To cite this chapter:

Saqr, M., Schreuder, M. J., & López-Pernas, S. (2024). Why educational research needs a complex system revolution that embraces individual differences, heterogeneity, and uncertainty. In M. Saqr & S. López-Pernas (Eds.), *Learning Analytics Methods and Tutorials* (pp. 723-734). Springer. https://doi.org/10.1007/978-3-031-54464-4_22

Why Educational Research Needs a Complex System Revolution that Embraces Individual Differences, Heterogeneity, and Uncertainty



Mohammed Saqr, Marieke J. Schreuder, and Sonsoles López-Pernas

1 Introduction

Learning analytics (LA) has emerged to harness the opportunities created by the abundance of data and advanced machine learning methods to improve learning and teaching and offer the much-needed personalized support. The premise was that the availability of massive amounts of data would enable novel insights, improve inferences, and deliver real-life impact [1]. A wide array of learning analytics applications has been developed over the years to realize such aspirations. One of the initial applications of learning analytics focused on predictive modeling: that is, collecting data of online activities, such as clicks, access to educational resources, or forum discussions to create a predictive model that would early flag underachievers. The early identification of an underachieving student in a course paves the way for proactive intervention [2]. Several studies have reported the successful identification of underachievers in individual courses or limited samples. Yet, transferring such models across programs or courses has been a consistent disappointment. All the more so, very few have reported a successful proactive intervention [2].

A recent massive study with data from 250,000 students tried to examine the effectiveness of a large-scale, evidence-based intervention, and reported small benefits. The researchers concluded that interventions are likely more effective when implemented for the right person, at the right moment in time. In fact, such a conclusion is far from new, Gordon Paul's stated in 1967 that the important question is “What treatment, by whom, is most effective for this individual with

M. Saqr (✉) · S. López-Pernas
School of Computing, University of Eastern Finland, Joensuu, Finland
e-mail: mohammed.saqr@uef.fi

M. J. Schreuder
KU Leuven, Leuven, Belgium

© The Author(s) 2024

M. Saqr, S. López-Pernas (eds.), *Learning Analytics Methods and Tutorials*,
https://doi.org/10.1007/978-3-031-54464-4_22

that specific problem, and under which set of circumstances?"[3]. This requires predictions at a dynamic (i.e., time-varying) and individual level [4]. Another recent large-scale study showed that a low proportion of variance in students' performance was explained by the behavior-based indicators [5], and thus, students should best be identified on internal conditions (e.g., knowledge, self-regulation, and motivation). Recent reviews of intervention using LA methods further emphasize the difficulty of these promises [6]. As Du et al. [7] stated that "every course has different course requirements, it is impossible to identify generalisable thresholds of individual behaviors across courses" (p. 510). This holds even when courses are similar, homogenous, and use the same teaching [8].

The lackluster of predictive LA has led to a wide range of research threads aiming to tap into other methods that help explain and optimize students' learning. Such methods have been used to analyze the relational temporal patterns of students' learning processes. For instance, building on the importance of time, Process Mining (PM) and Sequence Analysis (SM) have gained wide popularity in the analysis of online learning activities to explain the time-ordered patterns of learning activities and to capture patterns of learning strategies [9]. Social network analysis (SNA) has also gained renewed interest and wider application in collaborative learning settings to understand students' roles and interaction patterns and to find SNA measures that help predict performance [10, 11]. Nevertheless, most of such methods—which we covered with examples in the book—require an overarching framework or a theoretical underpinning to better ground the analysis. In this chapter, we discuss the importance and potential of complex systems in understanding learning, learners, and the educational milieu at large.

