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Profiles of Inconsistent Knowledge in Children's Pathways of Conceptual Change

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Conceptual change requires learners to restructure parts of their conceptual knowledge base. Prior research has identified the fragmentation and the integration of knowledge as 2 important component processes of knowledge restructuring but remains unclear as to their relative importance and the time of their occurrence during development. Previous studies mostly were based on the categorization of answers in interview studies and led to mixed empirical results, suggesting that methodological improvements might be helpful. We assessed 161 third-graders' knowledge about floating and sinking of objects in liquids at 3 measurement points by means of multiple-choice tests. The tests assessed how strongly the children agreed with commonly found but mutually incompatible statements about floating and sinking. A latent profile transition analysis of the test scores revealed 5 profiles, some of which indicated the coexistence of inconsistent pieces of knowledge in learners. The majority of students (63%) were on 1 of 7 developmental pathways between these profiles. Thus, a child's knowledge profile at a point in time can be used to predict further development. The degree of knowledge integration decreased on some individual developmental paths, increased on others, and remained stable on still others. The study demonstrates the usefulness of explicit quantitative models of conceptual change. The results support a constructivist perspective on conceptual development, in which developmental changes of a learner's knowledge base result from idiosyncratic, yet systematic knowledge-construction processes.

Keywords: latent profile transition analysis, conceptual change, knowledge integration, conceptual development, knowledge structures

Changes in a person's knowledge base are among the most powerful sources of cognitive development (Case, 1992; Siegler & Chen, 2008). Conceptual knowledge helps people to subsume objects and events under general categories, to understand general principles and rules in a domain, to draw generalizations, and to make predictions about future events (Machery, 2010). Accordingly, prior conceptual knowledge has been shown to strongly influence subsequent learning and to correlate with measures of academic achievement (e.g., Schneider, Grabner, & Paetsch, 2009).

From a developmental point of view, an important question is how long-term changes in a person's conceptual knowledge can be captured and whether general developmental patterns can be identified. Over the last decades, experimental psychology has made great progress in investigating the basic representations underlying conceptual knowledge (Machery, 2010). In contrast, less is known about how complex networks of conceptual knowledge evolve later in development, for example, learners' knowledge about specific phenomena in physical, biological, or mathematical content domains (Chi & Ohlsson, 2005; Schauble, 1996). In our study, we investigated such developmental patterns in the domain of floating and sinking of objects in liquids.

Knowledge Fragmentation and Integration

A person's conceptual knowledge in a domain is not a singular entity but instead comprises various elements, for example, observations, beliefs, exemplars, prototypes, explanations, or assumptions about causal relations (diSessa, Gillespie, & Esterly, 2004; Gopnik & Schulz, 2004; Machery, 2010). The structure of a person's conceptual knowledge is influenced by the processes of fragmentation and the integration of these elements.

Knowledge fragmentation occurs when learners are not attuned to the interrelations between knowledge elements ac-

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quired in superficially different situations. In this case, learners store the elements independently of each other in their long-term memory even when they are in fact related on the level of abstract principles (e.g., Clark, 2006; diSessa, 2008; diSessa et al., 2004; Izsák, 2005; Wagner, 2006). For example, a child might know that wood floats in water and that a hot air balloon floats in air but may not relate these two phenomena to each other or to their commonly underlying principle of buoyancy force in her memory.

Knowledge fragmentation might be stronger for novices than for experts in a domain because novices have been shown to frequently focus on the surface structure of problems and because they lack the prior knowledge relevant for interpreting new information in terms of underlying principles (e.g., Gobet, 2005). Pieces of fragmented knowledge that a learner might have in a particular domain might complement each other well, and the learner just does not realize their structural relations. However, some studies (reviewed later) support the more extreme view that even mutually inconsistent pieces of knowledge can coexist in a learner.

Knowledge integration occurs when learners organize new pieces of knowledge into broader knowledge structures (Linn, 2006; Schneider, 2012; Schneider & Stern, 2009). The integration of knowledge might result from learners' tendency to strive for a coherent view of the world and to minimize cognitive conflict (Vosniadou, Vamvakoussi, & Skopeliti, 2008). This can be achieved by integrating new insights in a domain into coherent knowledge structures. Integrated knowledge can be difficult to change because it is highly relational and integrates a wealth of different observations, experiences, and assumptions about the world into a coherent system (Vosniadou & Brewer, 1992). Some authors refer to integrated structures of conceptual knowledge as *subjective theories* or *naïve theories* in order to emphasize their explanatory power and coherence (e.g., Gopnik & Schulz, 2004; Vosniadou et al., 2008).

Mixed Empirical Evidence

In many previous studies, researchers have tried to find out whether learners' initial knowledge in a domain is integrated and consistent or fragmented and inconsistent. Empirical support for integrated knowledge comes from studies on misconceptions, which show that children already hold coherent explanatory frameworks in a domain prior to formal instruction. The studies have been conducted in age groups ranging from preschool children to adults and in various content domains of science, among them the concepts of matter (Jiménez Gómez, Benarroch, & Marín, 2006), evolution (Shtulman, 2006), astronomy (Vosniadou & Brewer, 1992), and force (Ioannides & Vosniadou, 2002).

A number of other studies have found evidence for fragmented knowledge in learners, as alternative and sometimes inconsistent ideas coexisted. The age range of the participants was similar to the studies described previously. The content domains included air pressure (Tytler, 1998), evaporation and condensation (Tytler, 2000), chemical bonding (Taber, 2001), thermodynamics (Clark, 2006), motion (Thaden-Koch, Dufresne, & Mestre, 2006), statistics (Wagner, 2006), astronomy (Straatemeier, van der Maas, & Jansen, 2008), and force (diSessa et al., 2004).

