82. doi: 10.4324/9781315768045-13.

Siemens, G. (2013) 'Learning Analytics: The Emergence of a Discipline', *American Behavioral Scientist*, 57(10), pp. 1380–1400. doi: 10.1177/0002764213498851.

Simões, J., Redondo, R. D., & Vilas, A. F. (2013). A social gamification framework for a K-6 learning platform. Computers in Human Behavior, 29, 345–353.

Sobral, D. T. (2001) 'Medical students' reflection in learning in relation to approaches to study and academic achievement', *Medical Teacher*.

Suthers, D. and Rosen, D. (2011) 'A unified framework for multi-level analysis of distributed learning', *ACM International Conference Proceeding Series*, pp. 64–74. doi: 10.1145/2090116.2090124.

Urh, M., & Jereb, J. (2014). Learning habits in higher education. Procedia-Social and Behavioral Sciences, 116, 350–355.

Warin, J. *et al.* (2006) 'Resolving identity dissonance through reflective and reflexive practice in teaching', *Reflective Practice*.

Wellman, B. (1999) *Networks In The Global Village: Life In Contemporary Communities*.

Wolpers, M. *et al.* (2007) 'Tracking Actual Usage: The Attention Metadata Approach', *Educational Technology and Society*, 10(3), pp. 106–121.

Wong, F. K. *et al.* (1995) 'Assessing the level of student reflection from reflective journals', *Journal of Advanced Nursing*, 22(1), pp. 48–57. doi: 10.1046/j.1365-2648.1995.22010048.x.