2 Complex Systems and Education

Most learning theories and frameworks can be conceptualized as systems, that is, composed of multiple components, phases, or elements that interact with each other. Typically, such interactions are non-linear and vary across people, contexts, and time scales resulting in the emergence of a unique learning process [12–14]. For instance, engagement can be considered as a complex system. Engagement is then viewed as the result of interaction between different components, namely behavioral, cognitive, and emotional dimensions [15, 16]. Such interactions vary between tasks, times, and contexts which are often referred to as *interaction-dominant systems* (Fig. 1b) [17, 18]. In interaction-dominant systems, the relationships between components may change intensity and direction across times and situations. For instance, a student may enjoy school in the early days which drives their engagement and achievement and boosts their motivation. These dynamics may change over time, where achievement could be the driving force of future engagement but also results in anxiety rather than enjoyment. In turn, anxiety may negatively affect school enjoyment and engagement. This dynamic view is more realistic than the common b*ox-and-arrow* models where the components of the system are

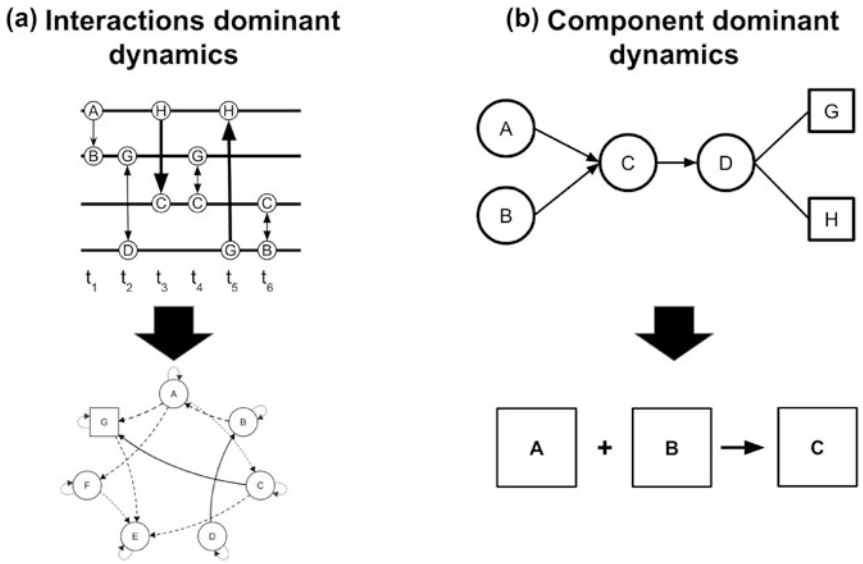

Fig. 1 (**a**) A complex dynamic system where the interactions vary across time, change direction and strength in a soft-assembled manner. (**b**) A box and arrow framework where the interactions are fairly stable and linear

rigidly assembled in a stable manner and the relationships between the components are deemed to be linear (Fig. 1b). Viewing the previous example from a linear perspective would entail that we see that the student will always have a stable relationship: enjoyment always drives engagement and achievement with little changes in the future nor any new patterns emerge. A linear view of engagement is then far from realistic.

Engagement follows Gestalt principles, meaning that engagement is considered more than just the sum of its parts (i.e., engagement $\neq$ emotions+cognition+behavior) [16], the interactions between these components are often multiplicative rather than simple linear sum and rely on the environment and contextual conditions (family, peers, teachers, school, etc.). Additionally, most engagement theories describe feedback loops (for instance, achievement drives further engagement and vice versa) [19]. Again, such feedback loops fit well with the salient features of a complex dynamic system [14].

Self-regulated learning (SRL), too, follows complex systems principles: the interaction between SRL phases across different learning scenarios and temporal scales results in unique learning strategies which are different mixtures of SRL phases. Such interactions may enhance, impede, or catalyze each other. For example, reflection on performance can lead to improved learning and better goal-setting in a student. In another student, reflection can lead to frustration, and low performance. We can expect vast amounts of variations and complex interactions in the same way. Such conceptualization of SRL as a state of a complex person-environment system

is necessary to understand the interplay of the intricate SRL process [13, 17]. Indeed, Boekaerts and Cascallar [20] argue that it is impossible to understand learning and achievement "unless one adopts a systems approach to the study of self-regulated learning". Similarly, other SRL theoreticians share the same conceptualization. For instance, [21] states that SRL is "a complex system of interdependent processes" [21], and so did Winne et al. when they described engagement as complex and dynamically changeable across contexts [22].