In our view, there is no integrative and empirically tested framework that could explain these contradictory findings, with evidence for fragmented and inconsistent knowledge in some studies and evidence for integrated and consistent knowledge in other studies. Specifically, the circumstances in which knowledge is fragmented or integrated remain unclear.

One possible reason for the mixed empirical results might be a high variability between and within persons with respect to how their knowledge is structured. Another reason may be the point in time at which conceptual knowledge is captured: some individuals may have already integrated some pieces of knowledge into more coherent structures due to informal or formal learning opportunities, whereas others may still be at a very novice state of knowledge construction. Thus, studies should systematically investigate the variability of knowledge structures between persons and within persons between measurement points.

The mixed empirical results also indicate problems with the prevailing research methodology in this field of research. The majority of studies have analyzed categories of interview data. However, there are no established standards for the development of such category systems. Studies using similar content domains and samples but different category systems have led to contradictory results (e.g., diSessa et al., 2004; Ioannides & Vosniadou, 2002).

The Investigation of Complex Knowledge Structures: Methodological Considerations

In the current study, we assessed children's agreement with different concepts by multiple-choice items and modeled the underlying knowledge states by means of a latent transition analysis. Our approach diverged in five points from the methods used in prior research on conceptual change. First, latent transition analysis allowed us to define explicit quantitative criteria for knowledge fragmentation or integration, which can be compared across different studies. Second, knowledge structures can comprise multiple elements and, thus, need to be assessed by multiple measures. Latent transition analysis is a multivariate method that is ideally suited for analyzing multiple measures and their interrelations. Third, latent transition analyses can be conducted with nominal, ordinal, or continuous data and, thus, offer the advantage of being compatible with categorized interview data as well as with scores from multiple-choice test. At least three studies (Hardy, Jonen, Möller, & Stern, 2006; Shtulman, 2006; Straatemeier et al., 2008) demonstrated that quantitative analyses of multiple-choice test data can yield valid new insights into conceptual change. Fourth, learners' overt behavior is only an indirect measure of the underlying knowledge structures, which cannot be directly observed. Latent transition analysis accounts for the indirect relations between overt behavior and covertly underlying knowledge by modeling learners' knowledge as latent variable that underlies overt behavior (cf. Schneider & Stern, 2010b; Straatemeier et al., 2008). Fifth, latent transition analyses can be conducted with categorical as well as with continuous measures. In the latter case, they can reveal gradual as well as abrupt changes in knowledge structures, as we demonstrate later. This is not possible with categorizations of interview data.

Distinguishing Misconceptions, Everyday Conceptions, and Scientific Concepts

The current study traced the coexistence of three partly incompatible types of conceptual knowledge during development, which had originally been proposed by Hardy et al. (2006): (a) misconceptions, (b) everyday conceptions (also called *explanations of everyday life* by Hardy et al.), and (c) scientific concepts (also called *scientific explanations* by Hardy et al.).

By *misconceptions*, we refer to children's naïve concepts that are inconsistent with scientific explanations and that have no explanatory power beyond very few observations (also see Nesher, 1987; Smith, diSessa, & Roschelle, 1993). When tested empirically in a systematic way, these misconceptions do not hold. For example, a child might say that a small stone will float on water because it is so light.

We classify knowledge as an *everyday conception* (Carey, 1992; Resnick, 1992) when it can coherently explain a set of observations from everyday life but still can be falsified by systematic observation, as practiced in scientific studies. For instance, a child might suggest that wooden objects float in water while iron objects sink because they are made of different material. This assumption explains correctly why a match floats and a key sinks. It also directs the child's attention toward the important dimension of the kind of material. However, this everyday conception cannot explain why an iron ship can float just as well as a wooden ship because it does not fully account for average object density.

Finally, *scientific concepts* are those explanations that are currently accepted by the scientific community in a domain. With young children, these explanations focus on mechanisms and concepts that explain a certain phenomenon, without necessarily involving computational formula and without being fully comprehensive. In the case of floating and sinking, central scientific concepts are material density and buoyancy force.

Misconceptions, everyday conceptions, and scientific concepts differ on at least three dimensions: (a) the specific content referred to in the explanation (e.g., holes, material kind, buoyancy force), (b) their degree of correctness from a normative point of view (incorrect, partly correct, correct), and (c) their functional characteristics (explanation of a very limited set of observations, explanation of observations commonly made in everyday life, explanation of systematic scientific observations). Demonstrating several types of conceptual knowledge at the same time, thus, provides strong evidence for the coexistence of inconsistent pieces of knowledge in a learner.

The Current Study

Hypotheses and Design

In the current study, we analyzed inconsistent pieces of knowledge in children's developmental pathways of their understanding of floating and sinking of objects in water. Our study aimed at testing three hypotheses. First, according to some empirical studies, conceptual knowledge is integrated during development; according to other studies, incompatible pieces frequently coexist in learners. Thus, we expected to find that knowledge can be integrated as well as fragmented and that there were strong individual differences between learners in a domain (Hypothesis 1).

Second, we hypothesized that we would find a limited set of knowledge configurations and well-ordered developmental pathways between them (Hypothesis 2) because conceptual change is not a random process but is constrained by social and physical environments (Chi & Slotta, 1993), by prior knowledge (Schneider et al., 2009), and by the learner's cognitive architecture, for example, limitations in working memory (Schneider, 2012; Sweller, van Merrienboer, & Paas, 1998). As a result, even in fragmented knowledge, there seems to be some weak systematicity in the sense that some observations can be made more easily than others in everyday life and that some ideas or transitions between ideas seem to be more plausible to learners than others and, thus, occur more frequently.

