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Transitions through lifelong learning: Implications for learning analytics

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ABSTRACT

The ability to develop new skills and competencies is a central concept of lifelong learning. Research to date has largely focused on the processes and support individuals require to engage in upskilling, re-learning or training. However, there has been limited attention examining the types of support that are necessary to assist a learner's transition from "old" workplace contexts to "new". Professionals often undergo significant restructuring of their knowledge, skills, and identities as they transition between career roles, industries, and sectors. Domains such as learning analytics (LA) have the potential to support learners as they use the analysis of fine-grained data collected from education technologies. However, we argue that to support transitions throughout lifelong learning, LA needs fundamentally new analytical and methodological approaches. To enable insights, research needs to capture and explain variability, dynamics, and causal interactions between different levels of individual development, at varying time scales. Scholarly conceptions of the context in which transitions occur are also required. Our interdisciplinary argument builds on the synthesis of literature about transitions in the range of disciplinary and thematic domains such as conceptual change, shifts between educational systems, and changing roles during life course. We highlight specific areas in research designs and current analytical methods that hinder insight into transformational changes during transitions. The paper concludes with starting points and frameworks that can advance research in this area.

1. Introduction

The concept of lifelong learning refers to a personal process of learning and meaning making, and also to the institutional systems that support education. The design of these systems has focused on the provision of knowledge and skills deemed necessary for productive participation in society and work. However, less attention has been paid to the support of individuals transitioning in and out of education, across workplace contexts, and career roles. As the type of work and associated economies rapidly change, there is a parallel increase in the frequency of transitions a learner undertakes. It is essential that education and workplace settings support individuals to overcome the challenges they encounter as they transition through schooling, further studies, and a career that is likely to change multiple times throughout their life.

Biographical and adult learning literature refers to transitions as the time between major life events, from adolescence into adulthood, across careers and life roles such as in marriage, parenting, or retirement. Scholssberg, Waters, and Goodman (1995) defined a transition as 'any event, or nonevent, that results in changed relationships, routines, assumptions, and roles' (Scholssberg et al., 1995, p. 27). Consistent in the literature on transitions is that the events are stress-causing and exert an emotional and physical toll on individuals, as they adjust and restructure their knowledge and practices to adapt to the new contexts and expectations (George, 1993). The changes, associated with transitions, are transformational. Individuals restructure what they know, how they behave, and what they think of themselves as they adapt to new roles. Holistic development involving a transformation of knowledge, skills, and identities, occurs in transitions between educational systems from primary to secondary, secondary to university, university to work, and throughout an individual's career.

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Learners in transitions often require support to manage the high degree of change impacting on work, study, or life. To assist individuals, organizations are starting to use data to personalise learning pathways, by analysing the data collected through technologies that mediate learning and work. Learning analytics (LA) is an emerging research field that focuses on the analysis of fine-grained data to improve learning. LA research addresses questions related to learning design (Macfadyen, Lockyer, & Rienties, 2020); feedback models (Pardo, Poquet, Martinez-Maldonado, & Dawson, 2017); supporting self-regulation (Jivet et al., 2021); and recommendation systems for learning (Bodily & Verbert, 2017). While LA offers novel approaches to support learning, current approaches lack the theoretical lenses and tools that are necessary to understand learning transitions and to support individual learners through them.

This paper synthesises a vast volume of literature on transitions to describe transitions as a transformational process recurrent throughout lifelong learning. Different disciplines have studied transitions. This has resulted in a disconnected literature. Nonetheless, the literature strands do describe transitions similarly, regardless of whether they involve micro-level conceptual changes, or shifts between primary to secondary education, university to workplace shifts, or that between life roles in one's life course. We synthesise this fragmented but substantial body of work, highlighting transitions as phase-based processes that are highly varied across individuals. These processes involve changes of individual knowledge, skills, and identity through dynamic and non-linear influences from a wide range of factors. As we develop our interdisciplinary argument, we demonstrate that research in areas such as LA has not yet adopted study designs, analytical pipelines, or even computational methods that can adequately capture the essential properties of transitions. We argue that the field requires both analytical reframing and methodological innovations to advance our understanding of learner transitions.

The paper is structured as follows. Section 2 highlights the commonalities of how transitions have been studied in the extant literature. Sections 3 and 4 draw out methodological and analytical implications for studying transitions in LA. Section 5 proposes focal areas and an extension of existing conceptual approaches that can advance research in this area.

2. Main features of transitions in lifelong learning contexts

A lifelong learning trajectory includes transitions across education, work, and life contexts that bring about transformational changes of individuals. These changes may occur at different levels, such as change of knowledge, competencies, and identity. To describe the properties of transitions, we review literature from a range of disciplinary fields: conceptual change in the learning sciences, transitions between educational systems, from primary to secondary education, secondary to tertiary education, and university to workplace, and sociological and biographical literature in adult learning across a life course. The similarities in how transitions are conceived suggest that these transformational processes are generic and can potentially be examined using computational methods.

2.1. Transitions are processes

Transitions describe a change in status that occurs during one's life trajectory (George, 1993). Different disciplines conceptualise the change from an old status to a new one as a process. For instance, adult learning scholarship, a domain that deploys biographical methods to understand how adults make sense of their experiences, defines transitions as 'periods of change in our lives that alternate with periods of stability' (Merriam, 2005, p. 3). Adult learning theorists describe transitions as processes of restructuring that involve separation from old relationships, routines, assumptions, roles, and the view of the self, and the formation of new ones (Scholssberg et al., 1995), all underpinned by strong emotions (Bridges, 1980).

Understanding transitions as a process of restructuring of what one knows and does to perform a new role required in a new situation is also present within studies that focus on how individuals transition between primary and secondary school, higher education, and the labour market. Jindal-Snape, Symonds, Hannah, and Barlow (2021) undertook a systematic review of conceptualisations of transitions from primary to secondary school. The authors defined transitions as 'an ongoing process of psychological, social, and educational adaptations occurring due to changes in context, interpersonal relationships and identity, which can be simultaneously exciting and worrying for an individual and others in their lives, and which requires ongoing additional support' (Jindal-Snape, Symonds, Hannah, and Barlow (2021), p.3). Similarly, Gale and Parker (2014) typify research on transitions to higher education around transitions as induction (entering a new role and a new environment through pathways), transitions as development (navigating sociocultural norms and expectations), and transitions as becoming (subjective experience of transition as a part of one's life and identity).

