

The differential development of epistemic beliefs in psychology and computer science students: A four-wave longitudinal study

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Abstract

This article analyses the differential development of discipline-specific epistemic beliefs (i.e., beliefs about the nature of knowledge) in computer science and psychology. With regard to computer science, a “hard” discipline, we expected absolute beliefs (knowledge as objective “truths”) to increase over time. In contrast, in the more “soft” discipline of psychology, we expected absolute beliefs to be low and stable, and multiplistic beliefs (knowledge as subjective “opinions”) to follow an inversely U-shaped trajectory. Hypotheses were tested in a three-semester long four-wave study with 226 undergraduates. Data were analysed by multi-group growth modelling for parallel processes. In computer science, absolute beliefs indeed increased over the study period. In psychology, an initial increase in multiplistic beliefs was followed by a steep decrease. We therefore suggest that epistemic “sophistication” should be conceived of as a flexible adaptation of epistemic judgments to the characteristics of specific contexts, and not as a generalized developmental sequence.

Keywords: epistemic beliefs, longitudinal study, higher education

1 Introduction

Beliefs about the nature of knowledge in a certain academic discipline will likely influence learning and information processing of those studying that discipline. Since Perry introduced his *scheme of the intellectual and ethical development* in 1970, such beliefs have been investigated under the term epistemic (or epistemological) beliefs. A growing body of literature emphasizes positive effects of more “sophisticated” epistemic beliefs on information processing (e.g., Kardash & Howell, 2000), learning (e.g., Cano, 2005; Mason, Ariasi, & Boldrin, 2011), and academic achievement (e.g., Schommer, 1993).

What constitutes “sophisticated” beliefs, in contrast, has been subject to much debate. More traditional approaches almost exclusively view high absolute beliefs (i.e., a view of scientific knowledge as an accumulation of certain facts and absolute truths) as obstructive for learning (Hofer & Pintrich, 1997; Kuhn & Weinstock, 2002). In contrast, multiplistic beliefs (i.e., a view of scientific knowledge as tentative, evolving, and personally constructed) are deemed sophisticated and thus beneficial. Research has repeatedly challenged this assumption (Bromme, Kienhues, & Porsch, 2010; Elby & Hammer, 2001; Elby, Macrander, & Hammer, 2016; Muis & Franco, 2010). For example, Elby and Hammer stress that it strongly depends on the discipline in question whether one may see a certain type of belief as *correct* (i.e., espoused by experts in that particular discipline) and *productive* (i.e., facilitating learning).

Longitudinal studies might shed light on such disciplinary differences regarding epistemic beliefs changes, which also allows making inferences about what constitutes a “sophisticated” set of beliefs in a certain discipline. Unfortunately, even though a significant part of epistemic belief research was initially founded on longitudinal data (e.g., Baxter Magolda, 1992; Perry, 1970; Schommer, 1993), such studies have become rare lately. Moreover, we are not aware of any longitudinal studies that explicitly investigated the role of

disciplinary differences in the development of epistemic beliefs. This is striking since especially newer approaches posit epistemic beliefs to be shaped by students' instructional environment (i.e., the TIDE framework; Muis, Bendixen, & Haerle, 2006; Muis, Trevors, Duffy, Ranellucci, & Foy, 2015). The present article therefore analyzes the following research questions: How do discipline-specific epistemic beliefs of students from two exemplary disciplines (psychology and computer science) differ at the beginning of their studies, and how do these beliefs subsequently evolve longitudinally?

1.1 Theoretical concepts

Kuhn and Weinstock (2002) conceive the development of epistemic beliefs as a sequence of three stages. Development begins in a stage called absolutism, in which individuals conceptualize knowledge in dualistic, absolute contrasts (e.g., right-and-wrong or truth-and-untruth; Kuhn & Weinstock, 2002). Once this view of certain and absolute knowledge is dismissed, the model posits that individuals move on to a stage called multiplism. Individuals holding multiplistic beliefs stress the subjectivity of knowledge and expect different opinions to be equally valid and exchangeable. In its extreme form, sometimes called *radical subjectivity* (Hofer & Pintrich, 1997), they devalue science as a whole since they expect laypersons' opinions to be just as valid as scientific findings. In the final stage, called evaluativism, individuals acknowledge that truth depends, to a large extent, on the issue in question and on its context. They thus compare, evaluate and weigh different positions to issues and try to integrate conflicting points of view.

Even though Kuhn and Weinstock's (2002) model has become well-established in the literature, one may criticize it for positing a fixed developmental sequence. In fact, already in 2001, Elby and Hammer argued that it strongly depends on the issue in question whether a certain belief type might be seen as *correct* (i.e., according to an expert consensus) and

productive (i.e., beneficial for learning). Take, for example, rapper B.o.B, who doubts that the earth is round (Brait, 2016). According to more traditional approaches, this would be classified as a multiplistic and thus rather “sophisticated” belief. Nevertheless, not only is this belief incorrect according to a vast majority of astrophysicists; it might also make it harder for B.o.B to study for a geography test. Laboriously weighting the pros and cons of the earth being round, which is deemed a core component of evaluativism, might not be that productive either. In contrast, just accepting the earth being round as an absolute truth can very well be seen as both productive and correct (Elby & Hammer, 2001). In this instance, absolute beliefs would thus be the most advanced belief type, which is not compatible with Kuhn and Weinstock’s (2002) assumption of a sequential development over time. More recent research has formulated similar arguments (e.g., Bromme, Kienhues, & Stahl, 2008; Bromme et al., 2010).

Bromme and colleagues (2010) further substantiate this point of view by arguing that due to the uneven distribution of knowledge in our societies, many claims *can* only be evaluated by specialized experts (since laypersons simply lack the necessary prior knowledge).

Evaluativistic beliefs would thus be unsuited in many situations. Determining the trustworthiness of an expert and subsequently adopting this experts’ judgment (which is a central component of absolutism), in contrast, might be more “advanced” than an evaluative approach. In addition, Muis and Franco (2010) argue that learning is facilitated when the epistemic nature of a learning task corresponds with the individual epistemic beliefs of a person (so-called *consistency hypothesis*). A development towards consistency between an individual’s beliefs and the epistemic nature of a learning task (or the typical learning tasks in a particular discipline) might thus be preferable over the fixed sequence suggested by Kuhn and Weinstock (2002).

1.2 Epistemic beliefs in psychology and computer science

The Theory of Integrated Domains in Epistemology (TIDE) posits that even though general (i.e., discipline-unspecific) epistemic beliefs are intertwined with discipline-specific beliefs, the latter become more influential throughout education (Muis et al., 2006; 2015). Accordingly, research has found both inter-individual (e.g., Paulsen & Wells, 1998) and intra-individual (e.g., Stahl & Bromme, 2007) differences in epistemic beliefs pertaining to different disciplines.

To categorize academic disciplines, researchers often refer to Biglan's (1973) classification scheme, in particular to the dimensions *hard/soft* (i.e., existence of a unified paradigm or not) and *pure/applied* (i.e., focusing on theory vs. on practice). Even though a specific classification might not apply to all facets of the respective discipline (Muis et al., 2006), research shows that the scheme is surprisingly persistent (Stoecker, 1993), even half a century later (Simpson, 2015).

Knowledge structures strongly differ depending on whether a unified paradigm exists in a specific discipline or not (Muis et al., 2006). Given that a discipline's knowledge structure likely explains a considerable amount of variance in students' conceptions of that knowledge, Biglan's (1973) first dimension (hard/soft) seems particularly relevant in research on epistemic beliefs. To avoid bias, we further argue that when empirically contrasting two disciplines, they should primarily differ in one of the two dimensions. Contrasting physics (hard and pure; Simpson, 2015) and psychology (soft and applied; Simpson, 2015) might thus be problematic since one does not know to which of the two dimensions potential differences in epistemic beliefs may actually be traced back to. In line with both these arguments, we chose to analyze epistemic belief development in two prototypical disciplines that primarily

differ in Biglan's (1973) first dimension: Psychology, which is assumed to be soft and applied, and computer science, which in turn is considered hard and applied (Simpson, 2015).