Third, if the knowledge profiles are related by a relatively small number of developmental pathways, then a student's profile at Time 1 (T1) should predict the student's profiles at T2 and T3 to some degree (Hypothesis 3). Such information would be useful for teachers who try to diagnose and optimize their students' learning processes.

We tested our hypotheses by reanalyzing data published by Hardy et al. (2006). They measured elementary school children's concepts about floating and sinking before (T1) and after (T2) an intervention phase, as well as 1 year later (T3). While Hardy and colleagues investigated treatment group differences in conceptual understanding, our reanalysis focused on the developmental patterns of the structure of children's conceptual knowledge. Hardy et al. used multiple-choice items to assess children's (a) misconceptions, (b) everyday conceptions, and (c) scientific concepts of the floating and sinking of objects in liquids. In the current study, we coded the multiple-choice answers into three sum scores, one for each type of conceptual knowledge. We used a latent profile transition analysis to model the configuration of each person's conceptual knowledge at each measurement point as a profile of the sum scores and to analyze persons' transitions between these profiles over time. We interpreted it as evidence of the coexistence of inconsistent pieces of knowledge when, in a profile, more than one of the three scores was significantly higher than the sample mean.

Content Domain

Floating and sinking, the content domain of our study, is rich in learning opportunities and has been used in many earlier studies on conceptual change (e.g., Inhelder & Piaget, 1958; Kloos, Fisher, & Van Orden, 2010; Siegler & Chen, 2008). Among the key concepts for understanding floating and sinking are object density, water displacement, and buoyancy force, which pushes up on an object in a liquid while the gravitational force is pulling it down. Conceptual learning in this domain requires a shift of attention from more concrete properties of objects (e.g., shape) to more abstract properties (e.g., buoyancy force) and a shift from one-dimensional thinking (e.g., size) to two-dimensional thinking (e.g., object density as proportion of mass and volume). Elementary school children can already understand some important relations in this domain (Kleickmann, Hardy, Jonen, Blumberg, & Möller, 2007).

Method

Participants

The data from all participants of the original study (Hardy et al., 2006) were included in the current analyses. The sample consisted of 161 third graders in eight elementary school classrooms from three schools in a mid-sized town in Germany. The sample comprised students from various social backgrounds and with a broad range of general cognitive ability; their mean age was 9.1 years (minimum = 8 years; maximum = 11 years). The high instructional support group comprised 66 students (26 girls) from three classrooms, the low instructional support group comprised 59 students (28 girls) from three classrooms, and the baseline group consisted of 36 students (23 girls) from two classrooms.

Procedure and Design

Children in the original study (Hardy et al., 2006) were first given a pretest (T1). Shortly after the pretest, the children entered a curricular intervention phase, which was followed by a posttest (T2) 1 week after the end of instruction as well as a follow-up test (T3) 1 year after the instruction had taken place. There were three experimental conditions, two with interventions and one with no intervention that served as a baseline control. The treatments consisted of two versions of an eight-lesson curriculum on floating and sinking. The eight participating classrooms were assigned to one of three experimental conditions so that three classrooms participated in a constructivist learning environment offering *high instructional support*, three classrooms participated in a constructivist learning environment with *low instructional support*, and two classrooms served as a *baseline* group without instruction on floating and sinking. In the group of high instructional support, but not in the low instructional support group, the topic was segmented into smaller instructional units, such as the investigation of water displacement or density. The content was presented successively in a structured manner, and the teacher used cognitively structuring statements, such as relating and contrasting ideas or hypotheses, in whole-class discussions (see Hardy et al., 2006, for details).

The tests were taken collectively by all students of a class. The test administrator read out loud sample items and explained how to proceed in answering them. The settings described in the sample items were demonstrated by the administrator, with all of the objects described in the test located at the front desk. Students were allowed to pick up these items throughout the testing period as they wished, but they were not allowed to immerse them in water. At T1, the term *water displacement* was briefly explained to students by demonstration. The students could work on the items at their own pace. The item ordering was the same for all students. It took approximately 60 min to administer the entire test.

Measures

Of all test items described by Hardy et al. (2006), we used only the multiple-choice items assessing students' understanding of floating and sinking. Each of the 41 items had between two and seven answer alternatives. The children were allowed to check none, some, or all of the answer alternatives in order to allow for the coexistence of alternative, and sometimes inconsistent, explanations of a phenomenon. The items were developed on the basis of elementary school students' spontaneous explanations derived from extensive analyses of interview data. They included verbal descriptions of the concepts of kind of material, density, and buoyancy force in child-appropriate language. The items tapped into students' understanding of specific situations (e.g., predicting and explaining floating or sinking of a wooden button, a flat piece of metal, a flat piece of Styrofoam, a piece of metal wire, a pin, a wooden block, and an iron ship) as well as into students' understanding of general principles (e.g., "Some types of material always float in water"; "Water pushes more against large objects than small objects"; "Any hollow object will float in water"). Throughout the tests, words such as *heavier than* or *pushes up*, which were used repeatedly in instruction, were offered in correct and incorrect answer alternatives within one item.