Research on transitions between higher education and the labour market has been less interested in the processual nature of adjustment to new roles. Rather, the focus has been on the mismatch of skills between the two contexts that prevents graduates from a quick transition and integration into the workforce. Through a systematic review, Grosemans, Coertjens, and Kyndt (2017) maintained that the focus of studies on transitions between university and labour market is on misfits, i.e. the misalignment between credentials and the job, an individual and a new environment, and the existing and expected competences (ability to meet new expected behaviours). Within this focus, there is implicit assumption of the process inherent within an understanding of transition. A misfit, for example, is experienced during the stages of encountering and adjusting to a new (work) environment during a simultaneous exploration of a new identity (Grosemans, Hannes, Neyens, & Kyndt, 2020).

2.2. Transitions have phases

Although disciplines conceptualise transitions in markedly different contexts, the conceptualisations are similar. In essence, the process of transition involves phases during which individuals adapt to a new context. The restructuring of the "self" often goes through stages or phases to be able to meet the expectations of the new environment. For instance, a generic model of transition behaviour developed by Nicholson (1990) analyses job shifts as experiences, consisting of preparation, encounter, adjustment, and stabilization phases. Despite the critiques of this model (see George, 1993), it has been widely adopted for studies of transitions from primary to secondary school (Jindal-Snape et al., 2021) and university to labour market (Grosemans et al., 2017). Other theories conceptualising transitions in primary to secondary school also imply the notion of phase-based transformation. In doing so, they focus on elements within the transition, such as changes needed to address the discrepancy between the contexts as in stage-environment fit theory of motivation (Eccles et al., 1997, p. 1993) or changes needed to resolve the disruption, as in theories from life course development (Elder, 1998).

Theories around status passage (Glaser & Strauss, 1971) and the rites of passage (Van Gennep, 1960), both with roots in sociology, are also widely used in research on transitions. Glaser and Strauss (1971) formalised the passage to transitions as a dynamic movement into a social structure, loss or gain of privilege, and changed identity, or sense of self, and behaviour. Similarly, Van Gennep's work on rites of passage has influenced an entire strand of higher education research –none more so than Tinto's (1988) integration theory. Van Gennep viewed human life as a series of passages that individuals move through, from membership in one group to another. As individuals move between these memberships, they undergo three distinct phases - separation, transition, and incorporation - each with its ceremonies and rituals. The change in membership would include the change in interaction patterns with previous group members. In line with this work, Tinto conceptualised the process of student persistence (as students enter, or transition, to university) as three major stages or passages: separation, transition, and incorporation. Aligned with other diverse conceptualisations of transitions, this theorization points to the evolving nature of transitions.

2.3. Transitions require a dynamic system-view

Conceptual work on transitions invites *a system-view of the learner or an ecosystem* that learner is a part of. This system-view suggests that transitions need to be analysed in a holistic and integrated fashion. In this context, transitions are seen as changes associated with the hierarchical, nested, and causal nature of interactions between factors internal and external to the system that changes. For instance, in drawing on Bronfenbrenner's ecological systems theory (1992), studies of primary to secondary school transitions understand child development within a complex system of relationships between the environment, family, school, and culture, all interacting and shaping the child's development. Similarly, Jindal-Snape (2016) takes a multi-dimensional and system-view in her transitions theory applied in primary-to-secondary-school transitions, as well as in higher education settings. In explaining primary to secondary school transition, Jindal-Snape uses a Rubik's cube analogy, where each colour represents one part of the child's ecosystem. As with each move of the cube, transition changes in one dimension trigger changes in other areas, including other children and their families. Jindal-Snape describes these changes as interacting in a nonlinear manner, evolving, and situated within other structures. Similar conceptualisations of transitions are echoed in the ecological views of learning that acknowledge the multi-layered nature of human development: from human biology to culture (Lee, 2010). Complex nonlinear influences of the environment are also a prominent theme of research on workplace integration. Interactions between the agency of the individual who is in transition and the environment where the transition is taking place are inherent to professional and workplace learning literature (Billett, 1996; Tuomi-Gröhn, Engeström, & Young, 2003), though less explicit in the university to labour market transition research. Billett (1996) offers examples of how agency interacts with the environment in workplace transitions. For instance, he describes work expertise as emergent in situations when individually held rule-based concepts and procedures are shaped by the social factors within the community of practice. The question of how changes at the micro-, meso-, and macro-level of a learning system interact, has also been noted in a variety of domains that focus on transitions. As pointed out by George (1993), sociological research on transitions needs to resolve how broader social aspects that influence transitions, such as family and occupational environments, can be captured within empirical work.

Conceptualizations of transitions as inter-related changes at multiple levels have also been proposed in the learning sciences. Although learning scientists do not necessarily use the term *transition* in their explanations of conceptual change, referring instead to changes in how individuals re-organise the information they learn. Conceptual change is a part of developing knowledge and competencies. Some notions of conceptual change are similar to how transitions are theorised in sociological and biographical studies (D. E. Brown & Hammer, 2008, pp. 155–182). Sherin (2017, pp. 61–78) draws on earlier work to synthesise a framework of conceptual change, suggesting that different scholars targeted different levels of conceptual change. Some theorists focus on the small constituent units, such as diSessa's (1993) p-prisms, small potentially flawed units of common-sense knowledge developed by learners through personal observations. Other theories target conceptual change at the level of what Sherin terms as 'ensembles' (Vosniadou, 2017, pp. 17–25), which reflect the higher-level organization of concepts containing smaller interconnected entities within them. Structured interrelationships between smaller entities contribute to a higher-level organization of concepts. Sherin proposes that by nesting these systems of units into one another, conceptual change can be observed as taking place within a conceptual ecology. Sherin theorises that this system represents a dynamic multi-level mental construct that can change, often slowly, in a non-linear manner based on interactions with the social environment.

A large body of research in higher education explores transitions in conceptual change through theories of troublesome knowledge and threshold concepts. In critically reviewing this literature, Markauskaite and Goodyear (2017, pp. 127–166) point out that so-called "threshold concepts" are distinct from the so-called "core concepts", fundamental concepts essential for progress in understanding the subject (p.145). The former are associated with disciplinary difficulties and provide a transformation to the learner's comprehension of the discipline. In other words, threshold concepts are troublesome, as they challenge the existing view (i.e. structure of the construct) the learner holds and provide turbulence to the dynamic mental models, causing a restructuring of the organization of knowledge. Threshold concepts are transformative, and the restructuring of the mental schema has a process-like quality. As learners interact with threshold concepts, they enter the state of reconfiguring their worldview to fit with the newly acquired understanding. The properties of this process of transition as a change in the existing knowledge at multiple levels are similar to the transitions described in sociological literature.

Transitions in what and how individuals know, described by dynamic multi-level changes, are at the foundation of restructuring knowledge and worldviews experienced by individuals learning between old and new contexts. Since the changes take place at different system levels, research methodologies need to be able to capture them over time, as they develop and interact.