APPENDIX

This Appendix includes all visualizations of the user simulations

A. Spider Graphs for the regression betas of the "Decision For Production"

Figure A1

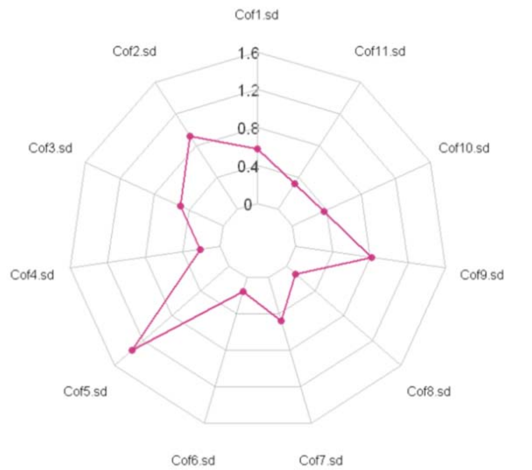


Figure A2

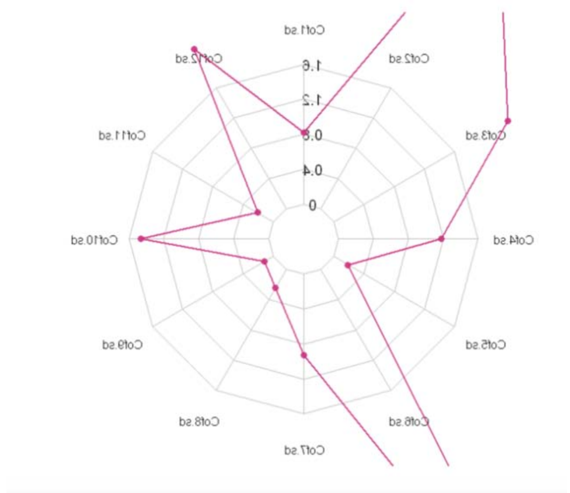


Figure A3

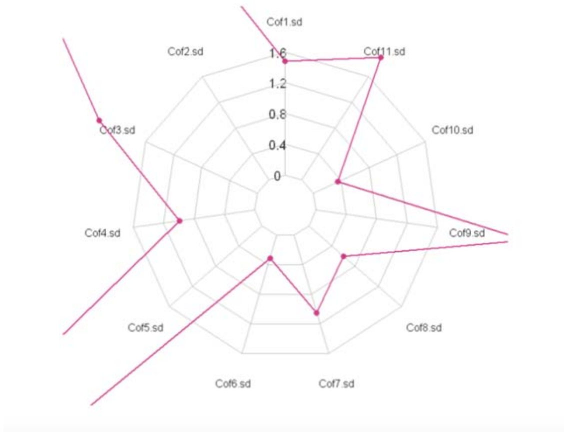


Figure A4

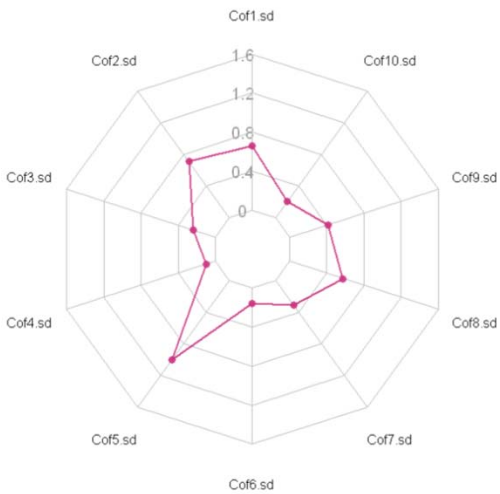