Answer Coding

For each marked answer alternative, children received 1 point. Hardy et al. (2006) categorized each answer alternative as referring to (a) a misconception (n = 32), (b) an everyday conception (n = 11), (c) a scientific concept (n = 17), or (d) a distractor (n = 12), which sounds plausible but does not fit into the categories a, b, or c. They computed separate sum scores for the categories of misconceptions, everyday conceptions, and scientific concepts. The descriptive characteristics of the scores are reported by Hardy et al. (2006, Table 4) for the three experimental groups and the three measurement points. We used these sum scores in our analyses. The internal consistencies of the three scales were satisfactory for knowledge tests (cf. Schneider & Stern, 2010b), with Cronbach's alpha at T1, T2, and T3 of .59, .62, and .75 for misconceptions; .57, .62, and .63 for everyday conceptions; and .70, .78, and .81 for scientific concepts, respectively. To aid interpretation, we standardized the pooled data from all three measurement points separately for each scale to a mean of 50 and a standard deviation of 7 prior to the analyses.

Hardy et al. (2006) had used some free-response items in addition to the multiple-choice items. Free-response items and multiple-choice items indicated similar mean differences between the three experimental groups and were in all but one case significantly correlated. The correlation coefficients lay between .25 and .42 for misconceptions, everyday conceptions, and scientific concepts at the three measurement points. This provides some evidence of the validity of the multiple-choice measures used in the present analyses.

Statistical Analyses

In our latent transition model, at each measurement point, the persons' latent class memberships were estimated based on three class indicators, that is, the scores for misconceptions, everyday conceptions, and scientific concepts. As a result, all persons grouped into a latent class have a similar pattern of scores on the three indicators, and each latent class can be characterized in terms of a profile of these scores. The number of latent classes indicates how many profiles are underlying the empirically observed data patterns. We constrained the latent class profiles (but not the number of persons in each class) to be equal over the three measurement points. This secured the comparability of the results across measurement points and reduced the number of parameters to be estimated.

We estimated the model parameters by means of the maximum-likelihood estimator for mixture models expectation maximization (EM; Muthén & Shedden, 1999) in the program Mplus, Version 4.1. We determined the number of latent classes, that is, the number of latent profiles, by estimating the fit of seven versions of the latent transition model. The versions differed only in the number of assumed latent classes, which was successively fixed to all values from 1 to 7. We compared these models to determine which had the best fit to the data using the model fit indices Bayesian information criterion (BIC) and Akaike information criterion (AIC). The smaller these coefficients are, the better the fit. The indices conceptualize model fit in slightly different ways and do not necessarily identify the same model as optimal (see Nylund, Asparouhov, & Muthén, 2007).

Results

Organization of the Results Section

In the following subsections, we describe (a) how we determined the number of latent classes in our model, (b) the characteristics of the latent classes and their knowledge profiles, and (c) the developmental transition paths between these profiles over the three measurement points. In the last two subsections, we describe findings of tests of (d) whether the persons' knowledge profiles predicted their knowledge profiles at later points in time and (e) associations between person characteristics, instruction and the transition paths.

Determining the Number of Latent Classes

In choosing the number of latent classes, we followed the recommendations by Nylund et al. (2007). Table 1 shows the model fit indices BIC and AIC for seven models, which differ in the number of latent classes. The BIC is lowest for the model with four classes, while the AIC is lowest for the model with six classes. However, rather than choosing the four-class model for its parsimony, we chose the five-class solution for three reasons: First, the model fit of the five-class model is significantly better than the fit of the more parsimonious four-class model, which was revealed by a likelihood ratio chi-square difference test, $\Delta\chi^2 = 2 * [(-4458.3) - (-4425.7)] = 65.2$, $\Delta df = 68 - 48 = 20$, $p < .001$. Second, the five-class model falls in the middle between the four-class model suggested by the BIC and the six-class model suggested by the AIC. Third, as shown in Figure 1, the mean profiles of the latent classes C1, C2, C3, and C4 for the four- and five-model solutions are very similar to each other. However, in the five-class solution, there is an additional class, C5, which has a low degree of misconceptions and everyday conceptions and a high degree of scientific concepts. This profile is theoretically interesting because it indicates an optimal learning outcome. Only the five-class model—and not the four-class model—allowed for the investigation of this profile. Therefore, all of our subsequent analyses focused on the model with five latent classes. The prevalence of five latent classes supports our assumption of a limited number of profiles in the sample (Hypothesis 2).

Characteristics of the Latent Classes

We tested, separately for each of the 10 possible pairs of latent classes, whether the two classes' mean profiles differed from each other. For all the 10 pairs of latent classes, constraining the two class profiles to be equal led to a significant decrease of model fit, with $p < .001$. Therefore, the mean profiles of all five latent classes are significantly different from each other. This further supports the adequacy of the model with five latent classes and indicates that the profiles reflect meaningful differences in the knowledge structures of latent classes rather than random variation in the answer patterns.

Table 2 shows the parameters of the latent classes. The middle columns of the table report the values of the three indicator variables for that class, together with the p values of likelihood ratio chi-square difference tests of the hypothesis that the respective value differs from 50. Each of the three variables—misconceptions, everyday conceptions, and scientific concepts—had been standardized to a mean of 50 for data in the entire sample over all three measurement points. The tests, thus, indicate whether a class mean differs significantly from the overall mean. The class means are presented visually in the right half of Figure 1. In line with our expectations, the three scores vary partly independently of each other and, thus, assess partly independent pieces of children's conceptual knowledge.

The second column of Table 2 lists the labels assigned to the latent classes based on our interpretation of the classes' mean profiles. Similar to factor labels in factor analyses, these labels are not a result of the statistical analyses as such but represent our interpretation of the quantitative results. We labeled the profile of Latent Class C1 as the *misconceptions profile* since it exhibits an above-average mean of misconceptions and below-average means of everyday conceptions and scientific concepts (see Table 2 and Figure 1). Class C2 displays above-average means on all three measures. In accordance with our conceptualization of knowledge fragmentation described previously, we labeled its profile the *fragmented profile*. Class C3 shows below-average means for

Table 1
Fit Indices of Models Differing in the Specified Number of Latent Classes

Index	One class	Two classes	Three classes	Four classes	Five classes	Six classes	Seven classes
Log likelihood	−4581	−4559.7	−4507.5	−4458.3	−4425.7	−4389.2	−4368.6
Free parameters	9	20	32	48	68	92	120
AIC	9180	9159	9079	9013	8987	8962	8977
BIC	9207	9221	9178	9161	9197	9246	9347

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion.