In fact, many learning concepts have been already described, operationalized, and framed in complex system terms including motivational [23, 24], achievement motivation theories [25], agency [26], and metacognition theories [27]. Also, the student has been described as a complex system [28], so have small collaborative groups [29], and the classroom as a whole to list a few. The merit of this complex systems view is that it not only accounts for many of the features of learning-related processes (e.g., being interaction-dominant, lacking central control) but also provides a framework for better understanding - and perhaps even predicting - such processes [13]. Nevertheless, endorsing that a system is interaction-dominant means that we also understand that forecasting and prediction of the system's future status may be more uncertain than the simple linear dynamics of component-dominant scenarios [30]. That is, the slightest change in initial conditions may lead to substantial differences in the end state (a phenomenon called "sensitive dependence on initial conditions"). It follows that in order to understand complex systems, one has to look into the dynamics of such systems.

2.1 Dynamics in Complex Systems

The interactions that maintain a complex system tend to give rise to relatively stable configurations, which can be considered attractor states that emerge again and again [31]. Attractors can take many different forms, ranging from chaotic to cyclic to simple point attractors. In the context of learning analytics, for instance, a point attractor could resemble a state of "being relatively engaged". Importantly, the attractors of complex systems may change over time. The aforementioned point attractor could for instance gradually lose its strength, up to a point where the attractor disappears. When reaching such a tipping point, the system switches to an alternate attractor [32]. Such a shift between different attractors is often labeled a transition. Transitions can be harmful—e.g., reflecting a shift from an adaptive state towards a maladaptive state—or beneficial—e.g., reflecting a reverse shift. Relatively well-investigated dynamics are "critical transitions", which entail a shift from one stable regime (i.e., point attractor) towards another regime [31] (i.e., other point attractor). For instance, countries can shift between a state of peace towards a state of war and the climate can shift from a greenhouse to an icehouse state. Similarly, a learning child may shift between a state of engagement towards a state of disengagement. An important premise of complex systems theory is that such transitions - albeit in very different systems - follow the same generic principles.

Among these principles is the idea of critical slowing down [30, 33]. Critical slowing down describes that, prior to a critical transition, it becomes increasingly difficult to recover from perturbations [33, 34]. In the case of engagement, such perturbations can be school problems (e.g., problems with other pupils). When the student is in a stable, engaged state—and thus, unlikely to experience a transition towards a disengaged state—such perturbations only have a brief effect on the student's attention. This means that, upon a perturbation, he/she quickly recovers his/her "baseline" engagement levels [35]. As the resilience of the engaged state declines, however, the student becomes increasingly affected by these perturbations. This means that recovering his/her normative engagement becomes more and more difficult. This in turn translates to altering system dynamics, meaning that the interactions between and within system elements changes. Monitoring such changes may then allow for anticipating otherwise unpredictable transitions in learning processes [30, 33, 34]. Ultimately, this could aid the prevention of harmful transitions or the fostering of beneficial transitions.

An important implication of viewing transitions in learning processes through a complex systems lens is that declining resilience may be detectable *within* systems, which in this case means that inferences are made on the level of the student. This approach contrasts with the common group-level inferences, which may allow for telling *who* is likely to undergo a transition. For instance, group-level approaches may lead to the notion that "individuals with this behavior, this personality, or this socio-economic background are more likely to drop out of school than others". Within-individual approaches, in contrast, may allow for determining *when* a specific individual will drop out. For the purposes of targeted and timely intervention, such insight is invaluable. A related merit of complex systems principles is that they allow for personalization. For instance, it is likely that vulnerability to major changes (e.g., transitions in engagement, school drop-out) manifests in different variables for different individuals. Because declining resilience can be monitored within individuals, such heterogeneity does not pose a challenge. Rather, it can be accommodated by monitoring resilience in those variables that are considered most relevant for this particular student, in this specific context [36]. In conclusion, the possibility to monitor generic indicators of declining resilience may pave the way for deriving person-specific insights in predicting (and potentially, preventing or stimulating) changes in learning-related processes.