Figure A5

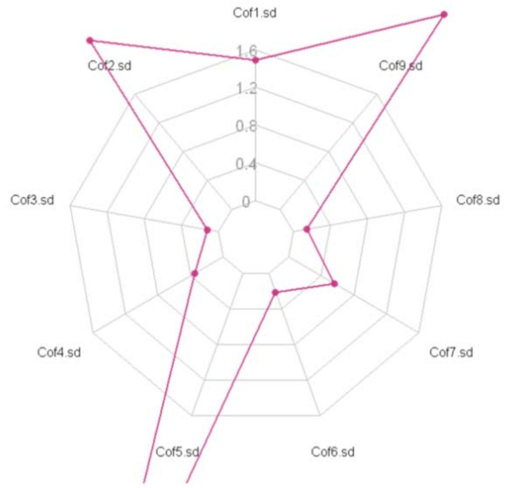


Figure A6

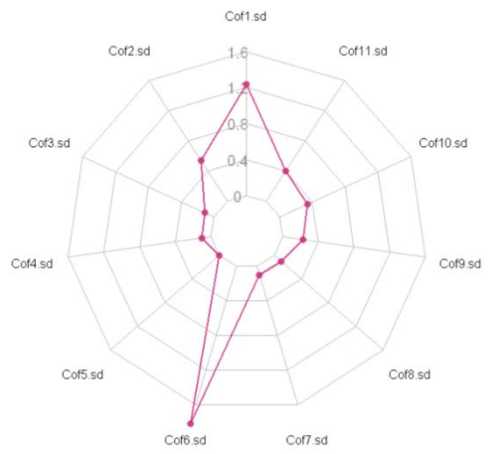


Figure A7

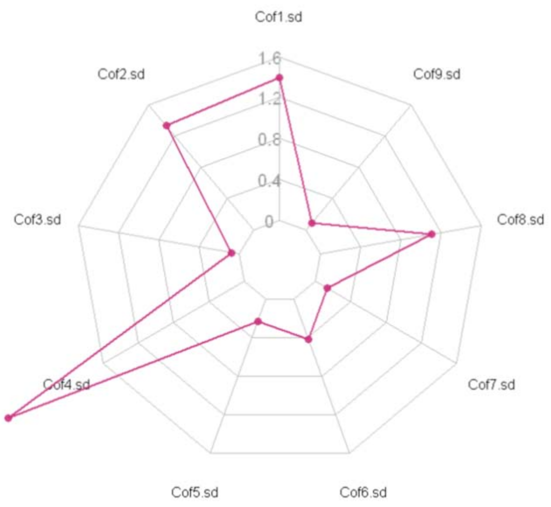


Figure A8

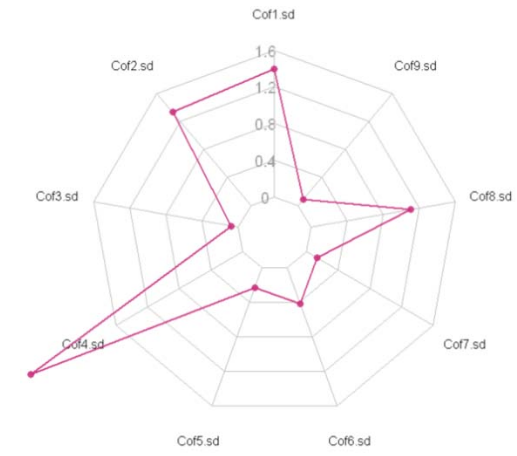


Figure A9

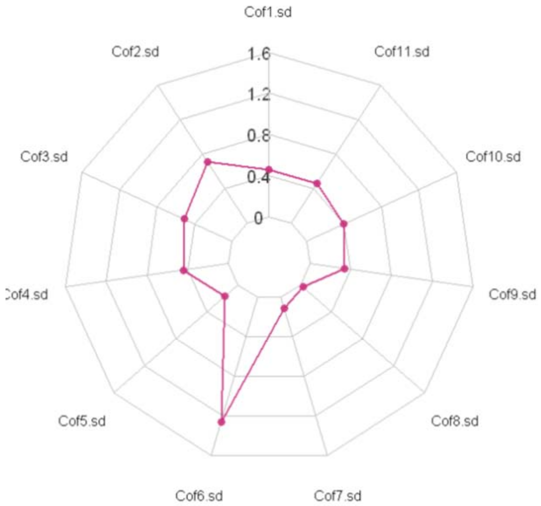


Figure A10

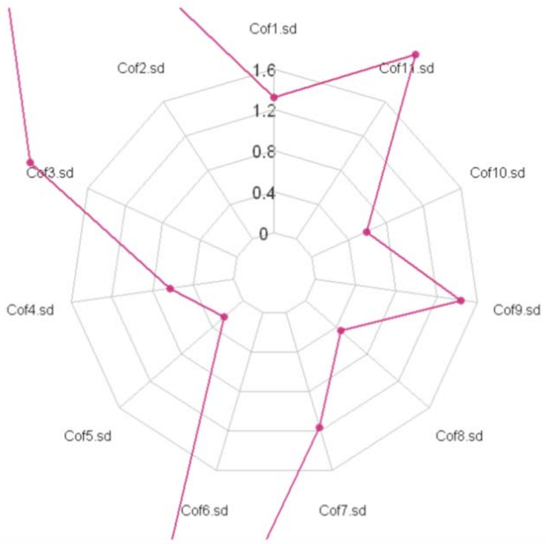


Figure A11

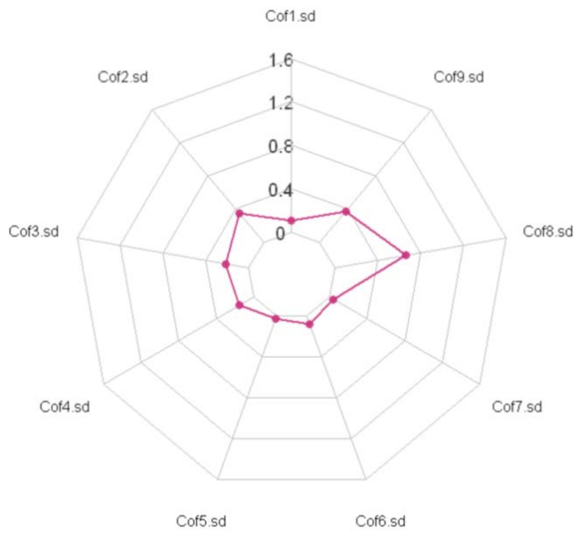