2.4. Transitions relate to development across the timescales

Transitions are 'a powerful processual unit of analysis' (Hviid & Zittoun, 2008, p. 123) of an individual's *development* throughout a lifetime of learning. Markauskaite and Goodyear (2017, pp. 127–166) provide a succinct account of *what* changes during learning processes by focusing on the different levels where restructuring occurs. The neurobiological perspective associates learning with changes in the brain, the mentalist approach tackles restructuring or replacement of symbolic entities in one's mind; the phenomenological approaches bring consciousness into how conceptual change occurs, with reflection on behaviours playing a major role, whereas sociocultural, situated and environmentalist approaches move attention towards interactions with the context. The authors explain that an understanding of change is situated within the theoretical premises of these perspectives that essentially address different levels within what can be conceived as a learning ecosystem.

Within such an ecosystem, learning and development are interrelated, process-based, and involve intra-individual changes at different levels and across varying time scales (for a review see Granott & Parziale, 2002, p. 4). Micro-development (micro-genesis) refers to a 'process of change in abilities, knowledge, and understanding during short time spans' (Granott & Parziale, 2002, p. 1). For instance, the reorganization of low-level abilities into higher-level ones can take from a few minutes up to weeks. Ontogenesis, or the development that occurs throughout one's lifetime, refers to the transformations of the individual as mediated and driven by a social context, lasting over longer time periods, such as weeks or months. Definitions of transitions presented earlier include both microgenetic and ontogenetic changes. A typical development model (Saxe & Esmonde, 2012) would also include sociogenesis, or development at the level of the group, community, or society, where transformations occur at much longer time intervals, such as years.

The relationship of transitions to development requires an understanding of the non-linear shifts that occur during learning at varying time scales. Levels of the learning ecosystem interact in ways that cannot be explained by modelling inter-level influences in a linear fashion.

2.5. Transitions are heterogeneous

Heterogeneity is among the implicit yet critical characteristics of transitions. Even at the high-level of life-course transitions (George, 1993) longitudinal patterns observed at the level of individual lifetimes are highly diverse. Rindfuss, Swicegood, and Rosenfeld (1987) showed that only around half the men and less than half the women completing high school in 1972 experienced a simple two-event sequence of education followed by work. This variability in longitudinal patterns is worth noting within a more generic understanding of transitions as process-units in learning and development. At a micro-scale variability is even greater. Individual developmental trajectories are influenced by personal qualities, and the myriad of experiences acquired through participation in multiple communities and the range of relationships with other people and the environment within the present temporal context.

Psychological conceptualisations of development as a dynamic system (Smith & Thelen, 2003) place high importance on the capture and analysis of intra-individual variability. Systems vary in their activity, and they vary in different ways. For example, in a study of micro-development, Yan and Fischer (2002) showed that adult novices learning a computer program had markedly different patterns of variability in their learning when compared with experts. Granott and Parziale (2002) provide multiple examples that show variability in behaviour among most consistent findings in micro-development studies. For instance, Siegler (2006), who studied children's thinking, revealed the presence of variability in learning across domains, tasks within a domain, and items within a task. Siegler's work suggested that the presence of variability was a useful source of information and a predictor of development and learning. Variability is an important factor since it signals developmental attributes and opportunity for learning (Granott & Parziale, 2002, p. 16).

2.6. Implications of transition properties on research approaches

Drawing on the literature from different disciplines reviewed above, we define transitions as a meaningful and fundamental process of transformation in knowledge, behaviour, attitudes, self-perceptions, and social relationships when individuals learn in new contexts. Transitions are processes of change experienced during a discontinuity of contexts that can trigger learning and development in individuals. The nature of transitions has serious implications for the methods and approaches that are needed to examine them:

1. Transitions to attain new knowledge, behaviours, relationships, and identity, during the adaptation to the expectations of a new environment, are temporal, dynamic, and undergo phases.
2. Transformations of various structures during the transition are non-linear, driven by interacting inter-dependent processes, and closely linked with development at various levels and at interacting timescales.
3. How individuals experience and undergo transitions varies, which means that attention to individual and environmental factors that explain heterogeneity is needed.

To gain insight towards personalised support of individuals in transitions, LA methodologies need to integrate educational research designs and methods that afford insights into variability, dynamics, and causal interactions between different levels of individual development, at varying time scales. The remainder of the paper argues that LA research currently offers limited insights into such aspects of transitions. The argument applies to studies that employ quantitative research designs and techniques typically used to implement them.

3. Limits of educational research designs and statistics for understanding transitions

A system-based approach to conceptualising, analysing, modelling, and estimating transitions necessitates the focus on dynamics and temporal history, as well as careful considerations of how and why meaningful changes occur. In this section we start to examine the limitations of fields (e.g. LA) that are derived from traditional research designs, quantitative studies, and associated statistical approaches in education and educational psychology. Research designs that build on qualitative methods can overcome some of the limitations we describe in this section due to their markedly distinct set of tools for producing knowledge. Yet, the limitations we highlight in this section are likely to apply to computational approaches that attempt to scale or triangulate insights obtained from qualitative studies, similarly limiting potential insights into lifelong learning transitions.

We start by explaining why commonly used quantitative research designs in traditional education and education psychology studies fall short of capturing process data and using analytical methods that reveal the mechanism of change. Chinn and Sherin (2014) argue that many educational research designs using quantitative methods are limited in understanding human development. As they note, cross-sectional studies that focus on attainment of learning outcomes (i.e., performance or skills), show that learners achieve certain levels of competence, but do not reveal if this was a result of a change, nor do they identify how and when the change occurred. Longitudinal studies also do not afford the capture of development, despite their temporal orientation to data collection. Although longitudinal studies do embed time within the research design, they collect information about change on one of the dimensions of change only. Specifically, these designs reflect a change in educational outcomes at the individual level. The approach does not provide insight as to why, when, or how critical learning processes at the lower interactional level have resulted in the observed higher-order change. Yet, it is at the interactional level that instructors can intervene. Missing the relationships between the temporal changes at the level of intervention and process of change at the higher-order levels limits the capacity to effectively support learners. Finally, experimental studies can illuminate the change caused by a particular intervention. However, traditional experimental designs allow for little, if any, data collection between pre-test and post-test. Therefore, the details of the process between these testing events remain unknown. These critiques are not new, and ways of combining designs have been previously suggested (A. Brown, 1992). Recent innovations in technology-based experimentation and experience sampling help to address some of the limitations as they allow for micro-level data collection and micro-trials (NeCamp, Gardner, & Brooks, 2019). However, these designs are yet to be widely adopted.