In computer science, knowledge can be conceptualized as more "absolute" than in softer disciplines. In fact, computer science has a strong focus on applied mathematics (Association for Computing Machinery & IEEE Computer Society, 2013), thus allowing that "the parameters of the problems can be specified with a high degree of certainty and ... deductive logic and complex, logical manipulations are central tools of the discipline" (King, Wood, & Mines, 1990, p. 170). Therefore, due to its highly formalized and axiomatic structures, computer science is often described as *well-defined* (King et al., 1990). According to the consistency hypothesis¹ by Muis and colleagues (e.g., Franco, Muis, Kendeou, Ranellucci, Sampasivam, & Wang, 2012; Muis & Franco, 2010), absolute beliefs will thus be *productive* (i.e., facilitate learning) in computer science because many learning tasks in that discipline have a more absolute epistemic nature. This is in line with Elby and Hammer's (2001) argument that absolute beliefs are productive with regard to complex and counterintuitive learning contents in introductory physics (e.g., Newton's laws). Moreover, given the strongly formalized structure in hard sciences and the relatively large consensus on what constitutes accepted proofs and theorems (King et al., 1990; Muis et al., 2006), absolute beliefs might also be more *correct* in computer science, especially when compared to soft sciences. We therefore expect computer science students to have higher absolute beliefs than students from "softer" sciences (e.g., psychology). Evidence for this expectation comes from King et al. (1990), who found that students majoring in computer science, applied

¹ We acknowledge that the consistency hypothesis is based on a different theoretical approach than the one of the present article (i.e., on the work by Royce [1978]). Due to its intuitive plausibility and clear theoretical rationale, we nevertheless think that it is worthwhile to further apply its assumptions to Kuhn and Weinstock's (2002) approach.

mathematics, or pure mathematics had stronger absolute beliefs than students from psychology or sociology. Further corresponding evidence can be found in a small-scale qualitative interview study by Whitmire (2003).

In psychology, by contrast, knowledge is structured much more loosely. Concepts often lack a clear definition and many theories are inconsistent, which is why the structure of psychological knowledge is often seen as *ill-defined* (Muis et al., 2006). This requires students and researchers to constantly weigh evidence, critically evaluate theories, and search for moderating factors (Rosman, Mayer, Peter, and Krampen 2016). In contrast to computer science, the nature of psychological knowledge is therefore significantly less absolute. Instead, the argumentation above supports a view of psychological knowledge as having an “evaluativistic” nature, which is why the consistency hypothesis would predict that absolute beliefs impair the acquisition of psychological knowledge and that evaluativism is beneficial. With regard to multiplism, however, matters are more complicated. Even though some might perceive psychological knowledge as “multiplistic” due to its ill-defined structure, multiplism is likely neither *correct* nor *productive* in psychology. First, one cannot reasonably expect that the scientific community espouses a view of psychological knowledge as an accumulation of subjective opinions. Viewing psychological knowledge as multiplistic would thus be *incorrect* in Elby and Hammer’s terms (Elby & Hammer, 2001; Elby et al., 2016). Moreover, high amounts of multiplism are likely to thwart students’ intellectual commitment (Hofer, 2001) since it inclines them to devalue expertise and see all views on an issue to be equally legitimate “opinions” (Hofer & Pintrich, 1997). In line with this, Rosman, Peter, Mayer, and Krampen (2016) have shown that high levels of multiplism impair the development of academic skills in psychology students. Moreover, several studies have shown that multiplism impedes information integration from multiple documents (a common task when dealing with psychological knowledge; Barzilai & Eshet-Alkalai, 2015; Bråten, Ferguson, Strømsø, &

Anmarkrud, 2013; Bråten, Strømsø, & Samuelstuen, 2008). In view of this evidence, multiplistic beliefs do not seem to be *productive* in psychology either. Unfortunately, probably because of the ill-defined knowledge structure in psychology, psychology students nevertheless seem to have rather high discipline-specific multiplistic beliefs, especially when compared to students from “hard” sciences (Green & Hood, 2013; Rowley, Hartley, Betts, & Robinson, 2008). This is why we see it as essential for psychology students to overcome multiplism and to orientate themselves towards evaluativism, so that they can cope with the “evaluativistic” nature of their field by evaluating and weighting different positions to issues.

1.3 Discipline-specific development of epistemic beliefs

In addition to its assumptions about the structure of epistemic beliefs, the TIDE framework also suggests that discipline-specific beliefs are shaped by the instructional environment of the discipline students engage in (Muis et al., 2006). It hardly needs mentioning that this instructional environment varies greatly among different disciplines. For example, undergraduate computer science curricula primarily aim at conveying facts and basic knowledge about central concepts and their interrelations (e.g., on algorithms or software development fundamentals; Association for Computing Machinery & IEEE Computer Society, 2013; Birke, Rosman, & Mayer, 2016). One might therefore suppose that computer science lecturers (and curricula) provide, especially in the first few study semesters, more guidance and practice in solving well-defined problems (Prince et al., 2002; King et al., 1990), so that students learn how to cope with typical study requirements. Over time, this will give the impression that clear and unambiguous answers are omnipresent in computer science, thus strengthening absolute beliefs. As outlined above, such a development is beneficial for learning in terms of the consistency hypothesis since many learning tasks in computer science have a more absolute epistemic nature. Moreover, in light of the absolute knowledge structure in computer science (King et al., 1990), it also implies a development towards more *correct*

beliefs. Due to the well-defined knowledge structure in computer science, we expect multiplistic beliefs, in contrast, to be rather low and stable (e.g., King et al., 1990; Whitmire, 2003).

In contrast to computer science, scientific inquiry and critical thinking are essential learning goals in psychology and in the social sciences (American Psychological Association, 2013; McGovern, Furumoto, Halpern, Kimble, & McKeachie, 1991; Yanchar, Slife, & Warne, 2008). For example, lecturers frequently emphasize the presence of multiple explanations for a phenomenon, and value discussion and social construction of knowledge as tools for learning (Palmer & Marra, 2008). Psychology students thus receive more guidance and practice in working with ill-structured problems. In view of the ill-defined nature of psychological knowledge, they nevertheless also have to cope with significantly *more* ill-structured problems (e.g., contradictory theories and findings) than students from harder disciplines (Muis et al., 2006). Kienhues, Ferguson, and Stahl (2016) as well as Bromme et al. (2008) argue that knowledge about the research methods in a certain discipline influences epistemic thinking. Therefore, the huge number of ill-structured problems will likely pose a significant challenge to psychology freshmen who still lack the necessary methodical competencies to adequately evaluate theories and weigh evidence.