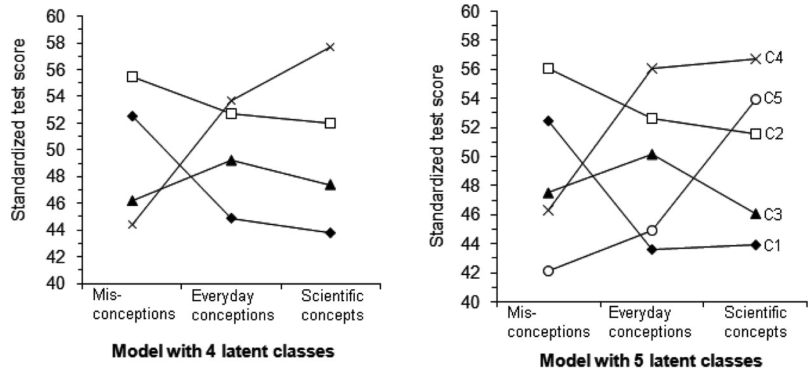

Figure 1. Knowledge profiles of the latent classes (C; left: model with an assumed number of four latent classes; right: model with an assumed number of five latent classes). C1: misconceptions profile, C2: fragmented profile, C3: indecisive profile, C4: prescientific profile, and C5: scientific profile.

misconceptions and scientific concepts and an average score of everyday conceptions. We termed the profile of this class the *indecisive profile* since the class members did not agree strongly with any answer alternatives. The profile of Class C4 is marked by above-average scores of everyday conceptions and scientific concepts together with a below-average score of misconceptions. The profile indicates an advanced conceptual understanding, albeit still rooted in everyday concepts, and was labeled the *prescientific profile*. Finally, Class C5 exhibits below-average scores for misconceptions and everyday conceptions and an above-average score of scientific concepts. Since this class exhibited integrated knowledge about scientific concepts we labeled its profile the *scientific profile*.

The scientific profile demonstrates rather homogeneous knowledge because the children displayed only one of the three types of conceptual knowledge. In contrast, the fragmented class and the prescientific class indicated that inconsistent pieces of knowledge can coexist in learners because members of these classes show above-average values for two or three types of conceptual knowledge despite the fact that these types differ in their content, their correctness, and their functional characteristics. This finding is in line with our Hypothesis 1.

The sizes of the latent classes (see Table 2) changed over time in plausible ways. At T1, most children were in classes with profiles indicating low levels of expertise, in particular, the misconceptions profile and the fragmented profile. At T2, most children showed the prescientific profile and the fragmented profile, indicating that the correct explanations of floating and sinking from the learning environments and the children's naïve misconceptions coexisted. The pattern for T3 was similar, with even fewer students exhibiting the misconceptions profile and more students showing the scientific profile, indicating further increases in the children's expertise on floating and sinking. The proportion of the sample with the fragmented profile decreased from 34% at T1 to 25% at T2 and, finally, to 20% at T3.

Latent Transition Paths

As each child was in one of the five latent classes at each of the three measurement points, theoretically, there are $5^3 = 125$ different transition paths possible within our model. However, the empirical results indicate that only 25 (i.e., 20%) of the 125 paths had actually been taken by at least one person, while 100 of the theoretically possible paths were not used by our sample. In addition, the majority of the 25 empirically found paths were taken only by small proportions of the sample, respectively. Only seven paths were used by at least 5% of the sample.. Taken together, these seven paths describe the development of 63% of our sample. Thus, in line with Hypothesis 2, the participants followed a limited number of different transition paths.

Table 2
Assigned Labels for the Knowledge Profiles of the Latent Classes, Means, Significance of the Deviation of Each Mean From 50, and Sample Proportions at the Three Measurement Points

		Misconceptions		Everyday conceptions		Scientific concepts		Proportion of the sample in percentage		
Class	Label	*M*	Significance	*M*	Significance	*M*	Significance	Time 1	Time 2	Time 3
C1	Misconceptions profile	52	***	44	***	44	***	51	5	9
C2	Fragmented profile	56	***	53	***	52	**	34	25	20
C3	Indecisive profile	48	***	50	*ns*	46	***	14	22	30
C4	Prescientific profile	46	***	56	***	57	***	1	38	24
C5	Scientific profile	42	***	45	***	54	***	0	11	18
	Total sample	50		50		50		100	100	100

Note. *ns* = not significant.
** $p < .01$. *** $p < .001$.

The properties of the seven most frequently used transition paths are listed in Table 3. From a statistical point of view, the number of persons in a class at a measurement point is an estimated parameter of the latent transition model. Due to the probabilistic nature of the estimation process, the estimated number of persons on a path can actually be a rational number smaller than 1. This is why the last row of Table 3 reports that a total of 5% of our sample took paths P26 to P125, even though none of these paths was taken by at least one person.

All of the latent classes along with the seven most frequent transition paths between them (from P1 to P7) are shown in Figure 2. In this transition diagram, each column stands for one of the three measurement points. The number in each circle is the percentage of the sample in a given class at a measurement point according to the estimated model. These numbers roughly add up to 100% at each measurement point. The number at each arrow refers to the percentage of the sample that shifts between the two classes connected by the arrows. As only arrows for the seven most frequent transition paths, from P1 to P7, are displayed, these frequencies only add up to 63%.