Numerous scholars have called out the methodological limitations in educational and psychological quantitative research, claiming that these limitations need to be overcome in cognitive, learning, and social sciences (Arocha, 2021; Davis & Sumara, 2005; Edmonds, 2020; Jacobson, Kapur, & Reimann, 2016; Jörg, Davis, & Nickmans, 2007; Koopmans, 2020; Marchand & Hilpert, 2020; Mathews, White, & Long, 1999; Reimann, Markauskaite, & Bannert, 2014; Richardson, Dale, & Marsh, 2014; Witherington, Vandiver, & Spinks, 2021). Much of the critique has come from recurrent arguments by the proponents of complex dynamic systems as an epistemological framework for educational research (Davis & Sumara, 2005; Garner, 2020; Hilpert & Marchand, 2018; Jacobson et al., 2016; Jacobson & Wilensky, 2006; Jörg et al., 2007; Koopmans, 2020; Koopmans & Stamovlasis, 2016; Reimann et al., 2014). Common to these critiques is a claim that research designs which reduce or remove effects related to context, variability, dynamics, and interactions between different levels of development, lack insight into how and why skills, attitudes, and social relationships change. Furthermore, experimental and quasi experimental designs and the general linear statistical models highly utilised in psychology and quantitative educational studies are limited in capturing intra-individual changes. In what follows we note some method-specific limitations raised through these arguments.

Limitation 1. ***Superficial approach to integrating contexts.*** Learning is context specific. Contexts have a pragmatic function: as system-specific factors they help to explain change, as well as enable the transfer of what is learnt from one situation to another (Edmonds, 1999). Context is an abstraction of the collection of background features, such as shared physical, social, and biological characteristics (Edmonds, 1999). Understanding how and why something occurs in a particular context establishes the generality of the phenomenon and transferability of the findings to other similar contexts. At minimum, contexts can be situational, social, and cognitive (Edmonds, 2020), but a range of more nuanced conceptualisations exist. In computational educational studies, context is a complex and poorly theorised concept that is often used imprecisely.

Quantitative analysis of learning has tended to adopt a reductionist approach to integrating contexts into modelling. Despite the specificity, variability and nuanced nature of context, the quantitative social and psychological scientific methods tend to average out contextual differences into generic models, suggesting trends and patterns that may not apply to real life scenarios (Edmonds, 1999). Kaplan et al. (2020) argue that the notion of evidence in educational research, as obtained from randomized-control trials, removes the specificity of contextual factors that explain the original effect sizes. Kaplan and colleagues go on to call for contextual information to be expanded, rather than smoothed over, in critiquing findings from their meta-analysis of a multi-site study.

Limitation 2. ***Focus on between-subject differences, rather than intra-individual variability.*** Assumptions embedded within some of the quantitative methods employed in educational research cannot capture intra-individual variability. This limits our understanding of transitions. A critique of quantitative methods that average variability comes from domains other than education. For instance, Arocha (2021) strongly argues against specific research practices that overlook variability when they want to understand human behaviour:

> 'Although the so-called "replication crisis" observed in the psychological and health sciences has led to various proposals for improving research quality, most of those proposals take the standard linear input–output approach for granted, where behavioral variability is seen as the result of uncontrolled random variables hiding the true input–output relations. Aggregate data and the computation of sample statistics are used to estimate population parameters, the true reality behind appearances.' (p.75).

This focus on averaging and aggregating across the populations is implicit to many statistical methods deployed in psychological research, since inter-individual variation (as opposed to intra-individual variation) helps describe the populations. However, as demonstrated by Molenaar and Campbell (2009), psychological processes, such as cognitive processing, perception, emotion, motor behaviour, are non-ergodic (i.e. they follow person-specific dynamic models). Therefore, data averaged to describe a group does not always accurately inform about the dynamics describing a specific individual (Molenaar & Campbell, 2009; Witherington et al., 2021). Understanding intra-individual differences is particularly relevant for researchers in educational domains where the intention is to offer feedback personalised to individuals (Saqr & López-Pernas, 2021).

Limitation 3. ***Assumption that data about learning are randomly sampled and independent.*** Data used for the above-mentioned methods are often assumed to follow a particular shape and have certain properties, such as 'prevalence of normal probability distribution, regression to the mean, the central limit theorem, and linear cause-effect relationships' (West, Deering, & Deering, 1995 in; Koopmans, 2020, p. 360). Yet, data collected from learning environments, such as human performance data or social interaction data often follow non-normal, heteroscedastic, and non-linear distributions, suggesting interdependencies and complexity within the data. This is particularly pertinent for studies into transitions where they generate data with similar properties, as they are described by heterogeneous sequences of events, of various granularity, at different time scales. These events, given the phase-based nature of transitions, could be, at least in part, path-dependent, i.e. described by 'a dynamical process whose evolution is governed by its own history' (David, 2011, p. 91). This concept of path-dependence has been broadly applied, from developmental sequences to social dynamics, and relates to the effects that system dynamics has on itself, through feedback loops and self-reinforcement (David, 2011).

Path-dependence and the effect of the system's history on itself may not necessarily be captured through conventional approaches for modelling time and patterns of change. Statistical models for time series or sequential data are often applied to already transformed data where information about intra-individual variability and event history is removed, and some randomness and independence of observations is assumed, though the events may be contingent on one another. This limitation applies, for example, to the first order Markov chain models. These are typically used in a range of social scientific applications (David, 2011) as they help quantify the probability of change from one state to another. When estimating the probability of change from one state to the next, the first order Markov chain model assumes that each current state depends only on the one state preceding it, not on the history of states describing the entirety of the process. Techniques, such as recurrence quantification analysis or sliding window models offer complementary ways to describe recurring patterns in the process, or evolving phases.

Limitation 4. ***Modelling phenomena by adding its components or causes.*** A number of researchers have pointed out the drawbacks associated with adopting an overly reductive approach to understanding educational phenomena. Mechanistic and reductionist assumptions of methods that decompose a whole into parts do not always offer explanations about dynamic, process-based, multi-level phenomena (Garner, 2020). In these methods, the elements of a phenomenon are examined separately, and results are then aggregated across the parts, as if the effects of elements and levels of the phenomena were additive. Richardson et al. (2014) explain that when system behaviour is produced by components (modules, agents, elements) with predetermined unchanging function (such as in a clock or assembly line), it is component-dominant, described by addition of the parts together. Hilpert and Marchand (2018) discuss why educational psychological research should be careful in applying a component-dominant approach to learning and education. In learning and educational systems, different levels and components are interdependent, they interact, may change functions, and therefore, cannot be modelled through addition (see Jacobson et al., 2016 for examples of such systems). When elements at the lower level of the system affect elements at higher level, and vice-versa, in a non-additive manner, the behaviour of such a system is described as interaction-dominant (Hilpert & Marchand, 2018; Richardson et al., 2014).