The development of epistemic beliefs in psychology students might thus not be as straightforward as in computer science. In fact, the heterogeneity of findings and theories in introductory courses (for an overview see Gurung et al., 2016) might, together with a lack of knowledge about psychological research methods, lead students to stress the subjectivity of psychological theories as well as findings and become more multiplistic at first (Peter et al., 2016). Upon completion of the first research methods courses, this trend might nevertheless invert. In fact, students then have the tools at hand to “scientifically” evaluate and weigh knowledge claims, thus allowing them to make evaluativistic judgments (Bromme et al.,

2008) and no longer inclining them to endorse multiplistic beliefs. This is in line with prior cross-sectional research suggesting that evaluativism constantly increases from second year to final year psychology students (Karttinen-Koutaniemi & Lindblom-Ylänne, 2012). Such a development towards evaluativism would again, in terms of the consistency hypothesis, be beneficial for learning and thus *productive* (Franco et al., 2012; Muis & Franco, 2010). Moreover, in light of the evaluativistic nature of knowledge in psychology (see above), it would imply a development towards more *correct* beliefs (Elby & Hammer, 2001; Elby et al., 2016). Absolute beliefs, in contrast, are likely to be rather low and stable since it is quite clear that absolute truths do not exist and that a certain amount of subjectivity is inherent in psychology (Rosman, Peter et al., 2016). Even though longitudinal research on the development of epistemic beliefs in higher education is rare, the denoted developmental patterns were found in cross-sectional analyses by Peter et al. (2016). Based on the differences between psychology and computer science outlined above, we suggest the following hypotheses:

Hypothesis 1: Compared to psychology students, computer science students start their studies with higher absolute beliefs (H1a). Compared to computer science students, psychology students start their studies with higher multiplistic beliefs (H1b).

Hypothesis 2: Absolute beliefs of computer science students increase over the first half of their undergraduate studies (H2a), whereas absolute beliefs of psychology students are rather stable (H2b).

Hypothesis 3: Multiplistic beliefs of psychology students follow an inversely U-shaped developmental path: An increase at the beginning of studies is followed by a subsequent decrease (H3a), whereas multiplistic beliefs of computer science students are rather stable (H3b).

2 Method

2.1 Participants and procedure

Hypotheses were investigated with data from a four-wave longitudinal study on knowledge development in psychology and computer science undergraduates (Rosman, Mayer, & Krampen, 2016). The complete dataset including additional variables not analysed for this article can be obtained as Mayer, Rosman, Birke, Gorges, and Krampen (2016) via the research data repository PsychData of the Leibniz Institute for Psychology Information ZPID. In total, $N = 226$ undergraduates participated in the study. All participants were seeking a Bachelor's degree. Psychology students were enrolled at a medium-sized German university that draws on a combination of lectures, seminars, and laboratory courses. The first three semesters include courses in introductory psychology (motivation & emotion, learning and memory), neuropsychology, developmental, differential, and social psychology, as well as in statistics and research methods. Computer science students were enrolled at three different medium-sized German universities and universities of applied sciences. Most content is conveyed in lectures that are complemented by tutorials and exercise sessions. Course topics were, among others, algorithms and data structures, programming, and applied mathematics.

The study approximately spanned across the first half of students' undergraduate curricula. Baseline data were collected at the beginning of participants' first semester, followed by three consecutive data collections at the beginning of the second, third, and fourth semesters, respectively. Participants were recruited by means of flyers and personalized e-mails. Additionally, enrollment lists were investigated to ensure that only psychology and computer science undergraduates would participate in the study. To reduce dropout rates, participants were financially compensated after each wave and compensation was doubled

upon participation in all four waves (i.e., in terms of a one-time bonus payment after the fourth wave).

Even though a large proportion of the data (including demographics and several additional variables) were collected in group sessions in computer labs, most self-report data (including epistemic beliefs) were collected in at-home modules scheduled to take 30 to 60 minutes. In all instances, epistemic beliefs were measured at the beginning of the at-home modules. At the first wave, psychology students ($n = 137$) were 81.8 percent females and were $M = 20.43$ ($SD = 2.53$) years old. Computer science students ($n = 89$) were only 22.5 percent females, and were, with $M = 20.83$ ($SD = 2.96$) years, slightly older than psychology students.

Table 1. Sample sizes at different waves.

| | First wave (t1) | Second wave (t2) | Third wave (t3) | Fourth wave (t4) |
|------------------|-----------------|------------------|-----------------|------------------|
| Total sample | 226 | 194 | 178 | 172 |
| Computer science | 89 | 68 | 62 | 57 |
| Psychology | 137 | 126 | 116 | 115 |

Participants who had missed one of the waves (e.g., second wave) were nevertheless invited to participate in the next wave (e.g., third wave). Only three participants made use of that option. Table 1 shows changes in sample size over the study period. In the total sample, dropout rates were acceptable with 23.9 percent over the study period. In psychology, dropout was rather low with 16.1 percent, whereas it was, with 36.0 percent, considerably higher in computer science. This discrepancy can be explained by computer science students – at least in Germany – abandoning their studies far more often than psychology students (Heublein, Hutzsch, Schreiber, Sommer, & Besuch, 2007). Differences between dropouts and non-dropouts were investigated – separately for psychology and computer science students – by

means of t-tests. In psychology students, no significant differences were found with regard to age, sex (via chi square tests), secondary school GPA, and baseline epistemic beliefs. In computer science students, the analyses revealed that elder students were more likely to belong to the dropout group ($t_{47.56} = 2.32; p < .05$), but no significant differences were found with regard to the other variables. Most importantly, no significant differences between dropouts and non-dropouts were found in epistemic beliefs for both computer science and psychology students ($.43 \leq p \leq .84$). We therefore conclude dropout to have occurred rather unsystematically in both groups.

2.2 Measures

Epistemic beliefs were measured, for each discipline, by two discipline-specific quantitative inventories. Since it allows to measure absolutism and multiplism on separate scales, the so-called *EBI-AM* questionnaire (Peter et al., 2016) was used as a primary measure. The relatively new German language questionnaire is based on established epistemic belief measures (e.g., Hofer, 2000; Schommer, 1990) and contains 23 epistemic statements to be rated on 5-point Likert scales. Variations in the questionnaire's instruction allow accounting for the discipline-specificity of epistemic beliefs (Peter et al., 2016): Computer science students were asked to indicate their agreement to the 23 statements with regard to computer science, whereas psychology students were asked to provide their answers with regard to psychology. As already stated above, one of the questionnaire's main advantages is that it measures absolutism ($k = 12$; e.g., "Truth doesn't change in this subject.") and multiplism ($k = 11$; e.g., "In this subject, only uncertainty appears to be certain.") on separate scales, thus allowing the separate consideration of absolute and multiplistic beliefs. In their 2016 article, Peter and colleagues present both exploratory and confirmatory factor analyses confirming this two-dimensional structure (i.e., absolutism and multiplism). Since the items of the *EBI-AM* are rather heterogeneous (Peter et al., 2016), we chose Guttman's Lambda 6 (λ_6) as

reliability indicator (Revelle, 2016). At the first wave, reliabilities of the absolutism scale were $\lambda_6 = .72$ for psychology and $\lambda_6 = .73$ for computer science students; for the multiplism scale, reliabilities were $\lambda_6 = .72$ for psychology and $\lambda_6 = .79$ for computer science students, respectively.

As a secondary epistemic belief measure, the *CAEB* (Stahl & Bromme, 2007) was employed. The questionnaire uses a semantic differential with adjective pairs of opposing terms, assessing whether participants view knowledge in a certain discipline to be, for example, rather “objective” or “subjective”. In their studies, Stahl and Bromme (2007) found a two-dimensional structure of the inventory: The first dimension (*texture*) encompasses beliefs about the accuracy and structure of knowledge, ranging from beliefs that knowledge would be, e.g., “exact” and “structured” (absolutism) to beliefs that it would be, e.g., “vague” and “unstructured” (multiplism). The second dimension (*variability*), encompasses beliefs about the stability of knowledge, ranging from beliefs that knowledge would be, e.g., “stable” and “inflexible” (absolutism) to beliefs that it would be, e.g., “dynamic” and “flexible” (multiplism). In terms of Kuhn and Weinstock’s model (2002), each dimension thus has an underlying absolute and an underlying multiplistic pole. We therefore suggest low scores on the questionnaire to reflect absolutism and high scores to reflect multiplism (see also Peter et al., 2016). Just like in the EBI-AM, the introduction of the questionnaire was changed, depending on the sample in question, with regard to computer science and psychology (Stahl & Bromme, 2007). At the first wave, reliabilities of the texture dimension were $\alpha = .72$ for psychology and $\alpha = .75$ for computer science students; for the variability dimension, reliabilities were $\alpha = .68$ for psychology and $\alpha = .70$ for computer science students, respectively.