2.2 From Theory to Practice: Measurement and Analyses

If we agree that the learning phenomena, process or construct can be conceptualized as states in a complex system, then it becomes essential that a complex system lens is used to map the structure and dynamics of the said phenomena [37]. This has profound consequences for both measurement and data analyses. With respect to measurement, a complex systems lens necessitates the collection of time series data. The reason is that systems—and the interactions between elements within

those systems—are by definition time-varying, and it is precisely the changes over time that contain information about the system as a whole. Thus, instead of a single, cross-sectional measurement, a complex systems perspective requires collecting repeated measurements for each individual. With advancing technology, collecting such measurements has become increasingly feasible. Broadly speaking, we can distinguish between passively collected data - which includes mobile sensing data (e.g., typing speed, scrolling, app usage, and sometimes also location) and actigraphy data (e.g., movement, heart rate, skin conductance) —and self-reported data—which is gathered through repeatedly prompting students with a questionnaire on their mood, motivation, or other psychological variables. Both modalities have their pros and cons. The main benefit of passively collected data is the amount of data that can be collected without burdening participants. The other side of the coin is that this amount of data often needs aggregation and intensive cleaning, which is far from straightforward, and in that sense the data can be "hard to handle". The main benefit of self-report data is that the content of measurement may be more closely related to the construct of interest. However, self-report data require considerable motivation from participants, and it is not inconceivable that such demanding research designs introduce sampling bias. Put differently, it is possible that the types of individuals who engage in studies involving long-term self-reports are not representative of the general population (e.g., in terms of conscientiousness [38]). At the same time, however, studies that investigated sampling bias in intensive longitudinal studies involving the collection of repeated self-reports did not find evidence for self-selection [39]. As intuitive as it may seem, scientific evidence for the self-selection of participants into intensive longitudinal studies is thus lacking. Besides these relatively practical considerations, the necessity of time series data also comes with more fundamental questions, for instance, related to the timescale of assessments. Ideally, this timescale should be informed by the timescale at which the system's dynamics unfold. This in turn varies between constructs: engagement may shift over minutes, while student's performance may shift over weeks.

Naturally, the focus on time series data has consequences for the analyses that are useful. Not only do we require time series analyses —which can handle the temporal dependency in the data—but we also need methods that can capture nonlinear and person-specific trends. This is because the dynamics of complex systems are typically non-linear, as illustrated by the erratic behavior and sudden shifts that govern complex systems. Examples of such analytical methods include dynamic time-warp analyses, generalized additive models, recurrence quantification analysis, state space grids, and moving window analyses [17]. Despite that most learning theories and processes can be described in complex system terms and the long history of theoretical foundations of complex systems in learning sciences, learners' and learning environments, the uptake of suitable methods and approaches is lagging behind [13, 17]. Furthermore, applications, framing, and operationalization of learning theories as complex systems are rare in educational research [13, 17]. In this book, we therefore provide some theoretical underpinnings of a complex systems perspective on learning and education, and we further included several chapters that deal with methods and analyses that accommodate a complex systems

lens e.g., psychological networks, Markovian models, and model-based clustering. In other fields, the adoption of such methods has resulted in the renewal of theories, understanding of human behavior, and the emergence of new solutions to real-life problems [40, 41]. Our aim was to help interested researchers to embrace such methods in their analysis.

2.3 Complex Systems and Individual Differences

Complex systems—as a paradigm—facilitates a better understanding of the heterogeneity and individualized nature of human behavior and psychological phenomena. In fact, many complex system methods, some of which described earlier, have a strong emphasis on person-specific fine-grained dynamics. The next section will offer a more in-depth discussion of the individual mechanisms and how they relate to the general average assumptions.

2.3.1 The Individual

The "individual", or the "self" is a central construct in several learning theories, methodologies, and approaches. For instance, self-regulated learning, self-concept, self-control, and self-directedness to mention a few [42]. Further, the literature is awash with the notion of personalization, student-centeredness, and adaptive learning. Nonetheless, research is commonly conducted using methods that essentially ignore the "individual" process. In that, research is performed using what is known as variable-centered methods where data is collected from a "group of others" to derive generalizable laws. In variable-centered methods, researchers compute standard tendency measures (mean or median) from a sample of individuals (often referred to as group-level analysis) to derive "norms" or "standard recommendations". The average is considered a "norm" where everyone is assumed to fit. What is more, the outcome of such analysis is deemed representative and therefore, generalizable to the population at large. Given that such an average is derived from a sample of others, it rarely represents any single student [43, 44]. An accumulating body of evidence is mounting that humans are heterogeneous with diverse behaviors, attitudes, cognition, and learning approaches. Thereupon, using insights based on group-level analysis has so far resulted in recommendations that don't work, assumptions that fail to hold, and replications that are hard to obtain. Furthermore, intervention programs or procedures based on such samples offered no more than negligible effects, e.g., [4].