We named transition path P1 the *increasing-indecision path* because children on this path start out with misconceptions at T1 but then move to the indecisive class at T2 and stay there at T3. Path P2 was termed the *decreasing-fragmentation path*, because these children agree with misconceptions, everyday conceptions, and scientific concepts at T1, but abandon their misconceptions from T1 to T2, so that only everyday conceptions and scientific concepts remain. This indicates a gradual decrease in knowledge fragmentation. We termed P3 the *increasing-fragmentation path*, since students here begin with misconceptions but then additionally adopt everyday concepts and scientific concepts from T1 to T2 and stay there at T3, indicating knowledge fragmentation. P4 is the *enduring-fragmentation path*, since children on this path are in the fragmented class at all three measurement points. We named P5 the *ideal-learning path*, because learners start with misconceptions and move to scientific concepts only from T1 to T2 and remain there at T3. P6 is the *prescientific-learning* path, which begins at the indecisive class at T1 and then moves to the prescientific class at T2 and T3. Finally, we called path P7 the *dynamic-learning path*, because students in this class moved from the fragmented class at T1 over the prescientific class at T2 to the scientific class at T3.

Overall, the individual learning paths show a general trend toward learning gains over time, a result also found by Hardy et al. (2006). For example, as shown in Figure 2, some of the transition paths lead from the misconceptions class to the scientific class, but none of the paths leads in the opposite directions. However, the individual transition paths show that this general increase in competence is not the entire story because there are considerable individual differences. As Hypothesis 1 led us to expect, knowledge fragmentation varied: It decreased over time for some individuals (e.g., on the decreasing-fragmentation path), stayed unchanged for others (e.g., on the enduring-fragmentation path), and increased for still others (e.g., on the increasing-fragmentation path).

The profiles on the seven most common paths (P1–P7) follow a developmental order; for example, a path leads from C1 to C2, but no path leads from C2 to C1 over time. Overall, 84% of the sample transitioned through the knowledge profiles in some ascending order, while only 16% of the sample regressed from "higher" to "lower" profiles between at least two measurement points. Consequently, the ordering of the knowledge profiles should be interpreted with caution and needs to be replicated in further research.

Associations Between Initial Knowledge Profiles and Further Development

In order to test whether children's profiles at 1 point in time predict their profiles at later points in time, we generated a frequency table with children's profiles at T1 in the rows and children's profiles at T2 in the columns. A chi-square test indicated a highly significant relation between the two variables, $\chi^2(8) = 88.961$, $p < .001$, Cramer's $V = .526$. We repeated these analyses for T2 and T3 and again found a strong association between the knowledge profiles, $\chi^2(16) = 267.790$, $p < .001$, Cramer's $V = .645$. The knowledge profiles at T1 and T3, which were separated by the intervention phase and the posttest and were months apart, were still associated with $\chi^2(8) = 38.883$, $p < .001$, Cramer's $V = .347$. These close relations between the knowledge profiles over the three measurement points support our Hypothesis 3: Learners' knowledge profiles at one point in time are useful for predicting their profiles at later points in time.

Table 3
Pathways of Conceptual Change (i.e., Model-Estimated Latent Transition Paths) in the Sample

Path	Label	Knowledge profile			Proportion of the sample (%)	
		Time 1	Time 2	Time 3	Alone	Accumulated
P1	Increasing-indecision path	Misconceptions profile	Indecisive profile	Indecisive profile	16	16
P2	Decreasing-fragmentation path	Fragmented profile	Prescientific profile	Prescientific profile	12	28
P3	Increasing-fragmentation path	Misconceptions profile	Fragmented profile	Fragmented profile	9	37
P4	Enduring-fragmentation path	Fragmented profile	Fragmented profile	Fragmented profile	8	45
P5	Ideal-learning path	Misconceptions profile	Scientific profile	Scientific profile	7	52
P6	Prescientific-learning path	Indecisive profile	Prescientific profile	Prescientific profile	6	58
P7	Dynamic-learning path	Fragmented profile	Prescientific profile	Scientific profile	5	63
P8–P25	Various paths (found for at least one person)	Various profiles	Various profiles	Various profiles	32	95
P26–P125	Remaining paths (not found for at least one person)	Various profiles	Various profiles	Various profiles	5	100

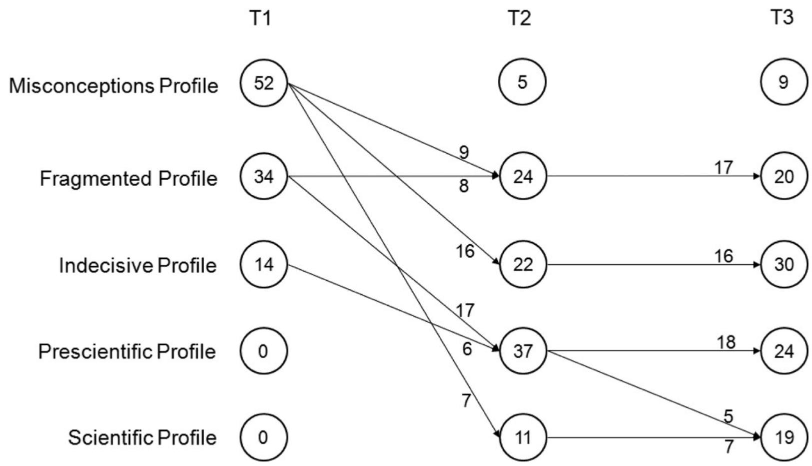

Figure 2. Diagram of the seven transition paths taken by at least 5% of the sample at three measurement points (T1, T2, and T3). All numbers are percentages of the sample. Numbers in circles refer to all persons (i.e., 100% of the sample). Numbers at arrows refer to persons on the seven most common transition paths (i.e., 63% of the sample).