2.3 Statistical Procedures

Hypotheses were tested by multi-group growth models for two parallel processes for continuous outcomes (Muthén & Muthén, 2015) in *Mplus 7*. Separate analyses were conducted for the EBI-AM and the CAEB. Discipline (psychology or computer science) served as grouping variable and parallel processes were changes in absolutism/multiplism (*EBI-AM*) or changes in texture/variability (*CAEB*).

Model development involved three steps (see Table 2): (1) explore if changes in *EBI-AM* and *CAEB* generally differ between disciplines, (2) assess the pattern of change for the *EBI-AM* and the *CAEB* subscales separately (linear vs. quadratic vs. cubic trajectory), (3) specify, based on this assessment, target (i.e., “final”) models for both questionnaires. In this third step, growth factors’ variances were also inspected to investigate whether an inclusion of covariates or control variables might explain additional variance in the target models. The assumed differences in developmental trajectories between psychology and computer science students correspond to models that incorporate discipline-specific trajectories (*EBI-AM_L* respectively *CAEB_L*) showing better model fit than models assuming equal trajectories in both disciplines (*EBI-AM_R* respectively *CAEB_R*). All hypotheses were tested based on the target models (*EBI-AM_T* and *CAEB_T*) by specifying model constraints introducing mean differences of discipline-specific intercepts and growth factors as model parameters.

Table 2. Overview of nested structural equation models.

| Model name | Description |
|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <i>Step 1: Latent intercept and linear slope for all outcomes (EBI-AM: absolutism and multiplism; CAEB: variability and texture).</i> | |
| EBI-AM _{_R} , CAEB _{_R} | Means and (co)variances of latent intercept and slope restricted to be equal across groups. |
| EBI-AM _{_L} , CAEB _{_L} | Means and (co)variances of latent intercept and slope not restricted to be equal across groups. |
| <i>Step 2: Latent intercept and linear slope for all outcomes (EBI-AM: absolutism and multiplism; CAEB: variability and texture). Means and (co)variances not restricted to be equal across groups.</i> | |
| EBI-AM _{_AQM_L} , CAEB _{_VQT_L} | Latent quadratic effects for absolutism (EBI-AM) and variability (CAEB). |
| EBI-AM _{_ALM_Q} , CAEB _{_VLT_Q} | Latent quadratic effects for multiplism (EBI-AM) and texture (CAEB). |
| EBI-AM _{_ACM_L} , CAEB _{_VCT_L} | Latent quadratic and cubic effects for absolutism (EBI-AM) and variability (CAEB). |
| EBI-AM _{_ALM_C} , CAEB _{_VLT_C} | Latent quadratic and cubic effects for multiplism (EBI-AM) and texture (CAEB). |
| <i>Step 3: Target model for EBI-AM/CAEB. Means and (co)variances not restricted to be equal across groups</i> | |
| EBI-AM _{_T} , CAEB _{_T} | Model incorporating all latent effects (linear, quadratic and cubic) whose inclusion resulted in an improved model fit as indicated by significant chi square difference tests comparing nested structural equation models outlined above. |

Note. *Mplus* input files can be found in the online supplement; subscript _{_R} indicates a restricted model; subscript _{_L} indicates a linear slope; subscript _{_Q} indicates a linear and quadratic slope; subscript _{_C} indicates a linear, quadratic and cubic slope; subscript _{_T} indicates target model.

3 Results

The present section begins with the description of our choice of target models (one for the EBI-AM and one for the CAEB). Subsequently, building on the parameter estimates of these target models, results concerning our hypotheses are presented. Figure 1 shows the developmental trajectories of mean epistemic belief scores (EBI-AM and CAEB) across the study period.

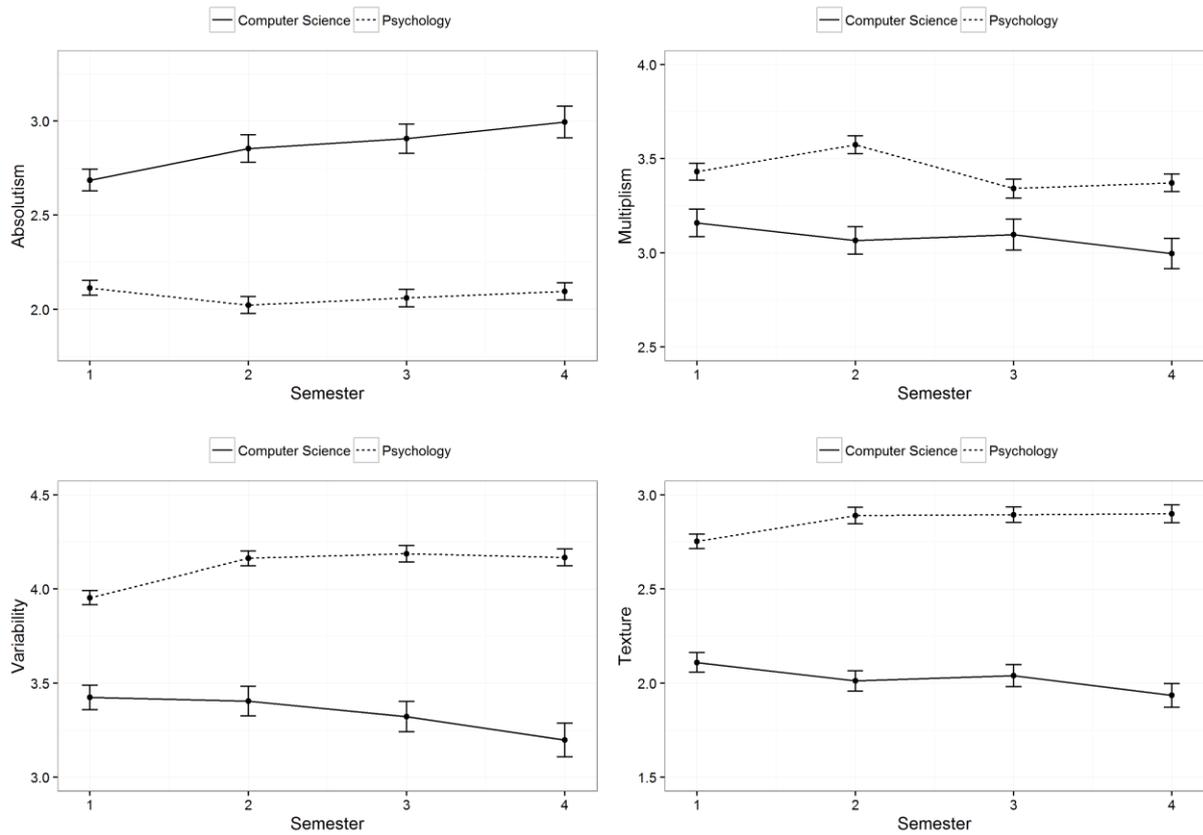


Figure 1. Means and standard errors for both epistemic belief measures (rawdata) across the study period.