Hypothesis testing methods in psychological research (e.g., regression analysis and methods following similar logic) often deploy an additive logic in estimating factors influencing an outcome. Koopmans (2014) views such 'linear causality' as dominating educational research and policy, where interventions are viewed in direct linear causal relationship with an educational outcome, and analysis seeks to identify these linear causal links. Transitions, however, are conceptualised through non-linear multi-level interactions. This indicates that causal influences in transitions may be not additive. Still, statistical tools modelling *interaction-dominant* phenomena in educational psychology are uncommon (Hilpert & Marchand, 2018; Richardson et al., 2014).

Limitation 5. ***Predicting long-term outcomes rather than trajectories.*** Lastly, much of the logic of statistical estimation in educational research relies on predicting outcomes using a set of variables. Studies tend to predict the ultimate state, such as success in fulfilling course requirements or long-term academic achievement. In doing so, they presume that relationships between variables predicting the outcomes do not change over time. One alternate approach is to recognise that relationships are not stable and focus on predicting the next possible state only. In complex systems research, the problem of predicting dynamically changing states can sometimes be addressed by introducing the so-called *adjacent possible* (Kauffman, 2000), a set of states that potentially can exist in the upcoming time, given the present state. As Thurner, Hanel, and Klimek (2018) noted, the *adjacent possible* describes possible states reachable in the next future time period, which significantly decreases the state space from that of all possible states in the entire development of a system until its end state. Such a perspective, when using computational models to describe or predict change in learning and development, suggests that estimation of a trajectory towards a state or a deviation from it may be more relevant, than prediction of the long-term outcome.

4. Can learning analytics in its current state inform research on transitions?

Learning Analytics (LA) is an applied research area that can potentially support individuals throughout their lifelong learning process. LA researchers examine micro-level learner trace data complemented with other diverse data sources. The data are interpreted to gain insights that can improve learning processes and educational outcomes.

Although LA has matured since its inception, we will argue here that current practice is not adequate to fully support lifelong learners. Lifelong learning transitions between various educational sectors and professional roles are process-based, dynamic, unfold at multiple levels, and are highly variable. As we have shown, dominant research designs and statistical methods used in psychological and educational studies fall short of analysing transitions. In this section, we demonstrate that LA replicates the same limitations; we then propose specific areas where LA research can start to address these pitfalls.

4.1. Controlling for context rather than modelling it

LA studies have incorporated contexts into the modelling of learning. Several studies, for example, have highlighted the prominence of context-related factors. Gašević, Dawson, Rogers, and Gasevic (2016) demonstrated that models built for one context (i.e. for a course) do not work well when contexts are aggregated (i.e. at the level of the department or an entire institution). In another example, Jovanovic, Mirriahi, Gašević, Dawson, and Pardo (2019) compared the performance of a predictive model they used to identify learner success with course-design-agnostic and course-design-specific indicators used for prediction. Their results show that models predicting performance using generic features of engagement lack sufficient explanatory power, whereas adding course-specific features of engagement significantly improves prediction. Other LA studies similarly provided evidence on the relevance of such context-related factors observed externally, such as course design (Conijn, Snijders, Kleingeld, & Matzat, 2016; Marras, Vignoud, & Käser, 2021), as well internal to the learners, such as learner states (Jovanović, Saqr, Joksimović, & Gašević, 2021). The information about the context can differ, ranging from socially shared spaces to internal learner states, to learner similarity in developmental processes, or navigational paths that reflect the journey of an individual within a learning resource. An example of the latter can be found in Goggins, Mascaro, and Valetto (2013), where learners' interactions were contextualised using information about the activities learners engaged with outside of the socially shared space. By capturing logs of what individual learners were doing in the course and what artefacts they interacted with, the authors explain why learners may have sought out peer interactions. Regardless of the sophistication in how the abovementioned work operationalised context, the contextual variables were integrated into the modelling to quantify what they can explain in the model (i.e., controlling for context), rather than modelling how they explain observed differences between the learners.

A more nuanced understanding of context is necessary in LA. The field sorely lacks a workable definition of what key terms like system, environment and context mean. The lack of clarity concerning terminology leads to category errors and misconceptions. This is clearly seen when the meaning of terms like context are compared across studies. For example, is *context* anything that remains unrepresented in trace data (e.g. Conijn et al., 2016; Marras et al., 2021)? Or is *context* a latent variable that impacts upon a student's outcomes (e.g. Jovanović et al., 2021)? In the above discussion we refer to papers that have adopted both definitions, but from a conceptual point of view these describe different interpretations of 'contexts'. Precise definitions of this critical term would help LA to move forward as it works to model lifelong learning transitions.

Other fields have worked to provide more rigorous models of context. For example, Kitto (2014) defined three types of contextuality in complex systems, and each of them could prove useful in attempting to model transitions through lifelong learning. Kitto suggested that we need to be careful about the class of contextuality under consideration, from interactions that occur: (i) between components (e.g. if one component of a system depends on input from another); (ii) between a system and experimental method (e.g. if a system demonstrates an effect based on the way in which it is measured); and (iii) between system and environment (e.g. if the environment in which a system is interacting can affect that system in a definable manner). Different models are likely to be required to deal with each scenario.

Akin to our understanding of "context" the definition and interpretation of "system" in LA studies requires further consideration. In educational transitions, we might choose to model a person as the system of interest, or the learning strategy that they adopt, or the system in which they are embedded (which could itself be a course, a group, an institution, etc.). In each case, the three types of interactions defined above would be different, along with what data streams could be used in the model. The modelling of context and system is non-trivial but being explicit about their meaning is possible. Describing this complex set of concepts and providing specificity to the studies of educational transitions will require such work.

4.2. Predicting yet not explaining

Providing personalised insights to learners throughout their lifelong learning transitions requires models that keep track of individual progress. Ideally, such learner models would also offer personalised suggestions to identify strategies to achieve stated learning goals. Such a vision requires that researchers can *explain* learning processes, inferred from the ubiquitous digital traces. Dawson, Joksimovic, Poquet, and Siemens (2019), however, found that 80% of studies in LA presented at the learning analytics conference in the past decade, focused on prediction problems. Only one fifth of studies framed their work through explanatory questions. A deeper examination showed that only a fraction of these focused on causal mechanisms. This is not surprising, given that predictive modelling has a long-standing history in LA, targeting primarily identification of at-risk students (Brooks & Thompson, 2017). Predominantly, such models focus on predicting learner outcomes at longer timescales than granular trace data.