Figure A12

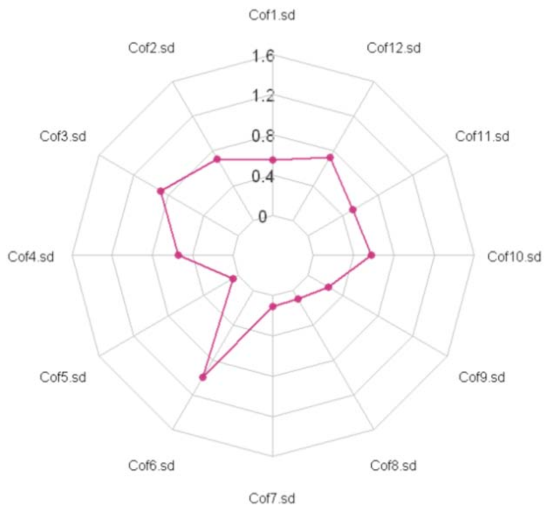


Figure A13

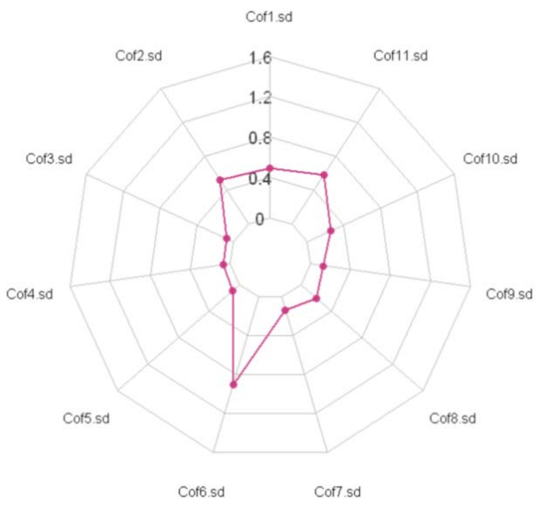


Figure A14

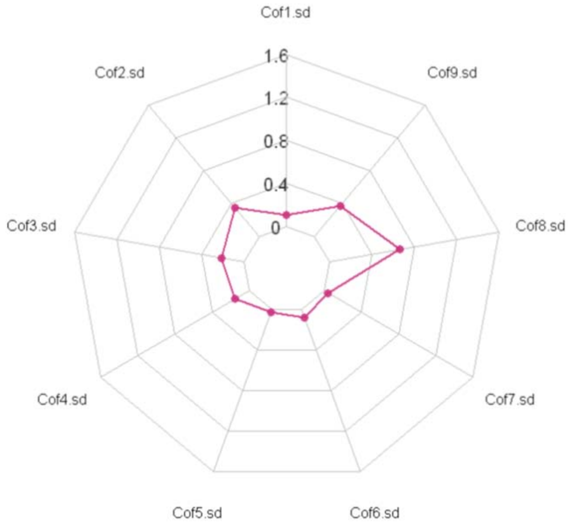


Figure A15

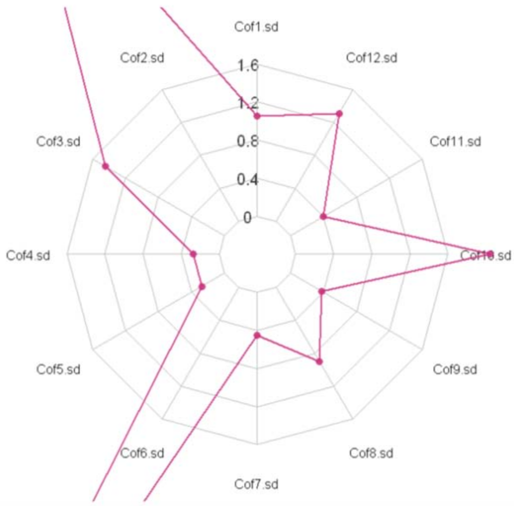


Figure A16

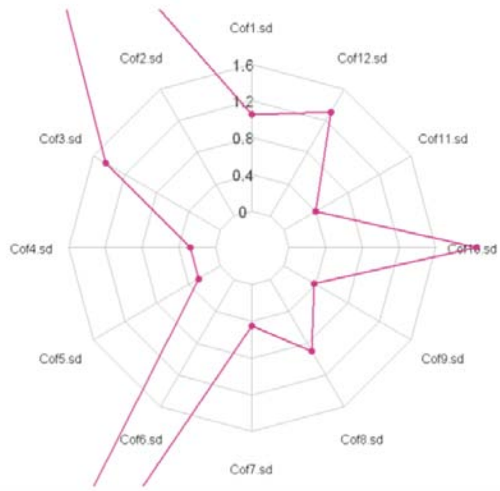


Figure A17

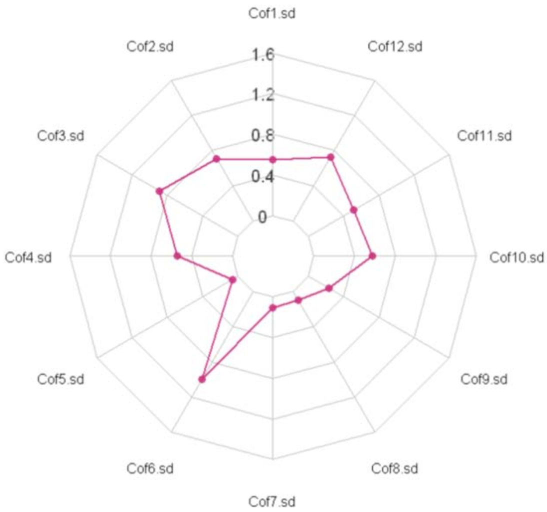
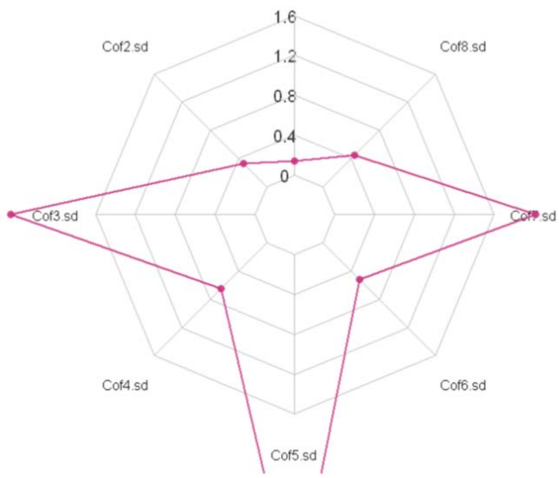