Influences on the Transition Paths

Some persons have the same knowledge profile at a point in time but subsequently follow different developmental pathways. We tested whether this can be attributed to different person characteristics or different instructional conditions. We compared eight groups of children: students on each of the seven transition paths and students in the rest category. None of these groups differed in the proportions of boys and girls, $\chi^2(7) = 8.940$, $p = .257$, $N = 160$, or in their age distribution, $\chi^2(21) = 26.908$, $p = .174$, $N = 156$. There was, however, a strong relation between transition path and instructional condition, $\chi^2(14) = 39.744$, $p < .001$, $N = 161$, which can be seen in Table 4. This distribution of children demonstrates the general importance of extensive instruction for reaching a scientific understanding in a domain. Only two paths (i.e., the ideal-learning path and the dynamic-learning path) led to the profile of scientific understanding, and only children from the two instructional groups, but no child from the baseline group, were found on these learning paths.

In line with the prior research (Schneider & Stern, 2009, 2010a), the frequency distribution in Table 4 also indicates a positive effect of instructional support on knowledge integration. On P2, the decreasing-fragmentation path, 30% of the children were from the group with high instructional support, but only 2% of the children were from the group with low instructional support. This pattern is reversed for P3, the increasing-fragmentation path, where 24% of children were in the low-instructional support group and 14% of the children were in the high-instructional support group.

Discussion

Inconsistent Pieces of Knowledge Coexist in Learners

Our results indicate substantial knowledge gains over the three measurement points. The proportion of children with the misconceptions profile decreased from 51% at the first measurement point to 9% at the third measurement point. The proportion of children with the scientific profile increased from 0% to 18%. This knowledge gain is mostly due to students in the two instructional conditions, which is in line with the results by Hardy et al. (2006).

Table 4
Percentage Distribution of Persons Over the Transition Paths for the Three Experimental Groups and the Total Sample

		Group			
Path	Label	High instructional support	Low instructional support	Baseline	Total sample
P1	Increasing-indecision path	14	24	22	19
P2	Decreasing-fragmentation path	30	2	3	14
P3	Increasing-fragmentation path	8	5	14	8
P4	Enduring-fragmentation path	5	10	14	9
P5	Ideal-learning path	8	15	0	9
P6	Prescientific-learning path	3	5	6	4
P7	Dynamic-learning path	3	7	0	4
P8–P25	Other paths taken by at least one person	30	32	42	34
	Total	100	100	100	100

The empirical results support all three of our hypotheses. We found clear evidence for the coexistence of inconsistent pieces of knowledge in learners. Most notably, one latent class of students exhibited a knowledge profile (the fragmented profile) with above-average misconceptions, everyday conceptions, and scientific concepts. These three types of conceptual knowledge are inconsistent as they differ in their content, the degree of their correctness, and their functional roles in a person's live. For example, persons with the fragmented profile will think correctly that an object's density in relation to the density of water determines whether it will float or sink in water. At the same time, these persons claim that an object with holes cannot float, thus producing explanations that are inconsistent with each other. This demonstrates the importance of theoretical accounts on how knowledge fragmentation occurs and how it can be reduced (Linn, 2006).

Profiles indicating inconsistent knowledge and profiles indicating integrated knowledge coexisted at all three measurement points. In line with our Hypothesis 1, this demonstrates substantial individual differences among learners. Knowledge fragmentation occurred commonly in our sample of third graders. For example, the proportions of children with the fragmented profile decreased from 34% of the sample at the first measurement point to 20% at the third measurement point. However, students also displayed integrated profiles of knowledge, for example, the scientific profile with 18% of the students at the third measurement point, which indicates well-integrated and coherent scientific knowledge. Thus, the debate about whether students' initial knowledge in a domain is always integrated or always fragmented is misleading. Students' knowledge can be fragmented or integrated throughout development, with strong differences between persons.

In theory, the fragmented knowledge profile could also be due to a positive response bias because the students were asked more frequently whether they agreed with a misconception, everyday conception, or scientific concept than whether they disagreed. Students who have the tendency to provide positive responses would have high scores for all three types of knowledge without actually showing fragmented knowledge. However, for two reasons, it is not likely that this happened in our study. First, Hardy et al. (2006) found positive correlations between the multiple-choice items and an additional set of free-response items with similar content. Thus, children's freely generated verbal explanations matched their multiple-choice answers. Second, the fragmented profile appears and disappears on the developmental paths in systematic ways. Knowledge fragmentation decreased over time, and it decreased more strongly in the instructional groups than in the control group. This is not consistent with the assumption of a strong response bias, which is usually seen as a stable characteristic of a person.

We used the triad of misconceptions, everyday conceptions, and scientific concepts as an example for the multifaceted nature of conceptual knowledge. We chose everyday conceptions because the literature emphasizes the importance of everyday experiences in conceptual learning and development. However, in other studies, distinctions between other dimensions of conceptual knowledge might be more helpful. These studies could, for example, assess the strength of several specific misconceptions or of several facets of a complex scientific theory.