It remains unclear if predicting long-term learner outcomes without understanding the mechanisms behind the dynamics of underlying processes is informative for personalised insights. To examine this, we can look at a strand of LA focused on analysing behavioural micro-level sequences. This work is firmly grounded in established educational theories around self-regulated learning. Examples include analyses of changes in self-regulation activities during a learning session (Bannert, Reimann, & Sonnenberg, 2014) or one or more course units (Greene et al., 2019, p. 101201) using sequence or process mining techniques to identify patterns of self-regulated learning (SRL) processes. Patterns of activity sequences during a task are considered manifestations of learning tactics, whereas patterns of tactic sequences over a longer time period, such as course unit or entire course are interpreted as manifestations of learning strategies. Learning strategies are often analysed at the level of duration of a course (Mirriahi, Jovanovic, Dawson, Gašević, & Pardo, 2018; Pardo, Gašević, Jovanovic, Dawson, & Mirriahi, 2018), and recently across multiple courses of a professional development study program (Barthakur et al., 2021). Changes between tactics associated with micro-level SRL processes have been analysed to examine effectiveness of interventions embedded in specialised learning systems to promote and facilitate SRL (Milikić, Gašević, & Jovanović, 2018; Siadaty, Gasevic, & Hatala, 2016). More often though, and similar to predictive modelling, these studies examine the association between prominent regularities in sequences and a longer-term outcome. Several such studies identified, interpreted, and compared learning tactics adopted by students during a course (Fan, Saint, Singh, Jovanovic, & Gašević, 2021) or were used to identify student strategy groups (Fincham, Gašević, Jovanović, & Pardo, 2018; Matcha, Gašević, Uzir, Jovanović, & Pardo, 2019). In both cases, comparison across tactics/-strategy groups was made based on a long-term outcome (ie. course performance).

Despite the focus on the process elements, the work on sequences of learner behaviour, does not always offer insight as to why or how these behaviours relate to the phases of self-regulation, or when and why improvement occurs. This makes it difficult to advise students as to how they might improve their strategy. Reimann et al. (2014) discussed why sequence- and process-based studies that focus on the association of micro-level sequences with long-scale performance outcomes do not offer explanations of the process itself. As posited by these authors, association of a process-pattern with an outcome variable does not offer insight that explains the underlying causal mechanisms that generate the observed process. Association of prominent regularities in student behaviour with final grade may be insufficient to explain differences in self-regulation or to contribute to self-regulation theory. Sequences both at the level of tactics and strategies can have different functions within the process of self-regulated learning. In micro-development research, for instance, sequences can have a trend of growth, or may cluster into specific types, generalised by the function they have within the unfolding process, such as backward transitions, ordered fluctuations, or iterations (Granott, 2002, p. 213). Some of these may signal that a shift to an improved state is approaching, whereas others may indicate stalling, or even regressive behaviours. In certain problem formulations, such as providing task-based feedback, it might be more useful to identify prominent sequences of behaviour, than to estimate the probability that a learner will "succeed" in the course.

4.3. Limited modelling of dynamics

LA studies often lack an analysis of change in learning across different levels. Although temporal aspects may be present as an element in modelling, their use is often limited to an analysis of traces aggregated across sequences of heuristically identified time periods. For example, Poquet et al. (2020a) modelled change in the types of discussion content across heuristically identified periods in the course (2–3 weeks that aligned with course design and observed participation patterns). The authors used regressions to estimate the rate of posting within each of these time periods. Such analysis of dynamics presumes that posting activity and other factors controlled for in the regression models, were independent, or interacted in a linear fashion. That is, the estimation was agnostic to potential multiplicative interactions between various factors that lead to someone posting (both those measurable in clickstream data and those not captured). Instead of capturing the dynamics of change, this study averaged the rate of posting within different time periods and compared them. These averaged dynamics were also not extrapolated to describe a potential higher-level process of group development. In short, although the study offered insights about the types of interactions at different time points throughout the course, the modelling itself considered temporal change in a superficial manner. Other examples involve temporal modelling of posting as a networked activity (Castellanos-Reyes, 2021; Chen & Poquet, 2020). These studies are more sophisticated in how they integrate dynamics into modelling, but they fail to recognise that these changes occur at multiple levels, and that the levels can also interact (i.e. may serve as input for each other's dynamics). These examples quantify dynamics but are limited in their potential to explain the mechanism/dynamics of change - be it change at the level of a learner, group formation, or an evolution of a collective discussion. Throughout these examples the change is modelled only at one level of the system, i.e. at the level of the posting event (Chen & Poquet, 2020) or at the level of the state of the network tie representing presence of communication between the learners (Castellanos-Reyes, 2021). These temporal analyses do not integrate different system-levels bridging individual posting with communication ties. On the other hand, those studies that bridge levels of a social system by modelling a generative process to explain the observed higher-order network interaction (peer communication) through the dynamics of lower-level events, i.e. posting behaviour, do not include time and change in their analyses (Poquet, Tupikina, & Santolini, 2020).

4.4. Can transitions be modelled using the 'clicks to constructs' approach?

LA faces challenges to conceptually conceive and implement links between fine-grained data as captured in logs and higher order learning and cognitive constructs. The 'clicks to constructs' approach (Wise, Knight, & Buckingham Shum, 2021) adopts the stance that the design of an analytic should work to create an intermediary layer, between low-level digital traces and higher-level constructs. Digital traces, such as clickstream data are transformed into analytic level constructs that can be further linked with well-established theoretical constructs from the learning sciences. These theoretical constructs can then be more closely aligned and interpreted through macroscopic behaviour and student outcomes. While the 'clicks to constructs' framework was not designed to model transitions, this is an interesting approach that may have deeper applications for transition research. Presently, this framework exemplifies how a researcher can move from traces to theory-informed analyses adopting a static view. This means that the behaviour captured is time-bounded and the constructs do not evolve over time. While the 'clicks to constructs' approach may potentially imply levels of analysis, it does not explicitly include them, nor the time scales upon which behaviour unfolds and the constructs could evolve. The static view within the 'clicks to constructs' approach does not provide an analytical frame where individual level traces can vary and correspond to the different phases of behaviour that are experienced by an individual, or other construct of interest (e.g., an individual's approach to learning). Further, the 'clicks to construct' view collapses time scales, which analytically suggests that constructs and behaviour map onto the same time scale, implying that the construct does not have a separate evolutionary trajectory. Put simply, 'clicks to constructs' framework is a useful analytical lens but is not currently well suited for understanding the development and processes of change that are inherent in an educational transition. This does not necessarily mean that such a framework *cannot* represent evolving constructs. However, more work is required to develop an analytical framework that is capable of embedding learner transitions as well as the causal and contextual factors that might affect them. In the next section we turn to an exploration of what methods could help to augment this promising approach with the temporal apparatus necessary to model lifelong learning transitions.