Figure A18



B. Spider Graphs for the regression betas of the "Decision For Order"

Figure B1

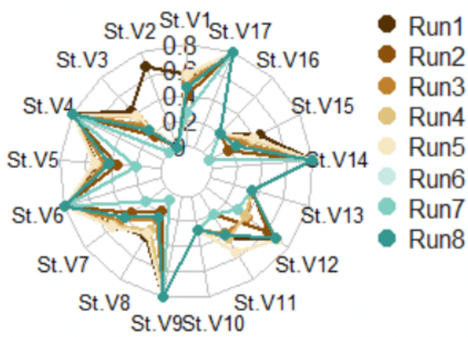


Figure B2

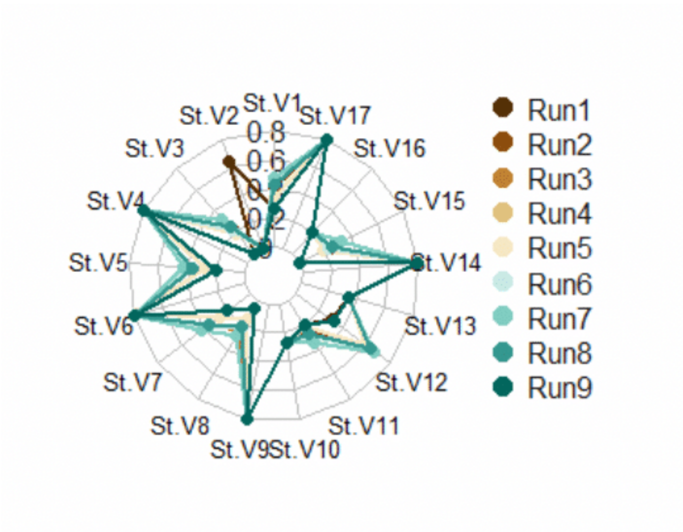


Figure B3

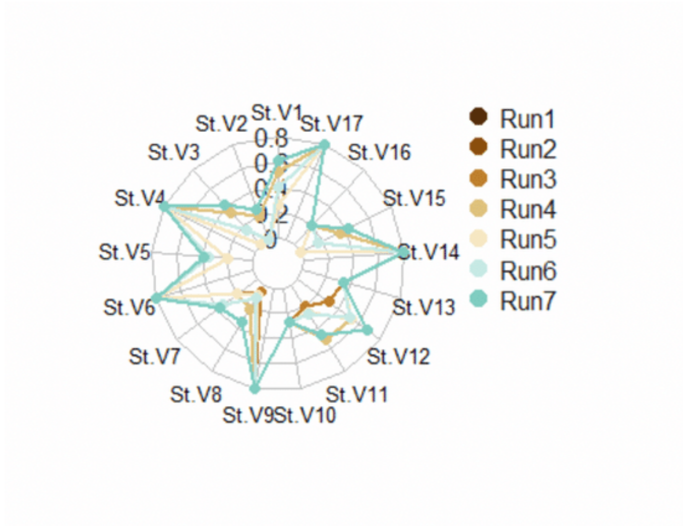


Figure B4