The fact that group-level analysis is less representative of the person is far from new and has been recognized for decades. Yet, the methods that are more suited for person-specific analysis may have not progressed fast enough. The last two decades have witnessed a revolution in data collection methods, statistical approaches, and procedures that allow such analysis, collectively known as person-specific analysis.

In many ways, person-specific methods are a paradigm shift in research which according to [45] represent a "brink of a major reorientation" that is "no longer an option, but a necessity". Endorsing a person-specific approach may change how research is performed and how findings are applied [46, 47]. The person-specific methods—being individualistic—have low potential for generating generalizable recommendations [46]. Therefore, a combination of group-level and person-specific methods may be the best way forward. Such a combination may augment our understanding and provide precise interventions *at the high resolution of the single student* and sharpen our insights of the group level that are generalizable to the wider population [48].

There is an abundance of digital tools and data collection methods that allow the gathering of fine-grained intensive data about students. Such data -where several measurements from the same person are gathered- can allow the analysis of more person-specific insights. In doing so, it can help obtain an accurate view of a student's learning processes and offer more precise personalized support [45–47].

2.3.2 Heterogeneity

As discussed in the previous section, a central assumption of group-level analysis is that "the average individual" represents every individual. Yet, the average individual very often does not exist [49]. To illustrate this problem, let us consider the story of Gilbert Daniels. Daniels was given the task to measure the physical dimensions of more than 4000 pilots who were part of the American Air Force around 1950. The goal was to find the average pilot size, so that cockpits could be re-designed accordingly. However, a remarkable finding of Daniels was that not a single pilot (out of all pilots who were measured) was approximately equal to the average of the 10 most relevant dimensions. Further, for any given combination of three dimensions, only 4% of pilots would match the average. Hence, he concluded that "The tendency to think in terms of the average man is a pitfall into which many people blunder [. . .]. Actually, it is virtually impossible to find an average man". The consequence of this discovery was that most cockpit material became adjustable so that it would suit everyone [50].

It is not difficult to translate Daniels' findings to the field of LA. Here, too, students are measured in many dimensions. It is often implicitly assumed that the average of those dimensions will illustrate "a representative student", but this is not the case. To accommodate this lack of "average students", we should embrace person-centered methods, similar to how the American Airforce embraced adjustable furniture and clothing. In contrast to group-level analyses, person-centered methods attempt to find patterns where differences are minimal, assumptions are likely to hold and apply to wider groups of people. Recently, the range of available person-centered methods has vastly increased, coupled with improving rigor and potential. Therefore, person-centered methods are increasingly endorsed to model heterogeneity and individual differences across a vast range of empirical designs. In the current book, we have introduced several methods for

capturing the heterogeneity of multivariate and longitudinal data, and we encourage researchers to take advantage of such data to capture the diversity and individual differences of learners [51–54].

3 Conclusion

The birth of learning analytics signaled a new wave of educational research that embraced modern computational methods. Whereas the field has matured, several methodological and theoretical issues remain unresolved. In this chapter, we discussed the potentials of complexity theory and individual differences in advancing the field bringing a much-needed theoretical perspective that could help offer answers to some of our pressing issues. In fact, a complex systems view on learning processes can address some of the major barriers that have hampered progress in the field of education and possibly offer a venue for the renewal of knowledge.