3.1 Choice of target models

Using the ML estimator, differences in model fit were assessed by simple chi square difference tests (i.e., without Satorra-Bentler-Correction). Chi square and chi square difference test statistics are given in Table 3 for the EBI-AM and in Table 4 for the CAEB. Model fit was considerably better for models incorporating variation in growth trajectories across disciplines (EBI-AM_L and CAEB_L) than for models assuming equal trajectories (EBI-AM_R and CAEB_R). This was confirmed through chi square difference testing (CAEB_L vs. CAEB_R: $\chi^2(10) = 204.89, df = 10, p < .001$; EBI-AM_L vs. EBI-AM_R: $\chi^2(10) = 134.32, df =$

7, $p < .001$), which indicates that the developmental trajectories of epistemic beliefs indeed differ between the two disciplines.

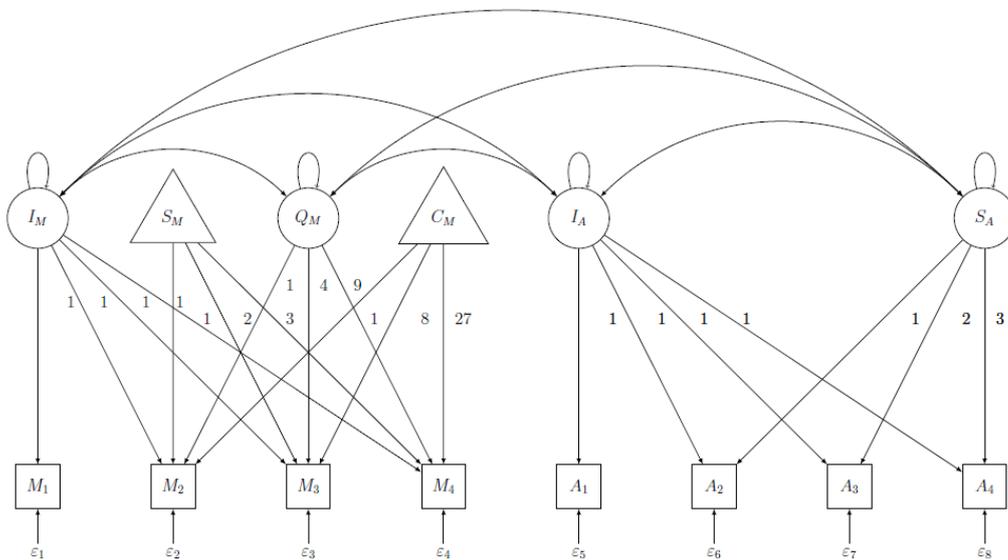
With regard to the EBI-AM, analyses of change patterns revealed a linear trend for absolutism (non-significant difference tests comparing EBI-AM_AQM_L and EBI-AM_AcM_L to EBI-AM_L). Moreover, a quadratic trend combined with a cubic trend was found for multiplism (significant difference test comparing EBI-AM_ALMc to EBI-AM_L [$\Delta\chi^2 = 24.42$, $df = 8$, $p < .01$], whereas no significant “simple” quadratic trend emerged (non-significant difference test comparing EBI-AM_ALMQ to EBI-AM_L). Concerning the CAEB, quadratic trends were found for both *texture* and *variability* (significant difference tests comparing CAEB_L to CAEB_VQT_L [$\chi^2 = 20.13$, $df = 2$, $p < .001$] and to CAEB_VLT_Q [$\chi^2 = 6.21$, $df = 2$, $p < .05$], and non-significant tests regarding cubic trends).

All latent growth factors whose inclusion resulted in an improved model fit were included in the target models (see Figures 2 and 3). For the EBI-AM, model EBI-AM_ALMc is chosen as the target model (EBI-AM_T). For the CAEB, an additional error covariance between *variability* and *texture* in the first measurement wave was included in the respective target model (CAEB_T). Finally, for 15 out of 16 growth factors, variances were too small to be estimated (i.e., model estimation resulted in negative variances or correlations greater one for latent growth factors – so called Heywood Cases) and were thus fixed to zero following suggestions of Dillon, Kumar, and Mulani (1987). This also indicates that growth rates are not affected by student-level covariates (e.g. gender or age) within each discipline. To keep the target models as parsimonious as possible, we therefore did not include any covariates or control variables for both growth factors and latent intercepts. Target models showed very good model fit for the EBI_AM ($\chi^2 = 50.25$, $df = 47$, $p = .346$, CFI = .994, RMSEA = .025) and good model fit for the CAEB ($\chi^2 = 71.11$, $df = 46$, $p = .010$, CFI = .962, RMSEA = .070).

Table 3. Fit indices and model difference tests for the EBI-AM.

| | χ^2 | df | p | CFI | TLI | RMSEA | SRMR |
|------------------------------------------------------------|--------------|-----------|-------------|--------------|--------------|--------------|--------------|
| Step 1 | | | | | | | |
| EBI-AM_R | 208.99 | 62 | <.001 | 0.717 | 0.745 | 0.145 | 0.424 |
| EBI-AM_L | 74.67 | 55 | 0.040 | 0.962 | 0.961 | 0.056 | 0.112 |
| Δ EBI-AM_L vs. EBI-AM_R | 134.32 | 7 | <.001 | | | | |
| Step 2 | | | | | | | |
| EBI-AM_AQM _L | 70.02 | 53 | .059 | 0.967 | 0.965 | 0.053 | 0.111 |
| Δ EBI-AM_AQM _L vs. EBI-AM_L | 4.65 | 2 | .098 | | | | |
| EBI-AM_AcM _L | 69.36 | 51 | .045 | 0.965 | 0.961 | 0.056 | 0.110 |
| Δ EBI-AM_AcM _L vs. EBI-AM_L | 5.31 | 4 | .257 | | | | |
| EBI-AM_A _L M _Q | 69.72 | 49 | .027 | 0.960 | 0.954 | 0.061 | 0.097 |
| Δ EBI-AM_A _L M _Q vs. EBI-AM_L | 4.95 | 6 | .550 | | | | |
| EBI-AM_A_LM_C | 50.25 | 47 | .346 | 0.994 | 0.993 | 0.025 | 0.095 |
| Δ EBI-AM_A _L M _C vs. EBI-AM_L | 24.42 | 8 | .002 | | | | |

Note. Boldface = target model; χ^2 = chi square; df = degrees of freedom.



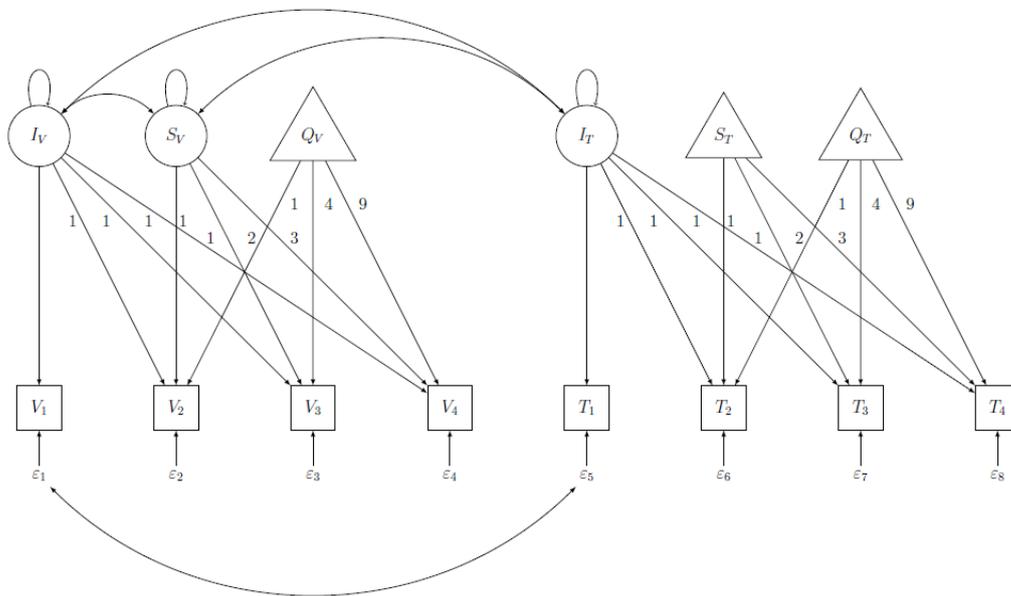
Note: M_1, \dots, M_4 are observed variables for multiplication, where indices 1, ..., 4 indicate study semester. I_M, S_M, Q_M, C_M are growth factors for multiplication where I_M is the latent intercept factor, S_M the slope factor, Q_M the quadratic factor and C_M the cubic factor. Analogously, A_1, \dots, A_4 are observed absolutism variables and I_A and S_A growth factors for absolutism. Growth factors which variances were fixed to zero are depicted as triangles while growth factors with non-zero variances are depicted as latent variables (i.e., circles). Separate models were estimated for *Psychology* and *Computer Science*.