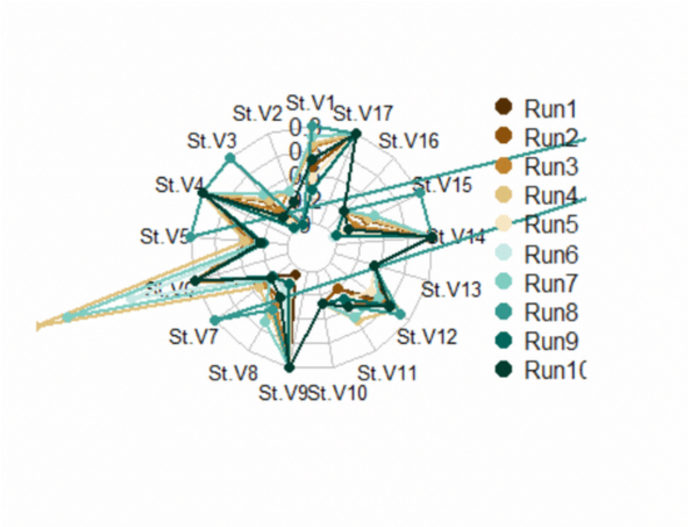


Figure B5

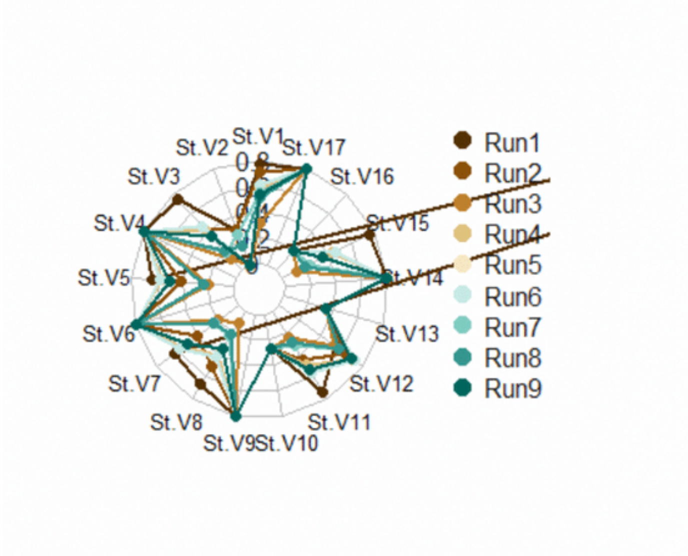


Figure 6

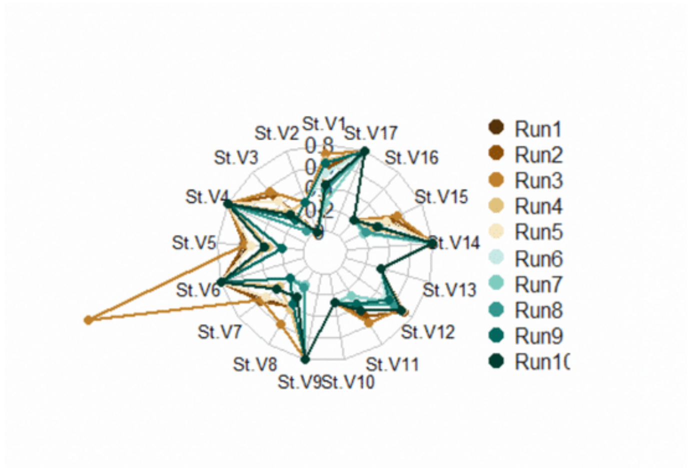


Figure B7

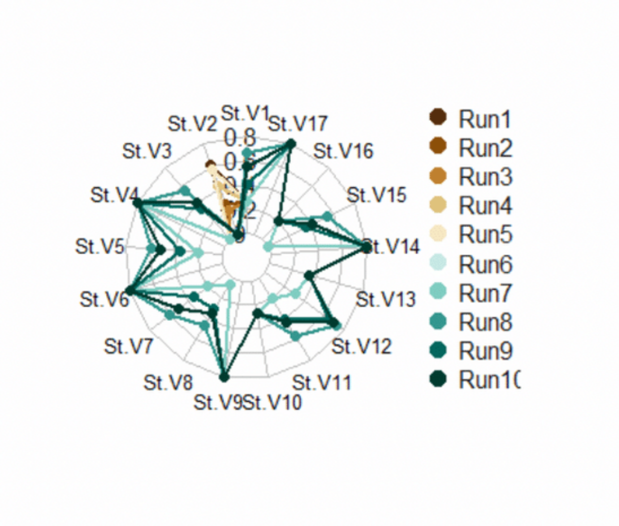


Figure B8

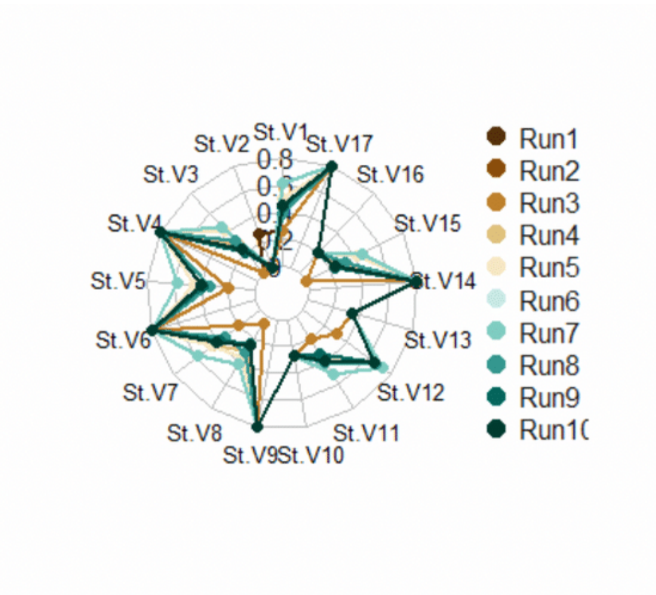