5. Advancing research on transitions

The analytical limitations discussed had been voiced before. For instance, Reimann et al. (2014) called for the research of electronic data to reach beyond process-based approaches, towards including (i) stratified ontological frameworks, which would support the modelling of change within a system where development unfolds at varying levels and timescales; (ii) multimodal data from multiple sources that describe events, states, behaviours, and enable triangulation from different viewpoints on the process of change; and (iii) dynamic analytical methods, which enable the modelling of multiple dependencies in the data to identify meaningful regularities and causes of change. The previous sections have shown that LA requires a substantial extension to its modelling infrastructure before it might be able to incorporate some of the requirements called for by Reimann et al. (2014). This argument largely applies to LA studies that employ quantitative research designs, less so to qualitative and mixed research designs. As we have discussed, studies using computational methods in LA tend towards static or cross-sectional designs, rather than those capable of reflecting the temporal nature of change and dynamics explaining the development that individuals tend to undergo during learning transitions.

When discussing the limitations of modelling in LA, we highlighted the need for more rigorous definitions of context and dynamics as means to describe and explain patterns of change. We acknowledge that there are methods that are already in use and can in part help overcome some of the challenges we identified in Section 2.6 when defining transitions. Namely, non-parametric approaches including network modelling (Castellanos-Reyes, 2021), recurrence quantification analysis (Vrzakova, Amon, Stewart, Duran, & D'Mello, 2020), simulations (Poquet, 2021), time-sensitive modelling using sliding-window models (Dowell, Nixon, & Graesser, 2019), as well as analytical pipelines rigorously operationalizing context (Suthers, 2015) can all in part address the requirements identified when we conceptualise transitions (Section 2.6). What we want to emphasise is that these methods are only in part sufficient and still largely under-utilised.

To advance computational analysis of transitions requires more than the adoption of relevant methods. Frameworks that take into account their complexities are also needed. In the remainder of the paper we propose two promising avenues that could be followed to build upon the 'clicks to constructs' framework introduced above, extending its notions of levels to model them as changing in time and causally interrelated.

Inspiration for the first avenue is drawn from cultural developmental models (e.g. Saxe & Esmonde, 2012). To provide an example of what frameworks to model change may look like, we adapt the cultural developmental model that demonstrates the relationships between microgenesis, ontogenesis, and sociogenesis, as originally conceptualised by Saxe. In Saxe's model, development is represented as an ordered networked grid linking processes at the micro-genetic level (e.g. communicative events occurring 'in the moment') with ontogenetic level processes (e.g. individual ways of thinking that evolve over periods of individual development) and with sociogenetic processes (e.g. common ground talk accepted in the group that evolves over long periods of time).

Fig. 1 presents a simplified representation of this model, where nodes of the grid correspond to states at different levels of system. A micro-level state directly affects an emergent meso-level state. A macro-level state acts as a context in which the evolution of this system occurs, driving its behaviour, and in turn is affected by the micro-states of all individuals within the system at a given moment. If meso-level state is conceived as internal to the individual, rather than socially shared, then it mediates the relationship between micro and meso states, but certainly other conceptualisations may exist. In lifelong learning transitions, we might see this type of process occurring where an individual (represented in the model as an emergent meso-state), who adopts a number of different learning strategies informed by key knowledge attributes and skills (the micro-state), interacts with a broader social context (a macro-state such as an employment market), which in turn impacts upon their consequent strategies, affecting individual conceptions of self-worth. The grid in Fig. 1 is ordered, with a left to right

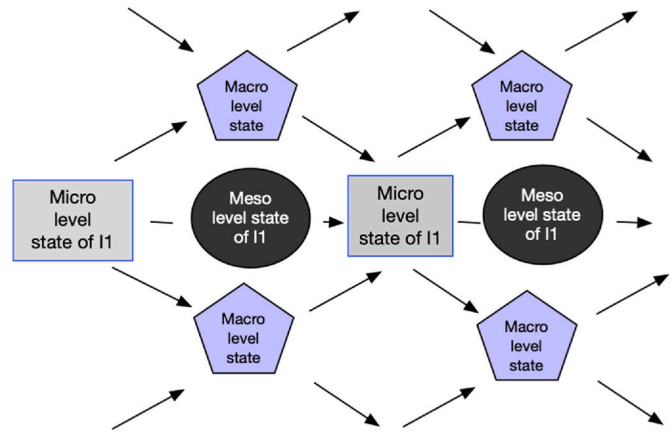

Fig. 1. Schematic fragment of a developmental model representing a trajectory of one individual (I1) in a socially situated environment, simplified from Saxe (2012).

progression representing change in time, and each row surrounded by macro-level variables representing an evolution of the individual in response to their social context and vice versa (Kitto & Boschetti, 2013). Such frameworks that incorporate dynamically evolving states impacted by, and in turn affecting, emergent processes at other levels should be a priority if LA is to work towards authentic models of lifelong learning transitions.

A variety of adaptations of this model are possible. The proposed model enables an explicit representation of the states related to a learner's change, ordered through time, across different levels that impact upon this change. The model can also represent many unique individual trajectories. Such a representation can be a natural extension of the 'click to constructs' framework, as it enables the preservation of lower-order to higher-order state relationships between a set of constructs defined at the level of a node within a developmental model. Once the system and its trajectory, including the transitions of interest, are defined, a set of three research questions associated with this new representation can be summarised as:

1. What changes in the system of interest occur, given a focus on educational or developmental outcomes? That is, what processes should be captured, by what constructs and states throughout a developmental trajectory?
2. Why does this system change? That is, what causal factors, external or internal to the system, need to be selected to explain the most change in this system?
3. How does the system change? Or what is the dynamics describing how and when states in the system change?

Formulating hypotheses around each of these questions and providing specific methods capable of addressing them is complex. Methods will vary, and a range of best practice solutions will be possible depending upon the system modelled.