A Small Set of Well-Ordered Developmental Pathways

As we had predicted in Hypothesis 2, students' profiles of conceptual knowledge did not change randomly over time and also did not show a simple trend from fragmented to integrated knowledge. The children in our sample followed a total of 25 transition paths, with a mere seven paths taken by at least 5% of the sample, respectively. The number of empirically found transition paths was low compared with the number of children in our sample ($N = 161$) and was low compared with the number of theoretically possible transition paths between five profiles over three measurement points ($5^3 = 125$). Thus, latent profile analyses and latent transition analyses are an effective data reduction technique. Similar to factor analysis, the complexity of all data patterns in the sample is reduced to a much smaller set of basic patterns which underlie the raw data.

The transition paths indicate a loose developmental ordering of the knowledge profiles. This can be seen in Figure 2. For example, there are paths progressing from the misconceptions profile and the fragmented profile but no paths leading toward them from prior profiles. Conversely, there are paths leading toward the scientific profile, but no paths progressing from it. This indicates knowledge gains throughout development: Once the score for misconceptions went down for a child, it usually did not go up again; and once the score for scientific concepts went up, it usually did not go down again. This was true for more than 80% of our sample and for all persons on the seven most frequently found developmental paths. Only 20% of the sample showed an increase in misconceptions or a decrease in scientific concepts between two of the three points in time. However, the developmental ordering of the profiles of most persons in the sample does not indicate developmental stages in the classical sense, for example, the stages suggested by Piaget (cf. Beilin, 1992). Developmental stages cannot be skipped because each one is a stepping stone for the subsequent stage. This is not the case with our knowledge profiles, where learners frequently skip intermediate profiles when switching to a more advanced profile (e.g., on the ideal-learning path). Our profiles rather indicate phases of students' ongoing and simultaneous evaluating, reconsidering, and adapting of developmentally more and less advanced ideas.

Knowledge fragmentation increased with some individual paths (e.g., the increasing-fragmentation path) and decreased with others (e.g., the decreasing-fragmentation path). This emphasizes the importance of accounting for individual differences between learners. Aggregated across subjects, knowledge fragmentation decreased over time, and especially with instructional learning opportunities, which is in line with previous findings (Clark, 2006; Straatemeier et al., 2008).

The pathways indicate a systematic relation between a student's knowledge at different points in time. This was further supported by chi-square tests that showed that the students' knowledge profiles were associated across all three measurement points, thus supporting Hypothesis 3. This is remarkable because the first and the last measurement points were 1 year apart, and students participated in one of three instructional interventions between the first and the second measurement points. The associations between the knowledge profiles were almost equally strong for the first two measurement points, where many participants changed their knowledge profiles, and for the last two measurement points, where most participants did not change their profile. The fact that the knowledge profiles were systematically related over such long periods of time and that they were independent of the instruction students received in the meantime demonstrates that the profiles are not methodological artifacts or due to measurement error, and instead reliably capture stable and important characteristics of the students' conceptual knowledge and its mental organization.

Implications for Further Research

Our results have theoretical, methodological, and practical implications. On a theoretical level, our results provide evidence that knowledge in a sample can be fragmented as well as integrated both before and after instruction. Theory theories of conceptual development assume that a learner's knowledge is often organized in the form of subjective theories (e.g., Vosniadou et al., 2008). According to Gopnik and Schulz (2004, p. 371), "these theories, like scientific theories, are complex, coherent, abstract representations of the causal structure of the world. Even the youngest preschoolers can use these intuitive theories to make causal predictions, provide causal explanations, and reason about causation counterfactually." Future accounts of the theory theories view must clarify how precisely the proposed coherent representations relate to the empirical finding of inconsistent knowledge in the current study.

Our results also highlight the importance of accounting for individual differences in knowledge fragmentation and integration. Knowledge fragmentation decreased over time when averaged across the entire sample. However, the individual developmental paths show that the underlying processes were more complex. Conceptual change was neither a succession of integrated subjective theories nor a simple progression from fragmented to integrated knowledge. Learners' knowledge construction was an idiosyncratic process during which knowledge could become more integrated but sometimes also more fragmented over time.

Despite this variability between persons and within persons over time, the number of knowledge profiles and developmental pathways was much smaller than the number of children in the sample. This highlights the role of constraints in conceptual change. Knowledge construction processes do not have unlimited degrees of freedom but instead underlie various cognitive and environmental constraints. This can explain why the same misconceptions have been found in many unrelated samples over the past decades.

How can conceptual change be constrained and at the same time lead to individual differences and to inconsistent knowledge structures? Kloos et al. (2010) gave an interesting answer to this question. They saw a constraint as "a relation between actor and task that changes the available degrees of freedom for task responses" (p. 625). Thus, persons who differ in their learning histories also differ in how their subsequent conceptual change is constrained. This can lead to systematic individual differences in developmental pathways. Future studies will have to show in detail when and how constraints increase or decrease the consistency of knowledge structures.

Finally, our study also has practical implications. According to some approaches, instruction should aim at replacing integrated naïve theories by a more advanced theory. According to others, instruction should aim at integrating numberless pieces of knowledge into a coherent knowledge structure. These two types of learning environments would look very different, and it has been asked which of the two types is more effective (diSessa, 2008). However, our results suggest that neither of the two types is optimal. Both of them are rooted in overly simplistic conceptions of knowledge acquisition that neglect the great differences between and within learners. When students are introduced to a new lesson topic, some students might hold integrated naïve theories that have to be rejected and replaced. At the same time, other students can have strongly fragmented knowledge that has to be integrated. Still others might already hold everyday conceptions and scientific concepts and only have to revise or give up the former. Teachers need to use types of formative assessments (Yin et al., 2008) to diagnose each student's knowledge before or during instruction, and teachers need a repertoire of instructional techniques that allows them to respond adaptively to each student's individual needs. Information about typical knowledge profiles and pathways in a domain, as found in the current study, can help teachers to prepare effective assessments and instructional interventions.

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