Figure B9

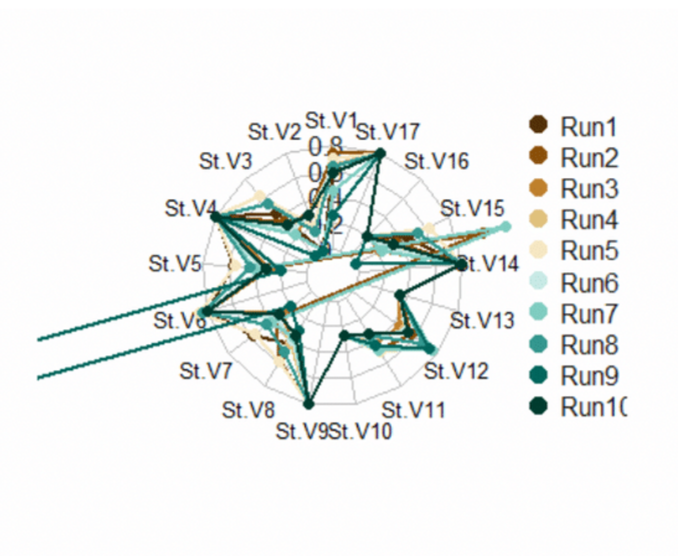


Figure B10

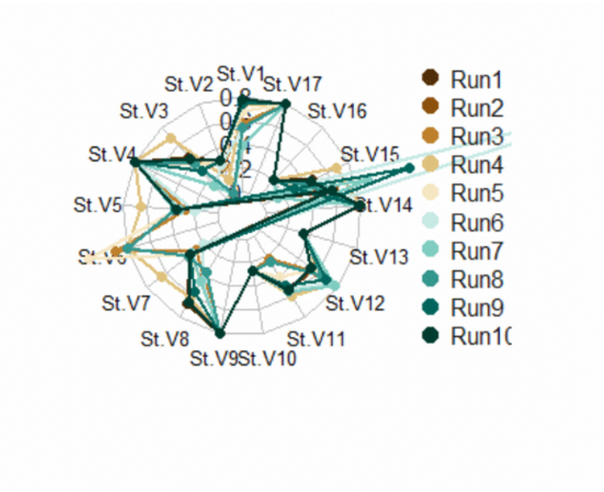


Figure B11

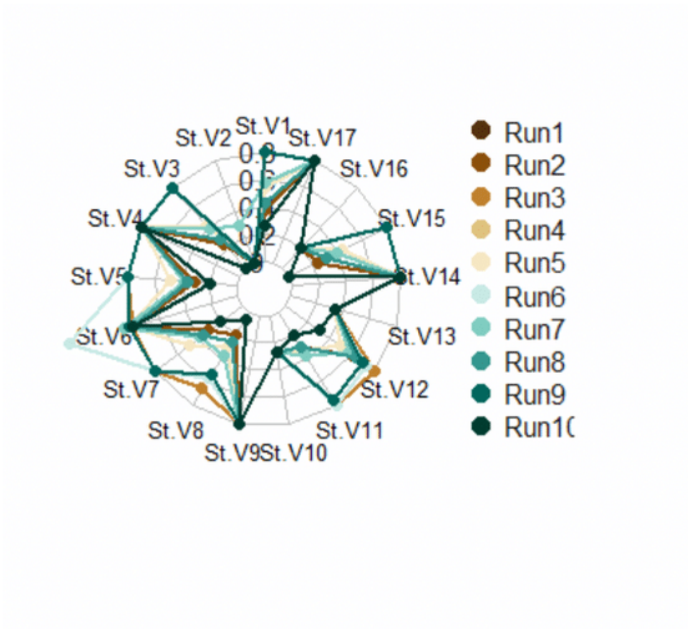


Figure B12

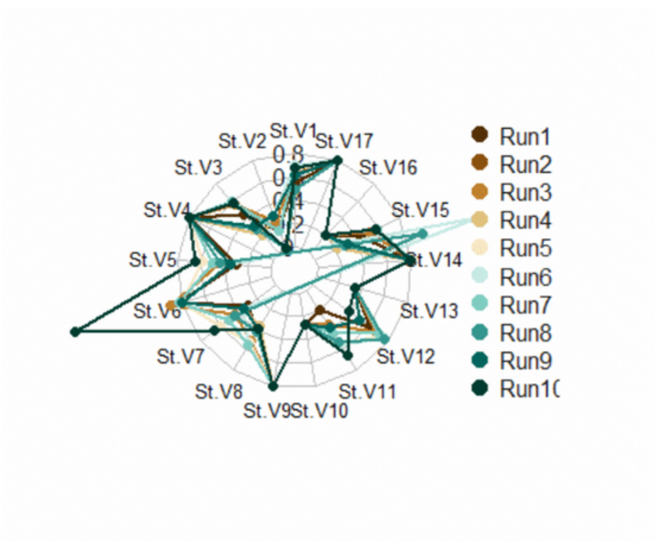


Figure B13