In the case of individuals undergoing lifelong learning transitions, one solution is to attempt to answer these three questions using idiographic research designs, (i.e., those describing individuals or single cases). Although much emphasis in LA has been on statistical models, and against the use of single cases, it is important to recognise that small explanatory case studies can bring much understanding, if they offer rich computational explanations of change and variability for particular individuals or groups of individuals. The mechanisms that underpin individual transitions have to be discovered by studying individuals. Newell and Simon (1972) understood this well, establishing think-aloud protocols with individuals before engaging in computational modelling of the associated thought processes (Newell & Simon, 1972). Single case research methods have a very long tradition in specific areas of educational research and avoid many of the limitations described above (see e.g. Riley-Tillman, Burns, & Kilgus, 2020). This makes them an ideal starting point for working towards modelling, understanding and explaining how change occurs in individuals over major transitional events. Few analytical methods exist for modelling this type of phenomenon, making it a key target for future research.

A number of modelling approaches have attempted to provide a mathematical formalism that is capable of describing systems outlined above. A strong example is provided by Baas (2019a, 2019b) who develops an extensive modelling framework for dealing with hierarchical structures, termed hyperstructures due to their cross-level linkages. This framework takes much of the theoretical apparatus of category theory to provide mathematical models of how one level in a system can affect the dynamics of the others (both above and below). This modelling framework owes much of its apparatus to the modelling of biological emergence, making it a viable candidate for describing the evolution of and emergence of novel psychological behaviour, but other approaches are possible.

The second opportunity for moving forward in modelling of educational transitions in LA is provided by *causal inference* (Pearl, 2009; Pearl & Mackenzie, 2018), which supports reasoning beyond the standard largely correlation-based statistical models of the educational sciences. Causal inference provides a sophisticated toolkit for reasoning about *why* a system is behaving like it is, not just making statements about the correlates of that behaviour. Pearl has spent decades developing a set of techniques that enable us to move beyond the frequently cited adage that "correlation does not equal causation" (Hartnett, 2018).

Pearl and Mackenzie (2018) provide an illuminating introduction to causal inference, arguing that a three-layer ladder of causation can be used to classify the causality of the different types of questions asked in a data analysis:

1. Association. This basic level of causality uses statistical relationships, correlations, curve fits etc. to infer relationships between variables in a dataset. No causal information can be extracted. Much of the work completed in LA covers this lowest level of the ladder, which means that there are very few opportunities for linking the insights obtained in these fields to causal claims.
2. Intervention. This level involves not just measuring an effect but changing an input and then recording an outcome. In performing this form of analysis, we learn much more about how we might *change* outcomes, rather than simply observing them (leading to a higher classification in the ladder). A/B tests provide a good example of this level of the ladder, and indeed, methodologies have been developed for modelling interventions in the field.
3. Counterfactual. This highest level of the ladder involves considering *what would have happened* had we done things differently. Beginning with Pearl (2009), an advanced mathematical apparatus has been constructed which enables us to construct counterfactual models in a precise way. Counterfactuals are placed at the top of the ladder because they subsume interventional and associational questions. That is, it is possible to answer questions about interventions and associations if we can answer counterfactual questions.

Considering the ladder of causation within the lens provided by the earlier sections of this paper, we quickly understand that the bulk of the work in educational research and LA has kept to the lowest level of causation. Although LA research offers examples of experiments (Kizilcec & Brooks, 2017) or simulations (Poquet, 2021), overall approaches for reasoning counterfactually in LA are under-represented, especially when it comes to explaining the trajectories followed by individuals over a lifetime of learning.

Promisingly, Pearl (2009) laid out a comprehensive theoretical framework for causal modelling, creating a "do-calculus" that enables us to ask (and answer) questions about "what would happen if I were to *do* this action?" and thence to reason counterfactually *and* statistically over a dataset. This is a significant improvement upon the current association-based modelling approaches that dominate LA, as it enables us to rigorously model causal effects without relying upon the unwieldy apparatus of A/B testing. Adopting an approach such as this, provides a significant boost for fields like education, which struggle with the ethical problems associated with establishing control groups and performing an intervention to test theory. Importantly, developing models at higher levels of the causal ladder requires that data analyses have a theoretical grounding. For example, in lieu of simply performing a correlation analysis where patterns between variables are discovered, both intervention and counterfactual levels require that a model is theoretically framed and sufficiently developed. Such hypotheses can be proposed early and appropriately tested. In our view this area has direct applications that would help improve our approach to modelling learning transitions in the short to medium term.

6. Conclusions

The paper has placed transitions experienced through lifelong learning at the centre of its argument and examined implications for LA. Understanding transitions and supporting learners as they shift between contexts, career roles, and sectors, becomes highly relevant with the increased demand on learning new skills and competencies, required for the future workforce. Complexity of learner changes during transitions stem from their holistic nature. Learning throughout one's lifetime transcends knowledge and skill acquisition, as professionals develop knowledge, skills, behaviours, relationships, and identities continuously through social interactions within emerging contexts. To understand the properties of transitions, we reviewed and synthesised literature about transitions in several domains, such as conceptual change, shifts between educational systems, and changing roles during life course. Through this review, we defined transitions as process-based, dynamic, multi-level, and highly contextual processes, with various factors interacting in a non-linear manner. Our argument is that a system-based approach to conceptualising, analysing, modelling, and estimating transitions is needed. Learning analytics and educational research however are under-prepared to examine lifelong learning transitions at scale. As discussed, properties of educational research designs and certain statistical models applied in educational psychology are limited in capturing variability, dynamics, and causal interactions between levels of individual development. We reviewed several strands in LA that contribute to limited insights about transitions, including lack of defining and modelling context, over-reliance on prediction, and limited focus on temporality. We suggested extending one of the common approaches to modelling in LA, namely "clicks to constructs", to include time and inter-level interactions. A focus on causal inference, although a challenging task, also offers an entry point to improve modelling of lifelong learning transitions in the short to medium term. We see research in lifelong transitions as an opportunity. Although a substantive body of literature about learning transitions has emerged in a wide variety of fields, we lack a sophisticated apparatus capable of modelling them. As a field, LA stands to gain much from developing new theoretical and methodological frameworks that can provide insights into this critical concept. This paper provides a commencement point to initiate further discussion, debate, and ideas to advance our research and understanding of both LA and the role it can play in lifelong learning transitions.

7. Citation diversity statement

Recent work in several fields of science has identified a bias in citation practices such that papers from women and other minorities are under-cited relative to the number of such papers in the field (Zurn, Bassett, & Rust, 2020). We have manually checked the first and the last author's names and inferred gender. By this measure, our references are written by woman (first author)/woman (last author) – 5% and 11% were solo woman authors. Some 14% of references were written by men (first)/woman (last), 22% by woman (first)/man (last), and 26% by man (first)/man (last), and 22% solo man authors. This method is limited as it is not indicative of gender identity, and it cannot account for intersex, non-binary, or transgender people. We look forward to future work that could help us to better understand how to support equitable practices in science.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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