References

1. Siemens G (2013) Learning analytics: the emergence of a discipline. Am Behav Sci 57:1380–1400. https://doi.org/10.1177/0002764213498851
2. Ifenthaler D, Yau JYK (2020) Utilising learning analytics to support study success in higher education: a systematic review. Educ Technol Res Dev ETR & D. https://doi.org/10.1007/s11423-020-09788-z
3. Paul GL (1967) Strategy of outcome research in psychotherapy. J Consult Psychol 31:109–118. https://doi.org/10.1037/h0024436
4. Kizilcec RF, Reich J, Yeomans M, Dann C, Brunskill E, Lopez G, Turkay S, Williams JJ, Tingley D (2020) Scaling up behavioral science interventions in online education. Proc Natl Acad Sci 117:14900 LP–14905. https://doi.org/10.1073/pnas.1921417117
5. Jovanović J, Saqr M, Joksimović S, Gašević D (2021) Students matter the most in learning analytics: the effects of internal and instructional conditions in predicting academic success. Comput Educ 172:104251. https://doi.org/10.1016/j.compedu.2021.104251
6. Larrabee Sønderlund A, Hughes E, Smith J (2019) The efficacy of learning analytics interventions in higher education: a systematic review. Br J Educ Technol J Council Educ Technol 50:2594–2618. https://doi.org/10.1111/bjet.12720
7. Xu Du BES Juan Yang, Zhang M (2021) A systematic meta-review and analysis of learning analytics research. Behav Inf Technol 40:49–62. https://doi.org/10.1080/0144929X.2019.1669712
8. Saqr M, Jovanović J, Viberg O, Gašević D (2022) Is there order in the mess? A single paper meta-analysis approach to identification of predictors of success in learning analytics. Stud Higher Educ 1–22. https://doi.org/10.1080/03075079.2022.2061450
9. Saqr M, López-Pernas S, Jovanović J, Gašević D (2023) Intense, turbulent, or wallowing in the mire: a longitudinal study of cross-course online tactics, strategies, and trajectories. Internet Higher Educ 57:100902. https://doi.org/10.1016/j.iheduc.2022.100902
10. Saqr M, Elmoazen R, Tedre M, López-Pernas S, Hirsto L (2022) How well centrality measures capture student achievement in computer-supported collaborative learning? – a systematic review and meta-analysis. Educ Res Rev 35:100437. https://doi.org/10.1016/j.edurev.2022.100437