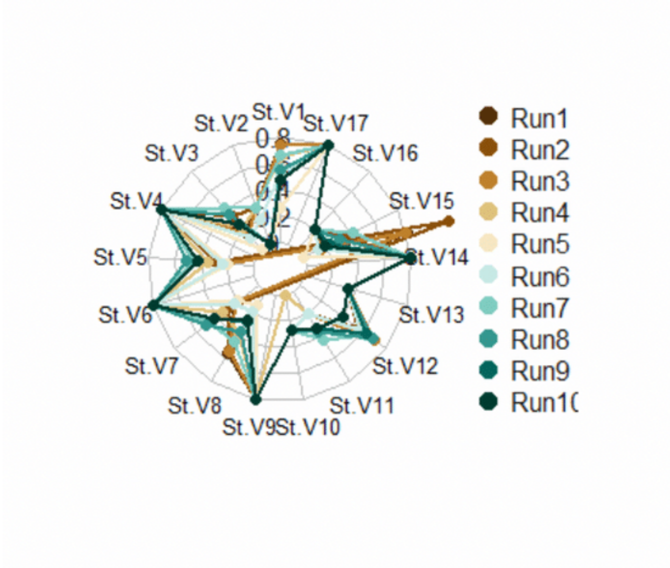


Figure B14

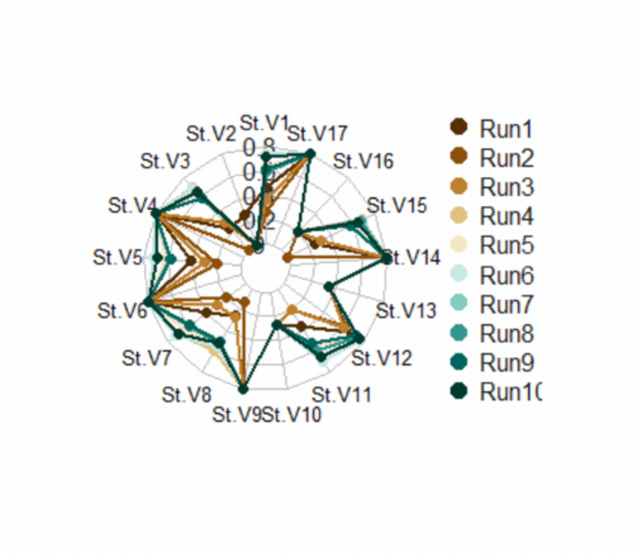


Figure B15

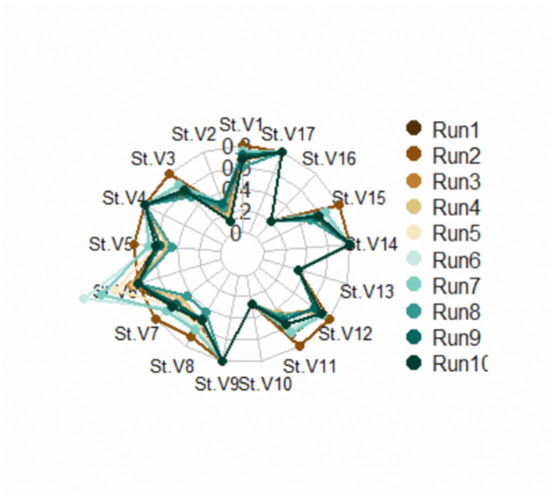


Figure B16

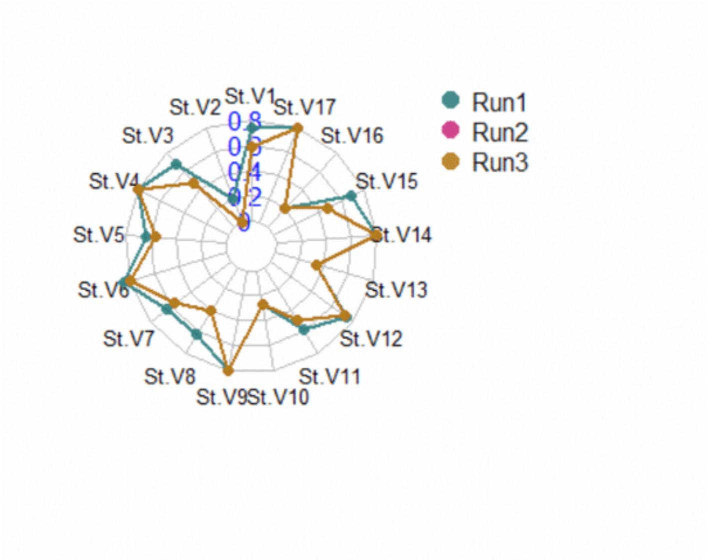


Figure B17

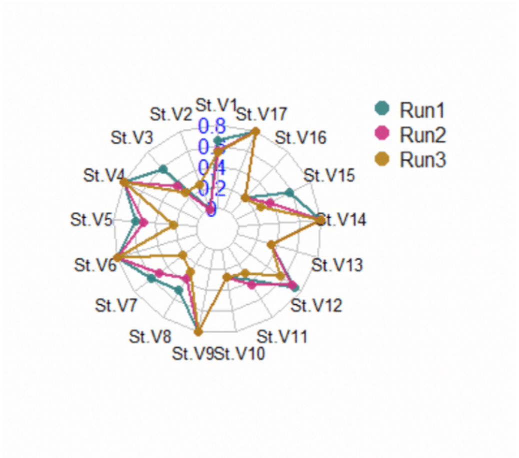


Figure B18