Figure 2. EBI-AM target model.

Table 4. Fit indices and model difference tests for the CAEB.

| | χ^2 | <i>df</i> | <i>p</i> | CFI | TLI | RMSEA | SMRI |
|------------------------------------------------------------------------------------|---------------|-----------|-------------|--------------|--------------|--------------|--------------|
| Step 1 | | | | | | | |
| CAEB_R | 322.80 | 62 | <.001 | 0.609 | 0.647 | 0.193 | 0.911 |
| CAEB_L | 117.90 | 52 | <.001 | 0.901 | 0.894 | 0.106 | 0.119 |
| Δ CAEB_L vs. CAEB_R | 204.89 | 10 | <.001 | | | | |
| Step 2 | | | | | | | |
| CAEB_V _Q T _L | 97.77 | 50 | <.001 | 0.928 | 0.920 | 0.092 | 0.121 |
| Δ CAEB_V _Q T _L vs. CAEB_L | 20.13 | 2 | <.001 | | | | |
| CAEB_V _C T _L | 96.78 | 48 | <.001 | 0.927 | 0.915 | 0.095 | 0.121 |
| Δ CAEB_V _C T _L vs. CAEB_V _Q T _L | 0.99 | 2 | .610 | | | | |
| CAEB_V _L T _Q | 111.69 | 50 | <.001 | 0.907 | 0.896 | 0.104 | 0.121 |
| Δ CAEB_V _L T _Q vs. CAEB_L | 6.21 | 2 | .045 | | | | |
| CAEB_V _L T _C | 108.33 | 48 | <.001 | 0.910 | 0.894 | 0.105 | 0.124 |
| Δ CAEB_V _L T _C vs. CAEB_V _L T _Q | 3.36 | 2 | .186 | | | | |
| CAEB_T | 71.111 | 46 | .010 | 0.962 | 0.954 | 0.070 | 0.129 |

Note. Boldface = target model; χ^2 = chi square; *df* = degrees of freedom; CAEB_T includes an additional error covariance.



Note: V_1, \dots, V_4 are observed variables for variability, where indices 1, ..., 4 indicate study semester. I_V, S_V, Q_V are growth factors for variability where I_V is the latent intercept factor, S_V the slope factor and Q_V the quadratic factor. Analogously, T_1, \dots, T_4 are observed texture variables and I_T, S_T and Q_T growth factors for texture. Growth factors which variances were fixed to zero are depicted as triangles while growth factors with non-zero variances are depicted as latent variables (i.e., circles). Separate models were estimated for *Psychology* and *Computer Science*.

Figure 3. CAEB target model.

3.2 Hypotheses tests

Parameter estimates for both target models are given in Tables 5 and 6. Concerning the EBI-AM, psychology entrants had lower absolute beliefs than computer science entrants, which is indicated by a significant mean difference in intercepts across the two groups ($B = -0.614, p < .001$). Moreover, psychology entrants started with higher multiplistic beliefs than computer science entrants ($B = 0.272, p < .001$; see Table 5). This pattern was corroborated by our findings on the CAEB indicating that computer science students started with higher levels of absolutism than psychology students, both with regard to the variability ($B = 0.542, p < .001$) and the texture dimension ($B = 0.662, p < .001$; see Table 6). Since, on the CAEB, higher absolutism implies lower multiplism, Hypothesis 1 (both H1a and H1b) is fully supported.

Table 5. Parameter estimates for latent intercepts and growth factors for the EBI_AM target model.

| <i>Parameter</i> | Absolute beliefs | | | | | | Multiplistic beliefs | | | | | |
|---------------------------------------|----------------------------------------|-------------|----------|-------------------------|-------------|----------|----------------------------------------|-------------|----------|-------------------------|-------------|----------|
| | <i>Psychology</i> | | | <i>Computer science</i> | | | <i>Psychology</i> | | | <i>Computer science</i> | | |
| | <i>B</i> | <i>(SE)</i> | <i>p</i> | <i>B</i> | <i>(SE)</i> | <i>p</i> | <i>B</i> | <i>(SE)</i> | <i>p</i> | <i>B</i> | <i>(SE)</i> | <i>p</i> |
| Intercept | 2.084 | 0.038 | <.001 | 2.699 | 0.058 | <.001 | 3.430 | 0.047 | <.001 | 3.158 | 0.071 | <.001 |
| Time | -0.003 | 0.017 | .848 | 0.106 | 0.023 | <.001 | 0.536 | 0.123 | <.001 | -0.212 | 0.184 | .251 |
| Time^2 | | | | | | | -0.496 | 0.108 | <.001 | 0.152 | 0.164 | .356 |
| Time^3 | | | | | | | 0.104 | 0.023 | <.001 | -0.033 | 0.037 | .368 |
| <i>Variances</i> | | | | | | | | | | | | |
| Intercept | 0.107 | 0.026 | <.001 | 0.185 | 0.037 | <.001 | 0.151 | 0.027 | <.001 | 0.231 | 0.043 | <.001 |
| Time | 0.014 | 0.006 | .012 | - | - | - | - | - | - | - | - | - |
| Time^2 | | | | | | | 0.001 | 0.001 | .404 | - | - | - |
| Time^3 | | | | | | | - | - | - | - | - | - |
| <i>Mean difference between groups</i> | | | | | | | | | | | | |
| | <i>Psychology vs. computer science</i> | | | | | | <i>Psychology vs. computer science</i> | | | | | |
| Intercept | -0.614 | 0.069 | <.001 | | | | 0.272 | 0.085 | .001 | | | |
| Time | -0.109 | 0.029 | <.001 | | | | 0.748 | 0.222 | .001 | | | |
| Time^2 | | | | | | | -0.648 | 0.197 | .001 | | | |
| Time^3 | | | | | | | 0.136 | 0.043 | .002 | | | |

Note. Time is coded as 0,1,2,3; dashes indicate growth factors with variances fixed to 0.