11. Saqr M, Poquet O, López-Pernas S (2022) Networks in education: a travelogue through five decades. IEEE Access 10:32361–32380. https://doi.org/10.1109/ACCESS.2022.3159674
12. Jörg T, Davis B, Nickmans G (2007) Towards a new, complexity science of learning and education. Educ Res Rev Teach Concerned Progress Educ 2:145–156. https://doi.org/10.1016/j.edurev.2007.09.002
13. Koopmans M (2020) Education is a complex dynamical system: challenges for research. J Exp Educ 88:358–374. https://doi.org/10.1080/00220973.2019.1566199
14. Ladyman J, Lambert J, Wiesner K (2013) What is a complex system? Eur J Philos Sci 3:33–67. https://doi.org/10.1007/s13194-012-0056-8
15. Reschly AL, Christenson SL (2022) Jingle-jangle revisited: history and further evolution of the student engagement construct. In: Reschly AL, Christenson SL (eds) Handbook of research on student engagement. Springer International Publishing, Cham, pp 3–24. https://doi.org/10.1007/978-3-031-07853-8_1
16. Wang M-T, Fredricks JA (2014) The reciprocal links between school engagement, youth problem behaviors, and school dropout during adolescence. Child Dev 85:722–737. https://doi.org/10.1111/cdev.12138
17. Hilpert JC, Marchand GC (2018) Complex systems research in educational psychology: aligning theory and method. Educ Psychol 53:185–202. https://doi.org/10.1080/00461520.2018.1469411
18. Van Orden GC, Holden JG, Turvey MT (2003) Self-organization of cognitive performance. J Exp Psychol General 132:331–350. https://doi.org/10.1037/0096-3445.132.3.331
19. Tinto V (2022) Exploring the character of student persistence in higher education: the impact of perception, motivation, and engagement. In: Reschly AL, Christenson SL (eds) Handbook of research on student engagement. Springer International Publishing, Cham, pp 357–379. https://doi.org/10.1007/978-3-031-07853-8_17
20. Boekaerts M, Cascallar E (2006) How far have we moved toward the integration of theory and practice in self-regulation? Educ Psychol Rev 18:199–210. https://doi.org/10.1007/s10648-006-9013-4
21. Zimmerman BJ, Risemberg R (1997) Becoming a self-regulated writer: a social cognitive perspective. Contemp Educ Psychol 22:73–101. https://doi.org/10.1006/ceps.1997.0919
22. Winne PH, Zhou M, Egan R (2011) Designing assessments of self-regulated learning. Assessment of higher order thinking.
23. Papi M, Hiver P (2020) Language learning motivation as a complex dynamic system: a global perspective of truth, control, and value. Mod Lang J 104:209–232. https://doi.org/10.1111/modl.12624
24. Yuan Y, Zhen H (2021) Teaching and researching motivation. Front Psychol 12:804304. https://doi.org/10.3389/fpsyg.2021.804304
25. Urdan T, Kaplan A (2020) The origins, evolution, and future directions of achievement goal theory. Contemp Educ Psychol 61:101862. https://doi.org/10.1016/j.cedpsych.2020.101862
26. Deakin Crick R, Huang S, Ahmed Shafi A, Goldspink C (2015) Developing resilient agency in learning: the internal structure of learning power. Br J Educ Stud 63:121–160. https://doi.org/10.1080/00071005.2015.1006574
27. Vollmeyer R, Rheinberg F (1999) Motivation and metacognition when learning a complex system. Eur J Psychol Educ 14:541–554. https://doi.org/10.1007/BF03172978
28. Brown JS (1997) On becoming a learning organization. About Campus 1:5–10. https://doi.org/10.1177/108648229700100603
29. Mennin S (2007) Small-group problem-based learning as a complex adaptive system. Teach Teach Educ 23:303–313. https://doi.org/10.1016/j.tate.2006.12.016
30. Wichers M, Schreuder MJ, Goekoop R, Groen RN (2019) Can we predict the direction of sudden shifts in symptoms? Transdiagnostic implications from a complex systems perspective on psychopathology. Psychol Med 49:380–387. https://doi.org/10.1017/S0033291718002064
31. Scheffer M (2009) Critical transitions in nature and society. Princeton University Press, Princeton. https://play.google.com/store/books/details?id=okT_DwAAQBAJ