Table 6. Parameter estimates for latent intercepts and growth factors for the CAEB target model.

| Parameter | Variability | | | | | | Texture | | | | | |
|---------------------------------------|----------------------------------------|-------------|----------|------------------|-------------|----------|----------------------------------------|-------------|----------|------------------|-------------|----------|
| | Psychology | | | Computer science | | | Psychology | | | Computer science | | |
| | <i>B</i> | <i>(SE)</i> | <i>p</i> | <i>B</i> | <i>(SE)</i> | <i>p</i> | <i>B</i> | <i>(SE)</i> | <i>p</i> | <i>B</i> | <i>(SE)</i> | <i>p</i> |
| Intercept | 3.961 | 0.038 | <.001 | 3.419 | 0.066 | <.001 | 2.764 | 0.041 | <.001 | 2.102 | 0.052 | <.001 |
| Time | 0.235 | 0.041 | <.001 | -0.003 | 0.072 | .962 | 0.143 | 0.043 | .001 | -0.045 | 0.061 | .456 |
| Time ² | -0.056 | 0.013 | <.001 | -0.026 | 0.023 | .260 | -0.035 | 0.014 | .012 | -0.001 | 0.019 | .949 |
| <i>Variances</i> | | | | | | | | | | | | |
| Intercept | 0.111 | 0.023 | <.001 | 0.228 | 0.054 | <.001 | 0.131 | 0.020 | <.001 | 0.125 | 0.024 | <.001 |
| Time | 0.008 | 0.004 | .070 | 0.006 | 0.009 | .509 | - | - | - | - | - | - |
| Time ² | - | - | - | - | - | - | - | - | - | - | - | - |
| <i>Mean difference between groups</i> | <i>Psychology vs. computer science</i> | | | | | | <i>Psychology vs. computer science</i> | | | | | |
| Intercept | 0.542 | 0.076 | <.001 | | | | 0.662 | 0.067 | <.001 | | | |
| Time | 0.238 | 0.083 | .004 | | | | 0.188 | 0.075 | .012 | | | |
| Time ² | -0.030 | 0.026 | .251 | | | | -0.034 | 0.023 | .151 | | | |

Note. Time is coded as 0,1,2,3; dashes indicate growth factors with variances fixed to 0.

Concerning Hypothesis 2, a significant increase in absolute beliefs was found on the EBI-AM with regard to computer science ($B = 0.106, p < .001$). In contrast, absolutism did not change significantly in psychology. The mean difference in absolutism slopes between the two groups was significant ($p < .001$; see Table 5). Concerning our secondary epistemic belief measure, no significant changes on the CAEB were found in computer science students. Hypothesis 2 (both H2a and H2b) is thus supported with regard to the EBI-AM.

Finally, testing Hypothesis 3, a significant linear increase ($B = 0.536, p < .001$) combined with a negative quadratic effect ($B = -0.496, p < .001$) and a positive cubic effect ($B = 0.104, p < .001$) of multiplism was found in psychology. The negative quadratic effect indicates that in psychology students, multiplistic beliefs first increase and then decrease. The positive cubic effect, however, works against this decrease, eventually creating positive acceleration for a second time (Hoffman, 2015). All these effects were non-significant in computer science and all mean group differences in growth factors were significant (all $p < .01$; see Table 5). With regard to the CAEB, linear slopes were positive and significant (variability: $B = 0.235, p < .001$; texture: $B = 0.143, p < .01$), and quadratic slopes were negative and significant (variability: $B = -0.056, p < .001$; texture: $B = -0.035, p < .05$). This suggests that multiplism (i.e., a view of psychological knowledge as variable and unstructured) first increases in psychology students but subsequently decreases. All these effects were non-significant in computer science (all $p < .01$; see Table 5). In sum, Hypothesis 3 (H3a and H3b) is confirmed for the CAEB and partially confirmed for the EBI-AM because a significant cubic trend was not expected.

4 Discussion

Longitudinal studies have a long tradition in epistemic beliefs research. Many “classic” approaches (e.g., Baxter Magolda, 1992; Perry, 1970; Schommer, 1993) primarily relied on longitudinal data to support their claims. In contrast, longitudinal studies on the development of epistemic beliefs across different academic disciplines have – to our knowledge – not been conducted yet. This is striking since many cross-sectional studies found discipline-specific differences in epistemic beliefs, but, due to their cross-sectional nature, do not allow straightening out how such discipline-specific belief patterns evolve in the long term. Our work thus significantly adds to the literature by contrasting differences in the development of epistemic beliefs in computer science (a so-called “hard” discipline) and psychology (a so-called “soft” discipline) over the first three semesters of the respective undergraduate curriculum.

4.1 Epistemic beliefs in computer science

A first finding is that on both epistemic beliefs inventories (EBI-AM and CAEB), computer science students had significantly higher absolute beliefs and significantly lower multiplistic beliefs than psychology students. Such findings are in line with cross-sectional findings that absolute beliefs are more prevalent in “hard” disciplines whereas multiplistic or evaluativistic beliefs dominate in “soft” disciplines (for a review of studies see Muis et al., 2006).

However, the focus of the current study was not cross-sectional, but longitudinal. With regard to computer science, we expected absolute beliefs to increase over time because higher absolute beliefs are likely to be *correct* and *productive* (cf. Elby & Hammer, 2001; Elby et al., 2016) in this field. On the EBI-AM, absolute beliefs indeed increased over computer science students’ first three semesters. On the CAEB, however, no significant effects were found. This

might be due to the CAEB – our secondary measure – being only partially suited to investigate Hypotheses 2 and 3. In fact, due to the measures' bipolar structure, a decrease in multiplism would be equivalent to an increase in absolutism and vice-versa. Since we expected multiplism to be rather stable in computer science, changes in absolutism conflict with the presumed invariance of multiplism, thus reducing the likelihood of corresponding findings.

From a theoretical standpoint, our findings on the EBI-AM are incompatible with almost all current epistemic belief frameworks (e.g., Hofer & Pintrich [1997] as well as Kuhn & Weinstock [2002], just to name two of the most influential ones). In fact, all these frameworks posit a development from absolute towards more relativist or constructivist beliefs as functional, and only recently, the field has begun to question this on a conceptual level (e.g., Bromme et al., 2010). Our study adds to this literature by empirically justifying that, depending on the disciplinary context, a development towards absolutism is not only possible, but even likely.

At least with regard to the beginning of the undergraduate computer science curriculum, we see this development as beneficial for learning. In fact, growing consistency between an individual's beliefs and the epistemic nature of learning tasks will, in terms of the consistency hypothesis, lead to better learning regarding these tasks (Muis & Franco, 2010). Due to the high levels of abstraction and the high complexity of knowledge in computer science, relying on experts and acknowledging that many theories are indeed *proven* mathematically might lead to learners becoming more persistent in their learning. This is in line with Elby and colleagues' argument that absolute beliefs are productive with regard to complex and counterintuitive learning contents in introductory physics (e.g., Newton's laws; Elby & Hammer, 2001; Elby et al., 2016). Nevertheless, one might question if absolute beliefs remain productive towards the end of the undergraduate curriculum and especially in the

graduate (Master) curriculum. For example, writing a thesis or a dissertation usually requires an integration of multiple viewpoints, and a student with high absolute beliefs might have trouble in this respect (Bråten, Britt, Strømsø, & Rouet, 2011; Elby & Hammer, 2001). Moreover, the *application* of knowledge acquired during the first semesters (i.e., the general concepts) becomes increasingly important towards the end of undergraduate computer science curricula (Association for Computing Machinery & IEEE Computer Society, 2013). Many of such more “practical” problems (e.g., developing a certain computer program) nevertheless allow for multiple approaches that have to be evaluated and weighted with regard to their specific context. Absolute beliefs might therefore not be that helpful after all when it comes to knowledge application. Future longitudinal research should straighten out whether the increase in absolute beliefs continues towards the end of the undergraduate curriculum, and, if so, inspect the influence of such a development on learning and achievement.

On a more general level – and issuing caution since generalizing from our findings onto other disciplines might be problematic – we suggest the following implications for practice: If a certain claim represents a (more or less) absolute truth (e.g., can be proven mathematically), lecturers should acknowledge this and present it accordingly. Moreover, when dealing with complex and counterintuitive learning contents, lecturers should encourage students to rely on their textbooks and the explanations presented therein, and not try to figure out issues all by themselves (i.e., through their own thinking). Obviously, absolute truths are more frequent in disciplines where claims are primarily justified by deductive logic and mathematical proofs (King et al., 1990), but these implications might also apply to established theories and findings in “softer” disciplines (e.g., on the effectiveness of systematic desensitization in the treatment of arachnophobia).

4.2 Epistemic beliefs in psychology

With regard to psychology, we expected absolute beliefs to be low but rather stable. This was, even though not particularly surprising, supported by our data. In fact, it is hard to deny that in psychology, absolute truths are rare and most claims cannot be justified by mathematical proofs. We expected that psychology students would already have realized this at study entrance, and that this belief type would not change much throughout the psychology curriculum. Our data confirmed this expectation. Regarding the second stage of Kuhn and Weinstock's (2002) model, we expected multiplistic beliefs to follow an inversely U-shaped developmental path over the first half of the undergraduate psychology curriculum. This expectation is based on the idea that high multiplism is neither correct nor productive in psychology, and that psychology lecturers should strive to reduce their students' multiplism (see also Rosman, Peter et al., 2016). Research skills are pivotal in reducing multiplism since they allow students to weigh and evaluate knowledge claims (Bromme et al., 2008). Nevertheless, acquiring research skills takes time, which is why we expected an initial increase in multiplism followed by a subsequent decrease. This was supported with regard to both the EBI-AM and the CAEB. Even though a model including a cubical trend fit the data better than a model including only a quadratic trend (which would best describe an inversely U-shaped trajectory), our data clearly show that an initial increase in multiplism is followed by a steep decrease over the second semester. Over the third semester, however, not much change in multiplism could be observed. Future research should clarify to what extent and in which direction multiplistic beliefs develop after the beginning of students' fourth semester.

In terms of Kuhn and Weinstocks (2002) model, such a development (low and steady absolutism, inversely U-shaped trajectory of multiplism) might indicate a shift from multiplism towards evaluativism sometime after study entrance. This is in line with Peter et al. (2016) arguing that low scores on both their scales (absolutism and multiplism) reflect

evaluativism, and with the results of Kaartinen-Koutaniemi and Lindblom-Ylänne (2012) who showed that evaluativism steadily increases in psychology students after their second year of studies. Considering that our results on psychology students support and those on computer science students contradict contemporary epistemic belief frameworks (e.g., Hofer & Pintrich, 1997; Kuhn & Weinstock, 2002), we are inclined to conclude that such frameworks probably work best in soft disciplines, but may have to be revised with regard to the hard sciences. In our opinion, the consistency hypothesis (Muis & Franco, 2010) constitutes an ideal starting point for such efforts since it explicitly accounts for the epistemic nature of learning contents.

As for practical implications, we consider it important to buffer the initial increase in multiplism in psychology students since it might reduce students' intellectual commitment towards their discipline (Hofer, 2001), and also have detrimental effects on their study satisfaction. Interventions on an explicit reduction of multiplism are rare. In a recent study, Rosman, Mayer et al. (2016) combined discussions of scientific controversies with instruction on how to resolve such conflicts (e.g., through the evaluation of evidence quality). Their results showed that reducing multiplism in first-semester psychology undergraduates is indeed possible. Therefore, we suggest that lecturers include such techniques in their courses. Earlier and more focused research methods and information literacy instruction might also be helpful since it allows students to develop skills to evaluate evidence and justify knowledge claims (Bromme et al., 2008). Nevertheless, our data also show that the increase in multiplism over the first semester is followed by a subsequent decrease. In sum, we therefore interpret the epistemic belief changes in psychology students over the first half of their undergraduate curriculum as desirable, both regarding the *productivity* and the *correctness* of their beliefs. This is especially true considering Peter et al.'s (2016) assumption that lower scores on both EBI-AM scales reflect evaluativism, which is doubtlessly the most advanced stance in the humanities and social sciences (Palmer & Marra, 2008).

4.3 Conclusions, limitations, and future directions

Cross-sectional research has long established that the discipline-specific context strongly influences epistemic beliefs (e.g., Muis et al., 2006). As our results show, this context also plays a pivotal role in the longitudinal development of epistemic beliefs. Our findings thus provide support for Muis et al.'s (2006; 2015) TIDE framework, which suggests discipline-specific beliefs to be socially constructed and bound to the instructional environment (i.e., the context) students engage in (Muis et al., 2006). Obviously, different instructional environments will lead to different developmental paths, and even though – up to now – this has not been examined longitudinally yet, our results provide ample evidence for an influence of discipline-specific factors on the development of epistemic beliefs. Apart from transferring our findings to other disciplines, future research should therefore investigate predictors and consequences of such developments. For example, future longitudinal studies spanning over a complete undergraduate curriculum (i.e., 3 years minimum) might examine relationships between developmental patterns and grade point average or Bachelor thesis results.

We concede that our approach has some limitations. First and foremost, our a priori assumptions on the nature of knowledge in the two disciplines (e.g., well-defined vs. ill-defined) are solely based on reviews of the literature, not on actual empirical data. Alternative explanations for the denoted developmental trajectories are therefore possible. For example, specific courses, teachers, or teaching practices that we are not aware of might have caused the changes, and not our more general assumptions about discipline-specific properties. While this is not as severe in computer science (where data were collected at three different institutions), it is a significant limitation with regard to psychology (where conclusions are based on students from the same semester at one single university). Further research is clearly needed, especially since teachers might also differ in their demands for a certain type of

epistemic thinking. For example, absolute beliefs might well be productive when a teacher requires psychology students to learn everything by heart in order to pass the final test. In some cases, this might even lead to a situation of students having to adopt beliefs that are harmful in the long term just to “survive” a specific course.

Secondly, discipline-specific differences in students’ psychological characteristics (e.g., personality or motivation) might have affected our findings. What speaks in favor of the discipline itself being primarily responsible for epistemic belief *changes* is that growth curves were homogenous and thus unaffected by student-level covariates (e.g., gender or age) within each discipline. This however does not rule out that such covariates might have biased our cross-sectional results (Hypothesis 1). Future research should investigate the issue.

A third limitation concerns our conceptualizations of the concepts in question. Both psychology and computer science are composed of a multitude of topics that differ, sometimes considerably, in their epistemic nature. Furthermore, many have advocated for a more fine-grained investigation of epistemic beliefs (i.e., on the different facets of Hofer and Pintrich’s [1997] *justification* dimension). One might therefore criticize our rather broad approaches concerning the measurement of epistemic beliefs and the properties of the disciplines in question. We nevertheless think that a too narrow view on the concepts in question limits the generalizability of findings and, ultimately, the practical usefulness of the resulting research. Since longitudinal studies require a considerable amount of time and effort, we therefore think that our rather broad approach is justified.

A fourth and final limitation concerns our approach to measuring epistemic beliefs. Firstly, our sample size (especially with regard to computer science students) did not allow conducting factor analyses, which is why we relied on the respective analyses by Peter et al. (2016) respectively Stahl and Bromme (2007). Moreover, neither the EBI-AM nor the CAEB

directly assess evaluativism, and even though Peter et al. (2016) present a “workaround” by suggesting low scores on both scales as an indicator for evaluativism, a direct assessment would be preferable. Furthermore, some scale reliabilities were on the lower bound of what is generally considered acceptable. This might be due to the multifaceted nature of the scales and the abstract nature of the concepts in question (DeBacker, Crowson, Beesley, Thoma, & Hestevold, 2008). Finally, in line with Greene and Yu (2014), future research might also try to complement quantitative analyses by in-depth interviews or open-ended questions.

Based on our results, we infer that a conceptualization of epistemic “sophistication” as a flexible adaptation of epistemic judgments to contexts (Bromme et al., 2008) might provide more insights than the idea of a fixed developmental sequence. Such a view is in line with Muis’ consistency hypothesis: If students align their epistemic thinking with the knowledge structure of a certain discipline, they will become better learners (Muis & Franco, 2010). We suggest that future research concentrates on refining and validating these ideas.

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