32. Scheffer M, Carpenter SR, Dakos V, Nes EH van (2015) Generic indicators of ecological resilience: inferring the chance of a critical transition. Ann Rev Ecol Evol Syst 46:145–167. https://doi.org/10.1146/annurev-ecolsys-112414-054242
33. Scheffer M, Bascompte J, Brock WA, Brovkin V, Carpenter SR, Dakos V, Held H, Nes EH van, Rietkerk M, Sugihara G (2009) Early-warning signals for critical transitions. Nature 461:53–59. https://doi.org/10.1038/nature08227
34. Scholz JP, Kelso JAS, Schöner G (1987) Nonequilibrium phase transitions in coordinated biological motion: critical slowing down and switching time. Phys Lett A 123:390–394. https://doi.org/10.1016/0375-9601(87)90038-7
35. Masten AS, Nelson KM, Gillespie S (2022) Resilience and student engagement: promotive and protective processes in schools. In: Reschly AL, Christenson SL (eds) Handbook of research on student engagement. Springer International Publishing, Cham, pp 239–255. https://doi.org/10.1007/978-3-031-07853-8_12
36. Olthof M, Hasselman F, Aas B, Lamoth D, Scholz S, Daniels-Wredenhagen N, Goldbeck F, Weinans E, Strunk G, Schiepek G, Bosman AMT, Lichtwarck-Aschoff A (2023) The best of both worlds? General principles of psychopathology in personalized assessment. J Psychopathol Clin Sci 132:808–819. https://doi.org/10.1037/abn0000858
37. Olthof M, Hasselman F, Oude Maatman F, Bosman AMT, Lichtwarck-Aschoff A (2023) Complexity theory of psychopathology. J Psychopathol. Clin Sci 132:314–323. https://doi.org/10.1037/abn0000740
38. Scollon CN, Kim-Prieto C, Diener E (2003) Experience sampling: Promises and pitfalls, strengths and weaknesses. J Happiness Stud 4:5–34. https://doi.org/10.1023/A:1023605205115
39. Schreuder MJ, Groen RN, Wigman JTW, Wichers M, Hartman CA (2023) Participation and compliance in a 6-month daily diary study among individuals at risk for mental health problems. Psychol Assess 35:115–126. https://doi.org/10.1037/pas0001197
40. Borsboom D, Haslbeck JMB, Robinaugh DJ (2022) Systems-based approaches to mental disorders are the only game in town. World Psychiatry Official J World Psychiatric Association 21:420–422. https://doi.org/10.1002/wps.21004
41. Quintana R (2023) Embracing complexity in social science research. Qual Quant 57:15–38. https://doi.org/10.1007/s11135-022-01349-1
42. Panadero E (2017) A review of self-regulated learning: Six models and four directions for research. Front Psychol 8:422. https://doi.org/10.3389/fpsyg.2017.00422
43. Fisher AJ, Medaglia JD, Jeronimus BF (2018) Lack of group-to-individual generalizability is a threat to human subjects research. Proc Natl Acad Sci USA 115:E6106–E6115. https://doi.org/10.1073/pnas.1711978115
44. Winne P (2017) Leveraging big data to help each learner and accelerate learning science. Teach Coll Rec 119:1–24. https://www.tcrecord.org/books/pdf.asp?ContentID=21769
45. Molenaar PCM, Campbell CG (2009) The new person-specific paradigm in psychology. Curr Dir Psychol Sci 18:112–117. https://doi.org/10.1111/j.1467-8721.2009.01619.x
46. Saqr M (2023) Modelling within-person idiographic variance could help explain and individualize learning. Br J Educ Technol. https://doi.org/10.1111/bjet.13309
47. Saqr M, Lopez-Pernas S (2021) Idiographic learning analytics: a definition and a case study. In: 2021 international conference on advanced learning technologies (ICALT), pp 163–165. https://doi.org/10.1109/icalt52272.2021.00056
48. Epskamp S, Waldorp LJ, Mõttus R, Borsboom D (2018) The gaussian graphical model in cross-sectional and time-series data. Multivariate Behav Res 53:453–480. https://doi.org/10.1080/00273171.2018.1454823
49. Molenaar PCM (2004) A manifesto on psychology as idiographic science: bringing the person back. Meas Interdiscip Res Perspect 2:201–218. https://web-a-ebscohost-com.ep.fjernadgang.kb.dk/ehost/pdfviewer/pdfviewer?vid=1&sid=257bbb8e-f698-4c63-8a11-d87feb3bbf63%40sessionmgr4010
50. Rose T (2016) The end of average: how to succeed in a world that values sameness. Penguin, London. https://play.google.com/store/books/details?id=w7-zCgAAQBAJ

51. Helske J, Helske S, Saqr M, López-Pernas S, Murphy K (2024) A modern approach to transition analysis and process mining with markov models: A tutorial with R. In: Saqr M, López-Pernas S (eds) Learning analytics methods and tutorials: a practical guide using R. Springer, Berlin. https://doi.org/10.1007/978-3-031-54464-4
52. López-Pernas S, Saqr M (2024) Modelling the dynamics of longitudinal processes in education. A tutorial with r for the VaSSTra method. In: Saqr M, López-Pernas S (eds) Learning analytics methods and tutorials: a practical guide using R. Springer, Berlin. https://doi.org/10.1007/978-3-031-54464-4
53. Saqr M (2023) Group-level analysis of engagement poorly reflects individual students' processes: why we need idiographic learning analytics. Comput Human Behav. https://doi.org/10.1016/j.chb.2023.107991
54. Scrucca L, Saqr M, López-Pernas S, Murphy K (2024) An introduction and R tutorial to model-based clustering in education via latent profile analysis. In: Saqr M, López-Pernas S (eds) Learning analytics methods and tutorials: a practical guide using R. Springer, Berlin. https://doi.org/10.1007/978-3-031-54464-4

Open Access This chapter is licensed under the terms of the Creative Commons Attribution 4.0 International License (http://creativecommons.org/licenses/by/4.0/), which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

